COMPUTATIONAL MODELS AND FRAMEWORK FOR AUTOMATIC PREDICTION OF WEB PAGE AESTHETICS

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COMPUTATIONAL MODELS AND FRAMEWORK FOR AUTOMATIC PREDICTION OF WEB PAGE AESTHETICS

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DOCTOR OF PHILOSOPHY

by

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under the supervision of

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DECLARATION

I certify that

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b. the work has not been submitted to any other Institute for any degree or diploma.

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This is to certify that the thesis entitled Computational Models and Framework for Automatic Prediction of Web Page Aesthetics, submitted by **Ranjan Maity** to Indian Institute of Technology, Guwahati, is a record of bona fide research work under my supervision and is worthy of consideration for the award of the degree of Doctor of Philosophy of the Institute.

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Dedicated to my beloved father and brother

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Abstract

The acceptability, and consequently, the usability of web pages depend on its aesthetic quality to a significant extent. Determining aesthetic of a web page is a complex task due to its qualitative aspect. Computational models can predict aesthetics during the development of a web page. The reported models found in the literature compute aesthetics either by the positional geometry of the web page elements or by their contents. Web page contents are broadly of three types – text, image, and white spaces. However, the existing content-based models were mostly developed by considering web pages as images. We have not found any computational model to predict the aesthetics of the other two types of contents – text and white space. Also, no model has been proposed by combining the web page elements and their positional geometry till date. In this thesis, we propose a framework for the computation of web page aesthetic. In order to design the proposed framework, seven computational models have been developed.

We first proposed a computational aesthetic model based on the positional geometry of the web page elements. Thereafter, models for the three primary types of web page elements – text, image, and white space, are designed. The text model is suitable for predicting the aesthetics of the onscreen text elements found in the web pages. It has been observed that the images present on a web page can be of two types – artificial and photographic. Therefore, two computational models have been developed to model the aesthetics of these two categories of images. Another computational model was developed for aesthetic computation of white spaces. We also proposed a model by combining the models of the text, image and white spaces, which we named the *Combined Contents Model* (CCM). The CCM acts as the computational model of web page aesthetics based on the contents of the web page. We further integrated the CCM with the model based on the positional geometry to propose a new model - *Combined Wireframe-Contents Model* (*CWCM*). As the name indicates, the CWCM serves as the model to compute aesthetics taking into account both the web page contents as well as their geometric arrangements.

The proposed CWCM, positional geometry model, text model and the two models of image aesthetics have been developed using a machine learning approach known as the Support Vector Regression (SVR). On the other hand, the CCM uses a weighted average of the aesthetic values predicted by its constituent models, where the weights are determined by the areas occupied by the individual content types. We used empirical data to build and validate the models. Altogether, ten empirical studies have been conducted to collect data. The cumulative duration of these studies were almost six months, spread over approximately two years of time. The minimum and maximum durations of these studies were three days and thirty five days, respectively. A total of nine hundred and thirty eight participants, covering different age groups, genders, educational qualifications and cultures took part in those studies.

The validation results show that the CWCM outperforms the model of positional geometry, as well as the CCM. It has also been observed that all our proposed models are capable of predicting aesthetics with high accuracies from 86.67% to 93.75%. The high prediction accuracies indicate the suitability and applicability of the proposed models and framework for the design and development of web pages.

Keywords: web page aesthetics, computational model, empirical study, wireframe model, text aesthetics, image aesthetics, hypothesis testing, Support Vector Regression, ANOVA.

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Introduction

1.1 Aesthetics and HCI

Advancement of the modern technology has resulted in electronic devices such as the desktops, laptops, and i-pads to become as an essential part of our daily life. These devices are generally interacted with using the Graphical User Interfaces (GUI). Due to the widespread applications of GUI, its design has become a vital issue for the Human-Computer-Interaction (HCI) researchers. A well-designed interface generally entices the users of it, whereas, a poorly designed interface may not be a choice of use. It has been reported [Galitz, 1997] that if an inefficient interface takes ten more seconds to interact and there are 4.8 million screens in the world, then approximately 7.1 person-year is required to communicate with those interfaces. It has also been observed [Cope and Uliano, 1995] that one graphical window, redesigned to be more effective, can save twenty thousand dollars of a company during the first year of use.

Good interface design requires knowledge about people: how they see, understand and think. *Usability* is the standard metric to judge an interface. It was reported that every dollar invested in *usability* returns ten to one hundred dollars [IBM, 2001]. In early 1980, the term *usability* was used to describe the *effectiveness* of human performance. In those days, *usability* was primarily measured by the *task completion time*; means how quickly a user can carry out a task. For example, a user is searching for some item in an interface, the *search time* was treated as the task completion time. Later in 1991, usability was reported in [Shackel and Richardson, 1991] as "the capability to be used by humans easily and effectively, where easily = to a specified level of subjective assessment, effectively = to a specified level of human performance." Nielsen [1995] reported usability could be defined by the five components enlisted below –

- ***Learnability:*** How easily a first time user can carry out a task?
- ***Efficiency:*** After the learning, how quickly a user can complete a task?

- ***Memorability:*** When a user wants to use a design after a long period of not using it, how easily he/she can restore proficiency?

- ***Errors:*** When using a system, how many errors an user encounter, and how easily he/she can recover from those errors?

- ***Satisfaction:*** How pleasant to use a design?

Satisfaction depends on how an interface can cater to its users' need – which is subjective in nature. Satisfaction is also associated with how the information on an interface is visually presented or the *aesthetics* of the interface. According to the Oxford dictionary [Oxford dictionary], aesthetics is "concerned with beauty and art and the understanding of beautiful things." Tractinsky reported [1997] about the vital role of aesthetics for determining the usability of an interface. However, they observed a wrong tendency among the HCI researchers not to emphasize the aesthetics, due to the misconception that it may reduce usability - "others while acknowledging the role of aesthetics in HCI, warn against a tendency among designers to emphasize the aesthetic elements of the user interface, because these might degrade usability." As a consequence, interface designers often ignored the role of the visual aesthetics up to late 1990.

In recent times, studies have shown the importance of aesthetics in shaping the overall user experience of an interactive system [Bartelsen et al., 2004; Norman, 2004 a; Norman, 2004 b; Petersen et al., 2008; Tractinsky et al., 2000; Tractinsky, 2005 and Tractinsky and Hassenzhal, 2005]. It is argued that aesthetically designed interfaces increase users' efficiency and decrease perceived interface complexity, which in turn help in improving usability, productivity and acceptability of the system [Tractinsky 1997 and Ngo and Byrne 2001]. The same philosophy is also applicable for web page design. Most of the web pages contain various types of information, put together using multiple design patterns. As a result, the complexity of the web pages in terms of information content and layout is usually high. Evidently, aesthetics of the design determines a great extent to its acceptability (and therefore, usability).

In order to illustrate the effect of aesthetics, two web pages are shown in Figure 1.1. It may be noted that the web page displayed in Figure 1.1 (a) was designed by using a large number of unorganized objects in the layout without following the grid-like structure - generally adopted in developing a web page [grid based design]. As a consequence, the aesthetic appeal of the interface may reduce. In contrast, Figure 1(b) shows the home page of Apple MacBook, which follows the grid-like structure and have less number of objects. The Apple MacBook web page received the Webby award [WAward] as one of the aesthetically pleasing web pages. Subsequently, it may be claimed that the design of an aesthetically pleasing web page has become a vital topic of research.

Over the last twenty years, a number of works were reported to judge the qualitative aspect of aesthetics. Among the different techniques of aesthetic measurement, computational models have the capabilities to predict the aesthetics of a web page. However, there are different opinions among the researchers on how these models could be built. Few of them believed aesthetics depend on the positional geometry of the web page objects, while the others found that the contents of those objects were important for aesthetics judgment. Again, most of the researchers in the second group, computed aesthetics by treating web pages as images. However, there are other components like – icon, link, text, tab, table, button, video, and white space often found in a web page. Unfortunately, we did not find any computational model to predict the aesthetics of these components. We do believe that both the positional geometry of the web page objects, as well as its content can determine the aesthetics of a web page. With the best of our knowledge, no such work on aesthetics computation is reported till date. Hence, there is a necessity to develop a computational model of web page aesthetics by considering both the contents and the positional geometry of the web page objects.

(a)

(b)

Figure 1.1: (a) unorganized web page (b) Webby awarded web page for best visual design.

1.2 Aesthetics Measurement of Web page

Impact of the web pages aesthetics changes with time. Sonderegger et al. [2012] reported that the effect of aesthetics almost disappeared after the initial phase of use. So, the initial impression is primarily responsible for determining the aesthetics of a web page. In other words, a first time user of an aesthetically pleasing web page has more chance to use it in future. Therefore, determining the aesthetics of a new web page is vital to determine its usability.

There is a famous statement – "***Beauty is in the eye of the beholder.***" In another word, we can say perceived beauty (aesthetics) measurement is a subjective task, due to the variations in the users' age, geographical location, and culture. As a consequence, measuring aesthetics is a challenging task for the web page designers. Although it is difficult, but not impossible to measure the aesthetics of a web page. Over the years, researchers came up with different solutions to measure aesthetics, which can be broadly categorized into the following three types.

a) Set of guidelines **–** Creating a set of guidelines by keeping the aesthetic as a key concern is one of them. During the design process, a web page designer can adhere to a set of guidelines. "Aesthetic and minimalist design" was one of the ten guidelines proposed by Nielsen [1995]. Galitz [1997] reported a set of factors affecting aesthetics, and guidelines to improve the overall aesthetics of an interface. Another set of guidelines for creating text components in a web page was reported in [Web page guidelines]. A detailed discussion of these works is reported in Section 2 of Chapter 2.

Designing a web page by considering the guidelines appears to be a simple task. However, designers either have to remember or check the guidelines during the development of a web page. It is difficult for the designers to remember the guidelines if the numbers of guidelines are large. The only option to cope up this situation is rechecking the guidelines, which needs extra time as an overhead. As a consequence, the web page development process may be delayed.

b) Empirical Evaluation **–** Another technique of aesthetics measurement is the use of empirical evaluation. Kurosu and Kashimura [1995] reported that usability has a strong relation with aesthetics among the Japanese people. The same observation was later asserted by Tractinsky [1997] for the Israelis. Based on an empirical study, Park et al. [2004] reported three factors – *reliability*, *variability* and *appropriateness*, which are associated with the web page aesthetics. Strong correlations of the three design factors – interestingness, complexity, and pleasingness (aesthetics) were reported by Pandir and Knight [2006]. Schmidt et al. [2009] found ten clusters that can affect the usability of a web page. Aesthetics – termed as "appeal", was reported as one of the ten clusters. Three design factors - *symmetry*, *balance* and *equilibrium* were used by Zheng et al. [2009] to characterize a design by means of an empirical study. Using empirical evaluation, Lai et al. [2010] reported that *balance* is responsible for determining aesthetics, whereas aesthetics has no such correlation with the *symmetry*. However, determining aesthetics using empirical evaluation may not be always feasible as it entails additional time and manpower during the design process.

From the above discussion, it is evident that both the techniques (set of guidelines and empirical evaluation) of the aesthetics measurement impose additional overhead for aesthetics measurement, which can slow down the design process. More importantly, both the techniques are unable to predict the aesthetics of a new web page during the development period.

c) Computational Models – The other way of aesthetic measurement is through the use of computational models (using quantitative measures). These kinds of models can assess the aesthetics of a whole web page as well as parts of it. The main advantage of a computational model is the ability to predict web page aesthetics *automatically*, thereby making it possible to integrate the model as a tool in a design environment. This may help the designers to check the aesthetics of their design quickly. As a result, such automation also helps to automate the design process itself, with its obvious implications for interactive engineering systems.

A number of such models were proposed over the last few years. All of them can broadly be categorized into two types – wireframe based and content based, as shown in Figure 1.2 and discussed below.

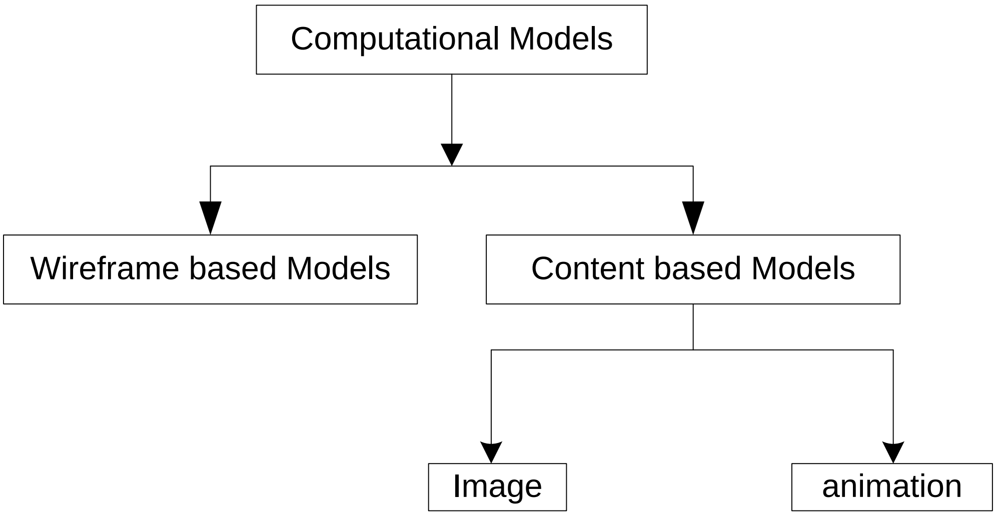


Figure 1.2: Different computational models found in the literature.

a) Wireframe based Models – A set of rectangular objects can represent a web page [Ngo et al., 2003]. All the elements of a web page are treated as the contents of these rectangular objects. An example of such representation is shown in Figure 1.3. Figure 1.3 (a) shows the SoundCloud web page, while Figure 1.3 (b) depicts the corresponding wireframe representation of the SoundCloud. The "search box" and "create account" of Figure 1.3 (a) are linked by the arrows, as shown in Figure 1.3 (b). Similarly, all the other contents are represented using the rectangular objects. It may be noted that the web page is represented by using rectangular objects only, whereas the contents are not considered. Representing a web page with the help of these objects is termed as the wireframe model. A group of researchers believed that the positions and the sizes of those rectangular objects are primarily responsible for determining the aesthetics of a web page.

Many works on the computational models of web page aesthetics based on the wireframe geometry were reported till date. Among them, Ngo et al. [2003] proposed a model by considering thirteen features of wireframe geometry. Later, Zain et al. [2008] developed another model by considering five out of the thirteen features. Altaboli and Lin [2011] reported another model by using three out of the thirteen features. The details of these types of works are reported in Chapter 2, Section 2.4.1 of this thesis.

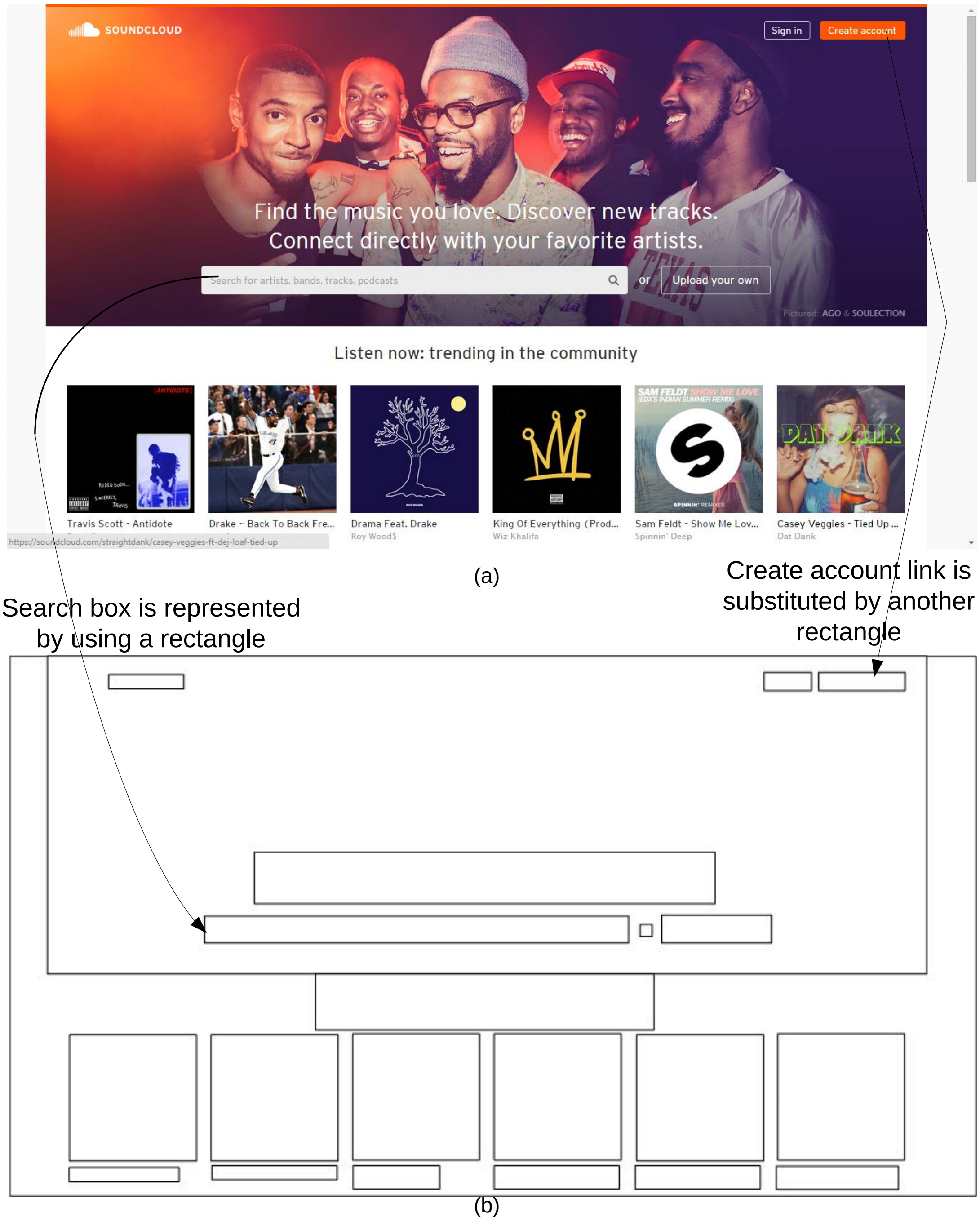


Figure 1.3: (a) Web page of Soundcloud[1] and (b) wireframe representation of it.

b) Content-based Models – Except the computational model of wireframe geometry, aesthetics of a web page can also be computed by developing a computational model of the contents present in a web page. The reported works in this category, found in the literature, can be classified into two types – image and short animation as shown in Figure 1.2 and discussed below.

[1] https://soundcloud.com/

- Image: In any web page, images contain a significant portion of its layout. As an example, the home page of National Geographic, containing two image components is shown in Figure 1.4. The two images are labeled by Image 1 and Image 2. Even a whole web page can be treated as a single image. Most of the reported works found in literature consider image representation of web page [Datta et al. 2006, Reinecke et al. 2013, Lai et al. 2010, and Miniukovich and Angeli 2015] to develop computational models for web page aesthetics. As a result, these models were developed by considering the image related features only.

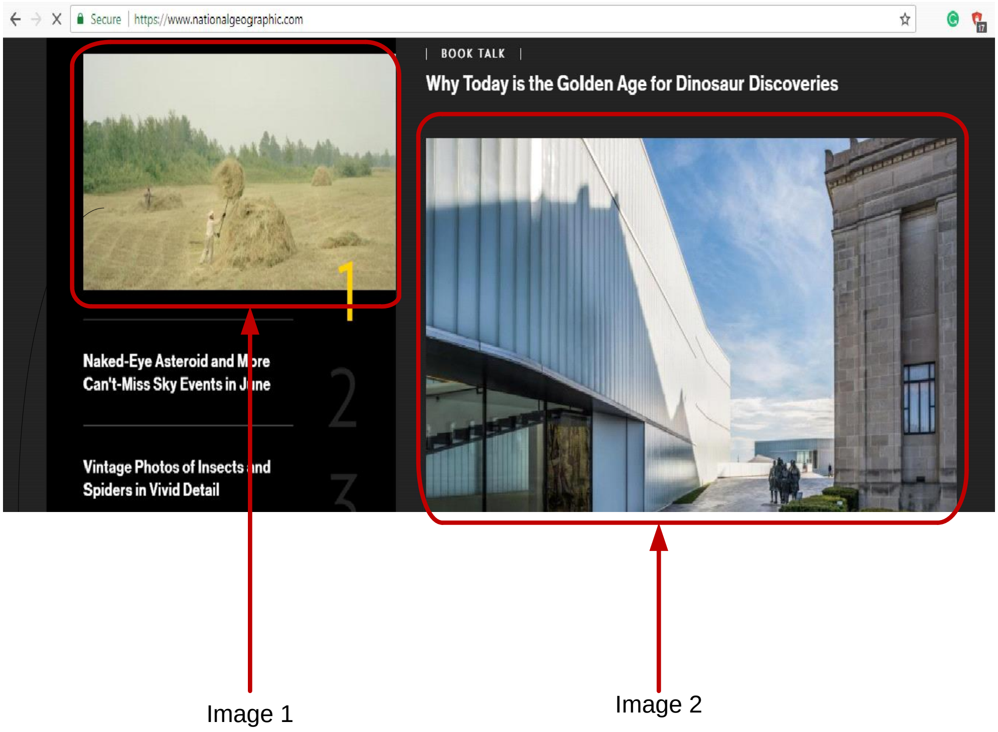


Figure 1.4: Homepage of the National Geographic, the two image components are marked and pointed by Image 1 and Image 2.

- Short animations: Short animations is another component, often present in a web page. Figure 1.5 shows the web page of The Assam Tribune newspaper[2], which contains three short animations marked as animation1, animation2, and animation3 in the Figure 1.5. The only work of aesthetics computation for such short animations present in a web page was reported by Bansal and Bhattacharya [2013].

[2] http://www.assamtribune.com/scripts/detailsnew.asp?id=jun0518

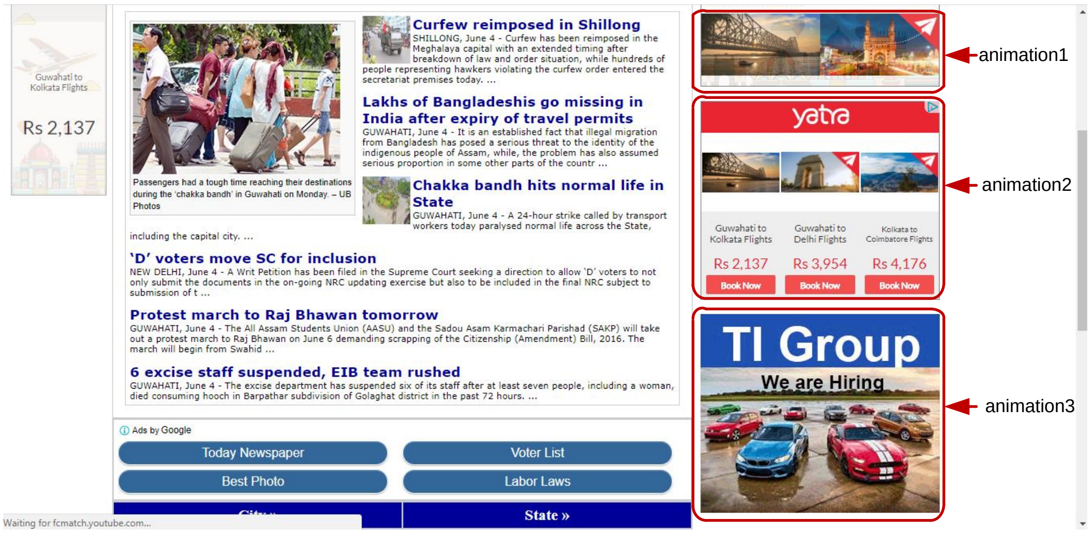


Figure 1.5: The three short animation components marked as animation1, animation2, and animation3 of the Assam Tribune web page[3].

Except the two components – image and short animation, a web page may have other elements, as discussed in the following section.

1.3 Components of a Web page

A web page is composed of different elements – image, text, video, short animation, icon, button, link, table, tab and search box. Apart from the image, table, video and short animations, the other web page components are shown in Figure 1.6, which is a snapshot of the ticket booking web page of the Indian Rail Tourism and Catering Ltd. (*irctc*). There are web pages like *youtube* which contains video, as shown in Figure 1.7. An example of a web page having a table within it is presented in Figure 1.8. The image and short animation components are already shown in Figure 1.4 and Figure 1.5 respectively. The different elements found in a web page along with their purpose are enlisted in Table 1.1.

[3] http://www.assamtribune.com /scripts/detailsnew.asp?id=jun0518

Table 1.1: List of components in a web page along with their objectives.

Component	Objectives
Image	An integral part of a web page, used to represent the information of a web page using pictorial form.
Text	All most every web page is composed of the text elements. There are web pages like Wikipedia, which are enriched with texts.
Icon	They are typically small in size (can be easily touched by a finger) and save space. However, an icon sometimes associated with a text label to clarify the meaning of it.
Video	Short animations or videos may be another component present in a web page. An example of such a web page –*youtube* is reported in Figure 1.7; a directed edge marks the video component of the web page.
Button	These are often used to submit data to a web page.
Tables	Tables are used to represent the relational data of a web page.
Tab	Tabs are often found in a web page for navigating from one web page to other as shown in Figure 1.6.
Search box	These are used to search for some information on a web page. For example, the search box marked by a directed edge in Figure 1.6 is used to search station name.
Link	Links are often used in a web page to link with the other web pages. An example of such link found in Indian Rail Catering and Tourism Corporation Limited (*irctc*) is shown in Figure 1.6. Among the several links present in the web page, the link "Cancel Ticket" is marked by a directed edge.
Short animation	These are often used for advertising and entertainment on a web page.
White space	It is another vital component of a web page which helps users to distinguish the different objects present within it.

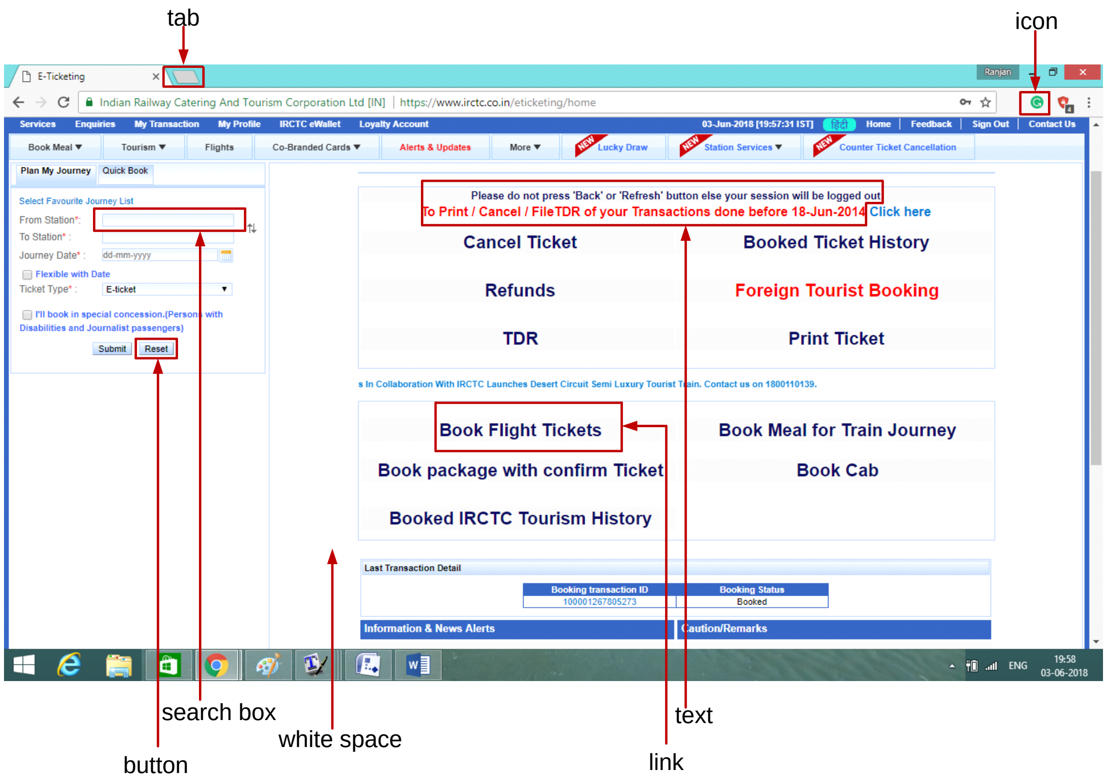


Figure 1.6: The web page of the Indian Rail Catering and Tourism Corporation Limited [4].

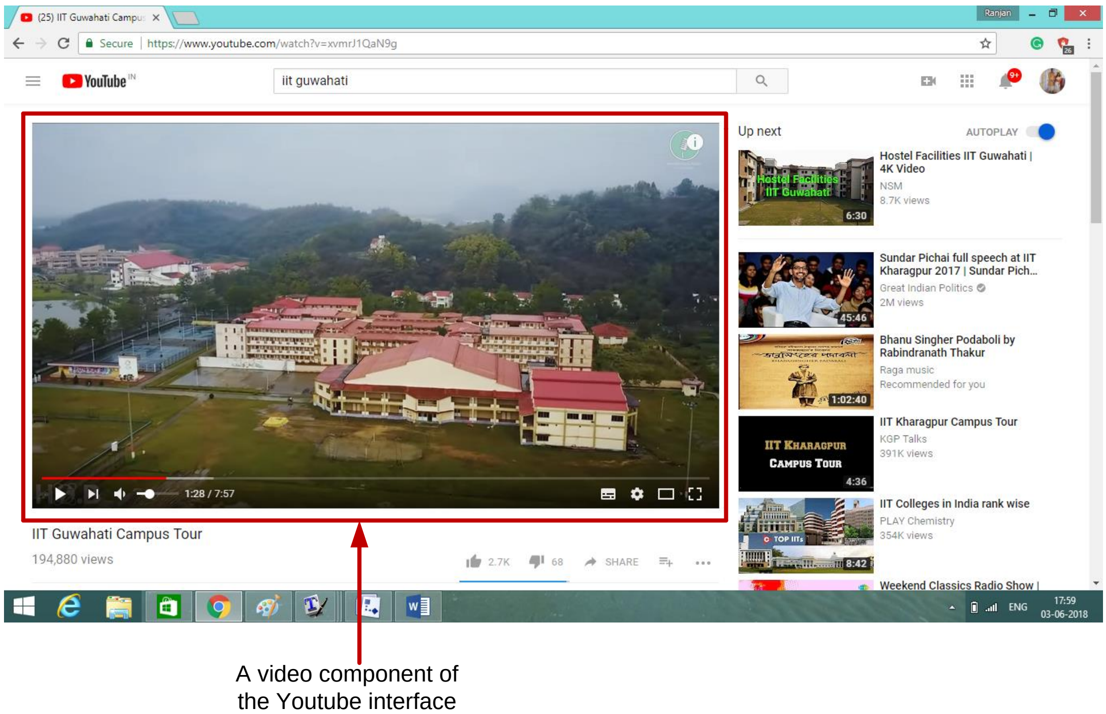


Figure 1.7: A video component on the Youtube web page.[5]

[4] https://www.irctc.co.in/eticketing/home

[5] https://www.youtube.com/watch?v=xvmrJ1QaN9g

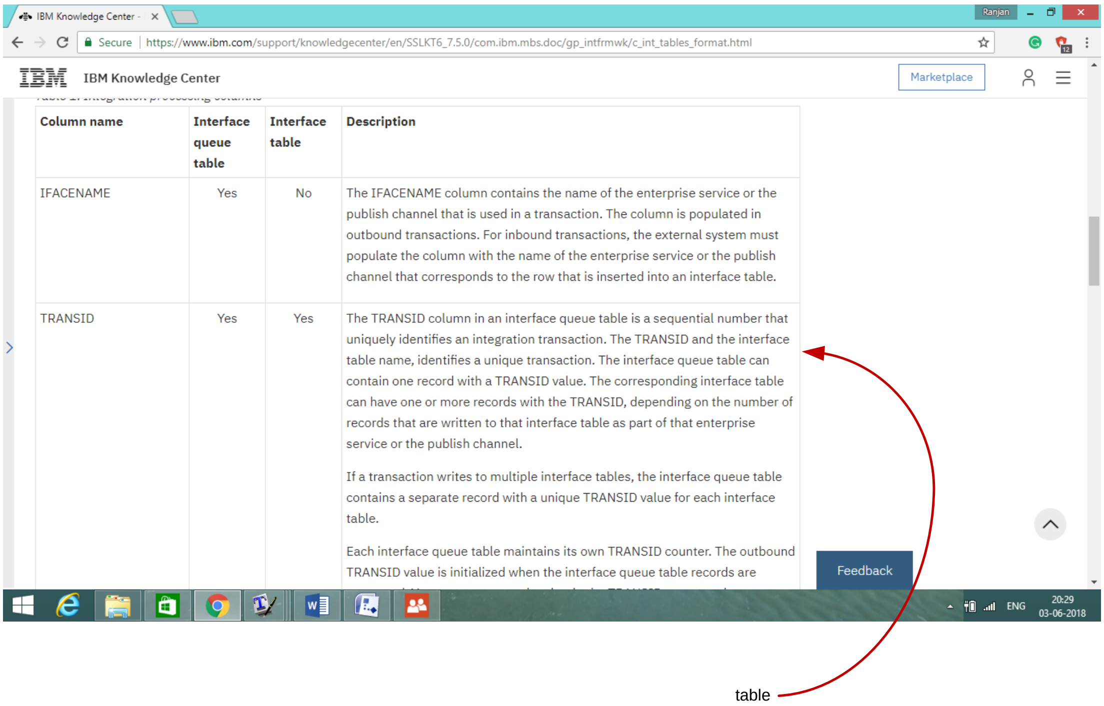


Figure 1.8: Table used in a web page. [6]

The components mentioned above are generally the parts of a web page. Unfortunately, most of the reported works computed aesthetics of a web page by considering it as an image only. Subsequently, using the image related features, computational models were developed for predicting aesthetics. The only approach to measure the aesthetics of the short animations present in a web page is reported in [Bansal and Bhattacharya, 2013]. However, we did not find any computational models developed by considering the other components of a web page – text, icon, link, table, buttons, tabs, and white space.

The components mentioned above are also found in the interfaces of mobiles, and desktop/laptop computers. Figure 1.9 and Figure 1.10 show the start screen of a mobile, and a laptop respectively. We may note that components of both the interfaces –

- image, text, and icon for the mobile home screen
- button, icon, and image for laptop start screen

are also found in the web pages, as reported in Table 1.1. Therefore, a computational model developed for web page aesthetics measurement may also help us to measure the aesthetics of the mobile user interfaces, as well as interfaces on the desktop/laptop.

[6] https://www.ibm.com/support/knowledgecenter/ en/SSLKT6_7.5.0/com.ibm.mbs.doc/gp_intfrmwk/c_int_tables_format.html

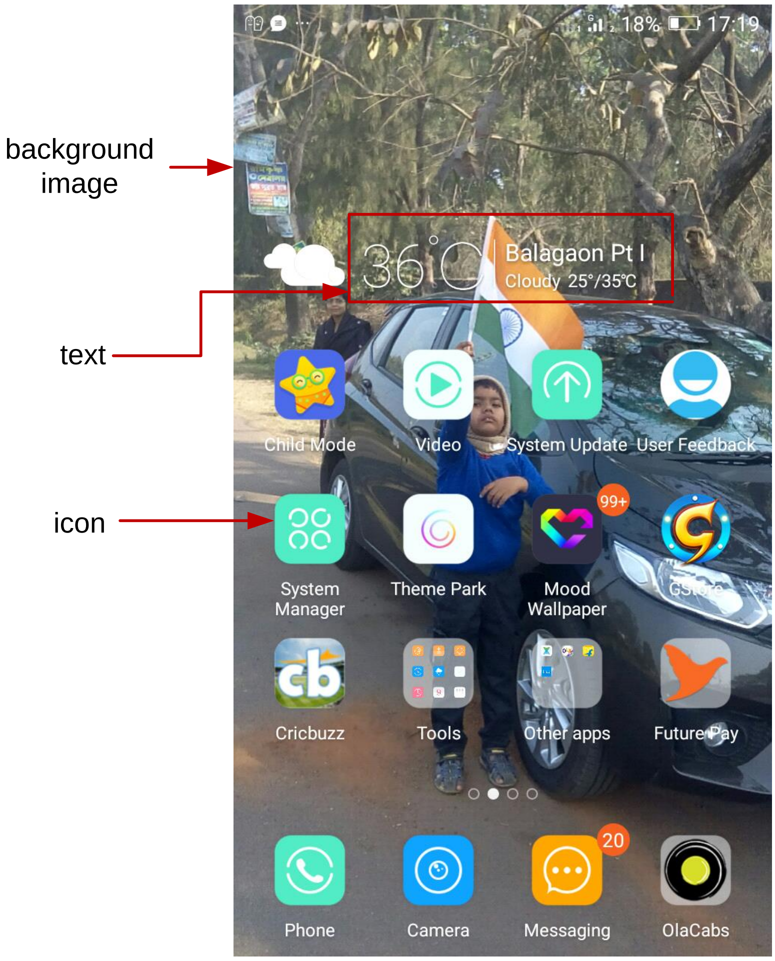


Figure 1.9: Home screen of a mobile.

Figure 1.10: The startup screen of a computer.

1.4 Motivation and Objectives

Computation of web page aesthetics is a challenging task, and computational models can help the designers by automatically providing the aesthetics prediction. It was discussed that the computational models are of two types – wireframe based and contents based. The model proposed by Ngo et al. [2003] considered thirteen features. Their model was reported fifteen years ago. However, the nature of web pages have changed over this period. Hence, there is a need to reassess those features and develop a computational model of wireframe geometry.

For modelling the contents of web pages short animations and images were considered. However, there are other elements present on a web page, such as text, icon, table, link, and white space, as noted before in Table 1.1. Therefore, computational models for these components need to be developed as well, as shown in Figure 1.11.

The contents of a web page can broadly be grouped into three types –image, text and white space. Icons can be represented by images, whereas table, tab button, search box, and links can be expressed by means of text elements. As we are interested in measuring the aesthetics of a web page based on the first impression (not by interacting) as mentioned in [Lindy, 2016], the videos, and animations of a web page can be represented by the initial impression, which is an image. Except this, there is a possibility to combine both the models of wireframe and content to develop a complete model of web page aesthetics prediction. We also did not find any combined model till date, as shown in Figure 1.11.

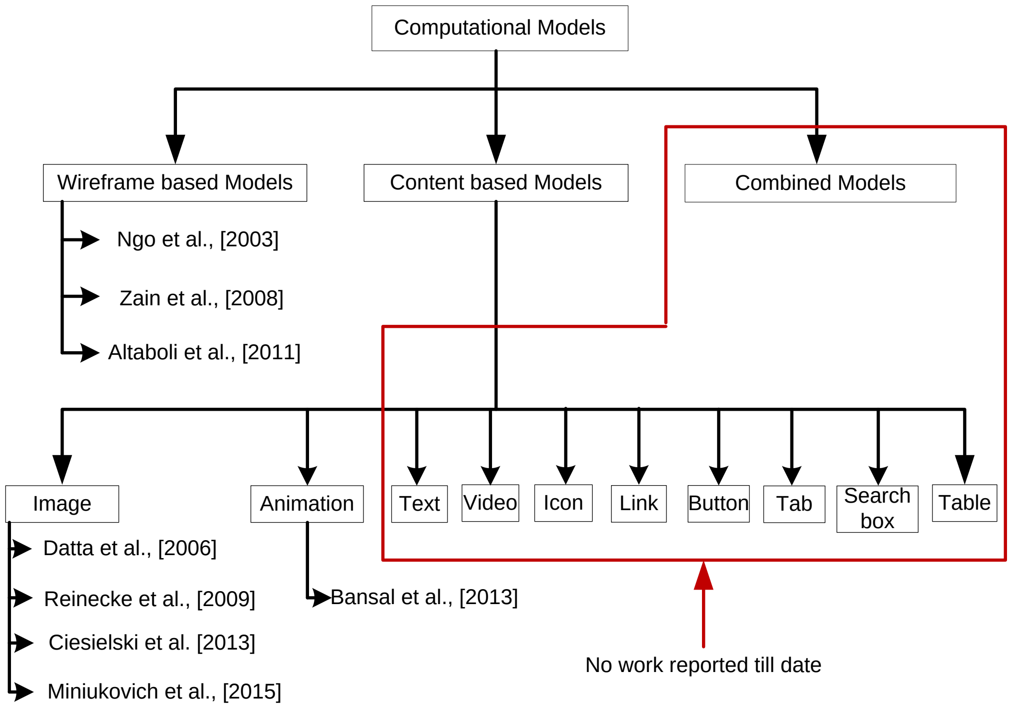


Figure 1.11: Computational models for web page aesthetics.

The specific objectives of the proposed work are summarized below.

1. Reassessing the features of wireframe geometry.
2. Design of computational model based on the significant features found in the previous objective.
3. Design of computational models for aesthetics prediction of web page elements: text, image and white space.
4. Design of computational model for aesthetics prediction of a whole web page by combining the previous two objectives.
5. Use of the model for desiging aesthetically pleasing web pages.

1.5 Brief Overview of Our Work and Contribution

In order to achieve the above objectives, we carried out a number of works. A summary of all those works is presented in the following.

1.5.1 Development of a Computational Model of Wireframe Geometry

The first problem we addressed was the development of a computational model for wireframe geometry. In order to achieve this goal, we carried out a set of tasks. All these tasks are discussed in the following sections.

1.5.1.1 Feature Selection by Parametric Analysis

The thirteen features of positional geometry – *balance, cohesion, density, equilibrium, economy, homogeneity, proportion, regularity, rhythm, sequence, simplicity, symmetry and unity* - reported by [Ngo et al., 2003] were selected to develop a computational model of wireframe geometry. However, statistical significance testing of these features was required, as the work was published long ago. In order to carry out this task, fifty two wireframe models were developed by systematically varying all the thirteen features in four levels. An empirical study was conducted by using all the wireframes. The empirical results were taken into consideration for statistical significance testing, which revealed that except the density, rhythm, economy and simplicity, the remaining nine features were significant for aesthetics computation.

Contribution: *parametric significance testing of the wireframe's features*

1.5.1.2 Binary Classification based Model Development

Using the nine significant features of wireframe geometry, a computational model was developed. The Support Vector Machine based classification was adapted to construct the proposed model. In order to validate the proposed model, the wireframes of ten real web pages (homepage) were selected. It was observed that the proposed model can predict nine out of the ten web pages accurately, with an accuracy of 90%.

As the model was validated with a small number of test samples, a further validation was carried out by two hundred and nine wireframes, where an accuracy of 78.94% was observed. This may be due to the development of the model by considering the features, obtained by the parametric analysis. Generally, non-parametric analysis are more suitable for the HCI data [Wobbrock and Kay 2016 and Wobbrock 2017]. As a consequence, a non-parametric analysis was conducted, as discussed in the following.

Contribution: *The proposed model which can predict web page aesthetics with an accuracy of 78.94%*

1.5.1.3 Non-parametric Analysis

The non-parametric analysis was carried out on the empirical data used for the parametric analysis. It was observed that ten out of the thirteen features (except the density, rhythm, and economy) were statistically significant for aesthetic computation. Based on the observations of parametric and non-parametric analysis, we decided to exclude the three statistically insignificant features - *density*, *rhythm* and *economy* and developed a new computational model of wireframe geometry by considering the remaining ten features.

Contribution: *The non-parametric analysis of the wireframe features*

1.5.1.4 SVR based Model Development

Based on the ten statistically significant features, a computational model of wireframe geometry has been developed. The proposed model is established with the help of Support Vector Regression (SVR). Two hundred and nine web pages used to validate the earlier model, have been considered to train and test the model.

Contribution: *The SVR based model of wireframe geometry, capable of predicting web page aesthetics with an accuracy of 92.25%.*

After the development of a computational model of wireframe geometry, we developed another model of aesthetics by considering the text contents present in a web page. The details of this model development and validation are discussed in the following section.

1.5.2 Text-based Computational Model

From the literature, we identified six features of the text readability – *font size*, *letter spacing*, *word spacing*, *line height* and *contrast* (*luminance contrast* and *chromatic contrast*). As no works on the computational model of text aesthetics are reported till date, the six features of readability were considered for the text aesthetics model development. We developed two computational models of text aesthetics, as discussed in the following sections.

1.5.2.1 Mathematical Model

In order to develop this model, an empirical study was conducted using fifteen text samples. Based on the empirical data, and the six features' values, an analytical expression was proposed to model text aesthetics. The proposed model can predict the aesthetics in terms of binary classes – aesthetically pleasing or not. The proposed model was validated using another fifteen text samples.

Contribution: *The proposed model having an accuracy of 86.67%*

As a small number of samples were used for the model validation, a further validation was carried out by using ninety five text samples, where the six features of text aesthetics were varied systematically. It was observed that the performance of the proposed model degraded from 86.67% to 62.10%. Due to the performance degradation, another computational model of text aesthetics was developed.

1.5.2.2 SVR based Model

The proposed model was developed based on the Support Vector Regression, which can predict aesthetics in terms of some rating, rather than a class. Empirical data were used to develop and validate the proposed model.

Contribution: *The SVR based model of text aesthetics with an accuracy of 90%*

After the development of the text aesthetics model, two computational models of image aesthetics was developed, as discussed in the following section.

1.5.3 Image-based Computational Model

It was observed that there are two kinds of images found in a web page – artificial images, and photographic images. Two different computational models were developed to compute the aesthetics of these two kinds of images respectively.

1.5.3.1 Artificial Image Aesthetics Model

In order to develop the artificial image aesthetics model, a group of fifteen features of layout geometry, and five image features were considered. The model was developed by using the Support Vector Regression. Empirical data were used for the model development and validation purpose.

Contribution: *The above mentioned model of artificial image aesthetics where an accuracy of 93.75% observed*

1.5.3.2 Photographic Image Aesthetics Model

To develop the photographic image-based aesthetics model we identified eleven features from literature, which includes – *colour contrast, hue, saturation, value, smoothness, aspect ratio, unique colour, sharpness, rule of third – hue, rule of third-saturation, rule of third – value*. The model was developed and validated using empirical data.

Contribution: *The proposed model capable of predicting photographic image aesthetics with an accuracy of 87.25%*

1.5.4 Combined Model

Two combined models were developed to measure the aesthetics of a web page. The first model – termed as *Combined Contents Model* (CCM) was created by using the three different components – text, image, and white space present on a web page. In order to develop this model, a white space aesthetics model was developed, as discussed in the following.

1.5.4.1 White Space Model

An empirical study was conducted to find out the effect of white space on aesthetics. It was observed that the median score (three on a five-point rating scale) is appropriate for the modeling of white space aesthetics.

Contribution: *A model for computing the aesthetics of the white space elements*

1.5.4.2 Combined Contents Model

Using the white space, SVR based text model, and two image models, a computational model of aesthetics prediction – termed as the *Combined Contents Model* (CCM) was developed. The CCM works based on the weighted average of the three basic web pages' components – image, text, and white space. The weighted average (area and predicted rating) of all the components is considered as the final predicted aesthetics score. The model was validated using empirical data.

Contribution: *The proposed CCM which can predict web page aesthetics with an accuracy of 89.5%*

As the CCM does not consider the positional geometry of the web page's object, the model was further extended by integrating the computational model of wireframe geometry, as discussed in the following.

1.5.4.3 Combined Wireframe-Contents Model (CWCM)

Finally, the proposed CCM was integrated with the wireframe model to develop a new computational model – Combined Wireframe-Contents Model (CWCM). In order to develop and validate the proposed model, empirical data were used. The predicted rating of the wireframe model and the CCM were considered as the inputs to the proposed CWCM.

Contribution: *The CWCM, having an accuracy of 92.25%*

1.5.5 Framework for Aesthetic Measurement

Using the SVR based wireframe model, the SVR based text model, the two models of image aesthetics, white space aesthetics model, the CCM, and CWCM, a framework for automatic aesthetic prediction was developed.

Contribution: *The proposed framework suitable for computing the aesthetics of a whole web page, as well as its parts*

1.5.6 Summary of Empirical Studies

In order to develop all the models mentioned above, we altogether performed ten empirical studies. The study results acted as a backbone for the development and testing of all our proposed models. The objective of these studies, total number of stimuli used, number of total participants, number of sessions (day)/participants, and total days required to carry out these studies are summarized in Table 1.2.

Table 1.2: Brief overview of the ten empirical studies.

#	Objective	Total stimuli	Total participant	Sessions (days)/ participant	Total days	Related Model
1	Feature identification of wireframe geometry	52	100	2 (1)	19	Wireframe- classification based and SVR based
2	Validation of the 1st Wireframe Model	10	80	1(1)	7	Wireframe – classification based
3	For the development and validation of wireframe model	209	150	4(2)	35	Wireframe- classification and SVR based
4	Development of the Mathematical based text aesthetics model	15	50	1(1)	11	Text- classification based
5	Validation of the previous model	15	50	1(1)	9	Text - classification based
6	Development and validation of the regression based text aesthetics model	95	185	4(2)	17	Text - classification based and SVR based
7	Development and validation of the artificial image aesthetics model	80	100	2(2)	15	Artificial image
8	For the development of the photographic image aesthetic model	250	83	4(2)	26	Photographic image
9	To develop the white space model	-	40	1(1)	3	White space
10	To develop the CCM and CWCM	209	150	4(2)	31	CCM and CWCM

1.6 Organization of the Thesis

The proposed work has been organized into seven chapters, including the present chapter as Chapter 1 – “Introduction.” A brief descriptions of the rest six chapters are reported below.

- Chapter 2 (Related Work): The second chapter contains the reported work on aesthetics computations that are related to the development of a computational model for aesthetics prediction.
- Chapter 3 (Computational Model for Wireframe Geometry): Two computational models of wireframe geometry are reported in this chapter.
- Chapter 4 (Computational Model for Text Aesthetics): In this chapter, two computational models – mathematical based, and regression based are reported.
- Chapter 5 (Computational Model for Image Aesthetics): Two computational models suitable for predicting aesthetics of artificial images, and photographic images respectively are presented in this chapter.
- Chapter 6 (Combined Models): A computational model of white space aesthetics was reported in this chapter, which was combined with the text and image aesthetic models to develop Combined Content Model (CCM). The CCM was integrated with the model of wireframe geometry, and termed as Combined Wireframe-Contents Model (CWCM). In this chapter both the CCM and CWCM are reported. The proposed framework is also presented in this chapter.
- Chapter 7 (Conclusion and Future Work): Conclusion and future scope of our proposed work are presented in this chapter.

Chapter 2

Related Work

2.1 Introduction

The concept of Graphical User Interface (GUI) took its place instead of command based system in 1970 at the Xerox's Palo Alto research center. The different types of layouts found in an interface - the *Mondrian layout*, the *picture-window layout*, the *copy-heavy layout*, the *frame layout* and the *cartoon layout* were reported by Reilly and Roach [1984]. It was also reported that the five basic design principles namely- *balance, proportion, sequence, unity,* and *emphasis* are required to design any interface. Galitz [1997] proposed the basic underlying principal for interface design in his book. The guidelines for usability testing were also presented in this book.

The three levels of beauty of an interface - *surface beauty, operational beauty* and *beauty in depth* or meaning was described by Norman [2004 b]. The *surface beauty* was stated as perceptually based, which was related to the judgment of an object like good or bad, safe or dangerous, etc. The property of *behavioral beauty* was found as expectation driven; which is associated with understanding and feeling the use of a product. It was also mentioned that the lack of control and mismatch among the expectation and actual experiences produce negative effect, and the surface beauty and operational beauty are subconscious and produce feeling but not true emotions. The third level of beauty was *beauty in depth* or meaning, which was based on the rich history of prior experiences, where full-fledged emotions resides.

The role of visual aesthetics in communication was surveyed by Hoffman and Krauss [2004]. They observed most of the authors emphasized on the usability of the websites, while the visual aesthetic got ignored. Tractinsky [2005] emphasized aesthetics as a differentiating attribute not only in IT related product but also in other products like mobile, car, etc. The overlapping relation of aesthetics with usability was reported in this work. It was also suggested that aesthetics is pervasive in the current world of information technology and cannot be neglected. Petersen et al. [2008] mentioned that the aesthetics of interaction is a foundational issue in HCI.

Measurement of web page aesthetic is a challenging task, and can be carried out by the following three ways –

- Set of guidelines
- Empirical evaluations, and
- Computational models

Works reported by using these three different approaches are discussed in the subsequent sections.

2.2 Set of Guidelines

Creating a set of guidelines, keeping aesthetics as a key design factor, can help web page designers to improve their design. A brief description of those guidelines found in literature are reported below.

2.2.1 Nielsen's Guideline [1995]

Nielsen [1995] proposed ten guidelines for user interface design. "***Aesthetic and minimalist design***" is one of them. The guideline states – "Keep clutter to a minimum. All unnecessary information competes for the user's limited attentional resources, which could inhibit user's memory retrieval of relevant information. Therefore, the display must be reduced only to the necessary components for the current tasks, whilst providing clearly visible and unambiguous means of navigating to other content." [Interaction Design 10 rules].

2.2.2 Guidelines of Galitz [1997]

Galitz [1997] in his book identified ten factors that can influence an interface design. He also proposed the guidelines (how to improve) for each of these factors. We enlisted those factors, along with the guidelines (to improve the factors) in Table 2.1.

Table 2.1: Ten factors, along with their guidelines.

Factor	**Guidelines**
Balance	Provide equal weight of the screen elements in left and right, top and bottom.
Symmetry	Replicate elements left and right of the screen centerline.
Regularity	Spaced horizontal and vertical alignment point consistently and also use elements having similar sizes, shapes, colors, and spacing.
Predictability	The consistent and conventional arrangement of screen elements.
Sequentiality	Arrange elements in a way such that eye can scan a screen in a logical, rhythmic and efficient manner.
Economy	Use few styles and colors as possible.
Unity	Leave less space among the screen elements than the space left at the margin
Proportion	Create screen elements with aesthetically pleasing proportion – square (1:1), square root of two (1:1.414), golden rectangle (1:1.618), square root of three (1:1.732) and double square (1:2).
Simplicity (Complexity)	Optimize the number of elements and minimize the number of aligning points.
Grouping	Functionally group the screen elements. ;

2.2.3 Text Design Guidelines

Text design guidelines was reported in [Interface guidelines], where the following guidelines were proposed -

- Letter spacing should be at least 0.12 times of the font size.
- Line spacing should be at least 1.5 times than the font size.

- Word spacing should be at least 0.16 of the font size.

Although adhering to these guidelines may appear to be simple, however, designers can face significant difficulties during the development process of a web page. In particular, when the number of guidelines is large, it becomes difficult for the designers to remember them. Even it becomes worse for a new designer, as he/she may not be familiar with those guidelines. Consequently, designers have to recheck the guidelines during the design process. Reviewing guidelines needs extra time as an overhead. As a consequence, web page development process may be delayed.

2.3 Empirical Evaluation

Web pages' aesthetics can also be measured by means of empirical study. In this section, we present the relevant works on empirical evaluations found in literature.

2.3.1 Kurosu and Kashimura [1995]

Using an empirical study, Kurosu and Kashimura [1995] established the strong correlation of usability with aesthetics among Japanese people. They considered the sample screens from the cash dispensers (ATM) having several objects - *numeric keys, special numeric keys (thousand and ten thousands), yen key, cancel key, correction key*, *main display*, and *sub display* as *graphical* elements. Twenty six users (nine GUI designers, six industrial designers, eight engineers and three secretaries) were participated in the empirical study. They placed the objects according to their convenience in the screen. The layouts were rated by two aspects (easy to use and beautiful) on a ten point rating scale by a group of two hundred and fifty two participants. The empirical study results were used to find the correlation between aesthetics and usability. It was reported that a high correlation exists among the aesthetics and usability. In other words, highly rated usable samples were more beautiful, while the low rated usable samples were less beautiful.

2.3.2 Tracktinsky [1997]

Tractinsky [1997] also used empirical evaluation in order to establish the correlation among aesthetics and apparent usability among the Israeli people. He conducted three experiments to test the robustness of Kurosu and Kashimura's findings [Kurosu and Kashimura, 1995] to cultural bias. The same twenty six layouts of [Kurosu and Kashimura, 1995] and the materials of those layouts were translated into Hebrew and considered for the empirical evaluation. It was reported that the magnitude of correlation between aesthetics and usability was higher among the Israelis than the Japanese participants. Based on this observation, they suggested that the correlation of aesthetics and usability is cultural specific.

2.3.3 Park et al. [2004]

Park et al. [2004] tried to identify critical factors that are related to the aesthetics of the web page by means of empirical study. Three empirical studies were conducted to find out those factors that are associated with the web page aesthetics. Based on the empirical observations, they found that the reliability of aesthetic dimension, variability of user perception and appropriateness of visual elements were closely related to the aesthetic fidelity of web pages.

2.3.4 Pandir and Knight [2006]

Pandir and Knight [2006] used empirical study for establishing the relations among complexity, interestingness, and pleasingness (aesthetics). Twelve homepages (three sets of color printout on white paper) were considered for finding the relations among the following pairs.

1. Interestingness vs. pleasingness
2. Interestingness vs. complexity
3. Pleasingness vs. complexity

The participants ordered the printouts of twelve homepages from simplest to complex. The same procedure was repeated for the other two relations - interestingness vs. complexity, and pleasingness vs. complexity . Based on the sorting, a score from one to twelve (one denotes simple, less interesting, less pleasing and twelve denotes complex, most interesting and most pleasing) was assigned to each homepage picture. Finally, those scores were plotted in three different graphs (interestingness vs. pleasingness, interestingness vs. complexity, pleasingness vs. complexity). It was reported that the least pleasing home page is not the least interesting and the most pleasing home page is not the most interesting. However, as complexity increases, interestingness decreases almost linearly. It was also reported that up to a certain level of complexity, pleasingness increases and then it starts declining.

2.3.5 Schmidt et al. [2009]

The role of design variables and their effects in web page aesthetics, performance and usability was proposed in [Schmidt et al., 2009] on the basis of empirical study. The objective of this study was to identify the underlying design variables that affect the perceived usability of a web page. Using empirical study, they identified fifty seven variables that can affect the usability of a web page during browsing. After performing the cluster analysis (which identifies groups of similar variables), ten clusters of those fifty-seven variables were determined, as mentioned in Table 2.2.

Table 2.2: Clusters and their variables as reported by Schmidt et al. [2009].

#	Cluster name	Cluster variables
1.	Page progress	Frames, Non-Frames, Opening of new browser window
2.	Basic visual structure	Visual design cues, Visual groups, coordinated video and audio, Pictures instead of description, simple images, image file size, font size, images for images and text for text, position in the screen
3.	Navigation	Clear Exits, wait-time feedback, printable content, navigation support, back button.
4.	Clarification/ Simplification	grouping and subheadings, simple headlines and/or titles, innovative, provide search, length of article, interactive, minimized scrolling, simple uniform resource identifier, accurate plain language error message
5.	Relevance/ Speed	Server response time, time to load, download time, speed, timely information, updated regularly, information layout, location of information, credible and original information
6.	Trust/ Flexibility	privacy, security, browser independent, system independent
7.	Marketing	advertisements, banners, sudden pop-up windows
8.	Appeal/ Diversion	Animations, images, background images, entertainment, drop down menus, free service
9.	Multimedia	songs, movies, games, icons, logos, 3-D images, multiple colors, standard colors for link
10.	Accessibility	accessible for users with disabilities

For further analysis of those design variables, they conducted another empirical study. It was observed that users were willing to sacrifice technical performance up to an extent for better aesthetics. It was also observed that users' performance is not a reliable factor of web page effectiveness. This is because of the users' aesthetic preference and ease-of-use ratings often diverge from their performance.

2.3.6 Zheng et al. [2009]

Zheng et al. [2009] iteratively decomposed a web page into quadrants of minimum entropy to characterize the *symmetry*, *balance*, and *equilibrium*. In order to establish the effect of these three factors with the following four comparative properties of a web page, they carried out an empirical study.

1. Repelling vs. appealing
2. Dull vs. captivating
3. Complicated vs. simple
4. Unprofessional vs. professional.

Analysis of the empirical data showed *balance* was essential to portray the three comparative behaviors – *repelling vs. appealing*, *unprofessional vs. professional* and *dull vs. captivating*. On the other hand, *Symmetry* distinguished the two comparative properties – *repelling* vs. *appealing* and *dull* vs. *captivating*, and the equilibrium can differentiate the *complicated* vs. *simple* and *un-professional* vs. *professional* characteristics of a web page.

2.3.7 Lai et al. [2010]

Lai et al. [2010] investigated the effects of the balance and symmetry on the aesthetics of text overlaid images. They considered the pixelated images with reduced image resolution, instead of the original images at four levels - 20×20, 10×10, 5×5 and 1×1. Two empirical studies, one with the twenty five color images, and the other with the monochrome images of those twenty five images were conducted to relate the two factors -*balance* and *symm*etry with the aesthetics. It was reported that aesthetics had a strong correlation with the balance. However, *symmetry* did not have any such association with the aesthetics.

The reported works mentioned in this section illustrate the use of empirical studies to establish the relations of aesthetics with the usability and the other factors of interface design. Empirical evaluation is an effective technique to judge the aesthetics of a newly developed web page. A web page designer can evaluate the aesthetics of his/her design by conducting an empirical evaluation. However, it is tedious to judge every design by means of empirical evaluations due to the huge amount of time required to evaluate by a group of participants. In order to reduce this overhead, computational models are proposed to determine the aesthetics of a design. In the following section, we discussed about those models found in literature.

2.4 Computational Models of Aesthetics

A model is often used to characterize the behavior of a system. There are models developed by using the concepts of mathematics, known as mathematical model. A mathematical model used for scientific computation of a system (example - weather forecast, flight simulator) is termed as computational model. Computational models of web page aesthetics helps to model the users' visual perception of a web page. The advantage of a computational model is the ability to evaluate web page aesthetics automatically. This will help to automate the design process. All the computational models of aesthetics measurement can be broadly classified in the following two types.

- Wireframe geometry based
- Content based

2.4.1 Wireframe based Approach

The wireframe model of aesthetics computation depends on the geometrical positions of the objects present in a web page. In the following sections, we briefly discussed about those models.

2.4.1.1 Model of Ngo et al. [2003]

Ngo et al. [2003] developed a computational model by considering thirteen features of wireframe geometry. Those features were *balance*, *equilibrium*, *symmetry*, *sequence*, *cohesion*, *unity*, *proportion*, *simplicity*, *density*, *regularity*, *economy*, *homogeneity*, and *rhythm*. A brief descriptions of these features are presented below.

Balance (BA): Balance measures the difference in the total optical weight of web page components on each side of the horizontal and vertical axis. It can be achieved by distributing equal weights of screen elements on each side –top, bottom, left and right. Balance is computed with the help of the following Equation 2.1, where BA_x and BA_y denote the balance across the horizontal and vertical axis of a web page.

$$BA = 1 - \frac{|BA_x| + |BA_y|}{2} \in [0,1] \tag{2.1}$$

Equilibrium (EQ): It calculates the difference between the center of mass of the objects and the interface center. Equilibrium is higher if the two centers are closer to each other. Equation 2.2 is used to compute the equilibrium of a web page, where EQ_x and EQ_y denote equilibrium with the horizontal and vertical axis respectively.

$$EQ = 1 - \frac{|EQ_x| + |EQ_y|}{2} \in [0,1] \tag{2.2}$$

Symmetry (SY): The extent to which an interface is symmetrical in vertical, horizontal and diagonal direction is computed with symmetry, as shown in Equation 2.3. SY_x, SY_y and SY_r denote the symmetry along the horizontal, vertical and radial axis.

$$SY = 1 - \frac{|SY_x| + |SY_y| + |SY_r|}{3} \in [0,1] \tag{2.3}$$

Cohesion (CO): The degree to which aspect ratios (ratio of width and height) are maintained in an interface is termed as cohesion, as reported in Equation 2.4. CO_{fl} and CO_{lo} denote the cohesion between a frame to layout and a layout to objects.

$$CO = \frac{|CO_{fl}| + |CO_{lo}|}{2} \in [0,1] \tag{2.4}$$

Unity (UN): The extent to which the interface objects seem to belong together is termed as *Unity*. It can be achieved by making similar sized objects and leaving less space between objects than that of the spaces left at the margins. Equation 2.5 shows the expression to compute Unity, where UN_{object} denotes the extent to which objects are related to size and UN_{space} denotes the space left at the margins is related to the space between elements of the screen.

$$UN = \frac{|UN_{object}| + |UN_{space}|}{2} \in [0,1] \tag{2.5}$$

Simplicity (SI): It refers to the idea that suitable number and placement of objects make it easier to convey the interface information easily. Simplicity can be computed by using Equation 2.6, where n_{vap}, n_{hap} denote the number of vertical and horizontal alignment point and n denotes the number of web page objects present in the layout.

$$SI = \frac{3}{n_{vap} + n_{hap} + n} \in [0,1] \tag{2.6}$$

Density (DE): The extent to which a web page is covered with objects is measured with density, as shown in Equation 2.7. A_i denotes the area of the object i, A_{frame} denotes the area of the frame and n is the total number of objects present in the layout.

$$DE = 1 - 2\left|0.5 - \frac{\sum_{i=1}^{n} A_i}{A_{frame}}\right| \tag{2.7}$$

Regularity (RE): It refers to the uniformity of the interface elements based on some plan. In web page design, regularity can be established by standardizing and minimizing horizontal and vertical alignment points for interface objects. Equation 2.8 shows the analytical expression for computing regularity. RE_{align} denotes the degree to which alignment points are minimized, and RE_{space} is the extent to which the alignment points are properly placed in the layout.

$$RE = \frac{|RE_{align}| + |RE_{space}|}{2} \in [0,1] \tag{2.8}$$

Economy (EC): Economy measures the variations of the different size objects present in a web page. It can be improved by using a fewer different sizes objects. Economy is computed with the help of the Equation 2.9, where n_{size} is the total number of unique size objects.

$$EC = \frac{1}{n_{size}} \in [0,1] \tag{2.9}$$

Homogeneity (HO): Homogeneity measures how evenly objects are distributed among the four quadrants-upper left (UL), upper right (UR), lower left (LL) and lower right (LR) of a web page, as shown in Equation 2.10. The total numbers of objects are denoted by n and n_{UL}, n_{UR}, n_{LL} and n_{LR} denote the number of objects present in the four quadrants of UL, UR, LL and LR respectively.

$$HO = \frac{\left(\frac{n}{4}\right)^4}{n_{UL} n_{UR} n_{LL} n_{LR}} \tag{2.10}$$

Rhythm (RH): It is a property that makes an interface exciting, on the basis of some regular pattern of changes. Rhythm is the degree to which the objects are systematically ordered in the layout, reported in Equation 2.11. RH_x, RH_y denote the rhythm across the horizontal and vertical axis of an interface. RH_a denotes the rhythm of the objects based on their area.

$$RH = 1 - \frac{|RH_x + RH_y + RH_a|}{3} \tag{2.11}$$

Proportion (PR): There are shapes that are found to be aesthetically pleasing. Proportion helps to compare relationship between the dimensions of the screen components and different known proportional shapes like square, square root of two, golden rectangle, square root of three and double square. Proportion of a web page can be computed with the help of the Equation 2.12. PR_{object} is the difference between the objects present in the layout and the closest proportional shapes like square, square root of two, golden rectangle, square root of three, and double square. PR_{layout} is the difference between layouts with the closest popular proportional shapes, as mentioned above.

$$PR = \frac{|PR_{object}| + |PR_{layout}|}{2} \in [0,1] \tag{2.12}$$

Sequence (SE): Normally our eyes start reading an interface from the top left corner and moves back and forth to the lower right corner. Sequence is a measure of the degree to which the arrangement of the objects on the layout facilitates eye movement. The quadrant values of Upper left (*UL)*, Upper Right (*UR)*, Lower Left (*LL)* and Lower Right (*LR)* (denoted by $QUAD_{UL}$, $QUAD_{UR}$, $QUAD_{LL}$ and $QUAD_{LR}$) are 4, 3, 2 and 1 respectively. The BIG_i indicates the values of 4, 3, 2, and 1 for the quadrants having largest, second largest, third largest and fourth largest object area respectively. Equation 2.13 represents the expression to compute the *sequence.*

$$SE = 1 - \frac{\sum_{i=UL,UR,LL,LR} |QUAD_i - BIG_i|}{8} \in [0,1] \tag{2.13}$$

The average of the thirteen features was denoted by the ***order***, as shown in Equation 2.14.

$$ORDER = \frac{BA + EQ + SY + CO + UN + SI + DE + RE + EC + HO + RH + PR + SE}{13} \quad (2.14)$$

Ngo et al. [2003] considered *order* to measure the aesthetics of an interface. They performed two empirical studies. In the first study, the wireframes of five interfaces, which were rated (aesthetically low, medium or high) by seventy nine users were considered. The median ratings were treated as the final ratings. They found strong correlation among the final ratings and the ***order*** values of those five interfaces. In the second empirical study, they considered the contents of those objects present on those interfaces, which were again evaluated by a group of one hundred and eighty users. After this evaluation, it was noticed that the result of the second empirical study was similar with the earlier study. In other words, the final ratings of the five interfaces in both the studies were identical. Accordingly, they concluded that the contents of those objects were not responsible for evaluating the aesthetics of those interfaces; rather the thirteen features of wireframe geometry were primarily important for aesthetic measurement.

2.4.1.2 Zain, Tey and Goh's Model [2008]

Zain et al. [2008] proposed a computational model of aesthetics prediction by using the five out of the thirteen features [Ngo et al., 2003] - balance (BA), equilibrium (EQ), symmetry (SY), sequence (SE), and rhythm (RH). The average of these five features was termed as ***order*** and used to judge the aesthetics of four groups of web pages, where each group consisted of three separate web pages. They reported that the order can model the aesthetics of those web pages. In other words, the highest ranked web page group has the highest order value. Similarly, the second highest ranked web page group has the second highest order value and so on.

2.4.1.3 Model of Singh and Bhattacharya [2010]

A genetic algorithm based approach to improve the web page aesthetics was reported in this work, where each layout was represented by the wireframe objects. Each object was mapped to a gene, and a web page was mapped to a chromosome. They decided to use one lakh as the size of population in each generation, and the fitness was determined by the aesthetic value. The aesthetic value was computed with the help of the thirteen geometric parameters namely: *balance, equilibrium, symmetry, sequence,* *cohesion, unity, proportion, simplicity, density, regularity, economy, homogeneity,* and *rhythm* as reported in [Ngo et al., 2003]. For creation of the off-springs for the next generation, they took 25% of population which had the highest fitness, and 5% from the unfit populations so that the solution avoids in local minima. Cyclic crossover technique was adopted for crossover operation, and the mutation was done randomly. They continued the iteration for five hundred times. For empirical study, thirty web pages' layouts were used and evaluated by ten users. For evaluation, they kept the original layout and the rearranged layout according to their genetic algorithm. For the fifteen layouts, they observed that allowing object overlapping in rearranged layout reduced aesthetics. For the remaining fifteen layouts, they got a mixed reaction from the users. Out of the fifteen layouts, most of the participatory users claimed eight of the rearranged layouts became more aesthetically pleasing than the original layouts. In the remaining seven layouts, majority users cannot recognize the differences between the original and rearranged layouts.

2.4.1.4 Altaboli and Lin's Model [2011]

Another computational model of interface aesthetics was proposed by Altaboli and Lin [2011] by considering the three features – balance (*BA*), unity (*UN*), and sequence (*SE*). By systematically varying these three features, they designed eight interfaces. These interfaces were rated by thirteen participants. ANOVA study on the empirical results showed that the three features were statistically significant for aesthetics computation. Again, they reported that the two way interactions among $BA \times UN$ and $UN \times SE$ were also important. However, no significant interaction among $BA \times SE$ and $BA \times UN \times SE$ were observed. Based on this, they constructed an aesthetics prediction model as mentioned in Equation 2.15.

$$AS = 0.497 - 0.0077BA - 0.286UN - 0.0717SE + 0.419BA \times UN + 0.375UN \times SE \quad (2.15)$$

Using a new set of forty two web pages, the model was validated, which showed high correlation exhibited among the predicted rating and the ratings of the users participated in their design. All the works of computational aesthetics based on wireframe geometry are summarized in Table 2.3.

Table 2.3: Works on wireframe geometry.

#	Work	Features considered	Model
1	Ngo et al. [2003]	balance, cohesion, density, equilibrium, economy, homogeneity, proportion, regularity, rhythm, sequence, simplicity, unity	$ORDER = \frac{BA+EQ+SY+CO+UN+SI+DE+RE+EC+HO+RH+PR+SE}{13}$
2	Zain et al. [2008]	balance, equilibrium, symmetry, sequence, and rhythm.	$ORDER = \frac{BA+EQ+SY+RH+SE}{5}$
3	Singh et al. [2010]	balance, cohesion, density, equilibrium, economy, homogeneity, proportion, regularity, rhythm, sequence, simplicity, unity	Genetic Algorithm based optimization for ORDER, where $ORDER = \frac{BA+EQ+SY+CO+UN+SI+DE+RE+EC+HO+RH+PR+SE}{13}$
4	Altaboli and Lin [2011]	balance, unity, sequence	$AS = 0.497 - 0.0077BA - 0.286UN - 0.0717SE + 0.419BA \times UN + 0.375UN \times SE$

2.4.2 Content-based Approach

A web page can be composed of different web page elements – text, image, video, short animation, icon, tables, links, icons, search box and tab. However, most of the reported model of aesthetics computation considered a web page as an image. The only work of aesthetics computation of short animation was proposed by Bansal and Bhattacharya [2003]. In the next few sections, we discussed about all those computational models developed by considering the contents only.

2.4.2.1 Model of Datta et al. [2006]

A computational model for aesthetics in photographic image was proposed in [Datta et al., 2006]. They downloaded three thousand five hundred and eighty one images and their metadata from *Photo.net* (researchers online communities at MIT). These metadata contains,

1. average aesthetics score between one to seven
2. average originality score between one to seven
3. number of times viewed by the member
4. number of peer rating.

From those metadata, they found image aesthetics has a linear relation with the originality. For aesthetics computation the following features - exposure of light, colorfulness, saturation, hue, rule of third, familiarity measure, wavelet base texture, size, aspect ratio, region composition, low depth of field indicator, and shape convexity were considered. For all the three thousand five hundred and eighty one images, they computed the features' values, and normalized them to zero to one.

They classified all three thousand five hundred and eighty one images based on aesthetic score:

High class, aesthetic score > 5.8
Low class aesthetic score < 4.2.

It was reported that the intermediate aesthetic scores of 4.2 to 5.8 does not have any distinguishing feature. Consequently, the images having the aesthetic score in this range were discarded, and one thousand six hundred and sixty four images were obtained. One dimensional SVM (support vector machine) was used for the classification. Out of the fifty-six features, the top fifteen features resulted in an accuracy of 70.12% for predicting image aesthetics. It was also observed that the photographic images pleasing to the eyes have higher aesthetic score than that of the less pleasing images.

2.4.2.2 Model of Ciesielski et al. [2013]

Ciesielski et al. [2013] found that the wavelet and texture features of an image have important role to play in determining the aesthetics. They considered two image databases -

1. Photos: Taken from //photo.net
2. Abstract Images: generated using an evolutionary art system.

They started with eighteen thousand one hundred and thirteen images whose rating was in the range of 2.33 to 6.90. All the images that got rating of less than 4.00 were put on a negative class, while the images that got rating more than 6.30 or higher were put on a positive class. This way they found four hundred and forty five images in the negative class and four hundred and forty eight in the positive class. Abstract images with rating of less than two were kept in the negative class and rating of six or more were placed in the positive class. They considered fifty two image features like [Datta et al., 2006], and reported a classification accuracies of 70% for photographic image, while it reached up to 90% for abstract images using different classification algorithms. It was also observed that the abstract images were distinguished mostly by the color features based on the whole image, rather than the color feature based on sub regions. On the other hand, the photographic images were mostly judged by the texture/wavelet features.

2.4.2.3 Model of Minukovich and Angeli [2015]

Miniukovich and Angeli [2015] proposed an approach for developing an automated tool for the computation of interface aesthetics, particularly image aesthetics. They considered eight automated metrics (*visual clutter, color range, number of dominant color, figure ground contrast, contour congestion, symmetry, grid quality and white space*) of GUI. In order to relate these features with interface aesthetics, they performed two validation studies. The first study was conducted on seventy five web sites by using a group of sixty two participants on a seven point rating scale. It was observed that the eight metrics are suitable for web page aesthetics measurement. The second study was conducted on the interfaces of the mobile apps. Three hundred screenshots of seventy five iPhone’s apps were considered here. Fifty three participants involved in this second empirical study. By analyzing empirical data, they found the dominant colour, symmetry, and white space are not suitable for modelling the aesthetics of the mobile apps.

2.4.2.4 Model of Bansal et al. [2013]

A semi supervised learning based computational model for aesthetic computation of short animation was proposed in [Bansal et al., 2013]. They considered two features sets. One set was composed of three design variables: *balance, symmetry*, and *color contrast*. The other set had five features: *total number of objects*, *fixed objects measure, measure of size changes across frame*, *measure of movement path and object shape measure.* They created a two stage model for their study. In the first stage, eighteen artificially created videos were labeled as good, average or bad by seventeen users. Another twenty four unlabeled dataset was created to increase the size of training data. Using co-training algorithm these twenty four videos were classified (seven as bad, eleven as average and six as good). In order to validate the model, they conducted another user study for sixteen short videos, by a group of twenty three participants. The result of their validation study showed that their proposed classifier was able to classify short videos according to their aesthetics appeal with accuracy of 75%.

2.4.2.5 Model of Reinecke et al. [2013]

Reinecke et al. [2013] reported that the *VC* (Visual Complexity) and *colorfulness* could be quantified with the help of image features. Using these two metrics, they proposed a computational model for aesthetics prediction of web pages. Regression analysis of the study showed their model measure aesthetics with an accuracy of 48%. They also claimed that up to a certain level of *VC*, the aesthetics increases and then it started decreasing. However, it was not reported that what would be the best level of VC for achieving better aesthetics. All the reported computational model based on the contents of the web pages are summarized in Table 2.4. The limitations of these works, along with the wireframe based works, are discussed in the following section.

Table 2.4: Works on the contents of web pages.

#	Work	Features considered	Model
1	Datta et al. [2006]	brightness of the second segment (Si>=XY/100), Hue, ROT-saturation, smoothness , familiarity, saturation –second segment, saturation, value of the first segment, low depth field indicator (saturation), region position, size.	SVM based classification
2	Ciesielski et al. [2013]	smoothness (wavelet), aspect ratio, size, colourfulness, saturation, brightness.	SVM based classification
3	Reinecke et al. [2013]	constant, text area, non-text area, number of leaves, number of text groups, number of image areas, colourfulness, and hue.	Regression analysis
4	Bansal and Bhattacharya [2013]	balance, symmetry, color contrast, total number of objects, fixed objects measure, measure of size changes across frame, measure of movement path and object shape measure.	Aesthetics = Order/ Complexity
5	Miniukovich and Angeli [2015]	visual clutter, color range, number of dominant color, figure ground contrast, contour congestion, symmetry, grid quality and white space.	Regression analysis

2.5 Scope of Our Work

Wireframe models of aesthetics computation need the positional geometry features of web pages' objects. Ngo et al. [2003] considered thirteen features of wireframe geometry to develop a computational model. It may be noted that Zain et al. [2008] and Altaboli and Lin [2011] considered two different subsets of the thirteen features proposed by Ngo et al. [2003]. However, no conclusive statements were reported in both these works about the reason of choosing such subsets. Again, the work of Ngo et al. [2003] was reported long ago. So, there is a necessity to review all those features on their suitability for modern web page design. The model of Ngo et al. [2003] computes the aesthetics by averaging the all thirteen features. It was reported that these features may not be equal contributor to the web page aesthetics. Hence, there is a necessity to develop a computational model of wireframe geometry suitable for web pages.

Most of the reported works (Datta et al., [2006]; Reinecke et al., [2013]; Ciesielski et al. [2013] and Miniukovich and Angeli [2015]) based on the contents of web page considered it as an image. Subsequently, computation models were developed by considering only the image related features. Reinecke et al. [2013] found that the text areas, and non-text areas were important for aesthetics computation. However, the visual aesthetics of text elements (affected by the features of text aesthetics) were ignored in their work; and with the best of our survey we did not find any computational model of text elements present in a web page. The only work of aesthetics prediction of short animation was proposed by Bansal et al. [2013]. These group of researchers neglected the role of wireframe geometry in aesthetics computation. To the best of our knowledge, Dutta et al.'s [2003] work reports the most comprehensive features of image aesthetics reported till date, which predict aesthetics of an image in binary class - aesthetically pleasing (good) or not (bad). In contrast, a longer scale can convey more useful information [scale], and aesthetics can be judged more precisely. For example, in a five-point rating scale, aesthetics can be represented by five items – very pleasant (5), pleasant (4), average (3), unpleasant (2), very unpleasant (1). However, it was also reported [scale] that using too many scale points can reduce response's meaning. Among different scales, the five-point rating scale is often used for subjective evaluations. Accordingly, we planned to develop our proposed model which can predict aesthetic scores on this scale, which also required that the content-based models must measure aesthetics on the same scale.

White space in an interface is another factor that may not directly affect aesthetics, but provide focus, resting points, create simplicity and ease of use for the readers [Julie, 2012]; and indirectly responsible for determining interface aesthetics.

The analysis described above shows that a group of researchers believed aesthetics is related with the wireframe geometry, while the researchers of the other group claimed the contents present in an interface are responsible for computing aesthetics. With the best of our knowledge, no works were reported till date by considering the white space, wireframe geometry and the contents of the wireframe objects – text, image, and white space. Therefore it is necessary to develop a computational model by considering the following tasks.

1. Analysis of the 13 features of wireframe geometry (Ngo et al. [2003]).
2. Development of a computational model based on the significant features of wireframe geometry.
3. Development of computational models for the contents – image, text, and white space.
4. Development of a computational model of the contents by integrating the three components mentioned in the previous step.
5. Development of a complete model of interface aesthetics by integrating the two models of wireframe geometry and contents as mentioned in step 2 and 4.

We worked on these limitations of the literature and report our work in the subsequent chapters.

2.6 Chapter Summary

From the literature review, we found that Ngo et al.'s [2003] work reported the maximum features of wireframe geometry. As the work was reported long back, there is a necessity to check whether the features used by them is significant for computing the aesthetics of modern web pages. Subsequently, there is a need to develop a computational model for aesthetics prediction by considering the significant features of wireframe geometry.

Datta et al. [2006] reported fifty six feature of image aesthetics, and using top fifteen features they predicted aesthetics of photographic images in terms of binary class. However, a longer scale can convey more useful information [Scale]. As a consequence, there is a need to develop an image aesthetics model in larger scale.

Although Reinecke et al. [2013] acknowledged that text area are important to determine aesthetics, unfortunately, no works on text aesthetics by considering the text related features was reported till date. Again, Julie [2012] acknowledge the effect of white space on creating simplicity, which in turn affect aesthetics of a web page. So there is a necessity to develop a computational model to predict web page aesthetics by considering the contents – text, image, and white space present in it. Again, there may be an effect of wireframe geometry, as well as the contents of web page objects for aesthetic measurement. Based on our literature survey, we did not find any work by combining both these factors. Therefore, a computational model can be developed by considering both these factors – wireframe geometry, and the content of the objects present in a web page.

In order to develop a computational model of web page aesthetics, we analyzed the significant features of wireframe geometry. Based on those significant features, a computational model was developed, which was discussed in the next chapter.

Chapter 3

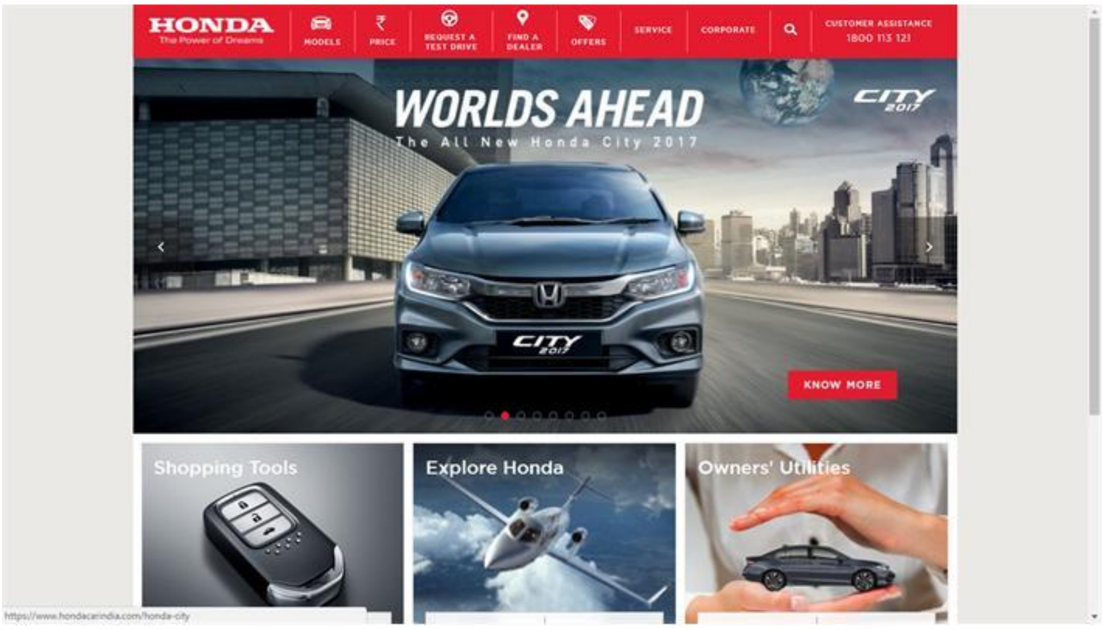
Computational Model for Wireframe Geometry

3.1 Introduction

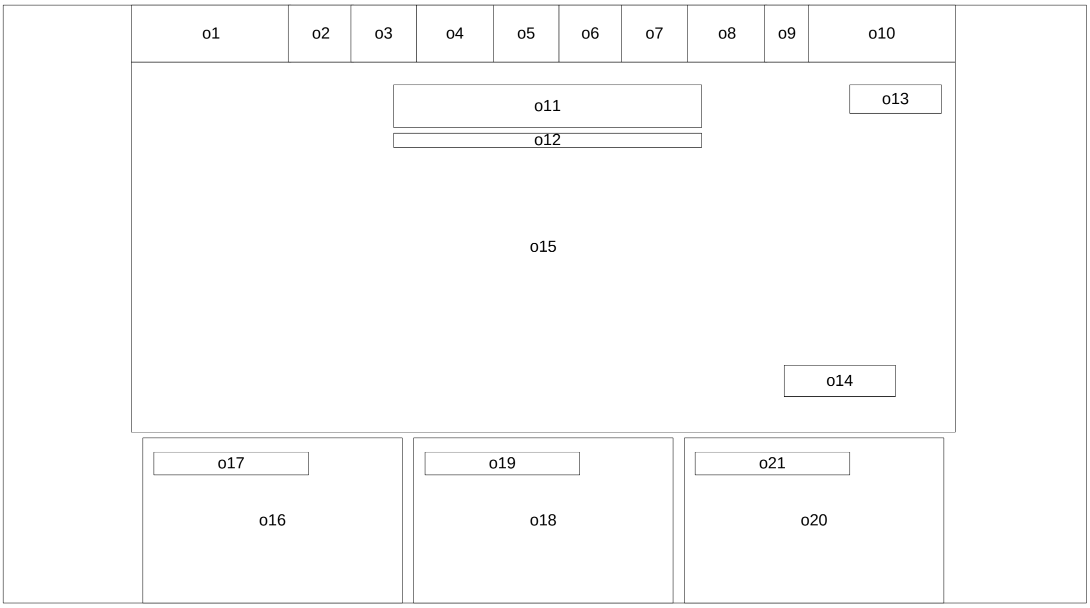
Aesthetics of a web page refers in part to the perceived beauty of it. Image, text, video, tables, links, icons, menus, and white spaces are the main elements found in a web page. All these elements can be approximated as the contents of rectangular objects (referred to as only "object" in subsequent discussion). A web page representation using such objects is referred to as the wireframe model of the web page. Figure 3.1 (b) depicts the wireframe model of the web page shown in Figure 3.1 (a). It may be noted that all the twenty one objects, labeled as o1, o2, … , o20, and o21 in Figure 3.1 (b) can characterize the web page using wireframe representation. Out of these twenty one objects, o1, o7, o8, o10 - o14, o17, o19, and o21 contain text elements, o2 - o6, and o9 holds three icons, o15, o16, o18, and o20 contain image elements.

All the twenty one objects can be placed in any position within the layout. In a layout of size $X \times Y$, theoretically, an object can be placed in $X \times Y$ ways, without changing its orientation. However, out of the $X \times Y$ locations, there may be a few locations where an object cannot be placed, because the objects could cross the layout boundary. Practically, out of these $X \times Y$ spaces, an object of size $P \times Q$ can be positioned in S ways, where S is computed with the help of the following equation.

$$S = (X - P + 1) \times (Y - Q + 1) \tag{3.1}$$



(a)



(b)

Figure 3.1: A web page composed of one image and five texts is shown in (a). The corresponding wireframe model is shown in (b), where Object 1 denotes the image component and the five text elements are represented by the Object 2- 6 respectively.

Let us consider an example where a designer wants to place an object of size 3×2 in a layout of 10×6 (sixty locations), as shown in Figure 3.2. Out of the sixty locations, the object can be placed in forty locations, which can be computed using Equation 3.1.

$S = (10 - 3 + 1) \times (6 - 2 + 1) = 40$.

In Figure 3.2, we marked these forty locations using green color. It may be noted that out of the sixty (10×6) positions in the layout, twenty locations cannot be used.

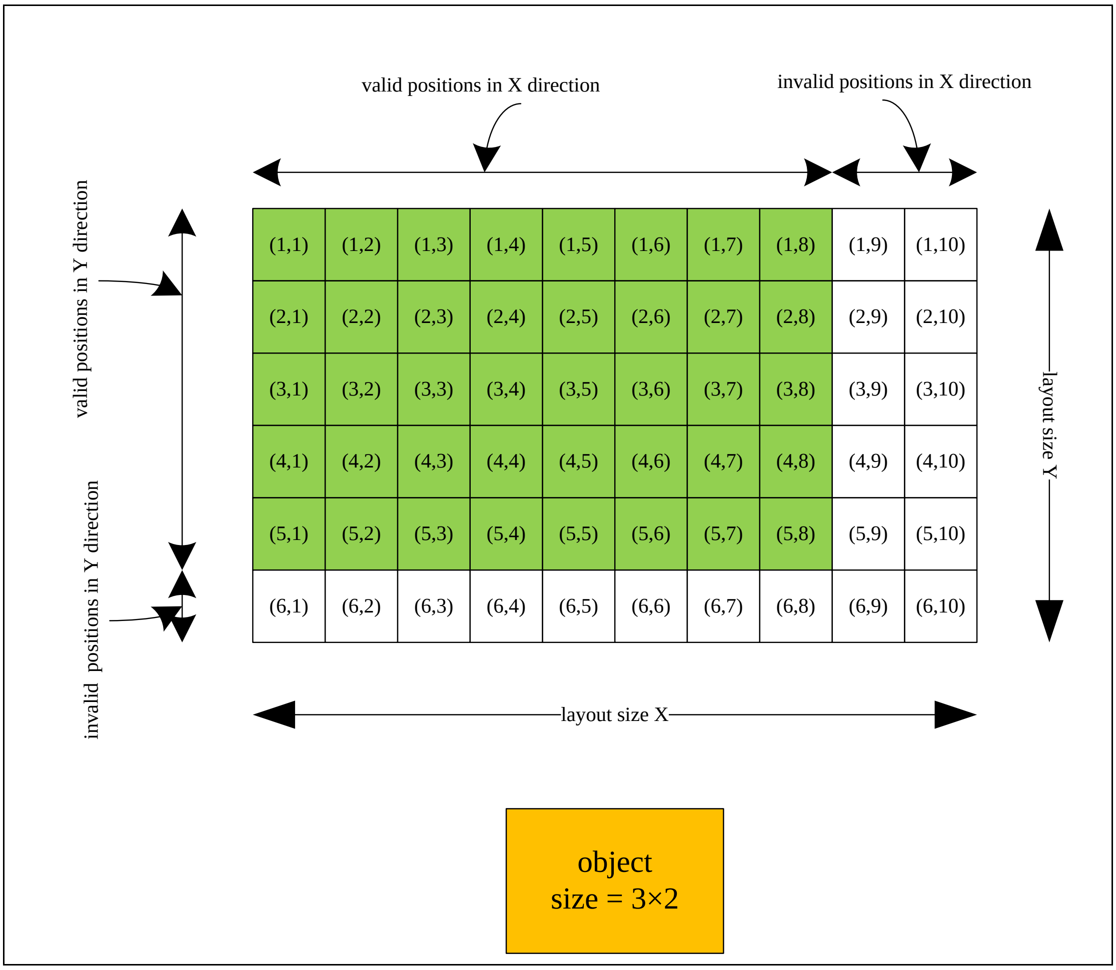


Figure 3.2: Forty positions (marked by green) of a layout (10×6), where an object (3×2) can be placed.

Unlike the previous case, where a single object was considered, a web page may have multiple objects, as shown in Figure 3.1. Let us consider another example where a designer wants to develop a web page using n number of objects. The total number of possible designs (P_D) can be computed by using Equation 3.2.

$$P_D = \sum_{i=1}^{n} (X_L - X_{oi} + 1) \times (Y_L - Y_{oi} + 1) \qquad (3.2)$$

where,

X_L =layout size in the X direction.

Y_L = layout size in the Y direction.

X_{oi} = size of the i-th object in the X direction.

Y_{oi} = size of the *i*-th object in the *Y* direction.

It may be noted that the design space also includes those designs, where an object is overlapped with the other objects. Out of these possible designs (P_D), a web page designer has to select any one for the development of a web page. However, selecting a design having better aesthetics than the others is a complex task.

A computational model of aesthetics, based on the features of the wireframe, can help web page designers to evaluate her/his design. Using the model, aesthetics of a web page can be predicted without subjective evaluation. As a consequence, the designer can evaluate the aesthetics of her/his design during the development period. Therefore, the design process can be automated, which is not possible if we have only subjective measures. This idea has encouraged researchers to develop computational models of web page aesthetics. The objective of these models is to predict the aesthetic quality of a web page in terms of some score or ratings or class.

The above mentioned *objective* measures (score or rating or class) of aesthetics are carried out based on the *wireframe features*, which are generally known to affect the aesthetic judgment. Ngo et al. [2003] reported the maximum number of wireframe geometry features for aesthetics computation. It was discussed in Section 2.4 of Chapter 2 (Scope of Our Work), that Ngo's model might not be suitable for modeling the aesthetics of modern web pages due to the fact –

- Significance of the thirteen features for modern web pages.
- Whether all the features will equally contribute to model the aesthetics judgment.

As a consequence, there is a need to –

- Check the significance of all the thirteen features [Ngo et al., 2003] for aesthetics computation of the modern web pages.
- Develop a computational model based on some weights (for different contributions) of those significant features, found in the previous step.

In order to achieve the above mentioned objectives, an empirical study using fifty two wireframe models (four layouts for each of the thirteen features) was carried out. The ANOVA study revealed that nine out of the thirteen features are statistically significant for aesthetics computation. Using these nine features, and the Support Vector Machine based binary classification, a computational model was developed. Validation of the model using ten web pages (wireframe) showed an accuracy of 90%

in web page aesthetics prediction. Due to the small number of test stimuli, the model was further validated using two hundred and nine web pages (this includes the earlier ten web pages). Out of the two hundred and nine web pages, the model predicted the aesthetics of one hundred and sixty five web pages accurately (accuracy -78.94%). The probable reason of the performance degradation from 90% to 78.94% may be due to the parametric analysis of the empirical data. It was reported [Wobbrock, and Kay 2016] that non-parametric analysis is more suitable for the studies in HCI.

As a consequence, the empirical data of the fifty two wireframes (for which a parametric analysis were already performed) are considered for a non-parametric analysis. Using the statistically significant features obtained from the non-parametric analysis, a computational model of aesthetics prediction was proposed. Unlike our earlier model which predicts aesthetics in two classes – good and bad, the new model was developed using the Support Vector Regression to predict the aesthetics in terms of ratings instead of class.

In this chapter, both the proposed models, which work based on the wireframe geometry are reported. Rest of the chapter is organized as follows. The significance testing of the thirteen features [Ngo et al., 2003] based on parametric analysis is discussed in Section 3.2. Based on the important features, a computational model of aesthetics prediction was developed. The proposed model along with its validation is reported in Section 3.3. In order to further validate, we conducted an empirical study using two hundred and nine web pages. Details of the empirical study was discussed in Section 3.4. Using the empirical results, the model is further validated, as discussed in Section 3.5. In Section 3.6, the limitations of the proposed model were reported. To overcome the limitations, another model of aesthetics computation based on the wireframe geometry was proposed. In order to develop the proposed model, the statistically significant features were identified by the non-parametric test as reported in Section 3.7. Using the statistically significant features, a computational model of aesthetics prediction was developed. In Section 3.8, the model was reported, followed by a brief discussion of the proposed model in Section 3.9. A summary of this chapter is presented in Section 3.10.

3.2 Identification of "Significant" Features

In order to find out the effect of the thirteen features [Ngo et al., 2003] of wireframe geometry associated with aesthetics, an empirical study was conducted. By systematically varying the thirteen feature values, we developed four wireframes for each feature. Altogether fifty two wireframes were designed, which was rated by a group of one hundred participants. Results of the empirical study were used for statistical significance testing. Details of the empirical study are discussed in the following.

3.2.1 Experimental Setup

In the previous chapter (Chapter 2), we mentioned the thirteen analytical expressions used to compute all the wireframe geometry features, reported by Ngo et al. [2003]. It may be noted that those mathematical equations can compute the feature values in a range of zero to one. In other words, the maximum and minimum value of a feature can be one and zero respectively. In order to systematically vary these feature values, for each feature, we created four wireframes at four levels – *very low (VL), low (LO), average (AV),* and *high (HI)*. The range for the feature values for each level is shown in Table 3.1. It may be noted that the range of feature values are equally distributed among these four groups.

Table 3.1: Four feature classes with their ranges.

feature class	minimum value	maximum value
Very Low (VL)	0	0.25
Low (LO)	>0.25	0.5
Average (AV)	>0.5	0.75
High (HI)	>0.75	1

Altogether fifty two wireframe models were developed by us. It may be noted that these fifty two models had no resemblance with any real web pages. The objective of choosing such wireframe models was to judge the significance of the thirteen wireframe features only. A relatively small number of objects were used in each layout to simplify the experimental conditions (design of four models in four levels as mentioned in Table 3.1).

Although we have designed fifty two samples for our study, the total number of possible samples by varying each of the thirteen features in four levels should be $4^{13} = 67108864$, more than sixty seven million! In our empirical study (discussed later in Section 3.2.3), we observed that the average time required to rate a wireframe was approximately thirty seconds. Then the time required to judge all the sixty seven million layouts would be

$$= 67108864 \times 30 \text{ Seconds}$$

$$= \frac{67108864 \times 30}{3600 \times 24 \times 365} \text{ Years}$$

≈ 64 Years - almost the lifespan of a human.

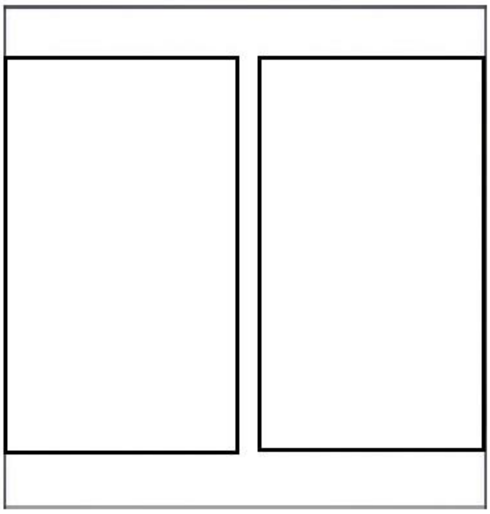
The extensive time requirement makes it impossible to judge the aesthetics of the sixty seven million wireframe layouts. In order to overcome this difficulty, we followed a simple approach.

For a particular feature - f_i ,($1 \leq i \leq 13$) we designed the four wireframes $-WF_{VL}^{i}$, WF_{LO}^{i}, WF_{AV}^{i}, and WF_{HI}^{i} (for four classes VL, LO, AV, and HI), where the feature f_i is systematically varied; while the other twelve features were varied randomly. As a consequence, we can claim that the aesthetics variations in this four wireframes - WF_{VL}^{i}, WF_{LO}^{i}, WF_{AV}^{i}, and WF_{HI}^{i} are due to the systematic variation of feature f_i , and the random variations in the rest twelve features. Table 3.2 shows the variations of the twelve randomly varied features when a particular feature varied systematically. The *LB* and *UB* are used to denote the lower bound and upper bound respectively. Let us consider the case where the *balance* varied systematically from 0.23 to 0.99. The average of the rest twelve features varied from 0.51 to 0.56. This signifies that only 5% variations were observed for the rest twelve features, as reported in Table 3.2. It may be noted that such variations lie from a minimum of 2% to a maximum of 9% for all the fifty two wireframe models. Due to this variation, the aesthetics score of a wireframe can be affected by 0.1 (5×.02) to 0.6 (5×.12), when judged in a five-point rating scale (as we planned to use 5 point rating scale for empirical evaluation). This small variation (0.1 to 0.6) signifies that the randomized variations of the twelve features (for each of the thirteen features f_i ($1 \leq i \leq 13$)) have no significant impact on aesthetics. However, the factor f_i (variation 61% to 90% as reported in Table 3.2) whose values were varied systematically, was the primary contributing factor to the aesthetic judgment.

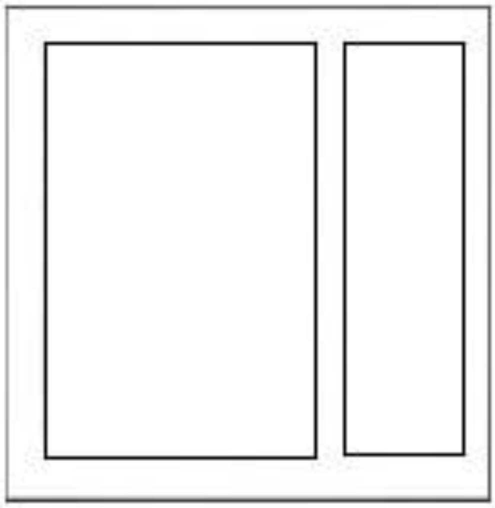
Table 3.2: Variations of the features' values for systematically and randomly varied features.

$feature_{sys\_varied}$				$feature_{ran\_varied}$		
Feature	**LB**	**UB**	**Variation (%)**	**LB**	**UB**	**Variation (%)**
balance	0.23	0.99	76	0.51	0.56	5
Equilibrium	0.21	0.92	71	0.42	0.44	2
sequence	0.25	1	75	0.42	0.46	4
symmetry	0.23	1	77	0.53	0.59	6
cohesion	0.21	0.82	61	0.53	0.62	9
unity	0.24	0.86	62	0.52	0.58	6
proportion	0.22	1	78	0.54	0.59	5
simplicity	0.2	1	80	0.54	0.56	2
regularity	0.24	1	76	0.59	0.65	6
economy	0.2	1	80	0.57	0.65	8
homogeneity	0.1	1	90	0.56	0.62	6
density	0.21	1	79	0.61	0.68	7
rhythm	0.23	1	77	0.48	0.57	9

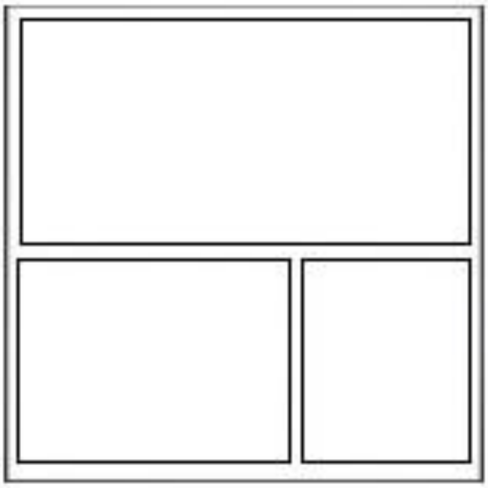
All the fifty two wireframe models were developed by using the Adobe Photoshop CS6™. The size of each web page was 700×700 pixels. Figure 3.3 shows a set of four wireframes where the *unity* feature varies. All the fifty-two wireframes were shown to the participants on PCs having *2.6 GHz AMD Phenom II X3 710*, processor running on Windows 8. Each PC had a 23 inch wide viewing angle color display.



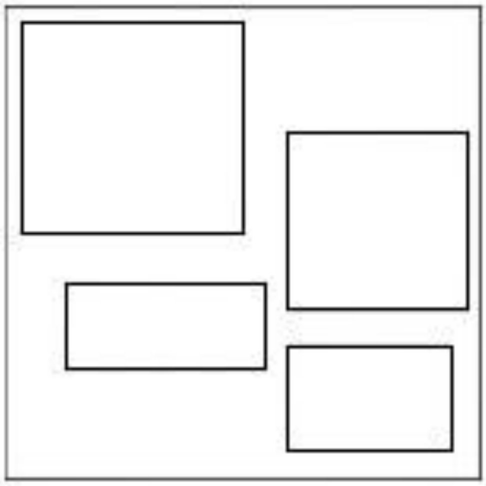
(a) unity = 0.8624 (class = high(HI))



(b) unity = 0.6308 (class = average(AV))



(c) unity = 0.4713 (class = low(LO))



(d) unity = 0.2462 (class =very low(VL))

Figure 3.3: Wireframes designed by varying the unity feature and their models.

3.2.2 Participants

In order to model the aesthetics of different types of users, we considered one hundred participants from different age groups, professions, genders, and cultures. Out of them, twenty were school students (ten male and ten female), sixty were under and postgraduate students (thirty male and thirty female), and the rest twenty were teachers (ten male and ten female). In Table 3.3, we reported the average, minimum, maximum age, and the standard deviation of these three group of participants. All of them had a normal or corrected-to-normal vision and were regular computer users. However, none was familiar with the screen design concepts.

Table 3.3: Participants' summary of the empirical study conducted for identifying the significant feature of wireframe geometry.

Participants	Total number of		Avg. Age	Min Age	Max Age	SD
	Male	Female				
school students	10	10	15.90	13	18	1.62
graduate students	30	30	22.17	19	25	2.10
Teachers	10	10	39.50	32	45	3.86

3.2.3 Procedure of Data Collection

The participants rated each wireframe in a five-point Likert's scale (1-5); five denoted *aesthetically pleasing*, and one denoted the *aesthetically least pleasing*. A browser-based viewer was created to view and rate the wireframe models, shown in Figure 3.4. Each participant rated all the fifty two wireframe models assigned to her/him in two sessions (twenty six each) in a day. They were allowed to take breaks in each session. These measures were taken to avoid discomfort to the participants that might have arisen due to a large number of web pages to be rated. To avoid the learning effect, we randomly varied the sequence of the wireframe models shown to the participants. Before data collection, we performed a small training session for the participants. In these sessions, participants were familiarized with the five point scale and the browser by which they had to rate the wireframe models.

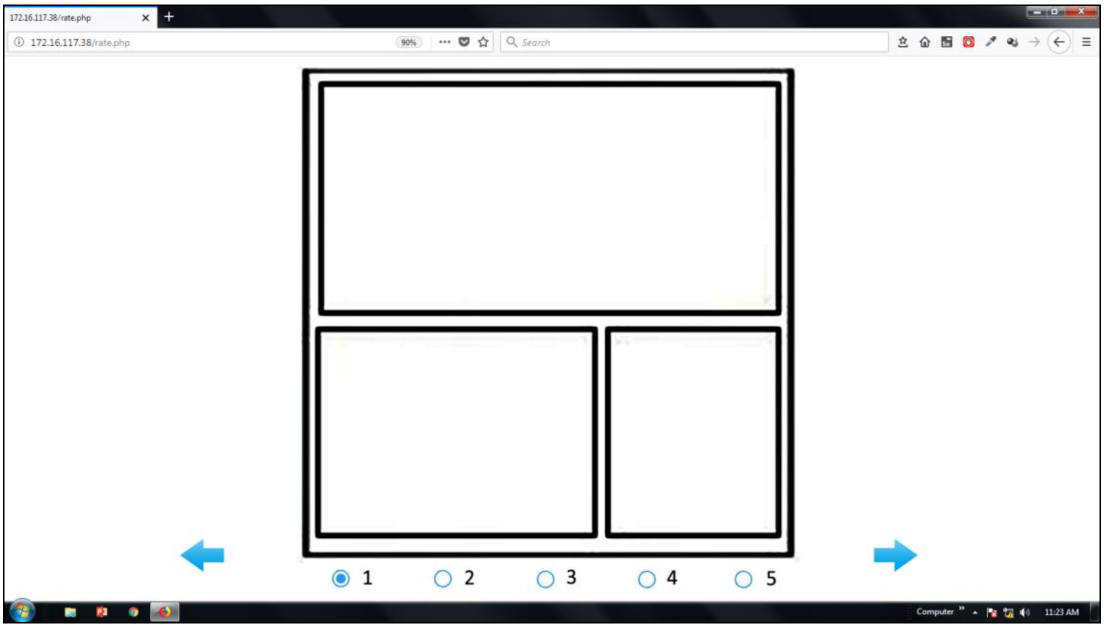


Figure 3.4: Developed interface for collecting empirical data.

3.2.4 Results and Analysis

The feature values along with the ratings by the one hundred participants are shown in Table 3.4.

Table 3.4: Empirical Study result for feature identification.

Feature	level	Value	Number of participants gave a rating				
			#1	#2	#3	#4	#5
Balance	HI	.99	8	22	28	22	20
	AV	.71	9	26	32	18	15
	LO	.49	2	15	34	26	23
	VL	.23	21	26	21	22	10
Cohesion	HI	.82	17	26	21	21	15
	AV	.73	6	19	24	26	25
	LO	.44	29	26	12	20	13
	VL	.21	3	12	20	33	32
Density	HI	1	3	16	32	25	24
	AV	.70	7	13	29	26	15
	LO	.41	8	23	27	25	17
	VL	.21	15	29	21	17	18
Economy	HI	1	6	14	24	27	29
	AV	.50	7	22	31	23	17
	LO	.33	7	12	29	26	26
	VL	.20	6	14	28	25	27
Equilibrium	HI	.96	3	9	23	28	37
	AV	.71	3	6	18	34	39
	LO	.39	3	14	27	31	25
	VL	.16	23	20	26	15	26
Homogeneity	HI	1	3	6	24	30	37
	AV	.73	1	6	10	27	56
	LO	.36	17	26	20	23	14
	VL	.10	3	16	41	18	22
Proportion	HI	1	0	12	29	31	28
	AV	.69	5	11	24	29	31
	LO	.50	1	7	17	21	54
	VL	.22	6	21	38	16	19

Regularity	HI	1	5	5	14	19	57
	AV	.62	6	27	30	23	14
	LO	.46	7	20	23	28	22
	VL	.24	22	22	26	11	19
Rhythm	HI	1	1	6	27	29	37
	AV	.71	5	15	19	21	40
	LO	.47	2	8	17	26	47
	VL	.23	3	5	22	25	45
Sequence	HI	1	3	13	23	29	32
	AV	.62	2	8	21	30	39
	LO	.5	4	18	25	30	23
	VL	.25	1	5	20	37	37
Simplicity	HI	1	2	13	21	40	24
	AV	.6	2	12	25	34	27
	LO	.43	4	19	25	30	22
	VL	.2	2	8	22	30	38
Symmetry	HI	1	6	21	22	32	19
	AV	.75	3	10	14	34	39
	LO	.45	23	23	26	13	15
	VL	.23	0	12	18	29	41
Unity	HI	.86	3	15	23	32	27
	AV	.63	6	24	24	31	15
	LO	.47	8	18	36	20	18
	VL	.24	1	10	18	22	49

Altogether, five thousand and two hundred ratings (which are the ratings of one hundred participants for the fifty two wireframe models) were considered for our study. To judge the impact of the feature variations with aesthetics, the following NULL hypothesis was formulated.

Null Hypothesis: *Variation of the feature values has no impact on aesthetics.*

Based on the empirical results, we performed thirteen independent one dimensional *ANOVA* (one for each feature) by using the *ANOVA1* command of *MATLAB 2014*. It was observed that the p values are higher ($p > 0.05$) for the three features - *density* (0.11), *economy* (.108), *rhythm* (.174) and *simplicity* (.053) as shown in Table 3.5.

Therefore, the variations of these feature values were not having a statistically significant impact on the web page aesthetics. On the contrary, the remaining nine features –*balance*, *cohesion*, *equilibrium*, *homogeneity*, *proportion*, *regularity*, *sequence*, *symmetry* and *unity* were found to be statistically significant for the web page aesthetics. Consequently, these nine geometry features were considered for web page aesthetics computation. Accordingly, we propose a computational model based on these nine features, as discussed below.

Table 3.5: Results of the ANOVA.

Feature	F value	P value
Balance	7.76	< 0.001
Cohesion	17	< 0.001
Density	2.18	0.11
Equilibrium	21.01	< 0.001
Economy	2.04	0.108
Homogeneity	30.05	< 0.001
Proportion	6.67	< 0.001
Regularity	22.04	< 0.001
Rhythm	1.67	0.174
Sequence	5.13	< 0.001
Simplicity	3.19	.053
Symmetry	25.21	< 0.001
Unity	12.68	< 0.001

3.3 SVM based Binary Classification Model

SVM [Cortes and Vapnik, 1995] is popularly used for solving the binary classification problems. The different applications where SVM based classifications are popularly used are –

- Text categorization [Text categorization]
- Cancer detection [Cancer Detection]
- Image classification [Image Classification]
- Handwritten character recognition [Hand- written character recognition]

SVM can handle large feature sets, and the soft margin technique helps to control the overfitting of data [Mingyue, 2004]. Due to these advantages, and the wide applications of SVM, we developed our model by using the binary classification of *Support Vector Machine* (SVM). The nine statistically significant features of wireframe geometry as discussed in the Section 3.2.4 were considered for our model development. The development of our proposed model, along with its validations are discussed below.

3.3.1 Model Development

The SVM based classification is a supervised learning method [Cortes and Vapnik, 1995]. As a consequence, there is a necessity to train the model using some training data. In order to train the proposed model, we considered a subset of the data (nine out of the thirteen features) reported in Table 3.4. From Table 3.4, it may be noted that we have five thousand and two hundred (100×4×13) data points which are the ratings of one hundred participants on the fifty two web pages; four web pages for each of the thirteen features. Out of these thirteen features, we considered nine features for the model training. Therefore, we had thirty six web pages (four for each feature) and their corresponding one hundred ratings, for these nine features. Altogether, three thousand and six hundred (9×4×100) training data points were considered. We considered nine SVMs to predict the nine features independently. Each of these nine SVMs was trained by the four hundred data points (100×4), which are the ratings for the four different wireframes of a particular feature. All the three thousand and six hundred unlabeled data were converted to the labeled training data by using the following logic.

Data Labeling Logic

```
 Input:  36 feature values and their ratings of 100 participants
Output: feature class (good or bad)

       if (feature value>= 0.5 and rating >= 3)
              feature class = good (labeled by +1)
       else
              feature class = bad (labeled by -1)
       end if
```

A particular feature of a web page was labeled as good (+1), only when a participant gave a rating of more than two on a five-point scale, as well as the feature value was more than or equals to 0.5 (computed by the average of the nine significant features) on a 0 to 1 scale. This was done to label almost half of the scale for aesthetically pleasing (good), and the rest was for aesthetically unpleasing wireframes. Using these labeled data, we trained our classifiers using the *SVMTRAIN* function of *MATLAB* 2014.

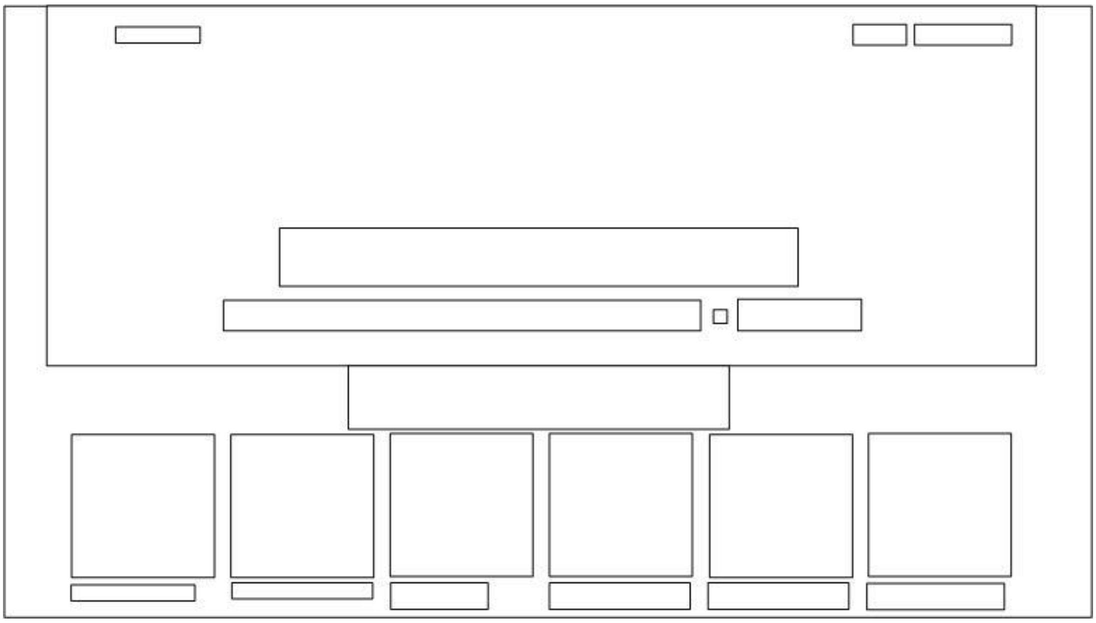
3.3.2 Model Validation

In order to validate the proposed classifiers, another empirical study on ten real web pages was conducted. The details of the empirical study, along with the performance of the proposed model are discussed below.

3.3.2.1 Experimental Setup

For model validation, we considered ten real web pages (home pages of 10 websites). These web pages are used in some popular applications – education, banking, e-commerce, social networking, entertainment, news and corporate sector, as shown in Table 3.6. In order to create the wireframe designs, we created and placed blank rectangles by manually analyzing the contents. The web page contents having similar types are grouped by a single rectangle. The wireframe models for all the ten web pages were developed by Microsoft Office Visio 2007. For illustration, the wireframe model of the *Soundcloud* web page (see Figure 3.5 (a)) is presented in Figure 3.5 (b). All the ten wireframe models were rated by the participants in PCs, having 2.6 *GHz AMD Phenom II X3 710* processor, running on *Windows 8*. Each PC had a 23 inch wide viewing angle color display.

(a)



(b)

Figure 3.5: (a) Homepage of the Soundcloud and (b) wireframe model of it.

Table 3.6: Home web page of 10 popular websites and their application area.

website no	Website	application area	website link	size
1	CIT, Kokrajhar	education	cit.ac.in	638×567
2	IIT Guwahati		iitg.ac.in	1345×747
3	Facebook	social networking and entertainment	facebook.com	1345×745
4	Sound Cloud		soundcloud.com	1366×768
5	Youtube		youtube.com	1339×737
6	Flipkart	e-commerce and baking	flipkart.com	1323×763
7	State Bank of India (SBI)		onlinesbi.com	1005×677
8	Amazon		amazon.com	1351×735
9	NewsLive	news	newslivetv.org	1349×767
10	TCS	corporate	tcs.com	751×759

3.3.2.2 Participants

All the ten web page models were rated by eighty new participants, not involved in our prior study. Out of them, forty were male, and the rest were female. Fifty participants were undergraduate students (average age twenty one years), twenty were postgraduate students (average age twenty seven years) and ten were faculty members (average age forty years). The details of the participants – average age, minimum age, maximum age, and standard deviation are reported in Table 3.7. All the participants were regular computer users, but none of them had any knowledge about the website design principles. All the users had normal or corrected-to-normal vision.

Table 3.7: Participants details involved in the empirical study.

Participants	Total number of		Avg.	Min	Max	SD
	Male	Female	Age	Age	Age	
under graduate students	25	25	20.62	18	23	1.74
post graduate students	10	10	27.3	25	30	1.64
teachers	5	5	39.8	35	45	1.42

3.3.2.3 Procedure for Data Collection

Each participant rated the ten web page models using the same browser-based viewer used in our previous study. After viewing each web page model, they rated it according to its *aesthetic appeal* in the five-point Likert's scale, where five denoted aesthetically pleasing, and one denoted aesthetically least pleasing. To avoid the learning effect, we randomly varied the sequence of the web page models shown to the participants. A participant rated the ten web pages assigned to him/her in one session in a day. Before data collection, we performed a small training session, where the participants were familiarized with the five point scale and the web interfaces by which they had to rate the web pages.

Table 3.8: Feature values of the 10 web pages.

Feature	Website										Feature Value		
	CIT, Kokrajhar	Sound Cloud	State Bank of India	Flipkart	Facebook	Amazon	NewsLive	Youtube	IIT, Guwahati	TCS	maximum	minimum	range %
balance	0.60	0.76	0.62	0.57	0.50	0.67	0.30	0.57	0.59	0.69	0.30	0.76	46
equilibrium	0.98	0.98	0.99	0.99	0.99	0.98	0.98	0.99	0.98	0.99	0.98	0.99	01
symmetry	0.35	0.39	0.34	0.40	0.43	0.40	0.39	0.42	0.41	0.37	0.34	0.43	09
sequence	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	00
cohesion	0.62	0.75	0.66	0.65	0.69	0.54	0.64	0.69	0.68	0.64	0.54	0.75	21
unity	0.21	0.66	0.18	0.11	0.17	0.49	0.07	0.24	0.07	0.21	0.07	0.66	59
proportion	0.76	0.46	0.85	0.90	0.88	0.79	0.92	0.84	0.87	0.71	0.46	0.92	46
simplicity	0.12	0.11	0.12	0.09	0.09	0.30	0.17	0.15	0.15	0.13	0.09	0.30	21
density	0.91	0.46	0.30	0.50	0.58	0.46	0.85	0.24	0.84	0.11	0.11	0.91	80
regularity	0.37	0.56	0.40	0.44	0.42	0.31	0.35	0.45	0.28	0.56	0.28	0.56	28
economy	0.16	0.16	0.14	0.08	0.09	0.25	0.14	0.12	0.14	0.11	0.08	0.25	13
homogeneity	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.02	02
rhythm	0.35	0.43	0.34	0.43	0.43	0.42	0.40	0.46	0.45	0.39	0.34	0.46	12
order	**0.47**	**0.52**	**0.43**	**0.47**	**0.45**	**0.51**	**0.45**	**0.44**	**0.50**	**0.45**	**0.43**	**0.52**	**07**

3.3.2.4 Results

The thirteen feature values and their average of the ten web page models were computed with the help of the formulas reported in [Ngo et al., 2003]. Although the nine out of the thirteen features were considered for the model development, computations of the thirteen feature values helped us to prove the efficiency of our model. Table 3.8 shows the values of all the thirteen features of the ten web pages. Using these web pages, we performed an empirical study. Results of the empirical study are shown in Table 3.9. The mode column denotes the rating, given by most of the users of a particular web page. Based on the mode value, we classified the web pages into two classes – good or bad, using the following logic.

```
if mode >= 3
       web page class=good(aesthetically pleasing(+1))
else
       web page class=bad(aesthetically unpleasing(-1))
```

Table 3.9: Empirical study result of 10 web pages along with their type.

Website	**No of user gave a rating**						**Web page class**
	#1	#2	#3	#4	#5	Mode	
CIT, Kokrajhar	3	14	41	17	5	3	+1
Sound Cloud	0	12	8	39	21	4	+1
State Bank of India	7	30	26	3	14	2	-1
Flipkart	5	34	12	18	11	2	-1
Facebook	12	15	28	21	4	3	+1
Amazon	3	9	19	33	16	4	+1
NewsLive	13	27	14	18	8	2	-1
Youtube	9	36	5	21	9	2	-1
IIT Guwahati	8	4	22	29	17	4	+1
TCS	3	9	16	31	21	4	+1

The nine SVMs were trained independently to predict the feature class (good or bad) of the nine features (for ten web pages), reported in Table 3.10. Feature class prediction was made using the *SVMPREDICT* function of *MATLAB* 2014 version. Based on the nine predicted features' classes, the aesthetics of a web page was predicted using the following algorithm.

Prediction Algorithm

```
Input:  9 feature class values (good or bad), count = 0
Output: web page class (good or bad)

        for i = 1 to 9
                if (feature class == good)
                        count = count+1
                endif
                i=i+1
        end for
        if (count>=5)
                web page class = good (labeled by +1)
        else
                web page class = bad (labeled by -1)
        endif
```

The prediction algorithm shows, if most of the predicted features (five out of the nine) are aesthetically pleasing (good), then the algorithm (as mentioned above) predicts the web page as good (aesthetically pleasing). Otherwise, it is treated as bad (aesthetically unpleasing).

Using the proposed model, we predicted the feature classes of the ten web pages, as shown in Table 3.10. Then the model predicted the web pages' aesthetics as aesthetically pleasing (+1) or not (-1). The rightmost column of Table 3.10 shows the result of the web page type (aesthetically pleasing or not) by the users' rating. In order to validate the proposed model, the predicted scores were compared with the scores, obtained from the empirical study.

Out of the ten web pages, our model accurately predicted the aesthetics of nine web pages, with an accuracy of 90% (nine out of ten).

Table 3.10: Empirical study result vs. predicted result.

Web Sites	Label predicted by our developed SVM									model predicted web page label	users' choice web page label
	balance	cohesion	equilibrium	Homogeneity	proportion	regularity	Sequence	Symmetry	unity		
CIT, Kokrajhar	-1	-1	+1	-1	+1	+1	+1	-1	-1	-1	+1
Sound Cloud	+1	+1	+1	-1	+1	+1	+1	-1	+1	+1	+1
SBI	-1	-1	+1	-1	-1	-1	-1	-1	-1	-1	-1
Flipkart	-1	-1	+1	-1	-1	-1	-1	-1	-1	-1	-1
Facebook	-1	-1	+1	-1	+1	+1	+1	+1	-1	+1	+1
Amazon	+1	+1	+1	-1	+1	+1	+1	-1	+1	+1	+1
NewsLive	-1	-1	+1	-1	-1	-1	-1	-1	-1	-1	-1
Youtube	-1	-1	+1	-1	-1	-1	-1	-1	-1	-1	-1
IIT Guwahati	+1	+1	+1	-1	+1	+1	+1	-1	-1	+1	+1
TCS	+1	+1	+1	-1	+1	+1	+1	-1	-1	+1	+1

3.3.3 Discussion

Ngo et al. [2003] claimed that the *order* value might be a measure for aesthetics computation. However, in this study, we observed that the *order* may not be relevant for real web pages. The *order* value of the ten real web pages lied in the range from 0.43 to 0.52 as shown in Table 3.11. It may be noted that the order value of the *facebook* is 0.45, was treated by the participants as an aesthetically pleasing web page. In contrary, the higher *order* value (than that of *Facebook*) of *Flipkart* 0.47 was treated as aesthetically unpleasing by the participants. Again, the lower *order* value (than that of *Flipkart*) of *TCS* and *CIT, Kokrajhar* (0.4532, and 0.4581 respectively) were marked as aesthetically pleasing. It may also be noted that the difference between the *order* value among the *NewsLive* and *Facebook* is only 0.1%. However, participants found *Facebook* as aesthetically pleasing, while the *NewsLive* as aesthetically unpleasing. Similarly, the difference in the *order* value is only 0.7% among *CIT Kokrajhar* and *Flipkart*. However, *CIT Kokrajhar* was considered as aesthetically pleasing, while the *Flipkart* was treated as aesthetically unpleasing.

Based on the above observations, it may be claimed that the *order* is not a suitable metric for aesthetics computation. In contrast, our model works based on the *SVM*; which has the capability for solving binary classification problems with high accuracy.

Table 3.11: 10 web pages sorted based on the order values.

web page	order value (increasing order)	participants rating	prediction by our model
State Bank of India	0.43349530	bad	bad
Youtube	0.44065420	bad	bad
NewsLive	0.45203010	bad	bad
Facebook	0.45325800	good	good
TCS	0.45811670	good	good
CIT, Kokrajhar	0.47062310	good	bad
Flipkart	0.47754585	bad	bad
IIT Guwahati	0.50035031	good	good
Amazon	0.51333154	good	good
Sound Cloud	0.52164992	good	good

SVM maps data into a higher dimensional input space and creates an optimal separating hyperplane in the higher dimensional space. As a result, two classes (good or bad) are created across the separating hyperplane. Then for a particular input, *SVM* predicts the corresponding class. However, selection of *SVM* kernel is a tricky task. The general convention is to use the linear kernel first, as they are easier and faster than that of the others kernels, like *polynomial*, *RBF*, and *Sigmoid* kernels. If the prediction result is satisfactory, then the linear kernel is the best option; otherwise, other kernels may be used. Using this convention, we used the *linear kernel* of SVM to develop the proposed model. We observed the accuracy of 90% in aesthetics prediction, which is good enough, and consequently refrained to consider the other kernels.

The proposed model was validated using ten real web pages. As the web pages were real, the variations of the feature values cannot be controlled in a systematic way. As a consequence, the performance of the proposed model needed to be further validated using a group of web pages where the feature values are varied systematically, in a wider range. In the following section, we describe further validation of our proposed model.

3.3.4 2nd Validation of the Model

The validation study was conducted by using the wireframe models of two hundred and nine web pages (where the features' values were varied systematically in a wider range). Detailed design of the test stimuli is reported below.

3.3.4.1 Design of Test Stimuli

Design of a web page requires the knowledge of the objects size, and their organization in real web pages. In order to analyze the size and organization of the web page objects, we considered fifty nine real web pages that are used in different applications - education, social networking, banking, e-commerce, travel, weather, news, sports and corporate sector, as mentioned in Table 3.12. Based on the web page object sizes and their organizations of the fifty nine real web pages, three properties of web page design were identified, which are reported in Table 3.13.

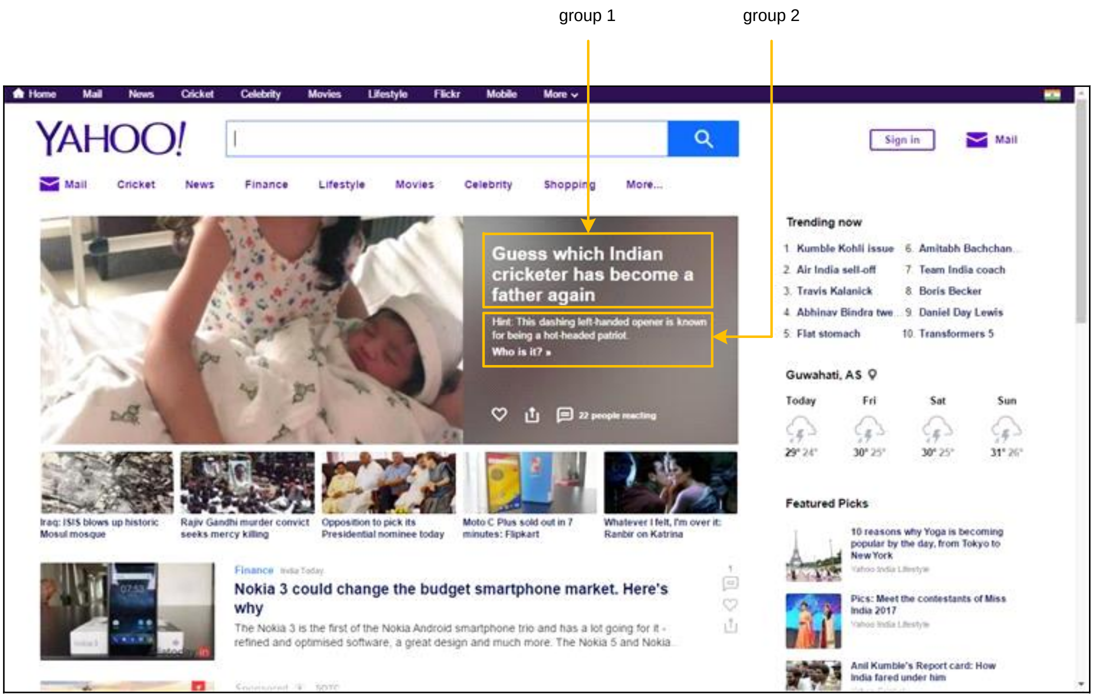
Table 3.12: Real web pages used for our study along with their applications.

Area	web no	Website	website link	web no	Website	website link
Education	169	IIM, Ahmedabad	iima.ac.in	181	NPTEL	nptel.ac.in
	170	IIM Kolkata	iimcal.ac.in	204	IIT Guwahati	iitg.ac.in
	171	IIT Kharagpur	iitkgp.ac.in	200	CIT, Kokrajhar	cit.ac.in
	172	IIT Bombay	iitb.ac.in			
Social networking and Entertainment	173	IMDB	imdb.com	194	Twitter	twitter.com
	175	Instagram	instagram.com	196	Wikipedia	wikipedia.org
	178	Linkedin	linkedin.com	198	Yahoo	in.yahoo.com
	180	MSN	msn.com	201	Facebook	facebook.com
	182	OZEE	ozee.com	207	Sound Cloud	soundcloud.com
	183	Reddit	reddit.com	209	Youtube	youtube.com
	184	Rediff	rediff.com			
E-commerce	154	Apple India	apple.com/in	185	Samsung	Samsung.com
	155	AXIX bank	axixbank.com	186	Sony	sony.co.in
	158	Big Bazaar	bigbazaaar.com	189	Tata Car	tatamotors.com

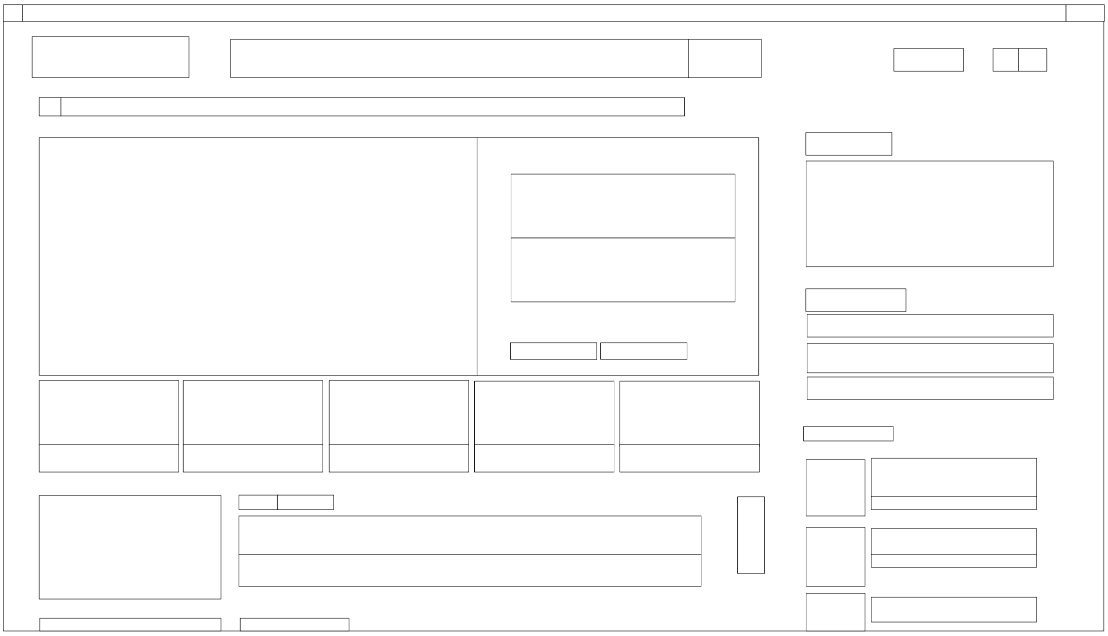
	162	Ebay	ebay.in	202	Flipkart	flipkart.com
	167	Honda	hondacarindia.com	203	Amazon	amazon.com
	168	ICICI	icicibank.com	206	State Bank of India	onlinesbi.com
News	153	Anandabazar	anandabazar.com	191	Times of India	timesofindia.indiatimes.com
	157	BBC	bbc.com	205	NewsLive	newslivetv.org
	190	Telegraph	telegraphindia.com			
Corporate	179	Microsoft	microsoft.com	208	TCS	tcs.com
Weather	151	Accuweather	accuweather.com			
Travel	152	Air India	airindia.in	187	Spicejet	spicejet.com
	160	British Airways	britishairways.com	192	Travelocity	travelocity.com
	174	Indigo	goindigo.in	193	Trivago	trivago.in
	176	Irctc	irctc.co.in	199	Yatra	yatra.com
Search	159	Bing	bing.com	166	Google	google.com
	156	Baidu	baidu.com			
Research	161	DRDO	drdo.gov.in	195	UCCN	iitg.ernet.in/cseweb/uccn
	177	ISRO	isro.gov.in			
Sports	163	FOX sports	foxsports.com	188	Starsports	www.hotstar.com/sports
Job	164	Freshersworld	freshersworld.com			
Mail	165	Gmail	gmail.com	197	Windows Live	live.com

Table 3.13: Summary of the survey results conducted on fifty-nine web pages.

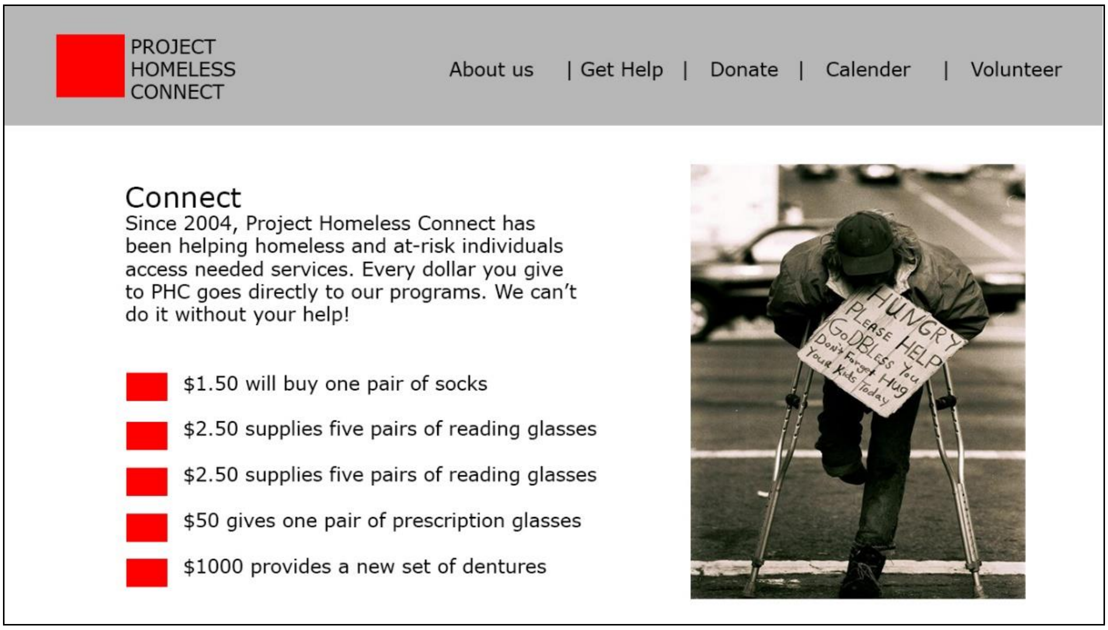
Property	Observation
Position of the largest object	89.83% in the center of the layout
Position of the smaller objects	Mostly (92.5%) above or the bottom of the larger objects
Average number of unique objects	Mostly less than five (81.35%)



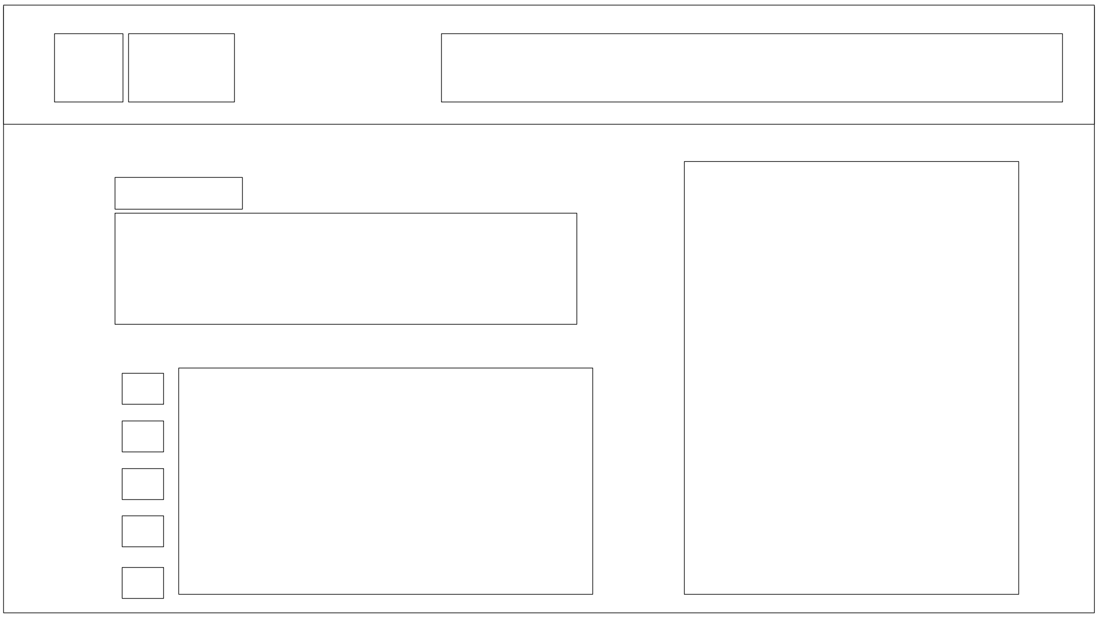
(a) yahoo web page.



(b) wireframe model of Yahoo (in.yahoo.com).



(c) web page developed by us.



(d) wireframe model of our web page.

Figure 3.6: Web pages and their corresponding wireframe models.

Based on the results (as reported in Table 3.13), and by varying the feature values systematically in a wider range, one hundred and fifty web pages were developed by us. An example of such web page is shown in Figure 3.6 (c). In order to model the aesthetics of the real web page, the fifty nine real web pages, as reported in Table 3.12 were also considered for the model validation. Altogether two hundred and nine web pages were used for the validation study.

3.3.4.2 Wireframes Development

Out of the two hundred and nine web pages, the wireframe models of the ten web pages were already developed for our earlier aesthetics prediction model as discussed in Section 3.3.1. The wireframes for the rest one hundred and ninety nine web pages were designed by using ***Microsoft Office Visio 2007***. For illustration, two web pages - one of them being real (the web page of Yahoo (*in.yahoo.com*)), and the other was developed by us, are shown in Figure 3.6 (a), and (c) respectively. The wireframes were designed by manually analyzing the contents, and placing blank rectangles (the same logic was also used for the generation of the wireframes for ten web pages as discussed in Section 3.3.2). The web page contents having similar types are grouped by a single rectangle. For example, as the contents labeled by group 1 and group 2 in Figure 3.6 (a) have different font sizes, instead of using one rectangle, we used two rectangles to denote them independently. The wireframe model of the two web pages shown in Figure 3.6 (a) and (c), are shown in Figure 3.6 (b) and (d), respectively. Similarly, the wireframe models of all the web pages were designed. The thirteen feature values for the two hundred and nine web page models (individually and their averages) were computed with the help of Ngo's formulas. Table 3.14 shows the range of the thirteen features values, along with their averages. It may be noted that the variations of all the features are more than 75%. As a consequence, using the two hundred and nine web pages the proposed model can be validated more appropriately than the earlier validation, where ten web pages were considered.

Table 3.14: Range of the feature values of two hundred and nine web pages along with their average.

	BA	**EQ**	**SY**	**SE**	**CO**	**UN**	**PR**	**SI**	**DE**	**RE**	**EC**	**HO**	**RH**
Max	0.93	0.96	1	1	0.83	0.88	0.99	0.90	0.99	0.84	1	1	1
Min	0	0.19	0.01	0	0	0.02	0	0	0	0.03	0.03	0	0.01
Variations (%)	93	77	99	100	83	86	99	90	99	81	97	100	100

3.3.4.3 Setup for Data Collection

All these two hundred and nine wireframe models were used for conducting an empirical study. In order to rate those pages, we created a feedback form, reported in each form contained five demographical attributes of a participant. Those attributes are – name, age, gender, profession, and the average time a participant spent for accessing web pages in a day. A participant can record the aesthetic score of all the two hundred and nine web pages using this form. We also asked the participants to relate the wireframes to any familiar web pages. To record this, another binary attribute with the answer of YES/NO was used. If the answer is YES, they can write down the name of the web page. The empirical study was carried out by the PCs, having 2.6 *GHz AMD Phenom II X3* 710 processor, running on Windows 8. Each PC had a 16 inch wide viewing angle color display.

3.4.4.4 Participants and Method

In order to remove any biases (due to the familiarity of the web pages), we considered a new group of one hundred and fifty participants (not part of the earlier empirical studies) from different parts of India. All the participants rated the two hundred and nine wireframe models on a five-point rating scale. Out of them, twenty were school students (ten male and ten female), one hundred were under and postgraduate students (fifty male and fifty female), and remaining thirty were teachers (fifteen male and fifteen female). In Table 3.15, we reported the average, minimum, maximum age, and the standard deviation of these three group of users participated in our study. All the participants considered for this study were regular users of web pages. However, they do not have prior expertise in web page designing.

Table 3.15: Participants' summary of the empirical study conducted for developing an aesthetics prediction model based on wireframe geometry.

Participants	Total number of		Avg. Age	Min Age	Max Age	SD
	Male	Female				
school students	10	10	15.10	14	16	0.72
graduate students	50	50	20.48	17	24	2.31
teachers	15	15	33.9	30	38	2.76

Before data collection, we arranged a small training session for all the participants. In this session, participants were familiarized with the five-point scale (five denotes aesthetically most pleasing and one denotes aesthetically least pleasant web page) and the feedback form. We did not provide any clue/training on how to perform aesthetic evaluation. This was done to keep all the participants unbiased. After the training session, each participant observed the two hundred and nine models using a browser-based viewer. All of them recorded the ratings of these web pages in the feedback forms. To avoid the learning effect, we systematically varied the sequence of the web page models shown to the participants. All the participants assessed the two hundred and nine models assigned to him/her in four sessions across two days. We allowed the participants to take breaks for avoiding any discomfort.

3.3.4.5 Validation Results

The statistical modes of the two hundred and nine web pages obtained from the empirical study were used to validate the proposed model. In order to classify those web pages in a binary class – (aesthetically pleasing, and aesthetically unpleasing), the same logic used earlier (Section 3.3.2) was adopted. For a particular web page, if the mode value was greater than two (in a five-point rating scale), then the web page was classified as aesthetically pleasing. Otherwise, it was treated as aesthetically unpleasing.

After the classification based on the empirical data, the aesthetics of the all two hundred and nine web pages were predicted by using our proposed model. The predicted classes (good, bad) for all the web pages were compared with the classes obtained from the empirical study. It was observed that out of the two hundred and nine web pages, our proposed model could predict the aesthetics of the one hundred and sixty five web pages accurately. In other words, the accuracy of the proposed model is 78.94%. It may be noted that the performance of the proposed model dropped from 90% (achieved in the earlier validation mentioned in Section 3.3.2.4) to 78.94%.

3.4 Limitations of the Proposed Model

One of the possible reason for the performance degradation may be the assumption that the data were distributed normally, and parametric analysis was done to identify the statistically significant features of wireframe geometry. In practical this assumption may not be true. It was reported [Wobbrock, 2017] that studies in HCI often generate non-parametric data, which are not distributed normally. As a consequence, there is a necessity to develop a computational model of wireframe geometry based on the non-parametric analysis.

The proposed model can measure aesthetics in two classes – aesthetically pleasing, and aesthetically unpleasing. However, it was reported in Chapter 2 that a more extended scale could convey more meaningful information. As a consequence, there is a necessity to develop a computational model of wireframe geometry capable of predicting aesthetics in terms of some score rather than a class. Development of such models is also suitable for the development of our final model. We planned to develop the final model capable of predicting aesthetics in terms of ratings or scores by developing and integrating the different component models – wireframe, text, image, and white space.

Therefore, there is a requirement of developing a computational model of wireframe geometry by considering the following objectives -

- Nonparametric analysis of the wireframe geometry features
- Development of a computational model
  - By considering the significant features found from the previous step
  - That is able to predict aesthetics in terms of a score rather than a class.

In order to achieve the objectives, we performed a non-parametric analysis of the empirical data of the fifty two wireframes (Section 3.2). It was observed that ten out of the thirteen features of wireframe geometry are statistically significant for aesthetics computation. Using these ten features, another computational model of aesthetics prediction was developed. As we were interested in computing the aesthetics in terms of score, *Support Vector Regression* was used to develop the model. The non-parametric analysis, development of the model, along with its validation is discussed in the following.

3.5 Identification of "Significant" Features using Non-parametric Approach

The *Friedman* test on the empirical data was used to judge the effect of each feature on aesthetics independently. Altogether, the test was performed thirteen times for judging each of the thirteen features. The ordinal variable of our study (user's rating) is suitable for this test[1]. Results of Friedman test along with the ANOVA test (as reported in Table 3.5) are shown in Table 3.16. It may be noted that the *p* values of the features - density (0.117), economy (0.108) and rhythm (0.11) are higher than 0.05 (satisfy the NULL hypothesis) for the Friedman test. On the other hand, the rest ten features reject our NULL hypothesis. Therefore, these ten features are statistically significant for aesthetics. We may note that the three features – *density, economy,* and *rhythm* are also not significant for the parametric analysis. Hence, we proposed to develop our computational model using the remaining ten features, as discussed in the next section.

Table 3.16: Result of the Friedman Test and parametric ANOVA.

	Friedman Test		**ANOVA**	
Feature	Chi-square value	P value	F value	P value
Balance	26.24	<0.001	7.76	< 0.001
Cohesion	51.84	<0.001	17	< 0.001
Density	4.29	0.117	2.18	0.11
Equilibrium	54	<0.001	21.01	< 0.001
Economy	7.12	0.108	2.04	0.108
Homogeneity	89.3	<0.001	30.05	< 0.001
Proportion	16.54	<0.001	6.67	< 0.001
Regularity	68.72	<0.001	22.04	< 0.001
Rhythm	6.03	0.11	1.67	0.174
Sequence	18.01	<0.001	5.13	< 0.001
Simplicity	12.28	< 0.05	3.19	.053
Symmetry	67.94	<0.001	25.21	< 0.001
Unity	40.27	<0.001	12.68	< 0.001

[1] The test was carried out by using the *ANOVA*1 (parametric test) and *friedman* (nonparametric test) command of MATLAB 2017a version.

3.6 Support Vector Regression based Model of Wireframe Geometry

The proposed aesthetics computation model is developed based on the Support Vector Regression (SVR) [Cortes and Vapnik, 1995]. The empirical study result on the two hundred and nine web pages, as reported in Section 3.3.4 were considered for the development and validation of the proposed model.

In the previous study, we observed that the participants were unable to identify the real web pages by viewing the corresponding wireframe models in most of the cases. As a result, in terms of familiarity, there were almost no differences among the two different types of wireframe models (of real web pages and that of our developed web pages). Accordingly, we planned to develop our computational model of aesthetics by considering the fifty nine real web pages and one hundred and fifty web pages (developed by us) together. The average participants' ratings and the ten statistically significant features' values of these two hundred and nine web pages were used to develop our proposed model.

We used the *Regression Learner Apps* of the *MATLAB 2017a* to build the model. Six kernels of SVM - *linear*, *quadratic*, *cubic*, *fine Gaussian*, *medium Gaussian*, and *coarse Gaussian*[2] were explored for suitability of the proposed model.

F*ive-fold cross-validation* technique was used for the model validation. C*ross-validation* is a helpful technique for the assessment of any model. *Five-fold cross-validation* method partitions the data (two hundred and nine for our case) into five randomly chosen subsets of almost equal size. Four subsets are used to train the model while the remaining one subset is used to validate the model. The same process is repeated five times in order to validate all the subsets. Cross-validation method is exceptionally beneficial to prevent the overfitting of data during the training procedure.

[2] During the process of regression, the box constrained mode, epsilon mode, and kernel scale mode in MATLAB were set to *auto*.

Table 3.17: Five-fold cross-validation study result using the different kernels of SVR.

	SVR					
	Linear	**Quadratic**	**Cubic**	**Fine Gaussian**	**Medium Gaussian**	**Coarse Gaussian**
MAE (Mean Absolute Error)	0.31	0.33	0.36	0.32	0.32	0.32
Training time (seconds)	1.40	1.71	1.94	1.84	1.75	1.60

Table 3.17 contains the results of our validation study. The linear kernel perform better (MAE = 0.31) than that of the others. A computational model developed with the linear kernel can be trained more quickly (1.40 seconds) than the others. So, we used the most straightforward kernel of SVM - *linear kernel* for the development of our aesthetics prediction model. Figure 3.7 shows the plot of the average users' rating and rating predicted by our model for the ten samples (out of two hundred and nine samples). The average users' ratings, and the model predicted ratings of all the two hundred and nine web pages are reported in Table A.1 of Appendix A.

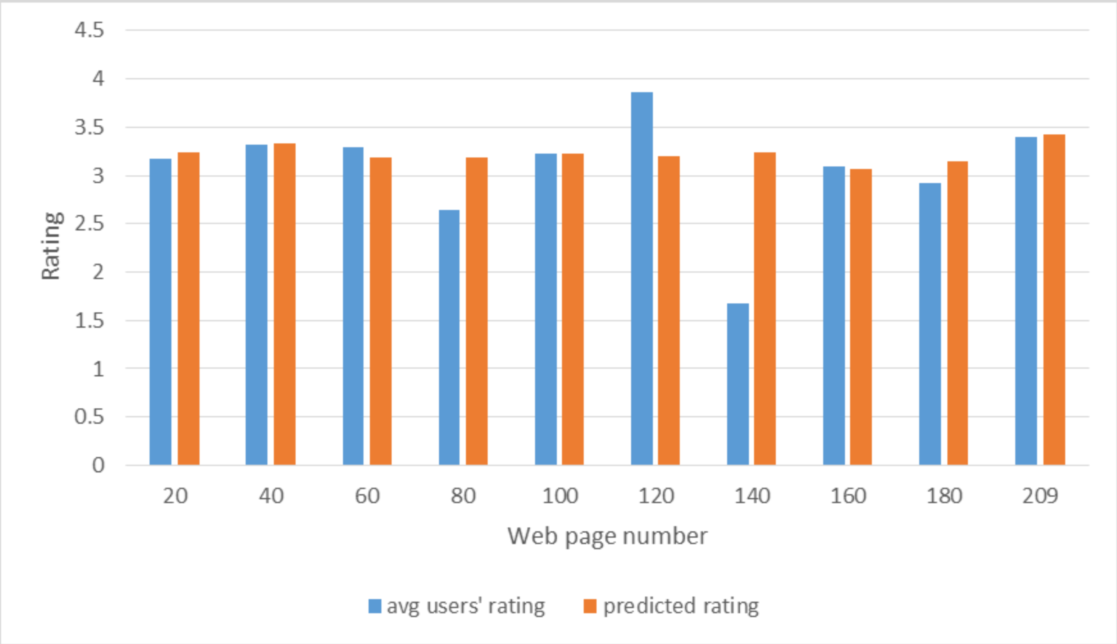


Figure 3.7: Plot of true rating (average users' rating) – blue color (dark), and the predicted ratings by our model - orange color (light) for the ten web pages.

3.7 Discussion

The objective of this work was to develop a computational model for predicting web page aesthetics on a five-point rating scale. Our proposed model can measure web page aesthetics with a MAE of only 0.31. Ngo et al. [2003] claimed that the order which is the average of the thirteen geometry features could determine web page aesthetics. In our study, we observed the minimum *order* value of 0.246 and the maximum of 0.576. In other words, we can say that the variation in the order value is about 33% only. On the other hand, the average user's ratings vary from 1.61 to 4.2, nearly 37.97%. Although these two variations are almost equal, the real challenge of Ngo's [2003] work is to map the order value with the users' ratings. They claimed that there exists a linear relationship between the order and aesthetics (measured by users' ratings). However, such conclusive statement seems incorrect from our study. Figure 3.7 shows the plot of order value vs. average users' rating. It was mentioned [Ngo et al., 2003] that the *order* has a linear relation with the aesthetics. Accordingly, we used a straight line, which shows the *linear* trend. The low R^2 value of 0.0044 signifies that the *order* cannot model the web page aesthetics judgment (based on wireframe) of the users. So, computing aesthetics in terms of *order* value may not be suitable for modern web pages. In contrast, our proposed model was developed by using the SVM regression technique. SVM maps non-linear data into a higher dimensional input space using kernel function. Then a linear model is constructed in this high dimensional space. SVM performs regression in this feature space. In other words, we can say SVM can remove the non-linearity of data, as we observed in Figure 3.8. Therefore, we can claim that our model is more efficient than the model proposed by Ngo et al. [2003].

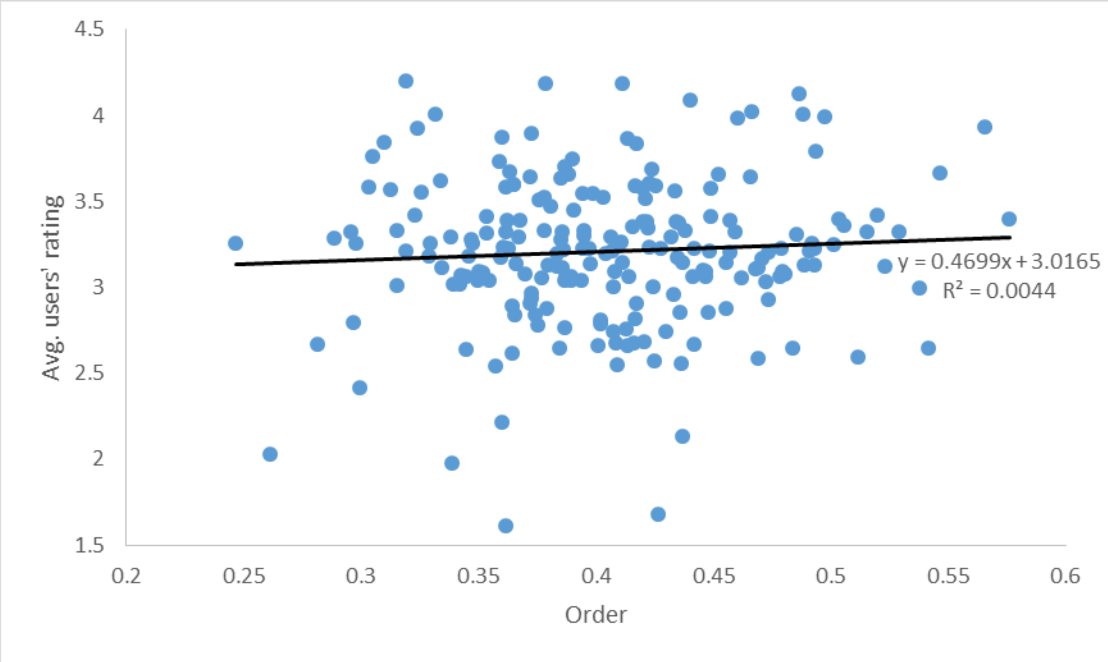
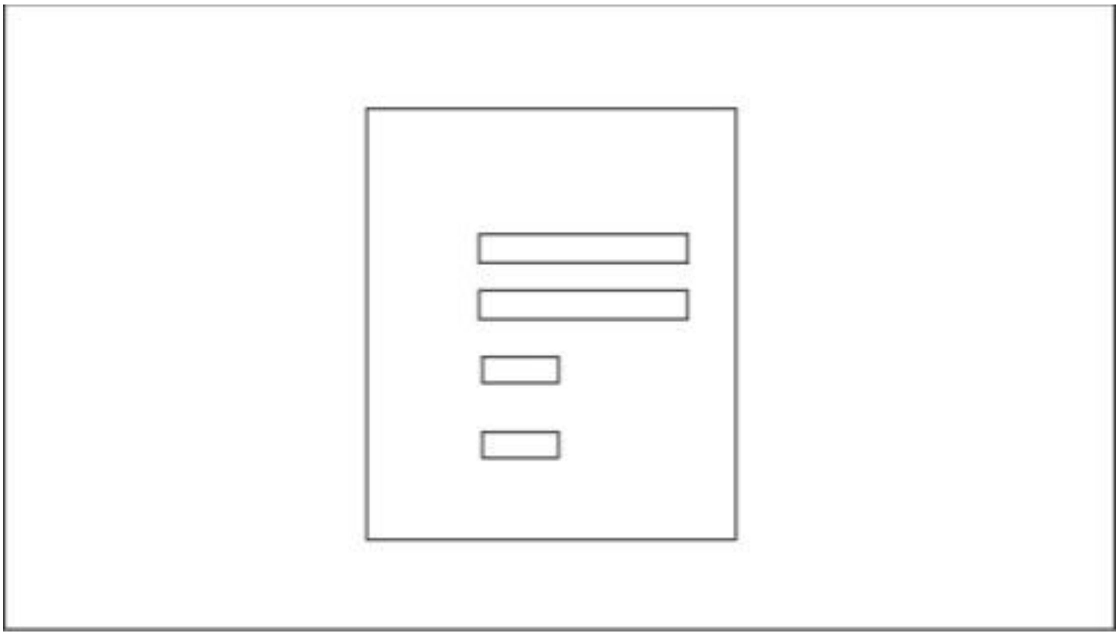


Figure 3.8: Relationship with the order (Ngo et al. [2013]) and average users rating.

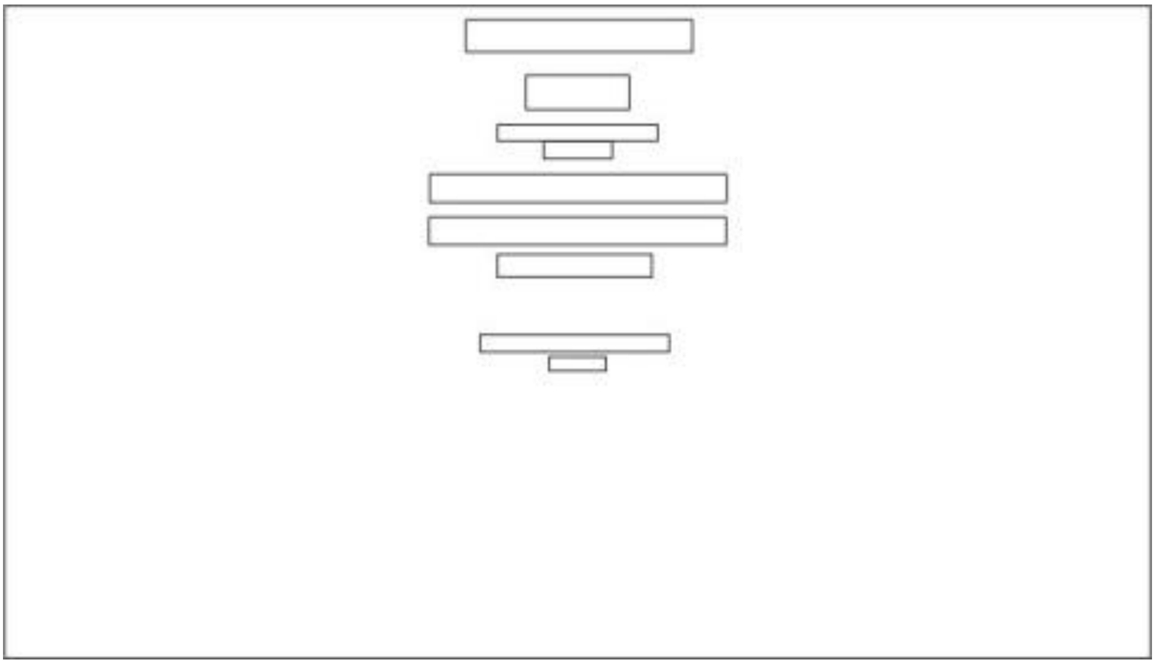
Our computational model can help the designers to improve the web page design. A low predicted aesthetics score indicates that there is likely to be some problem with the design (specifically for wireframe geometry); which can reduce aesthetics and consequently, decrease the usability of the web page. Hence, the designer should take some corrective measures to improve the design.

During the empirical study conducted with the two hundred and nine web pages, we were interested to check whether the familiarity of the wireframes biased our empirical study. It was observed that out of thirty one thousand three hundred and fifty observations (one hundred and fifty participants rated two hundred and nine web pages), only for fifty five times (0.18%) participants could correctly identify the original web pages associated with the wireframe models. Therefore, it can be claimed that participants were largely unable to distinguish between wireframe models and their corresponding web pages. In other words, familiarity of the web pages almost did not influence the empirical study, consequently the proposed model remained unbiased.

In our study, we informally asked the participants about the factors that affect aesthetics. Some of them reported that they prefer a web page having less empty space. In other words, users prefer a web page which is full of contents. We also found that the participants gave low rank to those web pages having larger empty space, as shown in Figure 3.9. So, the area of empty spaces may be considered to be an additional feature which needs to be looked into for web page aesthetics.



(a)



(b)

Figure 3.9: Low ranked web pages.

Our proposed model can predict aesthetics efficiently (*MAE* = 0.31) for the subjects having wide variations in cultures, age groups. The maximum absolute error in a five point rating scale is four, when the original rating is one, but predicted as five or vice versa. Therefore, the accuracy of the proposed model can be computed using the following Equation 3.3.

$$Accuracy_{wireframe} = \left(1 - \frac{MAE}{MAE_{\max}}\right)\% = \left(1 - \frac{0.31}{4}\right)\% = 92.25\% \tag{3.3}$$

As a result, we may claim that the proposed model can predict aesthetics with a high accuracy. It may be noted that the model was developed and validated by considering the structural organizations (wireframes) of web page objects. However, the contents of the web page objects were not considered. It was reported in the literature that the contents are also important to determine the aesthetics, which requires further investigation of the aesthetic model by considering the contents present in a web page.

3.8 Chapter Summary

In this work, we reassessed the best-known positional geometry features related to web page aesthetics. In order to assess the thirteen features of wireframe geometry that affect aesthetics, an empirical study was conducted using fifty two wireframe models. Parametric analysis (ANOVA) on empirical data revealed that nine out of the thirteen features are statistically significant for aesthetics computations. Based on these nine features, a computational model of web page aesthetics was developed. *SVM based binary classifier* was used to develop the model. The model was tested on ten real web pages. An accuracy of 90% (9 out of 10) was observed in the experimental results. In order to validate the model with a large test data, two hundred and nine web pages were designed. It was observed that the accuracy of the model reduces from 90% to 78.94%. This may be due to the assumption of considering parametric analysis of the empirical data collected from the fifty two wireframe models. The same empirical data was used for a non-parametric test. It was observed that out of the thirteen features of wireframe geometry, ten were statistically significant. Using these ten significant features, another computational model was developed. The linear kernel of Support Vector Regression was used to develop the model. The empirical results of the two hundred and nine web pages used to validate our earlier model were also used to train and test the proposed model. It was found that the proposed model can predict aesthetics of web page with an accuracy of 92.25%.

Except for the wireframe geometry, contents present in a web page is also vital to determine the aesthetics of a web page. In the next chapter, we proposed a computational model of web page aesthetic by considering the contents of a web page.

Chapter 4

Computational Model for Text Aesthetics

4.1 Introduction

Text elements are one of the essential element present in a web page, reported in Section 1.3 of Chapter 1. It was also mentioned that the different web page elements – tables, menus, and links can also be represented using the text elements. Therefore, to measure the aesthetics of a web page; it is essential to measure the aesthetics of the text elements. A computational model of text aesthetics will help a web page designer to predict the aesthetics of the textual contents present in his/her design.

In order to develop a computational model of text aesthetics, features of the text aesthetics needs to be identified. As there was no work reported on the text aesthetics, we identified six features from literature that affect the readability of the text elements. These six features are listed below.

1. *font size (FS)*
2. *letter spacing (LS)*
3. *word spacing (WS)*
4. *line-height (LH)*
5. *luminance contrast (LC)*
6. *chromatic contrast (CHC)*

Except the above mentioned six features, we also identified two other features – *font family* (example – Arial, Times New Roman), and *word style* (plain, italics, bold) from the literature. However, Hill [1997] reported that there is no one font family and word style which leads the fastest readability. As both these features have no significant effect on readability, we did not consider them for the text aesthetics model.

With the six features, we proposed two computational models of text aesthetics. The first model was developed by using the trend analysis of empirical data, obtained using fifteen text stimuli. The model can predict the aesthetics in terms of two classes – aesthetically pleasing or unpleasing. To validate the proposed model, another fifteen test samples were developed. Validation results shows the proposed model can predict aesthetics with an accuracy of 86.67%.

A further analysis on the test stimuli showed that the variations of the features' values used to validate the model were not systematic in nature, and there was a necessity to revalidate the proposed model. By systematically varying the feature values, ninety five text samples were designed and used for the model revalidation. Experimental results show the accuracy of the model dropped from 86.67% to 62.10%. Due to the degradation of the model's performance, a second model of text aesthetics was proposed by using the *Support Vector Regression* (SVR), which can predict text aesthetics in terms of score, rather than a class. Using the ninety five test stimuli, the model was trained and tested. The *five-fold cross-validation* shows the model can predict text aesthetics with an accuracy of 90%. In this chapter, both the models of text aesthetics prediction are discussed.

Rest of the chapter is organized as follows. In Section 4.2 the features associated with the text aesthetics considered for our study are reported. Our proposed model of text aesthetics using the trend analysis is presented in Section 4.3. A brief discussion of this model is reported in Section 4.4. In Section 4.5 the revalidation of the proposed model is discussed. Section 4.6 represents our second model of text aesthetics developed with Support Vector Regression, followed by a brief discussion of the model, reported in Section 4.7. Finally, the chapter ends with a summary in Section 4.8.

4.2 Features of Text Aesthetics

The six features of text aesthetics – *font size, letter spacing, word spacing, line height, luminance contrast,* and *chromatic contrast* found in the literature, used to develop our text aesthetics prediction model are discussed below.

Font Size (FS): Font size is an important feature to determine the readability of text elements. A larger font size makes a text readable from a larger distance. For instance, the font size of an advertisement in a banner can be up to 4320pt! [Large font size]. The objective of choosing such massive font size is to attract us from a long distance up to 2500ft. However, this is not true for the web pages, which are often accessed with a distance of an arm's length, which is generally 18 - 26 inch [Font viewing distance]. Therefore choosing a large font size (used in the banners) can reduce the readability, as reported in [Tullis, 1981]. It was also reported that the readability of text elements increases with font size up to an extent, called threshold; and any font size above the threshold level decreases the readability. Similarly, there exists a smallest font size termed as - *Critical Print Size*, and any font size below the critical print size can reduces the readability. Figure 4.1 shows an English pangram – "The quick brown fox jumps over a lazy dog," which is represented using three different font sizes – 4pt, 16pt, and 48pt. It may be noted that 16pt and 48pt may be read more easily than that of the 4pt. However, 48pt needs more spaces on a web page. So writing a longer text using the 48pt font may need the scrolling operation, which in turn can reduce the readability. Therefore, choosing an appropriate font size is essential to improve the readability. This may also be true for the aesthetic appeal of the text elements found in a web page.

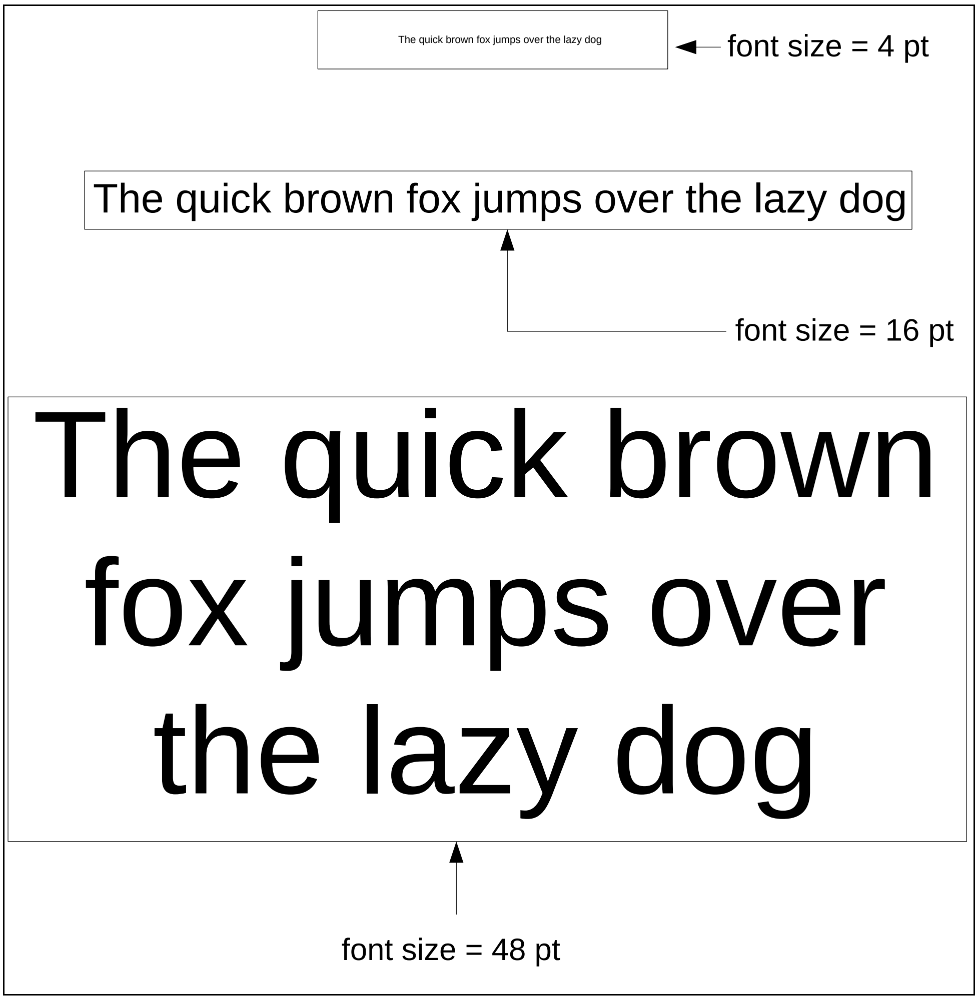


Figure 4.1: An English language pangram, "The quick brown fox jumps over the lazy dog" is shown using three different font sizes – 4pt, 16pt, and 48pt.

Letter Spacing (LS): Spaces between the two letters –letter spacing or *kerning* is another bearing for readability and legibility. Letters separated with a larger spacing can reduce the readability. This may be due to the fact that the larger spacing needs more time to read. Again, if the letter spacing is made almost equals to the word spacing as shown in Figure 4.2, then it will be difficult for the users to identify a word. In Figure 4.2, two words "beautiful terrain" is represented in two ways – words spacing = letter spacing (Figure 4.2 (a)), and words spacing > letter spacing (Figure 4.2 (b)). It may be noted that when both the word and letter spacing are equal, the word "beautiful terrain" can be read as "beautiful ter rain," which means three times beautiful rain. As a consequence, it is important to maintain appropriate letter spacing in the text elements. Chung [2002] found increased letter spacing beyond a standard size cannot improve readability. In the context of aesthetics judgment of the textual elements, present in a web page, letter spacing can also play a vital role.

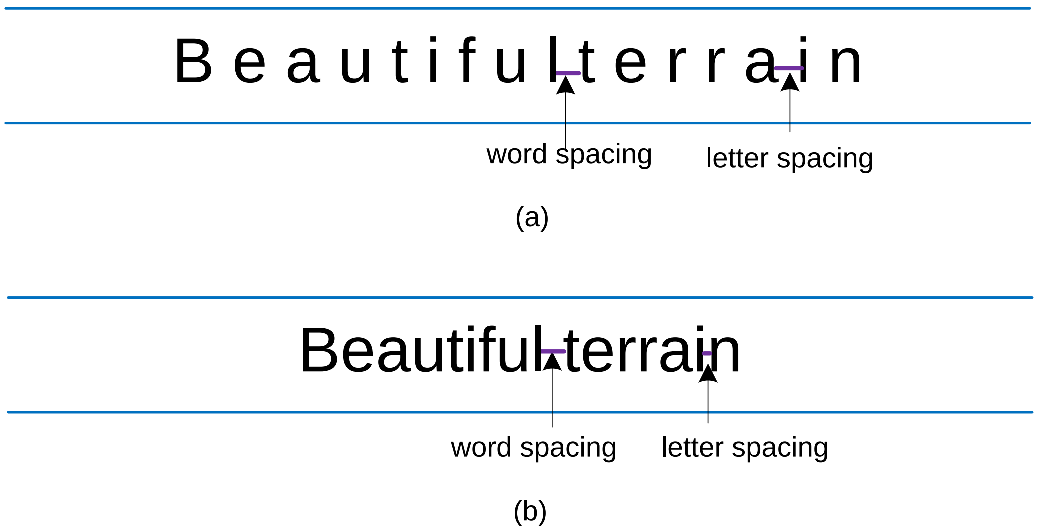
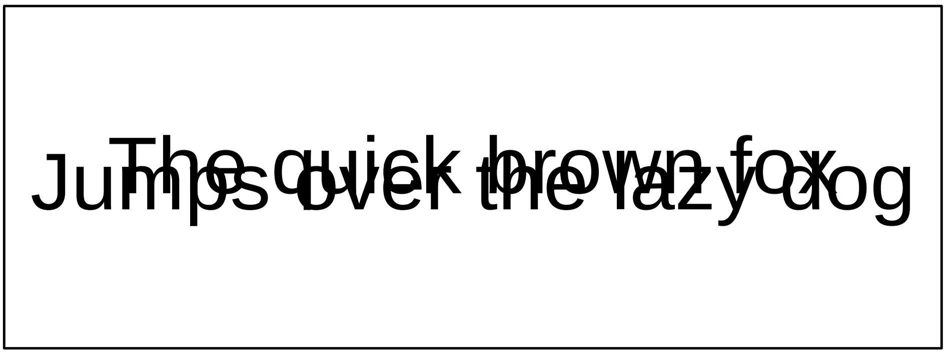


Figure 4.2: Two words "beautiful terrain" represented by (a) word spacing = letter spacing, and (b) word spacing > letter spacing.

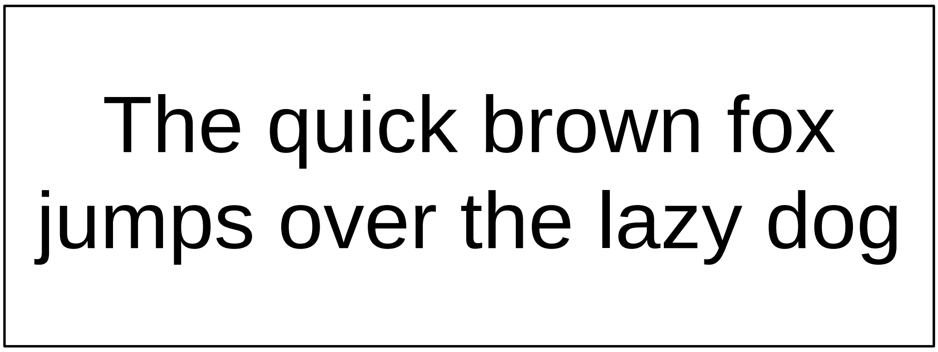
Word Spacing (WS): Unlike letter spacing which signifies the amount of space between two consecutive letters, word spacing is used to measure the amount of space between two successive words. In order to design text elements, the spacing between two words can be chosen from the two ways – regular, and irregular. It was advised to use the regular word spacing [Word spacing guideline] because the irregular word spacing can distract the users. As a consequence, designers often followed the regular word spacing to develop their design. In regular word spacing, the amount of spaces between two words helps to identify them clearly, as shown in Figure 4.2. However, word spacing more than a certain level can affect the readability of a text [Word spacing guideline]. Similarly, two words kept long apart can affect the aesthetics judgment. Again, two overlapping words (very small or no word spacing) can also reduce the aesthetic appeal. As a result, word spacing may be considered as an important factor to compute the aesthetics of the text elements present in a web page.

Line Height (LH): The line-height signifies the amount of spaces found on top of the inline text elements and the bottom of it. In CSS, if the content height is 10pt, and the line height is 14pt, then the difference of them 4pt is distributed equally among the top and bottom of the content. Line height can also determine the legibility of the text elements. A line height less than the font size could cause a severe hindrance to the readability, as well as aesthetics. This is due to the fact that less rooms are provided between the lines when they come closed. As a consequence, it becomes hard to distinguish the lines separately, which may reduce the aesthetics of the text elements.

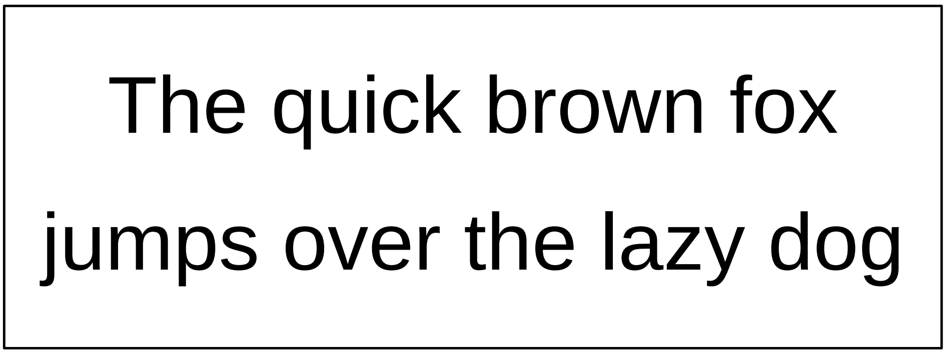
Standard guidelines [Line height guideline] suggest line height must be 1.2 times larger than font size; however, it was also found that line height of 1.5 times larger than font family or more can help to improve the readability of those people having low visions, as well as with cognitive difficulty such as Dyslexia. Figure 4.3 (a) shows an example when line height (3pt) is less than the font size (6pt), whereas Figure 4.3 (b) and (c) show the instances when line height is 1.2 times and 1.5 times larger than font family respectively. From the above discussion, we may claim line height is an essential feature for the readability of text elements. Similarly, line height may also be vital to determine the aesthetics of the textual contents. As a result, line height was also considered for the text aesthetics models development.



(a)



(b)



(c)

Figure 4.3: Three instances where line height varies - (a) LH (4 pt) < FS (8pt), (b) LH (10 pt) > FS (8 pt) [almost 1.2 times larger], and (c) LH (12pt) > FS (8pt) [1.5 times larger].

Luminance Contrast (LC) and Chromatic Contrast (CHC): Contrast makes a text discernible from its background. Zuffi et al. [2007] reported the role of contrast on readability and legibility. It was also reported that sharp contrast must be avoided to improve readability. Contrast - luminance contrast (LC) and chromatic contrast (CHC) can also affect the aesthetics of text elements. These two features of text aesthetics can be computed by using the following two equations Equation 4.1, and 4.2. L_t and L_{bg} denote the luminance of text and background respectively, whereas R_t, G_t, and B_t denote the *R*, *G*, *B* components of the text and R_{bg}, G_{bg} and B_{bg} denote the *R*, *G*, *B* values of the background.

$$LC = \frac{L_t - L_{bg}}{L_{bg}} \tag{4.1}$$

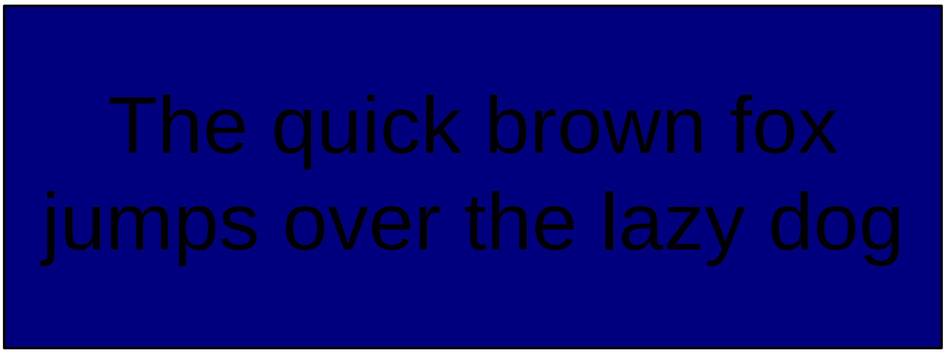
$$CHC = [\max(R_t, R_{bg}) - \min(R_t, R_{bg})] + [\max(G_t, G_{bg}) - \min(G_t, G_{bg})] + [\max(B_t, B_{bg}) - \min(B_t, B_{bg})] \tag{4.2}$$

The luminance of an *RGB* image can be obtained [Luminance computation] by using the following equation-

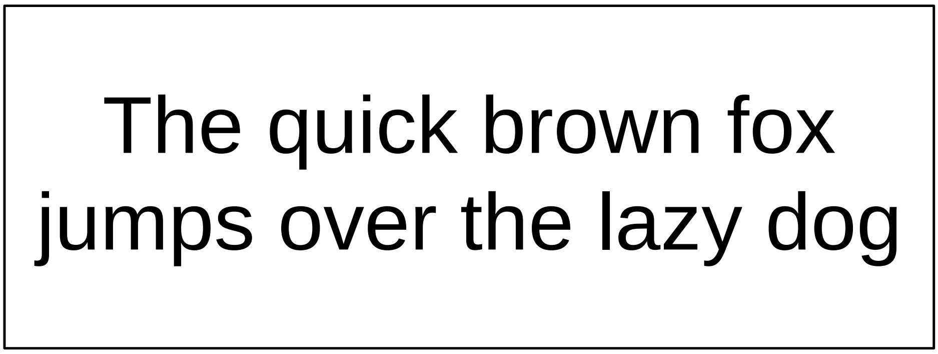
$$E = (0.299 \times R + 0.587 \times G + 0.114 \times B) / 255 \tag{4.3}$$

$$Lu\min ance = 16 + 219 \times E \tag{4.4}$$

Figure 4.4 (a), and (b) shows two texts. The background *RGB* value (represented by blue colour) of the first text shown in Figure 4.4 (a) is = [0, 0, 127], whereas the *RGB* of the font (black) = [0, 0, 0]. Hence, the *CHC* value = 127, as computed with the help of Equation 4.2. The Luminance of the background and the text is computed with the help of Equation 4.3 and 4.4, which will be 28.43, and 16 respectively. Using Equation 4.1, the *LC* of the text will be -0.44. Similarly, the *CHC*, and *LC* of the second text whose background *RGB* = [255, 255, 255], and the font colour = [0, 0, 0] are 765, and - 0.93 respectively.



(a)



(b)

Figure 4.4: Two texts (a) CHC = 127, LC = -0.43 and (b) CHC = 765, LC = - 0.93.

Using the above six features, two computational models were developed for predicting the aesthetics of the text elements present in a web page. The first model is reported in the following section.

4.3. Mathematical Model

A two-stage model for aesthetics prediction of the text elements present in a web page is proposed in this section. In the first stage, the *aesthetic score* (AS) for a text element was computed. Subsequently, the text is categorized as *satisfactory* or *unsatisfactory*, on the basis of the score. In order to calculate the score, we proposed an analytical expression by combining the six features. To develop this model, an empirical study was conducted. In the following, the details of the empirical study, and the development of the proposed model are discussed.

4.3.1 Design of Stimuli

In order to develop this model, we designed fifteen text samples. All the fifteen samples were designed by Adobe Photoshop CS6^{TM}. A sample text is shown in Figure 4.5. The contents of the text samples (termed as *TC1*, and used in subsequent discussion) were taken from wikipedia[1]. The contents of the all text samples were – "Within the field of literary criticism, "text" also refers to the original information content of a particular piece of writing; that is, the "text" of a work is that primal symbolic arrangement of letters as originally composed, apart from later alterations, deterioration, commentary, translations, paratext, etc. Therefore, when literary criticism is concerned with the determination of a "text," it is concerned with the distinguishing of the original information content from whatever has been added to or subtracted from that content as it appears in a given textual document (that is, a physical representation of text)." The *Times New Roman* font was used to design all the text stimuli. The analysis of the text is shown in Table 4.1.

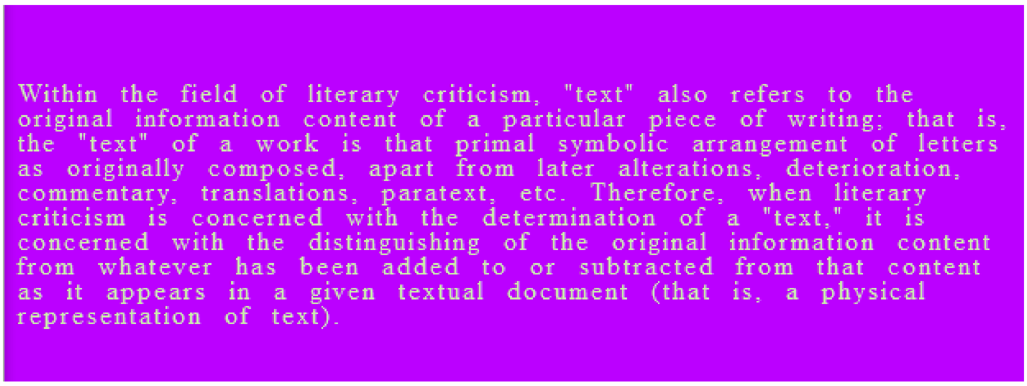


Figure 4.5: A sample text used in the study.

[1] https://en.wikipedia.org/wiki/ Text_(literary_theory)

Table 4.1: Analysis of the text contents - TC1.

Frequency of each character in the stimuli																			
a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	t
45	3	20	12	55	16	8	19	50	0	1	17	15	37	40	10	0	43	24	69
u	v	w	x	y	z	,	"	W	.	T	;	(	)						
5	2	6	6	6	0	11	6	1	1	1	1	1	1						
Number of words						95													
Number of characters						626													
Number of spaces						94													
Maximum word length						14													
Minimum word length						1													
Average word length						= 626/95 = 6.59													

The six feature values of the fifteen text samples are shown in Table 4.2. It may be noted that the *Line height* and *Word spacing* are represented in terms of point (pt). The font size is represented as the multiplication factor of line height. For example, the line height of the text sample #1 (in Table 4.2) is 20pt, while the font size is 1.05. Therefore, the font size is 21pt (20pt×1.05). Similarly, the letter spacing was represented by the multiplication factor of Word Spacing. For example, the Word Spacing of the text sample #1 (in Table 4.2) is 1. So the Letter Spacing is

1 × Word Spacing

= 1× 3pt

= 3pt.

Table 4.2: Six feature values of the fifteen sample texts, along with the mode of the users' rating denoted by UR of the last row.

Text#	FS	LH	CHC	LC	WS	LS	UR
1	1.05	20	351.606	0.702	3	1	1
2	1.1	18	325.524	0.709	4	0.8	3
3	1.2	15	221.652	1	10	-0.5	4
4	0.5	7	251.017	0.697	13	1.5	5
5	0.9	18	441.672	1	3	0.8	2
6	1	15	441.672	1	3	1	2
7	0.8	9	273.06	0.939	7	-0.5	5
8	1	25	221.652	1	5	1.5	3
9	0.5	10	251.017	0.697	1	3	5
10	1.2	20	137.058	0.408	10	2	2
11	1	20	251.017	0.697	7	1	2
12	0.8	20	221.652	1	15	-0.5	4
13	1.05	20	301.405	0.4	3	1	1
14	0.75	10	273.06	0.939	12	1.5	5
15	0.8	25	257.256	0.731	1	-0.5	4

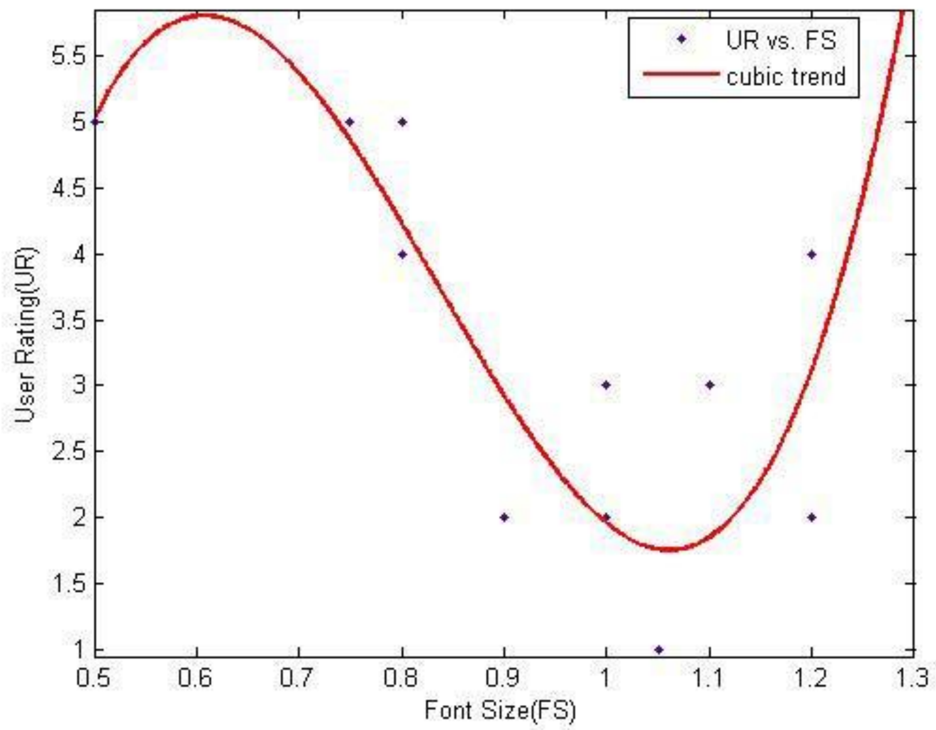
Fifty participants (twenty five males and twenty five females, average age = 21.2) viewed all the fifteen text samples on PCs having 2.6 GHz AMD Phenom II X3 710 processor, running on Windows 8. Each PC was equipped with a 17" wide viewing angle color display. All the participants were undergraduate students, and had normal or corrected-to-normal vision. However, none of them was color blind (self-reported). They were the regular users of computers. However, they did not have any knowledge on screen design.

4.3.2 Procedure of Data Collection

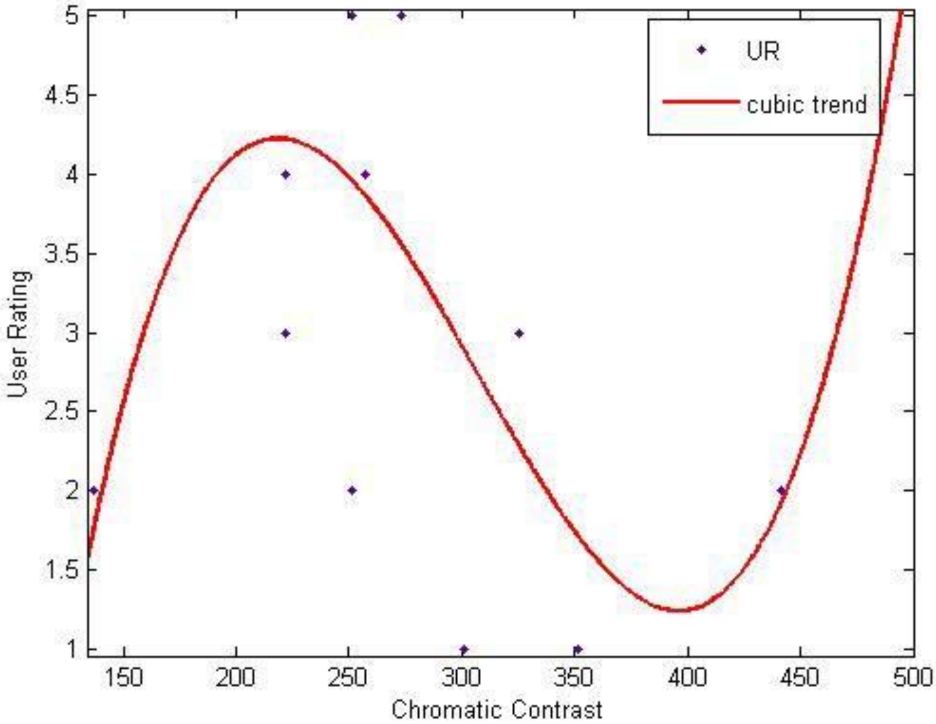
All the participants rated the fifteen text stimuli on a five point rating scale (one denoting *most appealing* and five denoting *not appealing*) in one session of a day. We did not influence the participants' thinking in any way by making any suggestions or arguments. The text sample order was changed for each participant. In this way, we tried to take into account the *learning effect*. The participant could view a text as long as (s)he wished and was allowed to go back to the previous samples already viewed. The same browser-based viewer used for the emprical studies on wireframes was also used here.

4.3.3 Model Development Procedure

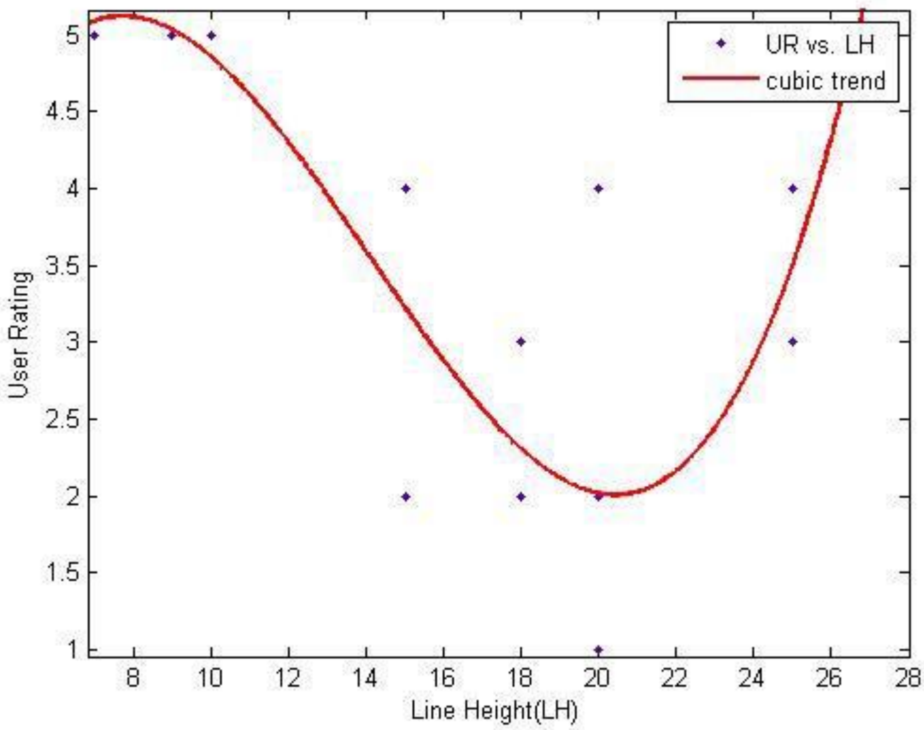
The *statistical mode* of the users' ratings for each sample was considered as the final rating, as shown in the last row of Table 4.2. In order to identify the relations of the aesthetics with the six features, six diagrams are plotted as shown in Figure 4.6 (a) – (f).



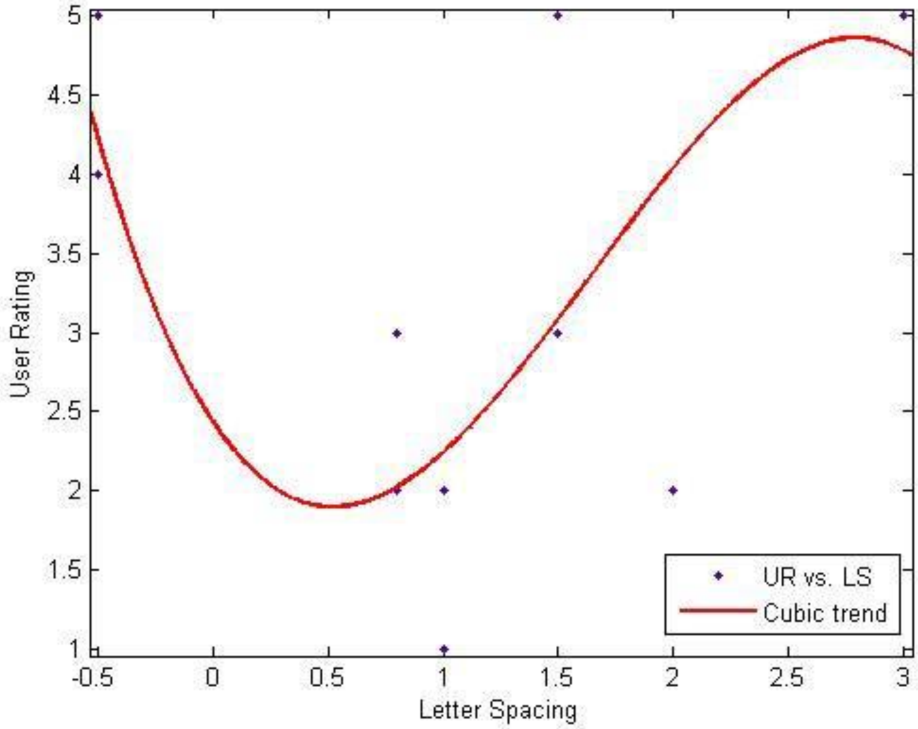
(a)


UR
cubic trend
User Rating
Chromatic Contrast
5
4.5
4
3.5
3
2.5
2
1.5
1
150
200
250
300
350
400
450
500

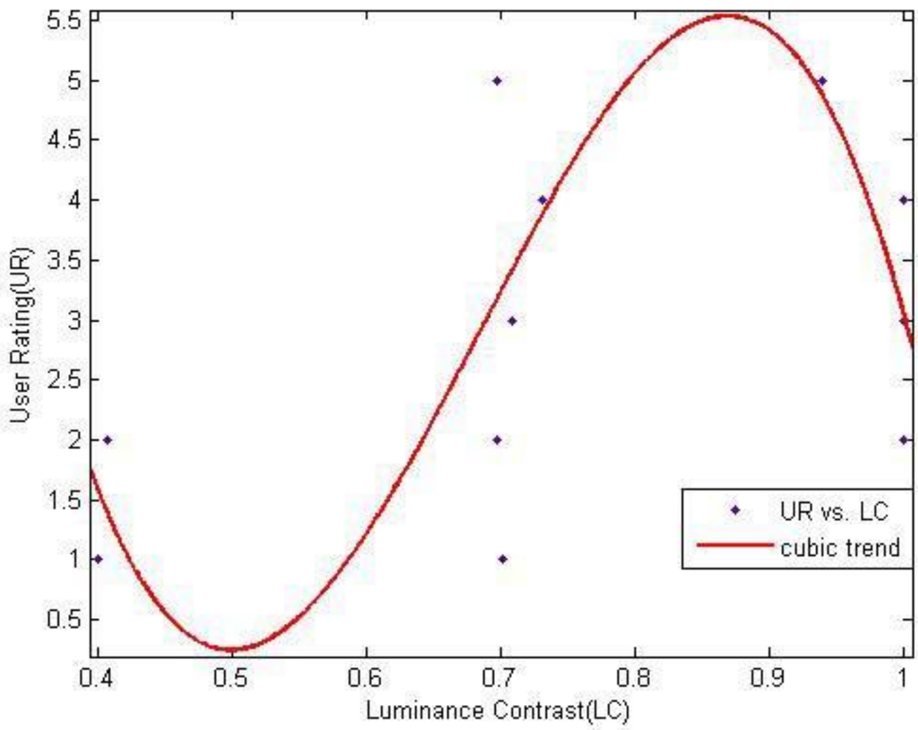
(b)


UR vs. LH
cubic trend
User Rating
Line Height(LH)
5
4.5
4
3.5
3
2.5
2
1.5
1
8
10
12
14
16
18
20
22
24
26
28

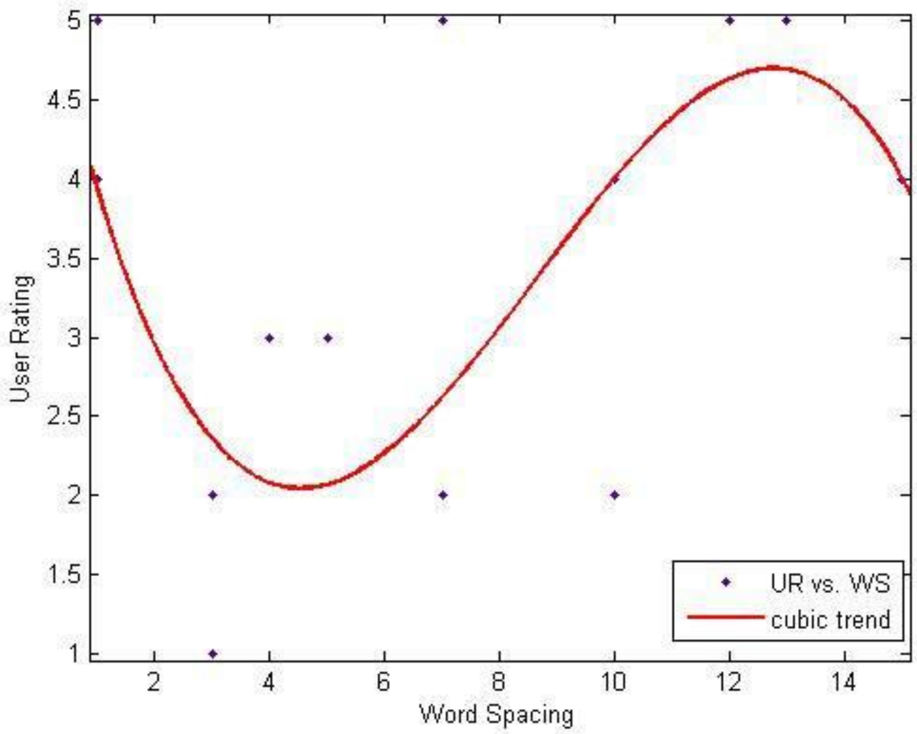
(c)


User Rating
Letter Spacing
UR vs. LS
Cubic trend

(d)


User Rating(UR)
Luminance Contrast(LC)
UR vs. LC
cubic trend

(e)



(f)

Figure 4.6: Plots of user rating with the feature values.

After plotting the values in the diagram, the ***MATLAB*** curve fitting tool ('***cftool***') was used to find out the *trendlines* (i.e., the equation fitting the data points). We experimented with various polynomial curves and found that the cubic curves are good enough to model the aesthetics of the text elements. The red color line in each plot denotes the cubic trend. The cubic equations corresponding to the trend lines are shown in Equations 4.5 - 4.10.

$$UR_{FS}=87FS^3-220FS^2+170FS-35 \tag{4.5}$$

$$UR_{LH}=0.003LH^3-0.13LH^2+1.4LH+0.3 \tag{4.6}$$

$$UR_{CHC}=-0.000001CHC^3-0.00098CHC^2+0.28CHC-20 \tag{4.7}$$

$$UR_{LC}=-210LC^3-430LC^2+270LC+55 \tag{4.8}$$

$$UR_{WS}=-0.0095WS^3+0.25WS^2-1.7WS+5.3 \tag{4.9}$$

$$UR_{LS}=0.51LS^3+2.5LS^2-2.2LS+2.4 \tag{4.10}$$

The terms UR_{FS}, UR_{LH}, UR_{CHC}, UR_{LC}, UR_{WS} and UR_{LS} denotes the user rating font size, user rating line height, user rating chromatic contrast, user rating luminance contrast, user rating word size and user rating letter spacing respectively. Moreover, we normalized each of the feature values (in -10 to +10 scale) using the maximum allowable values. Finally, the Aesthetics Score (AS) was computed by using the following equation (Equation 4.11).

$$AS = (UR_{NFS}+UR_{NLH}+UR_{NCHC}+UR_{NLC}+UR_{NWS}+UR_{NLS})/6 \tag{4.11}$$

The terms UR_{NFS}, UR_{NLH}, UR_{NCHC}, UR_{NLC}, UR_{NWS} and UR_{NLS} denote the normalized values of the *font size*, *line height*, *chromatic contrast*, *luminance contrast*, *word spacing*, and *letter spacing*, respectively.

The ratings of the text samples along with their aesthetic scores computed using Equation 4.11 are shown in Table 4.3. It may be noted that among the eight samples which got ratings between 1-3 (implying high or average aesthetic appeal), seven samples (or about 87.5%) were having sores less than zero (except sample #3). On the other hand, the remaining seven samples that got rating of 4 or 5 (implying poor or very poor appeal) had aesthetic scores greater than zero. Based on these observations, we further proposed the following binary classification based on the aesthetic score:

a) Aesthetic score < 0; aesthetic quality: Satisfactory

b) Aesthetic score ≥ 0; aesthetic quality: Unsatisfactory

Table 4.3: The aesthetics scores computed using Equation 7 of the text samples used in the study along with their consolidated (final) ratings.

Text #	Normalized Score	Rating
5	-7.89	2
6	-7.60	2
1	-5.24	1
2	-5.18	3
8	-4.82	3
11	-3.56	2
13	-3.56	1
3	0.45	4
12	1.00	4
10	2.30	2
7	2.42	5
15	3.18	4
14	3.80	5
4	6.53	5
9	7.28	5

4.3.4 Model Validation

In order to ascertain the validity of the proposed model, another empirical study was conducted. We designed fifteen more sample texts using Adobe Photoshop CS6^{TM} and got those rated by a new set of fifty volunteers. The details of the empirical study, along with the model validation are discussed next.

4.3.4.1 Experimental Setup and Procedure

The contents of the fifteen text stimuli was same with the earlier stimuli, designed for the model development. The feature values of the sample texts are shown in Table 4.4. The texts were shown to a group of fifty new participants (twenty five males and twenty five females) on PCs with a similar configuration as in the previous study. All the participants were volunteers, with an average age of 24.32 years. All of them had normal or corrected-to-normal vision. None was color blind (self-reported). They were all regular computer users, but none was familiar with screen design concepts.

Table 4.4: Feature values of the sample texts used in the second (validation) study.

Text #	LS	LH	WS	FS	LC	CC
1	2	10	5	0.8	0.7315	189.99
2	-1.5	20	1	1	0.9368	248.86
3	-0.5	15	10	0.5	1	215.38
4	1.5	7	13	1.2	-0.697	177.39
5	3	15	7	0.6	0.408	195.68
6	-1.5	15	13	0.6	0.7315	230.34
7	-0.5	7	7	0.8	0.9368	288.87
8	1.5	25	5	1	1	256.67
9	3	10	1	0.5	-0.697	210.04
10	2	20	10	1.2	0.408	279.63
11	-0.5	25	1	1.2	0.7315	181.10
12	1.5	10	10	0.6	0.9368	230.06
13	3	20	13	0.8	1	89.92
14	2	15	7	1	-0.697	132.29
15	-1	7	5	0.8	0.408	201.13

Table 4.5: The AS computed using Equation 4.11, and the users' ratings.

Text #	Score	Rating
8	-8.32	1
14	-3.93	2
10	-3.21	1
7	-3.01	2
2	-2.16	1
11	-1.21	3
13	-0.91	4
3	-0.67	3
1	0.26	2
4	0.42	4
12	1.30	4
9	1.56	4
5	1.95	5
15	2.81	4
6	5.54	5

Each participant viewed all the sample texts. The text sequence for each participant was also changed to remove the learning effect. The participants were allowed to view a text as long as (s)he wished and was allowed to go back to the previous samples already viewed. The same browser-based viewer used for the earlier study was also used. After viewing each text, they were asked to rate it according to its *aesthetic appeal* on the same 5-point scale as in the previous study.

4.3.4.2 Results

The ratings given by the participants are shown in Table 4.5. The statistical mode of the participants' ratings was used as the final ratings, shown in the last row. Table 4.5 also shows, out of the fifteen samples, eight received a rating of three or less. In other words, the aesthetic qualities of those eight text samples were found to be satisfactory by the participants, while they found the remaining seven to be unsatisfactory with respect to aesthetics. The aesthetic scores of the fifteen samples were computed by our proposed model, as shown in the middle row of Table 4.5.

It may be noted that among the eight texts which were rated *satisfactory* by the participants, one (#text 1) had AS greater than zero whereas the remaining seven stimuli got AS less than zero, as predicted by our proposed model. Similarly, among the seven texts which were rated *unsatisfactory* by the participants, one (#text 13) was having AS less than zero whereas the remaining six got score greater than zero, as predicted by our proposed model. Thus, out of the fifteen samples, the aesthetic quality of thirteen samples were correctly predicted by our proposed model, with an accuracy of 86.67%.

4.4 Discussion

Because of the reasonably high prediction accuracy of our proposed model, we feel that it can be used to compare text elements in a web page on their aesthetic appeal. The approach that can be adopted is as follows. Suppose a set of text elements T = **{**t_1, t_2,...,t_n**}** is given. Using Equation 4.11, the aesthetic score for each t_i is computed. Next, the texts are sorted in ascending order according to the aesthetic score. This sorted list indicates the *relative goodness* of a piece of text with respect to the others in T. Moreover, by categorizing (as *satisfactory* or *unsatisfactory*) the elements of T on the basis of the score, the model also helps a designer decide if a text element design needs to be improved to increase its aesthetic appeal. For the texts belonging to the *satisfactory* category, improvements may not be necessary. However, for the *unsatisfactory* category, it is definitely required.

During the empirical studies, we have made another significant finding. Careful observation of the plots shown in Figure 4.6 (a) - (f) reveals that for all the features the user rating lies between 1-3 (implying aesthetically pleasing) for a particular range of the corresponding feature values. The rating increases (implying decrease in aesthetics) when the feature values are out of that range. The ranges of the feature values for which we observed aesthetically pleasing text may be used as a guideline for designing text elements. The text element of an interface has the feature values within these ranges, the element is likely to be aesthetically pleasing and be categorized as *satisfactory*.

The model was validated with fifteen text samples, where the features' values are not varied systematically. The systematic variations can be achieved by varying one feature, while the other features should be kept constant. This idea works only for those features, which are independent in nature, and not true for the others. Except the two contrasts (chromatic contrast, and luminance contrast), all the features used to in the proposed model are independent. Therefore, the performance of the proposed model need to be further validated with a group of text samples where the features are varied systemetically. In order to carry out this task, ninty five text samples were generated by varing the features systematically. A validation study was of the proposed model was conducted by using all the ninety five samples, as reported in the following.

4.5 Second Validation of the Model

Using the ninety five test samples, an empirical study was conducted. The details of the study, along with the design of the test samples are reported below.

4.5.1 Test Stimuli Design by Systematic Features' Variations

It may be noted that the text stimuli used in our prior study have – alphabetes (both the lower case, and upper case), and special symbols. However, the stimuli have no digits (from 0 - 9); and sometimes digits are often found in real web pages. The digits are often required to represent the date, time, month, year, and mathematical calculations. A text sample, having numbers within it, is shown in Figure 4.7. The text snippet was taken from [Text Snippet].

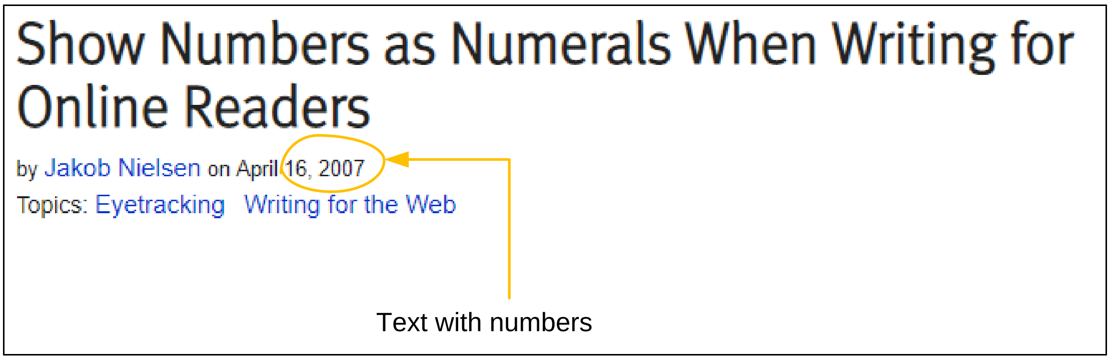


Figure 4.7: Text snippets having digits[2] .

Unlike our earlier empirical study where a paragraph was considered for the design of a text stimuli, here we planned to design the stimuli by determining the length of the text found in real web pages. A pilot study using five web pages was conducted for this purpose. Those five pages were selected from the fifty nine real web pages (reported in Table 3.12 in Chapter 3), based on the five different application areas, as mentioned in Table 4.6.

[2] https://www.nngroup.com/articles/web-writing-show-numbers-as-numerals/

Table 4.6: The maximum length of a text block in five web pages.

Web page	Application area	Maximum word count in a text block
IIT BOMBAY	Education	40
Times of India	Newspaper	68
UCCN	Research	43
TCS	Corporate	47
Irctc	travel	46
average		48.8

The texts having same features (six features mentioned in Section 4.2), and located contiguously was considered as a text block. The maximum number of words observed in a text block for all the five web pages are reported in Table 4.6. It may be noted that the average word length of the text blocks found in the five real web pages is 48.8. However, the word length of our prior text stimuli was ninety five. Therefore, the size of the stimuli might be reduced almost by half to capture the aesthetics of the textual contents present in a web page.

In this study, the contents of the stimuli was designed by considering digits, as well as the alphabets (both lower and upper case), and special symbols, and reducing the text size at least by half. The following two sentences, termed as *TC2* (Text Content 2) were used to design the new text samples.

- The most straightforward theory for Western Rome's collapse pins the fall on a string of military losses sustained against outside forces[3].
- The reasons for the collapse are major subjects of the historiography of the ancient world, and they inform much modern discourse on state failure. Relevant dates include 117 CE[4]

The reason behind choosing these two sentences was they covered all most all the lower case alphabets (except k, q, x, and z). The frequency of each character (including few capital letters – C, E, R, T, W; numbers – 1, 7; and special symbols – ', .), the number of words, number of characters, and spaces are reported in Table 4.7. In this table, we also reported the maximum, minimum, and average length of the words. It may be noted that the size of the text used here has two hundred and sixty six

[3] https://www.history. com/news/8-reasons-why-rome-fell
[4] https://en.wikipedia.org/wiki/Fall_of_the_Western_Roman_Empire

characters, unlike the earlier samples having six hundred and twenty six characters. The reduction in the size of text stimuli is almost 58%, and suitable for judging aesthetics within thirty seconds of time (which we had planned for, discussed in the previous paragraph).

Table 4.7: Characteristics analysis of the text contents in TC2.

Frequency of each character in the stimuli																	
a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r
20	1	8	9	29	10	4	12	15	2	0	12	7	15	24	4	0	20
s	t	u	v	w	x	y	z	C	E	R	T	W	1	7	’	.	
25	22	7	1	2	0	4	0	1	1	1	2	1	2	1	1	2	
Number of words						50											
Number of characters						266											
Number of spaces						49											
Maximum word length						15 characters											
Minimum word length						1 character											
Average word length						= 266/50 = 5.32 characters											

To judge the similarity of the text contents TC2 with the English Language, based on the frequency of the each letter a-z (unigram), the work reported in [Norvich, 2013] was considered, where the frequency of each letter alphabets (a-z) was reported by consulting the Google books raw data, denoted by TCG (Text Contents Google). The sorted sequence (descending order, based on the frequency) of all the alphabets as found in TCG [Norvich, 2013], the text contents of our prior stimuli (*TC1*), and the text contents considered here (*TC2*) are presented in Table 4.8. The characters' distances of the two test stimuli, termed as *D(TC1)*, and *D(TC2)* with respect to the Norvich' s work are also shown in Table 4.8. The *D(TC1)*, and *D(TC2)* are computed by using the following two equations.

$$D(TC1_i) = absolute(i - position(TC1_i)) \tag{4.12}$$

$$D(TC2_i) = absolute(position(TCG_i) - position(TC2_j)) \tag{4.13}$$

The $position(TC1_i)$ denotes the position of i-th character of TCG, in TC1. Similarly, the $position(TC2_i)$ denotes the position of i-th character of TCG, in TC2. Let us consider the first entry (i = 1) of Table 4.8, the position of the character *e* in TCG is 1, which is represented by *i*. The position of character e in $TC1_i$ is 2. Hence, the $D(TC1_i) = absolute(1-2) = 1$. Similarly, the position of character e in TC2 is 1, consequently $D(TC2_i) = absolute(1-1) = 0$. Similarly, the $D(TC1_i)$, $D(TC2_i)$ for all the other entries in Table 4.8 were computed. It may be noted that the average distance of the alphabets in the earlier test samples (TC1) is 8% larger (1.62) than the test samples considered for this study (1.54). Even the maximum distance (7), and the number of alphabets with distance zero (5) are also larger in the earlier sample. As a consequence, we planned to design the text stimuli by considering the contents of TC2.

In order to design the text samples, there was a necessity to identify a font family. It was reported that the serif fonts are better readable for printed media, while *sans-serif* is better readable for digital media [Lindy, 2016]. Consequently, we considered the *Arial* – which is a *sans-serif* font to design our all text samples.

All the text samples were developed using Adobe Photoshop CS6™. The numbers of the text samples designed by systematically varying each feature (while the other features are not changed). It may be noted from the table that the number of samples for each of the four features – *FS*, *WS*, *LS*, and *LH* are fifteen; while thirty five samples (almost double) were considered for judging the variations of the two types of contrast (luminance, and color). It was reported in [Optimal font size] that the 10 – 14pt fonts are frequently used in web pages.

In order to cover a broader range, we considered 1pt – 27pt for designing the fifteen stimuli of *FS*. The same range were also adopted to generate the fifteen samples of *WS*, *LS*, and *LH*. In order to design the thirty five samples of contrast, we surveyed the colors of the text components found in the fifty nine real web pages (used in our study), as discussed in Section 3.3.4 of Chapter 3. Based on the survey results, we designed thirty five stimuli by varying the text color and background color. Out of these thirty five samples, three stimuli are shown in Figure 4.8 (a) - (c). Similarly, three samples for each of the four features *FS*, *LS*, *LH*, and *WS* are reported in Figure

4.8 (d) – (n) respectively. The range of the six feature values adopted in our study is reported in Table 4.9. The areas of all the text samples are 400×300.

Table 4.8: Sorted alphabets in [Norvich, 2013], prior text stimuli, and the text considered here, along with their analysis.

i	TCG [Norvich]	TC1	*D(TC1)*	TC2	*D(TC2)*
1	e	t	1	e	0
2	t	e	1	s	2
3	a	i	1	o	3
4	o	a	2	t	1
5	i	r	2	r	2
6	n	o	1	a	2
7	s	n	1	i	5
8	r	s	3	n	3
9	h	c	1	h	0
10	l	h	1	l	0
11	d	l	3	f	1
12	c	f	3	d	1
13	u	m	7	c	2
14	m;	d	1	m	0
15	f	p	3	u	4
16	p	g	1	g	1
17	g	w	1	p	1
18	w	x	1	y	1
19	y	y	0	w	1
20	b	u	1	j	1
21	v	b	1	b	1
22	k	v	1	v	1
23	x	k	5	k	2
24	j	j	0	q	4
25	q	q	0	x	1
26	z	z	0	z	0
	Analysis				
	Average Distance		1.62		1.54
	Min Error		0		0
	Max Error		7		5
	Number of alphabets in proper position		4		5

Table 4.9: Minimum and maximum values of all the text samples.

Feature	**LC**	**CHC**	**FS**	**WS**	**LS**	**LH**
Min	-0.93	128	1	1	1	1
Max	12.12	765	27	27	27	27

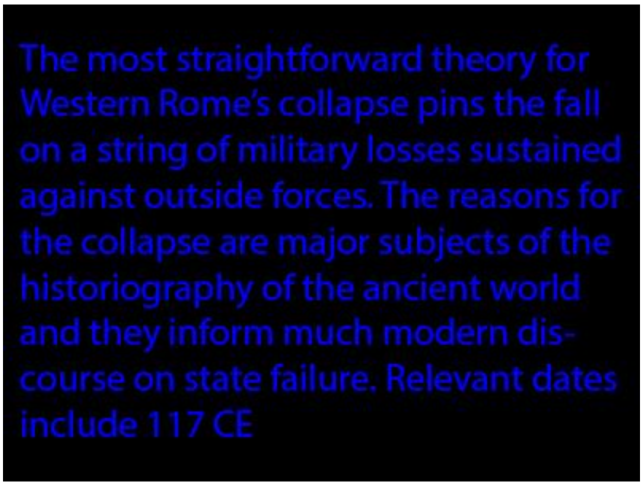
To rate those text samples, we used the web-based browser used in our earlier empirical study. The texts were shown to the participants on the PCs having 1.8 *GHz Intel Quad Core i7* processor running *Windows* 10; each had a 17" wide viewing angle color display.

Table 4.10: Participants' details and the number of text samples used for the empirical study.

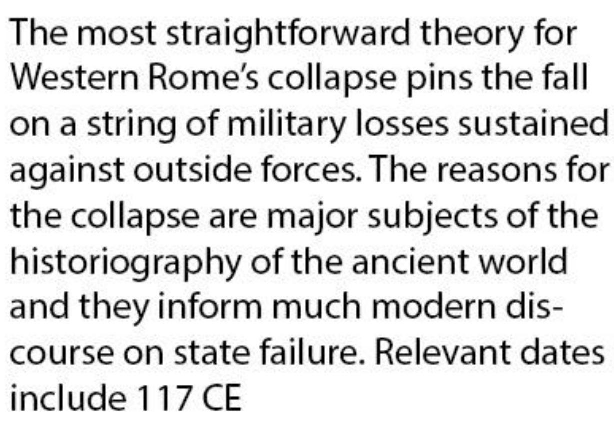
Feature	**LC and CHC**	**FS**	**WS**	**LS**	**LH**
No of text samples	35	15	15	15	15
No of the users rated	65	30	30	30	30
No of female users	33	15	15	15	15
No of male users	32	15	15	15	15
Average age	21.58	20.39	21.81	23.55	20.74

4.5.2 Participants

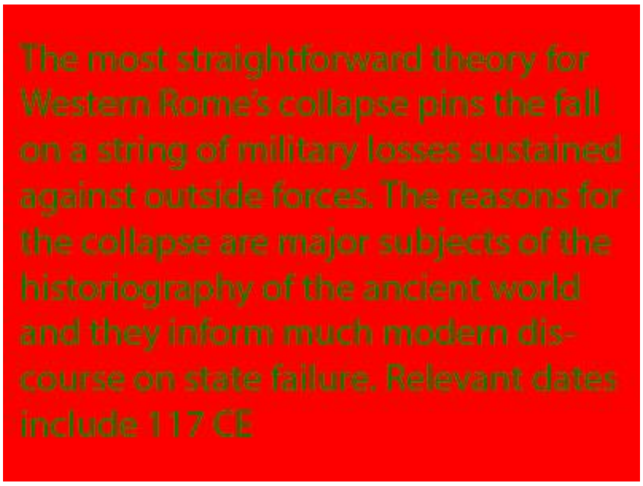
The number of the participants, along with their average ages and gender are shown in Table 4.10. To rate the ninety five text samples, we considered five group of participants [{*LC* and *CHC*}, *FS*, *WS*, *LS* and *LH*]. All the participants belong to a group rated the samples of that group only – *between groups*. For example the thirty-five text samples of *LC* and *CHC* were rated by the group of sixty five participants; similarly, the fifteen samples of *FS* were rated by another group of thirty different participants. In Table 4.10, we reported the number of male and female participants and their average age of each group. All together we considered one hundred and eighty five participants. The participants considered for this study had a normal or corrected-to-normal vision, without color blindness (self-reported). All of them were regular computer users, but not familiar with the screen design concepts.



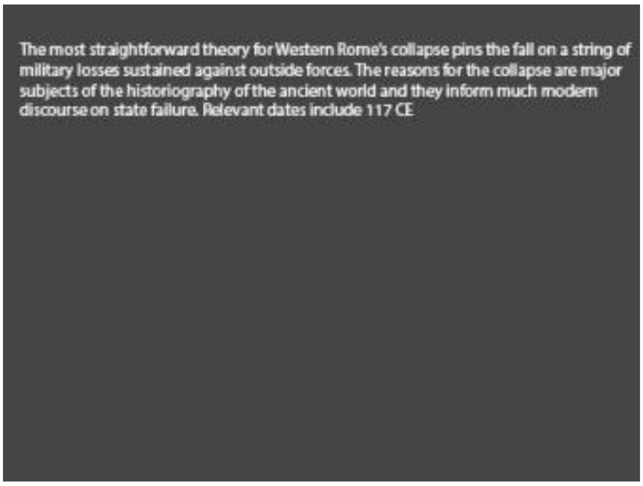
(a)CHC= 255, LC = 1.56 (background colour = black, text colour = blue)



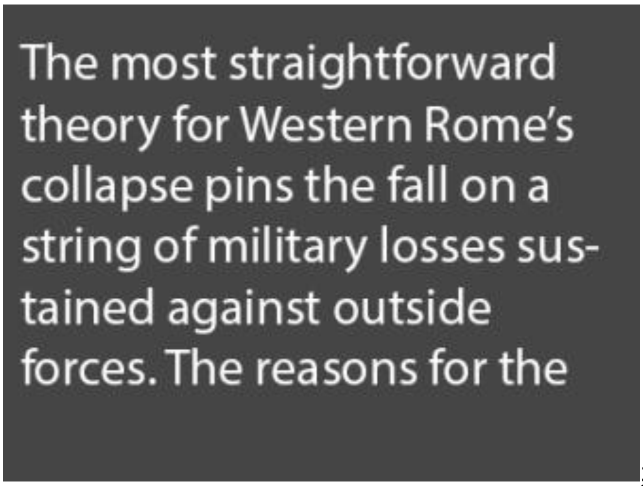
(b) CHC = 765, LC = - 0.93(background colour = white, text colour = black)



(c) CHC = 383, LC = -0.01 (background colour = red, text colour = green)



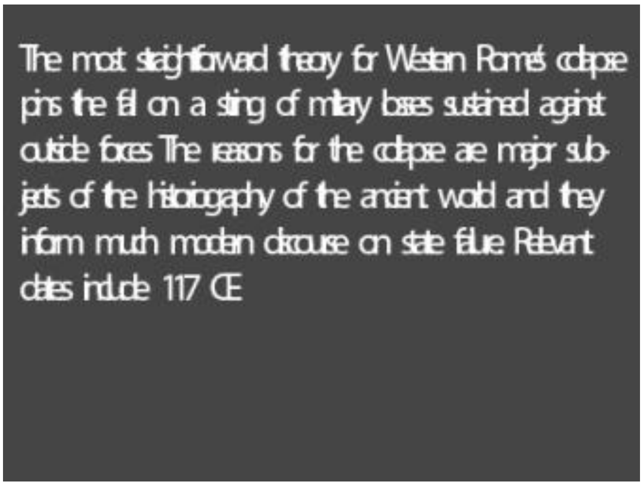
(d)FS= 1pt



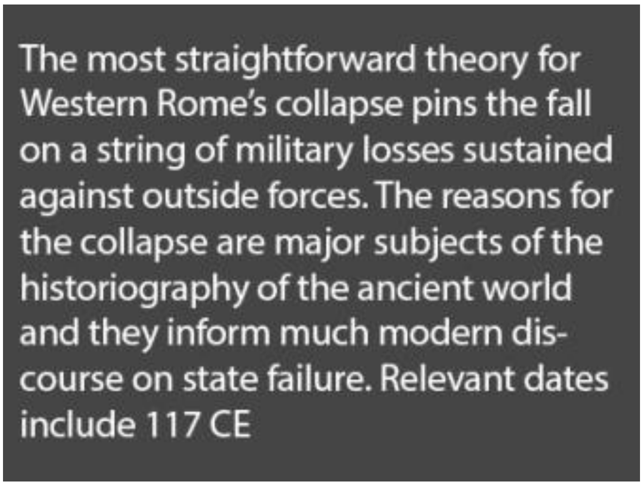
;

(e)FS = 9pt

(f) FS = 27pt

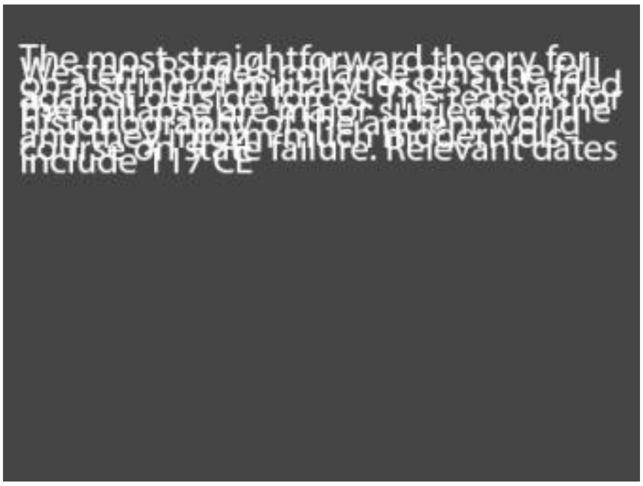


(g)LS=1pt

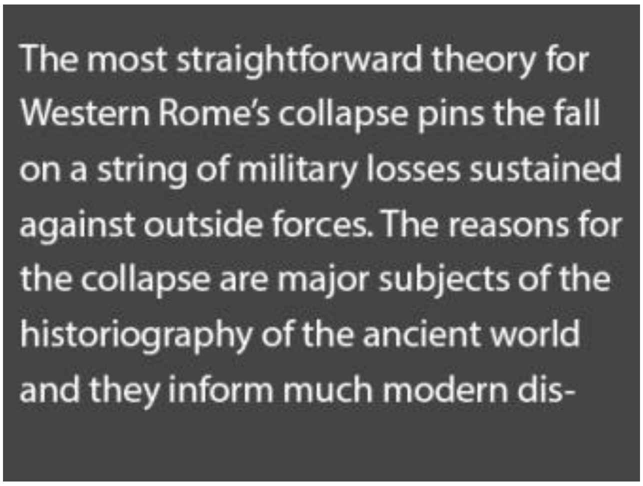


(h)LS =13pt

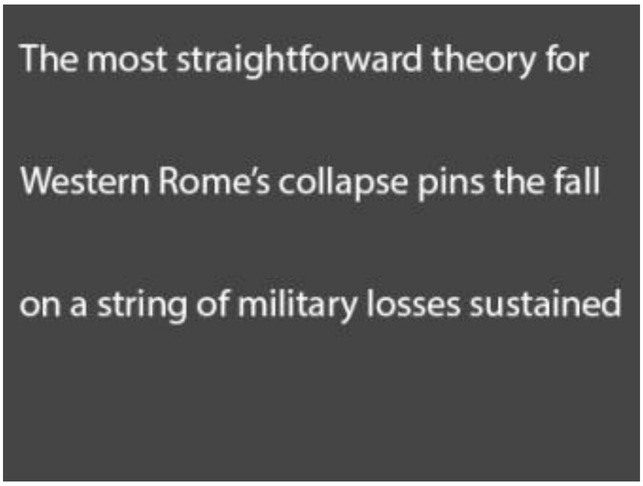
(i) LS=27pt



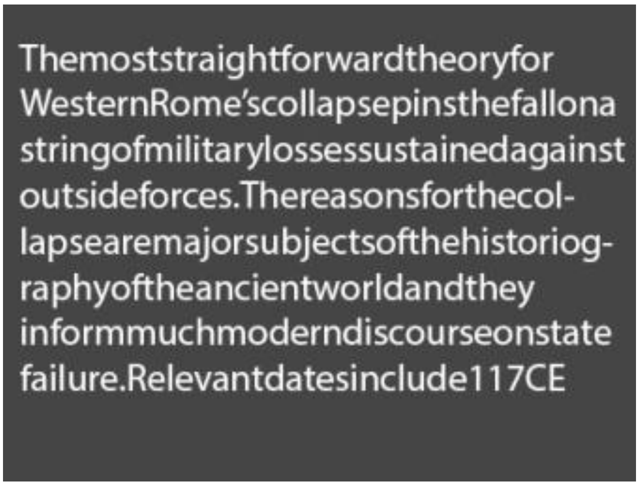
(j)LH = 1pt



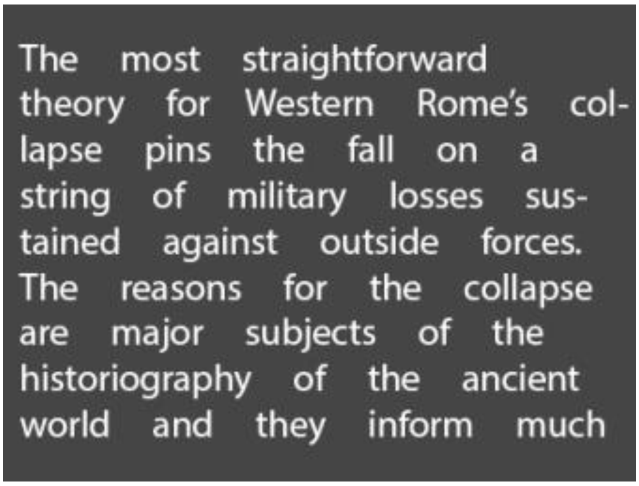
(k) LH =11pt



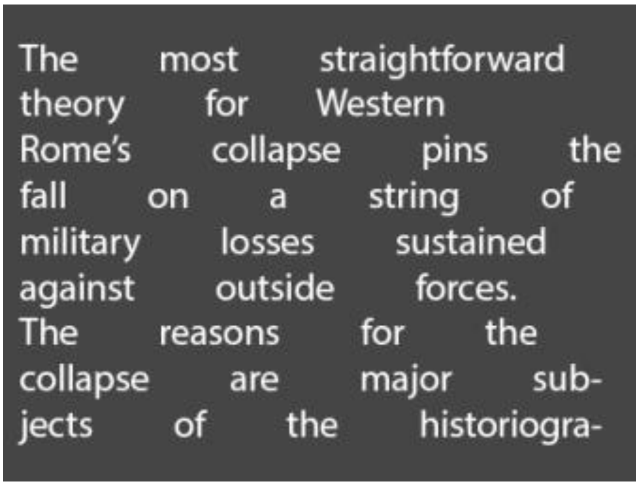
(l) LH =27pt



(m)WS =1pt



(n)WS =15pt



(o) WS=27pt

Figure 4.8: Text sample with different feature values.

4.5.3 Data Collection

The participants of a group viewed all the text samples belong to it – between groups. In order to avoid the *learning effect,* the sequence of the texts was changed for each participant. A small training session was organized to familiarise the participants with the web-based browser and the five-point rating scale. A participant could view a text sample as long as (s)he wished and was allowed to go back to the previous samples already viewed. The browser-based viewer could facilitate to view a previous/next sample. After viewing each text, they were asked to rate it according to its *aesthetic appeal* in a five-point rating scale (one denotes *least aesthetically appealing*, and five denotes *most aesthetically appealing*) the text samples. The statistical mode of the users' ratings of all the ninety five samples were used for the validation of the proposed model, as discussed in the following.

4.5.4 Validation Results

The aesthetic scores of all the ninety five stimuli were computed by the analytical expressions, Equation 4.11. Based on the aesthetics scores, all the text samples are categorized in a binary class. In order to categorize, the logic (if the aesthetic score < 0 then aesthetically pleasing, else unpleasing) used for the earlier validation is also adopted here. In Table 4.11, the model predicted classes of the ninety five samples are reported, where one stands for aesthetically pleasing, and zero signifies aesthetically unpleasing text.

In order to compare the performance of the model, the statistical mode of the users' ratings were considered as the final rating, shown in Table 4.11. The modes of all the ninety five samples were converted to a binary class, if the mode is >= 3 then aesthetically pleasing (denoted by 1), else unpleasing (represented by 0). The rightmost column of the Table 4.11 shows out of the ninety five test stimuli, our proposed model predicted only fifty nine samples accurately (with an accuracy of 62.10%). The possible reason for the performance degradation was the small number of test samples, where the features are not varied systematically considered for the model development.

The proposed model predict aesthetics in terms of a binary class. However, a computational model capable of predicting aesthetics in terms of some scores or ratings can express more precise information than that of a binary class. As we planned to develop a computational model capable of predicting the whole web page aesthetics in terms of scores or ratings, the component models must be developed in the same way. As a consequence, there is a need of a computational model of the textual elements capable of predicting aesthetics in terms of score or rating. In the following section, another computational model of text aesthetics capable of predicting text aesthetics in terms of scores is reported.

Table 4.11: Second validation result using ninety five samples.

Text Sample#	Predicted AS	Model Predicted Class	Statistical Mode of Users' Ratings	Users Choice based on Mode	Correctly Predicted?
1	3.092275	0	3	1	NO
2	-0.12615	1	5	1	YES
3	1.751962	0	3	1	NO
4	2.317029	0	1	0	YES
5	-0.12563	1	4	1	YES
6	0.443352	0	4	1	NO
7	3.027396	0	3	1	NO
8	1.635021	0	4	1	NO
9	3.204662	0	2	0	YES
10	3.172109	0	1	0	YES
11	3.191198	0	1	0	YES
12	1.956721	0	4	1	NO
13	3.044512	0	4	1	NO
14	3.040532	0	2	0	YES
15	2.948191	0	1	0	YES
16	2.520583	0	4	1	NO
17	2.764274	0	4	1	NO
18	-0.12631	1	4	1	YES
19	3.059744	0	3	1	NO
20	2.761988	0	1	0	YES
21	3.176479	0	2	0	YES
22	2.949711	0	3	1	NO
23	2.523742	0	4	1	NO
24	2.945992	0	3	1	NO
25	1.205785	0	4	1	NO
26	2.764491	0	4	1	NO
27	2.766035	0	2	0	YES
28	1.914453	0	4	1	NO
29	3.103403	0	2	0	YES
30	1.831516	0	4	1	NO
31	1.18857	0	4	1	NO
32	2.131361	0	3	1	NO

33	3.101054	0	4	1	NO
34	-1.18311	1	4	1	YES
35	2.150229	0	1	0	YES
36	3.103385	0	1	0	YES
37	-0.35616	1	3	1	YES
38	-0.34924	1	3	1	YES
39	-0.33516	1	3	1	YES
40	-0.35715	1	4	1	YES
41	-0.31162	1	3	1	YES
42	-0.27634	1	2	0	NO
43	-0.36346	1	1	0	NO
44	-0.1614	1	2	0	NO
45	-0.22703	1	2	0	NO
46	-0.35684	1	4	1	YES
47	-0.35767	1	4	1	YES
48	-0.02734	1	1	0	NO
49	-0.35821	1	3	1	YES
50	0.027986	0	2	0	YES
51	-0.35801	1	3	1	YES
52	-0.21665	1	3	1	YES
53	-0.33948	1	4	1	YES
54	-0.43811	1	1	0	NO
55	0.125076	0	1	0	YES
56	-0.07064	1	1	0	NO
57	-0.40831	1	3	1	YES
58	-0.35715	1	4	1	YES
59	0.071117	0	1	0	YES
60	-0.4389	1	1	0	NO
61	0.02058	0	2	0	YES
62	-0.38642	1	4	1	YES
63	-0.14944	1	2	0	NO
64	-0.43331	1	1	0	NO
65	-0.42366	1	1	0	NO
66	-2.19664	1	4	1	YES
67	-3.3759	1	3	1	YES
68	-0.35715	1	4	1	YES
69	-0.56856	1	3	1	YES
70	-0.47197	1	5	1	YES
71	-0.90183	1	4	1	YES
72	-3.66156	1	3	1	YES
73	0.695307	0	1	0	YES
74	-0.32648	1	3	1	YES
75	-1.51153	1	4	1	YES
76	-2.85285	1	3	1	YES

77	-1.26913	1	1	0	NO
78	-3.60559	1	3	1	YES
79	-3.10379	1	3	1	YES
80	-2.05195	1	2	0	NO
81	-0.29745	1	3	1	YES
82	-0.43239	1	3	1	YES
83	-0.35715	1	4	1	YES
84	-3.59291	1	2	0	NO
85	-1.7095	1	2	0	NO
86	-0.69235	1	3	1	YES
87	-0.24427	1	4	1	YES
88	3.024471	0	1	0	YES
89	-0.33452	1	4	1	YES
90	-2.52769	1	2	0	NO
91	-0.27974	1	4	1	YES
92	-0.39569	1	4	1	YES
93	-0.38752	1	3	1	YES
94	-0.25687	1	3	1	YES
95	-1.10788	1	3	1	YES

4.6 SVR based Model for Text Aesthetics

Our proposed model of text aesthetics prediction works based on the *RBF* kernel of *Support Vector Regression* [Cortes and Vapnik, 1995]. To develop this model, the empirical data gathered by using the ninety five text samples were used. The six features' values (*CHC, LC, FS, LS, LH,* and *WS*) of the ninety five text samples along with their average users' ratings were considered for the model development and validation. The proposed model was developed by using the *Support Vector Regression* (SVR), by using *MATLAB 2017 regression learner* apps for *Support Vector Machine*. The six different kernels of *SVM - linear, quadratic, cubic, fine Gaussian, medium Gaussian,* and *coarse Gaussian* were considered in this study. Furthermore, the proposed model was validated by using the *fivefold cross-validation* technique. Results of the validation study are reported in Table 4.12, which shows that out of the six different kernels of SVR, *medium Gaussian* provides least a *MAE* of only 0.40. As the *medium Gaussian* kernel outperforms others, we considered it to develop our text aesthetics prediction model. Figure 4.9 shows the comparison among the *average users rating* or *true rating* (represented by the deep color (blue) line) with the predicted rating (represented by the light color (orange) line) of the ten text stimuli used in our study. In Appendix B, the average users' ratings and the model predicted ratings for all the ninety five samples are reported.

Table 4.12: Comparative study of different kernels of SVM for text aesthetics.

	SVM					
	Linear	Quadratic	Cubic	Gaussian		
				Fine	Medium	Coarse
MAE	0.74	0.58	0.58	0.52	0.40	0.72

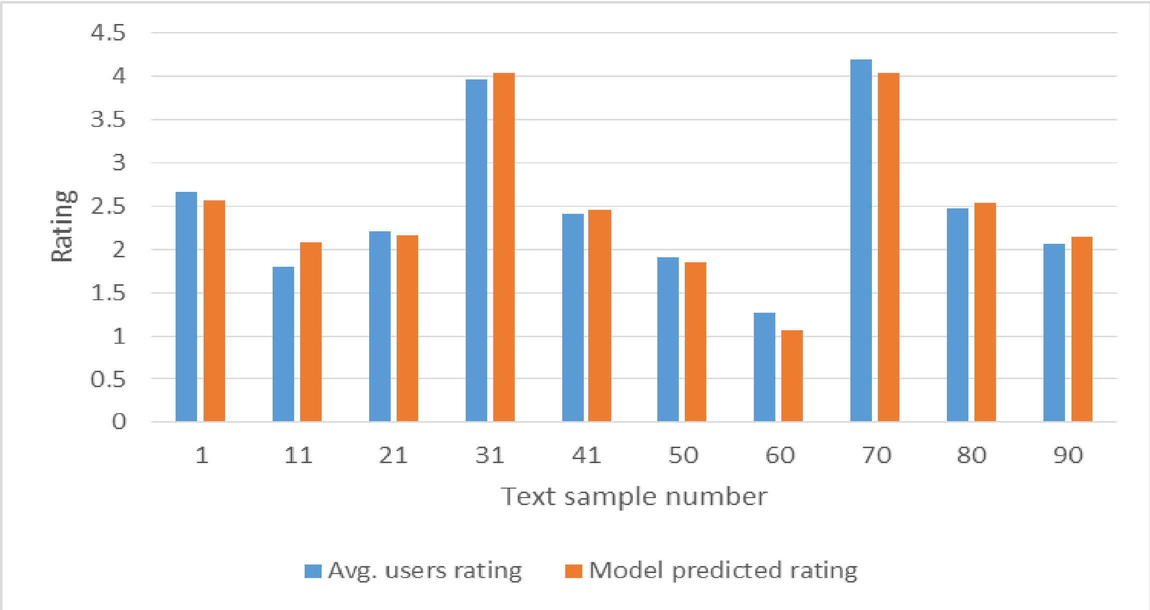


Figure 4.9: Average users' ratings (dark color-blue) and model predicted ratings (light color-orange) of all the ninety five text samples.

4.7 Discussion

In this work, we proposed a computational model to predict the aesthetic quality of the text element present in a web page. The six features - *LC* and *CHC*, *FS*, *WS*, *LS*, and *LH*, were considered for our study. The proposed model was developed by using the *medium Gaussian kernel* of the *Support Vector Regression*. The *five-fold cross-validation* technique shows our model can measure text aesthetics with a *MAE* (Mean Absolute Error) of our model was 0.40. In a five-point rating scale, the maximum absolute error is four. This happens when the original rating of text elements is one but predicted as five, or vice versa. As a consequence, we can claim that our model predicts the aesthetics of the text elements with an accuracy of 90% as mentioned in the following equation.

$$Accuracy_{text} = \left(1 - \frac{MAE}{MAE_{\max}}\right)\% = \left(1 - \frac{0.4}{4}\right)\% = 90\% \qquad (4.14)$$

It was mentioned earlier that the features considered for the model development of text aesthetics was inspired from the features used for judging the readability of textual elements. However, in order to check whether the features were statistically significant or not for modelling the text aesthetics, we formed five hypothesis as mentioned below –

H1: ***Variations of Contrast (Colour and Luminance) has no effect on aesthetics.***

H2: ***Variations of Font Size has no effect on aesthetics.***

H3: ***Variations of Letter Spacing has no effect on aesthetics.***

H4: ***Variations of Line Height has no effect on aesthetics.***

H5: ***Variations of Word Spacing has no effect on aesthetics.***

To test the above mentioned hypothesis (**H1** – **H5**), non-parametric analysis of the empirical data was carried out. The non-parametric analysis can handle the data that are not distributed in nature. Such non-parametric analysis are often suitable for HCI data, as reported in [Wobbrock, and Kay 2016]. The five hypothesis were tested by five independently *Friedman tests* (non-parametric) [Friedman, 1937]. The tests were carried out on the empirical data collected by using the ninety five test samples, as the feature values are varied systematically than the fifteen samples considered for the previous model development (discussed in Section 4.3.3). It may be noted that the users' ratings of the thirty five samples were considered for testing of the hypothesis H1. Similarly the users' ratings of the fifteen samples, where font size was varied, used for testing the Hypothesis H2, and so on. The test results are reported in Table 4.13. It may be noted that all the six features are statistically significant ($p < 0.001$) for modelling the aesthetics of the text elements.

Table 4.13: Results of non-parametric analysis (*friedman* test).

	Non-parametric (F*riedman* test)	
Feature	***F-value***	***p value***
Contrast (colour, chromatic)	1203.96	< 0.001
Font Size	273.4	<0.001
Letter Spacing	265.32	<0.001
Line Height	241.57	<0.001
Word Spacing	250.91	<0.001

The proposed model was developed by using ninety five text samples, where the six significant features of text aesthetics were varied systematically. The range of the four features (LH, FS, WS, and LS) were more than the range followed for designing web pages [Optimal Font Size]. Even the ranges of the rest two features (LC, and CHC) of the ninety five samples were equal with the ranges, of the textual contents found in the fifty nine real web pages. It may be noted that the fifty nine real web pages were selected from the different application areas, and popularly used in our daily life. We believed that the design of those web pages were done by the professional web page designers by considering the design guidelines standards. Therefore, the fifty nine web pages may be considered as the representatives samples of all the real web pages. As our proposed model was developed by considering the range of the feature values observed on those fifty nine representative web pages and the standard guidelines [Interface guidelines], it is likely to work efficiently for any text sample, suitable for designing the textual contents of a web page.

It may further be noted that the proposed model out performs (with 90% accuracy) our earlier model (62.10%). Therefore the model is more robust than the earlier model, and can help a web page designer to predict the aesthetics of the text elements present in his/her design. A low predicted aesthetics score (less than three on a five point rating scale) indicates that there is a necessity to redesign the text elements. The redesigned text element may be further validated using the proposed model. This process may be repeated several times unless the predicted aesthetics score is high (more than four on a five point scale).

4.8 Chapter Summary

In this chapter, using six statistical significant features – *font size, letter spacing, word spacing, line height, color contrast,* and *luminance contrast,* we proposed two computational models for text aesthetics prediction. The first model works based on the trend of the data obtained from the empirical data. The proposed model can predict aesthetics on two classes – good (aesthetically pleasing), and bad (aesthetically unpleasing). Validation result shows that our model can predict the aesthetics of text elements with an accuracy of 86.67%. The model was validated with a small size of test stimuli where the feature values were not varied systematically. As a consequence, the model was further validated with a group of ninety five samples, where the features (text aesthetics) were varied systematically. It was observed that the performance of the model degraded from 86.67% to 62.10%. As a result, another model of text aesthetics prediction using the *Support Vector Regression* was developed. The empirical data of the ninety five text samples used for the validation of the earlier model was used to validate the new model, which performs aesthetic prediction with an accuracy of 90%. Except the text elements, images are often found in a web page. As a result, there was a necessity to develop a computational model for predicting aesthetics of the images. In the next chapter, we reported two computational models for predicting the aesthetics of images, present in a web page.

Computational Model for Image Aesthetics

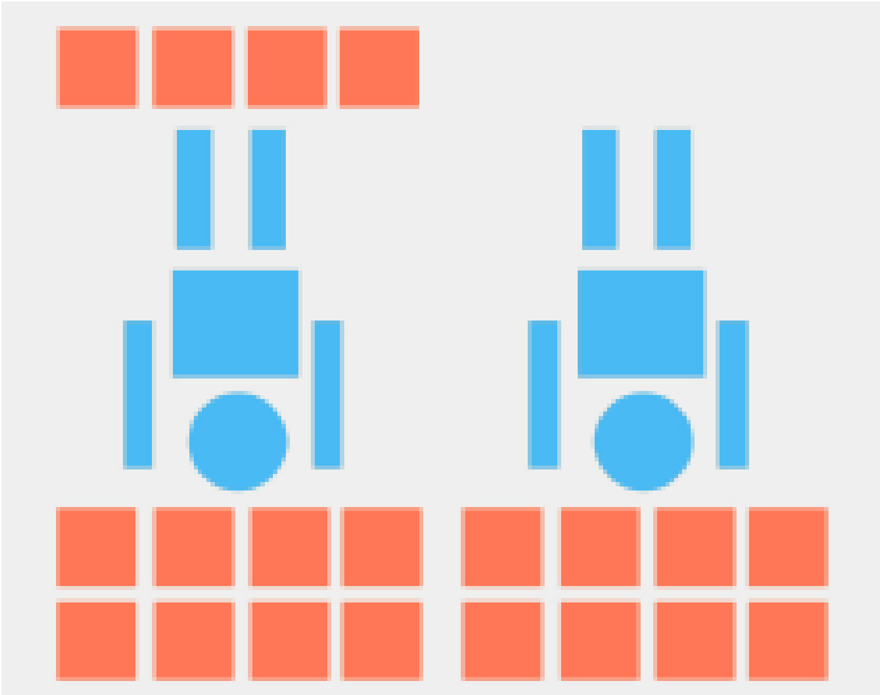
5.1 Introduction

On-screen images are one of the key component present in a web page. Except the image elements, icons, videos, and short animations are also found in a web page. An icon can be characterized by means of an image. Again, the initial impression of a video (present in a web page), can be judged using the initial frame, which is an image. This is also true for the short animations whose initial impression – used to judge the aesthetics is an image. It was reported in Section 1.4 of Chapter 1 that the initial impression is responsible for determining the aesthetics of a web page. Therefore, images are also essential to determine the aesthetics of videos and short animations found on a web page.

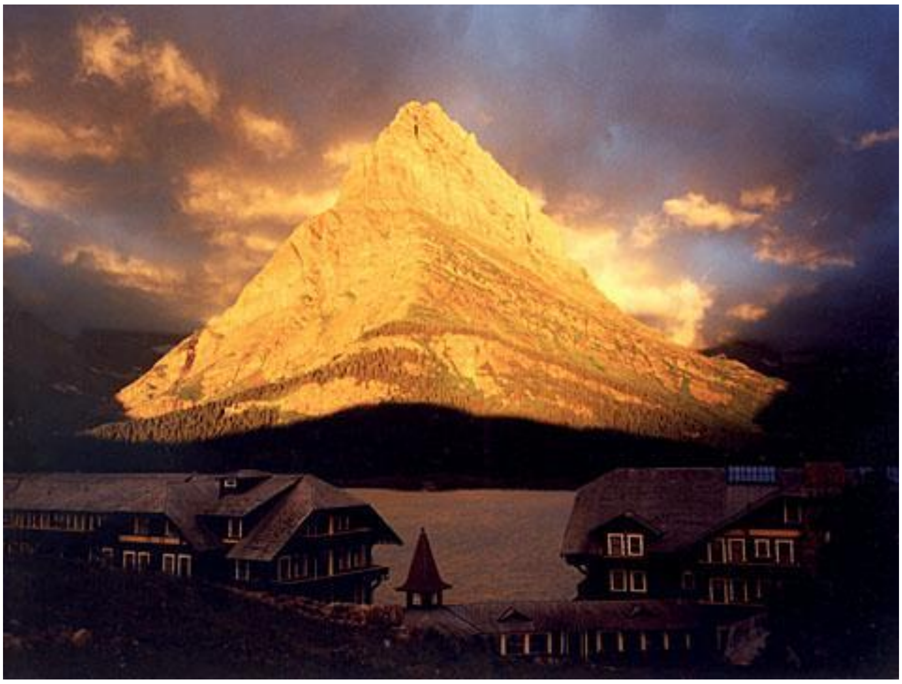
Measuring image aesthetics is again a subjective task, and a computational model can help web page designers to predict the aesthetics of the image elements present in a web page. As a consequence, web page designers can save a lot of time during the design process, which is required for the subjective evaluation of the images, present on a web page.

All the images present in a web page can be classified in the following two types –

- Artificial images (generated by software).
- Photographic images (captured by cameras).



(a)



(b)

Figure 5.1: Two different types of images (a) an artificial image, and (b) photographic image.

In order to measure the aesthetics of these two types of images, in this chapter, two different computational models were proposed. The first model is suitable for computing the aesthetics of artificial images, while the other can predict the aesthetics of the photographic images.

The artificial image aesthetics model was developed by considering two group of features –

- Layout geometry features
- Image related features

Fifteen features of layout geometry, and five features of images were considered to develop the proposed model, which was developed by the Support Vector Regression. The model was trained by the empirical data obtained for a group of sixty one artificial images. Nineteen artificial images were used to validate the model. Experimental results show that the proposed model can predict the aesthetics of the artificial images with a MAE of 0.25 on a five-point rating scale.

On the other hand, the contents of photographic images often cannot be realized with regular size objects, and the geometry based features were not suitable for measuring their aesthetics. The standard practice found in the literature [Datta et al., 2006; Ciesielski et al., 2013] is to measure aesthetics by means of the image related features only. From the literature, eleven features that affect the aesthetics of a photographic image were identified. Using these features another computational model, suitable for predicting aesthetics of the photographic images was developed. The proposed model works based on the Support Vector Regression. The model was trained and tested using a group of two hundred and fifty images. A MAE of 0.51, on a five-point rating scale was observed during the model validation.

Both the models of image aesthetics are reported in this chapter. Rest of the chapter is organized as follows. In Section 5.2, the artificial image aesthetics model is discussed. The photographic image aesthetics model (works for photographic image) is presented in Section 5.3. A detailed discussion of this model is presented in Section 5.4. Finally, the chapter ends with a summary reported in Section 5.5.

5.2 Computational Model for Artificial Images

The computational model suitable for predicting the aesthetics of the artificial images is presented in this Section. The proposed model was developed by considering twenty features. In the following Section, a summary of all the features is reported.

5.2.1 Features of Artificial Images

An artificial image, as shown in Figure 5.1 (a) can be considered as a group of individual objects present in it. Therefore, image aesthetic is likely to be determined by two factors: how the objects are arranged (layout geometry), as well as the visual properties of these objects. Accordingly, the following two broad groups of features were considered to capture the aesthetic of an artificial image.

- Geometry related features
- Image related features

5.2.1.1 Geometry Related Features

All together twenty features were considered for developing the proposed model. Out of these twenty features, fifteen features were geometry related. Among these fifteen features, eleven were inspired by the work of Ngo et al. [2003]. These eleven features include -

- Total Symmetry
- Horizontal Symmetry
- Vertical Symmetry
- Radial Symmetry
- Balance
- Total Rhythm
- Rhythm – X
- Rhythm –Y
- Rhythm - Area
- Equilibrium
- Density

All the features mentioned above were already discussed in Section 2.3.1 of Chapter 2. Except for these eleven features, total no of objects present in an artificial image also affects the aesthetic of an image. Therefore, the number of objects was considered for the model development. For simplicity, we assumed that the objects present in an image are approximated by regular shapes, namely, *rectangles*, *circles*, *triangles*, and *ellipses*. Accordingly, we used the following four features.

1. Number of rectangles
2. Number of circles
3. Number of triangles
4. Number of ellipses

Apart from for the fifteen geometry related features, image related features are also important for the aesthetics measurement. In the following section, the image related features considered for the model development are reported.

5.2.1.2 Related Image Features

To capture the visual properties of an artificial image five more features were considered. We decided to use these features as they were found to affect the aesthetics of photographic images, as reported in [Datta et al., 2006].

Measure of Color Contrast

Contrast is the difference in visual properties that makes an object distinguishable from other objects and the background. In visual perception of the real world, contrast is determined by the difference in the color and brightness of the object and other objects within the same field of view.

The three-stage approach, reported in [Shyam and Bhattacharya, 2012] was used to calculate the color contrast of objects of an image. In the first stage, we converted a color image to gray image. Each gray image was then converted to a standard color enhanced image by histogram equalization, in the second stage. Finally, the original gray image was compared with the corresponding enhanced image to determine the color contrast of the image, as shown in Equation 5.1.

$$CC = \left| \frac{\sum_{i=1}^{p} std_i - org_i}{255 \times p} \right| \quad (5.1)$$

In Equation 5.1, std_i is the intensity of the pixel of the enhanced image and org_i is the intensity of the i^{th} pixel of the original gray image, and p is the total number of pixels per image.

For the other four features, we converted all images from the RGB color space to the HSV color space. HSV color space where three (two dimensional) matrices I_H, I_S, and I_V were created. The computation of the feature values follows the work reported in [Datta et al., 2006].

Measure of Hue

We have calculated the hue as the summation of I_H component of *HSV* space over all the pixels in the image. The sum is then normalized by the number of pixels in an image, which gives us the *average hue* for the image (H_{avg}). The corresponding expression is shown in Equation 5.2.

$$H_{avg} = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} I_H(x, y) \quad (5.2)$$

Measure of Saturation

Saturation indicates the chromatic purity of an image. Pure colors in a photo tend to be more appealing than dull or impure ones. The saturation of an image was computed by the average *saturation* (S_{avg}), as shown in Equation 5.3.

$$S_{avg} = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} I_S(x, y) \quad (5.3)$$

Measure of Lighting

Light exposure or pixel intensities can often be a good discriminant between high and low-quality images. Usually an image becomes less appealing if it has too much light exposure. The average *intensity* (I_{avg}) was used as an indicator of the lighting effect on an image, reported in Equation 5.4.

$$I_{avg} = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} I_V(x, y) \quad (5.4)$$

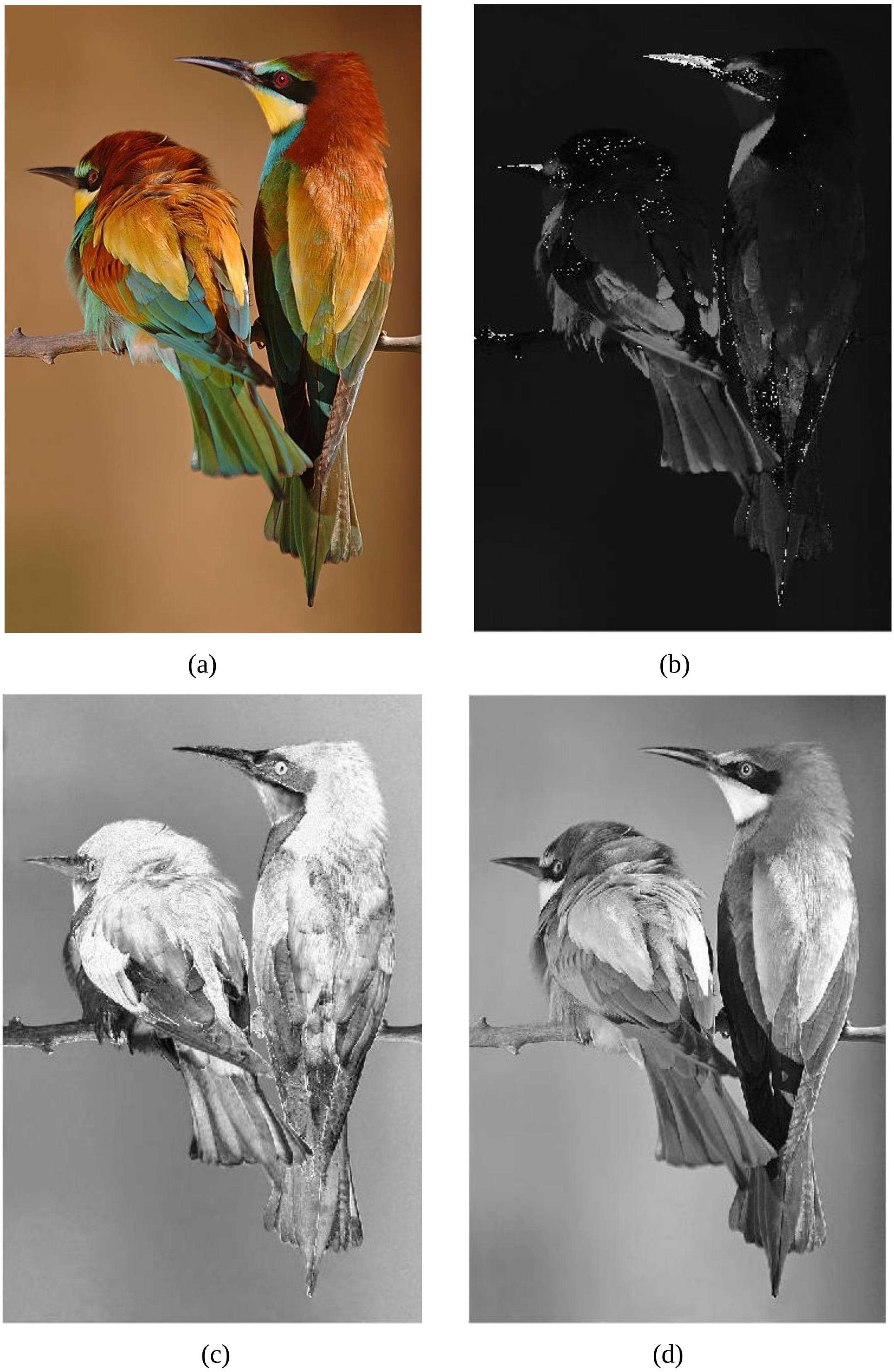


Figure 5.2: An image considered in our study (a), and its (b) Hue, (c) Saturation, and (d) Value.

Figure 5.2 (a) shows an image used in our study and its hue, saturation, and value are shown in (b) - (d) respectively.

Measure of Smoothness/Graininess

The texture used in an image can be useful for judging the aesthetic of an image [Ciesielski et al., 2013]. The extent of texture in an image can be determined by computing image smoothness (or graininess). We used the Daubechies Wavelet Transform [Daubechies, 1992] to calculate the spatial smoothness of an image. The computation included the following steps [Datta et al., 2006].

At first, three-level wavelet transforms on all the three color bands I_H, I_S and I_V were applied. The three levels of wavelet bands are arranged from top left to bottom right in the transformed image, as shown in Figure 5.3. Let the four coefficients for I_H at level i be c_i^{ll}, c_i^{hl}, c_i^{hh} and c_i^{lh}. Then, the smoothness f_i for the i^th^ level for I_H was computed with Equation 5.5.

$$f_i = \frac{1}{S_i}\left(\sum_x\sum_y c_i^{hl}(x,y) + \sum_x\sum_y c_i^{hh}(x,y) + \sum_x\sum_y c_i^{lh}(x,y)\right) \tag{5.5}$$

where $S_i = |c_i^{hl}| + |c_i^{hh}| + |c_i^{lh}|$.

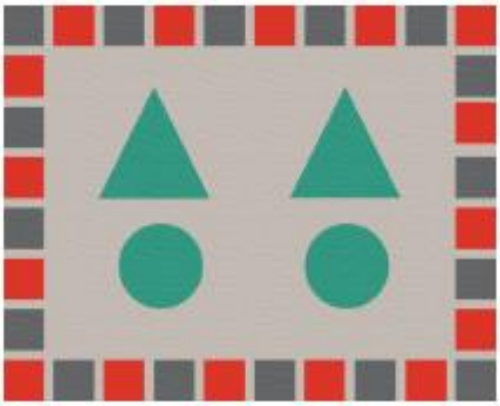
The average smoothness for color band I_H was computed by $f_H = \sum_{i=1}^{3} f_i$. Similarly, we calculated the average smoothness for the other two bands f_S and f_V. Finally, the average of the three colour band - f_H , f_S and f_V to determine the average smoothness of the image.

The list of all the features we used in this work is shown in Table 5.1.

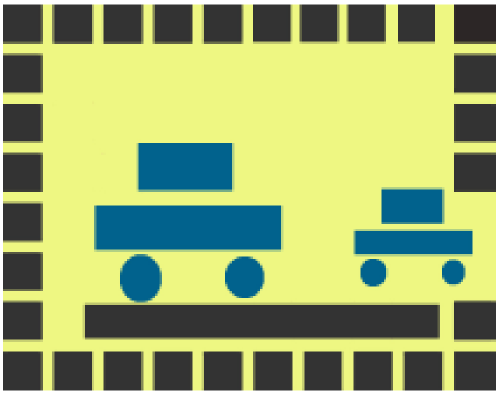
Table 5.1: The list of features used to predict aesthetics.

Geometry related features (15)		Image related features (5)
1. Total Symmetry 2. Horizontal symmetry 3. Vertical symmetry 4. Diagonal symmetry 5. Balance 6. Density 7. Equilibrium 8. Total rhythm 9. Vertical rhythm 10. Horizontal rhythm 11. Aerial rhythm Computed using the formulation reported in [Ngo et al., 2003]	1. Number of rectangles 2. Number of triangles 3. Number of circles 4. Number of ellipses	1. Color contrast (computed using the formulation reported in [Shyam et al., 2012]) 2. Hue 3. Saturation 4. Lighting 5. Smoothness/graininess (all the above four computed following the approach reported in [Datta et al., 2006])

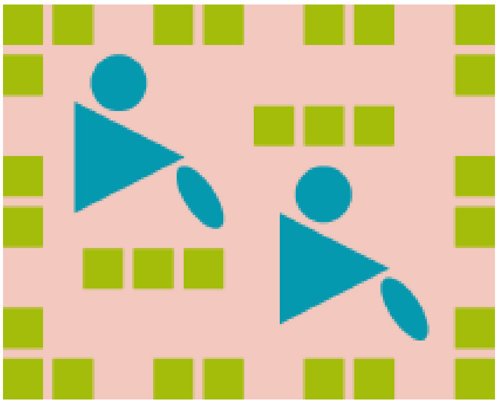
Figure 5.3: The 3-level wavelet transforms for measuring smoothness. The leftmost figure is the original image. The naming convention is shown in the rightmost figure.



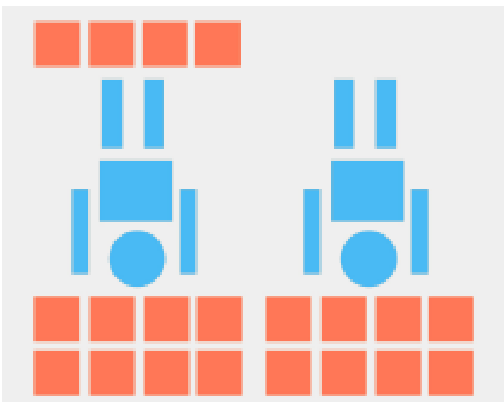
(a)



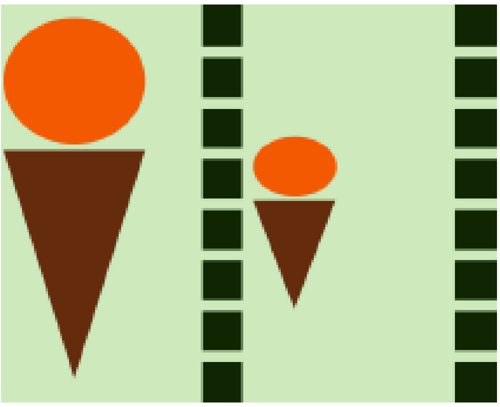
(b)



(c)



(d)



(e)

Figure 5.4: Five of the images we designed for the study. In these images, the symmetry feature was systematically varied.

5.2.2 Empirical data collection

In order to develop the model, an empirical study was conducted by eighty artificial images. All these images were rated by a group of one hundred participants. The empirical data were used to train and test the proposed model.

5.2.2.1 Experimental Setup

The eighty images were designed by the Adobe Photoshop CS6™. We studied popular web pages to decide on the image layouts. It was observed that the web pages typically follow a grid pattern of regularly shaped objects. Therefore, we followed the same for designing the test samples. We first created a grid layout of regular and same sized squares for our base images. We chose the grid dimensions as 10×8 squares. Then, we removed and replaced the squares with other regular shapes to create new images. These shapes include squares, rectangles, circles, ellipse, and triangle. The size of each image was 882×702 pixels.

In these images, we tried to vary the feature values (mainly those related to layout geometry) systematically. Figure 5.4 shows a set of five images we designed, where the *symmetry* feature is varied systematically. The other feature values varied randomly, as presented in Table 5.2. It may be noted that the images contained real-life objects made from the elementary shapes (e.g., cars, human figures). This allowed us to cover a wide range of feature values.

In order to rate the images, the same web based interface used for our earlier empirical studies was used. On this interface, an image can be rated on a five-point scale based on its *perceived appeal*, where one implied “least appealing,” and five implied “most appealing.” There were the *previous* and *next* buttons on the interface. Through these buttons, a participant can surf all the images and can change the earlier ratings if s/he wants to. It was also possible to rate the images *after* all the images were viewed using the buttons.

Table 5.2: The feature values for the images in Figure 5.4.

Features	Images				
	1	2	3	4	5
Total Symmetry	0.007575	0.096976	0.121766	0.226028	0.567457
Horizontal Symmetry	0.000545	0.021882	0.052957	0.075572	0.280762
Vertical Symmetry	0.003513	0.037501	0.016584	0.07558	0.005957
Radial Symmetry	0.003518	0.037594	0.052225	0.074876	0.280738
Balance	0.052898	0.375039	0.149128	0.797766	0.500078
Total Rhythm	0.000168	0.000828	0.000981	0.002084	0.006
Rhythm X	0.000065	0.0004	0.000398	0.000173	0.005405
Rhythm Y	0.000101	0.000382	0.000548	0.001892	0.000539
Rhythm Area	0.000003	0.000046	0.000036	0.000019	0.000056
Equilibrium	0.047636	0.154726	0.042986	0.29075	0.19421
Density	0.379324	0.404062	0.327517	0.32421	0.317569
No of Triangles	2	0	2	0	2
No of Circles	2	4	2	2	1
No of Rectangles	32	35	28	30	16
No of Ellipses	0	0	2	0	1
Hue	0.186448	0.185068	0.20983	0.099596	0.225928
Saturation	0.244943	0.39365	0.466571	0.222429	0.434839
Lighting	0.70774	0.68792	0.874492	0.951264	0.763594
Color Contrast	-0.012597	0.002083	-0.009206	0.057842	0.005098
Smoothness	6.89034	7.429401	8.809873	7.555219	8.532671

5.2.2.2 Participants

Altogether one hundred participants took part in the study. They were within the age group of sixteen to fifty years. Among the participants, there were fifty males and fifty females participants. We considered five group of participants – school students (25, avg. age = 16), undergraduate students (25, avg. age = 21), graduate students (25, avg. age = 25), and faculty members (25, avg. age = 40). All of them are residents of India. They are regular computer users and had normal or corrected-to-normal vision. None of them was color blind (self-reported).

5.2.2.3 Procedure

The study was divided into two phases. In the first phase, fifty participants rated forty images on the five-point scale. The remaining fifty participants rated the other forty images on the same five-point scale in the second phase.

In each phase, a participant rated the forty images assigned to him/her in two sessions (twenty images each) spread over two days. Participants were allowed to take breaks in each session. These measures were taken to avoid discomfort to the participants that might have arisen due to a large number of images to be rated.

Before data collection, we performed training sessions for the participants. In these sessions, participants were familiarized with the web interface and the five-point scale. We customized for each participant the sequence in which the forty images were shown to him/her following the counterbalancing measure. This was done to avoid any learning effect.

5.2.2.4 Details of the Data Collection

Once the ratings were obtained from the participants, we calculated the *weighted average rating* for each image, where the weights were the numbers of participants giving a particular rating. Sample data for the five images of Figure 5.4 are shown in Table 5.3 for illustration. Here w_i is the number of participants giving R_i rating to the image.

Table 5.3: Sample data collected in the study.

	Number of participants giving a rating					
Images	1	2	3	4	5	Weighted Average Rating $\sum_{i=1}^{5} w_i R_i$
(a)	8	18	15	9	0	2.50
(b)	0	4	10	17	19	4.02
(c)	2	2	7	16	23	4.12
(d)	0	9	26	6	9	3.30
(e)	4	13	16	15	2	2.96

5.2.3 Development of the Proposed Model

The weighted average ratings collected from the empirical study were used to train and test the non-linear regression model [Erdman and Little, 1997]. We decided to go for the regression model since we are interested in predicting a *rating* for a given image, rather than a *class*. The regression model we developed uses Support Vector Regression.

5.2.3.1 Implementation Details

In order to calculate the feature values, we have used the *MatLab*^{TM} and *OpenCV* libraries. The detection of objects and related features were implemented in three steps.

Step 1. The Canny Edge Detection Algorithm [Canny, 1986] was used to detect the object edges in an image.

Step 2. After getting the object edges, we determined the *contours* of those objects, i.e., a 2-D matrix of all the points contained inside an object, using the *OpenCV* library function *findcontour()*.

Step 3. On the object contours, we applied a polygon approximation algorithm to find the polygon shape of the contour. After getting an approximated polygon for the contour, we mapped the polygon to square or rectangle, circle or ellipse, and triangle based on its properties. After identifying the shape of each object, we computed its area and centroid. We have used the *MATLAB*^{TM} Library function *approxPolyDP()* to complete the task.

The image related features were calculated in MATLAB^{TM}. We have converted the *RGB* data of an image into the *HSV* space and used the *H, S* and *V* components, as discussed before. We made use of the *Wavelet toolbox in* MATLAB^{TM} for the *wavelet* transformation. The implementation of regression was also done in MATLAB™. We have used the *libsvm* library for the regression method.

5.2.3.2 Selection of Training and Testing Set

In order to ensure that the proposed model is developed taking into account as many variations in feature values as possible, the *k-means clustering* algorithm was applied to our empirical data. We decided to use $k = 4$ after several trials. The algorithm was implemented using the *kmeans()* function in MATLAB™.

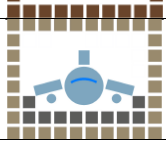
We randomly picked images from each of the four clusters and had put those in the training set. The remaining images in the cluster were put in the testing set. The ratio of images selected from each cluster for training and testing was directly proportional to the number of images present in the cluster.

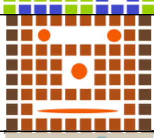
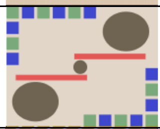
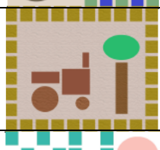
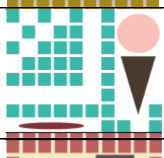
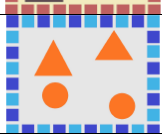
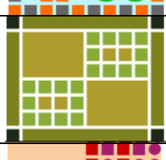
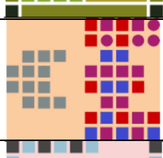
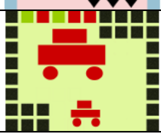
Following the above method, a training set with sixty one images and testing set with nineteen images were created.

5.2.3.3 Results

Our model was developed using the training data of the sixty one images. The model was then tested on the images in the test set (comprising of the remaining nineteen images). In the testing phase, the weighted average rating, obtained for each image in the empirical study were compared with the model predicted rating. The comparative results for the nineteen test images are shown in Table 5.4 and Figure 5.5.

Table 5.4: The predicted and empirically obtained aesthetic ratings for the 19 test images.

Image #	Image	Empirical rating	Predicted rating
1		3.24	3.213
2		4.12	3.80
3		3.28	2.92
4		3.72	3.02

5			3.8	3.23
6			3.12	2.85
7			3.24	3.36
8			2.52	2.95
9			3.32	3.02
10			3.24	3.05
11			3.12	2.88
12			3.08	2.80
13			3.48	3.15
14			2.88	2.87
15			2.96	2.82
16			3.08	3.03
17			2.84	3.03
18			3.24	3.25
19			3.2	3.04

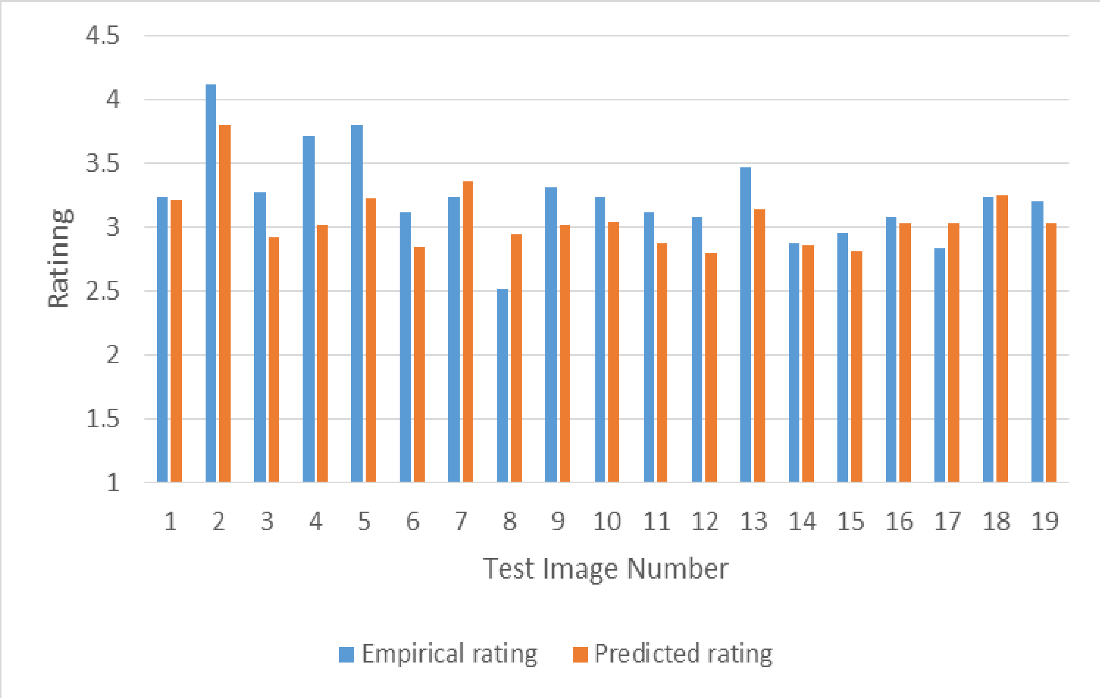


Figure 5.5: The plot of empirical ratings vs. model predicted ratings.

5.2.4 Discussion

In this work, we proposed that aesthetic quality of the artificial images depend on the geometric arrangement, shapes, sizes, and the number of objects in the images along with color combination and texture. We further proposed a model that combines these features of an image and predicts an aesthetic rating. We have tried to demonstrate the validity of our proposals by training and testing the model with empirical data. The testing result shows that the proposed model was able to closely predict the aesthetic ratings (MAE = 0.25) of test images given by the participants. The accuracy of the proposed model can be computed with the following Equation 5.6.

$$Accuracy_{artificial\_image} = \left(1 - \frac{MAE}{MAE_{\max}}\right)\% = \left(1 - \frac{0.25}{4}\right)\% = 93.75\% \tag{5.6}$$

The proposed model can predict the aesthetics of the artificial images by considering both the image, and geometry related features. In order to compute the geometry related features, an artificial image was considered as a group of individual objects of regular size (*rectangles*, *circles*, *triangles*, and *ellipses*). However, characterizing a photographic image using these types of regular sized objects may not always be possible. The usual approach found in the literature [Datta et al., 2006; Ciesielski et al., 2013] is to consider the only image related features for aesthetics computation. Based on this observation, we planned to develop a computational model suitable for photographic images by considering image related features. Using the image related features, a computational model was developed to predict the aesthetics of the photographic image. The proposed model is reported in the following section.

5.3 Computational Model for Photographic Images

In order to develop this model, we considered eleven features of image aesthetics found in the literature. In the following section, we briefly discussed about the eleven features.

5.3.1 Features of Photographic Images

Out of the eleven features of image aesthetics, the five features used to develop our earlier model are also considered here. Those five features include -

- Colour Contrast (CC)
- Hue (H)
- Saturation (S)
- Lighting or Value (V)
- Smoothness (SMT)

A brief discussion of the rest six features is reported below.

Aspect Ratio (AR): It was computed by the height, width ratio of an image as shown in Equation 5.7.

$$AR = X \,/\, Y \tag{5.7}$$

where X and Y are the size of an image in the X and Y direction respectively.
It was reported [Datta et al., 2006] that the human eyes love to perceive the images closure to the "Golden Ratio." The 4:3 and 16:9 are pleasing to our eyes and approximate the "Golden Ratio."

Number of Unique Colours (NUC): Human eyes love to visualize colors. As a result, a color image is more attracting than that of a grey image. Generally, a large number of unique colors makes an image exciting [Unique color]. As a consequence, the number of unique colors is another essential feature for determining the aesthetics of an image.

Sharpness (SRP): Sharpness can measure the clarity of an image. Sharpness is influenced by the contrast along the edges – termed as *acutance*. Most of the times, soft images (not sharp) can be aesthetically pleasing to the users. Sharpness can be improved by increasing differences along the edges in an image [Sharpness]. Sharpness can be measured by the gradient-based estimation technique as shown in the equation below.

$$SRP = \frac{G_X + G_Y}{n} \tag{5.8}$$

G_X, G_Y denotes the gradient in the X and Y direction respectively, and n is the total number of pixels in an image.

Rule of Third (ROT): This specifies that the topic of the interest must be at the center of an image. In another word, the center of interest must be at the any one of the four intersections as shown in Figure 5.6. It was reported [Datta et al., 2006] that human eyes love to observe the significant object along the periphery or inside the inner rectangle as demonstrated in Figure 5.6. The average hue of the inner rectangle - ROT_H can be computed by Equation 5.9.

$$ROT_H = \frac{9}{XY} \sum_{x=X/3}^{2X/3} \sum_{y=Y/3}^{2Y/3} I_H(x, y) \tag{5.9}$$

where $I_H(x, y)$ denotes the hue of the pixel positioned at (x, y) location.

Similarly, ROT_S (Rule of Third – saturation) and ROT_V (Rule of Third- value) can be computed by the Equation 5.10 and 5.11 respectively,

$$ROT_S = \frac{9}{XY} \sum_{x=X/3}^{2X/3} \sum_{y=Y/3}^{2Y/3} I_S(x, y) \tag{5.10}$$

$$ROT_V = \frac{9}{XY} \sum_{x=X/3}^{2X/3} \sum_{y=Y/3}^{2Y/3} I_V(x, y) \tag{5.11}$$

where $I_S(x, y)$, and $I_V(x, y)$ denotes the saturation, and value of the (x, y) pixel.

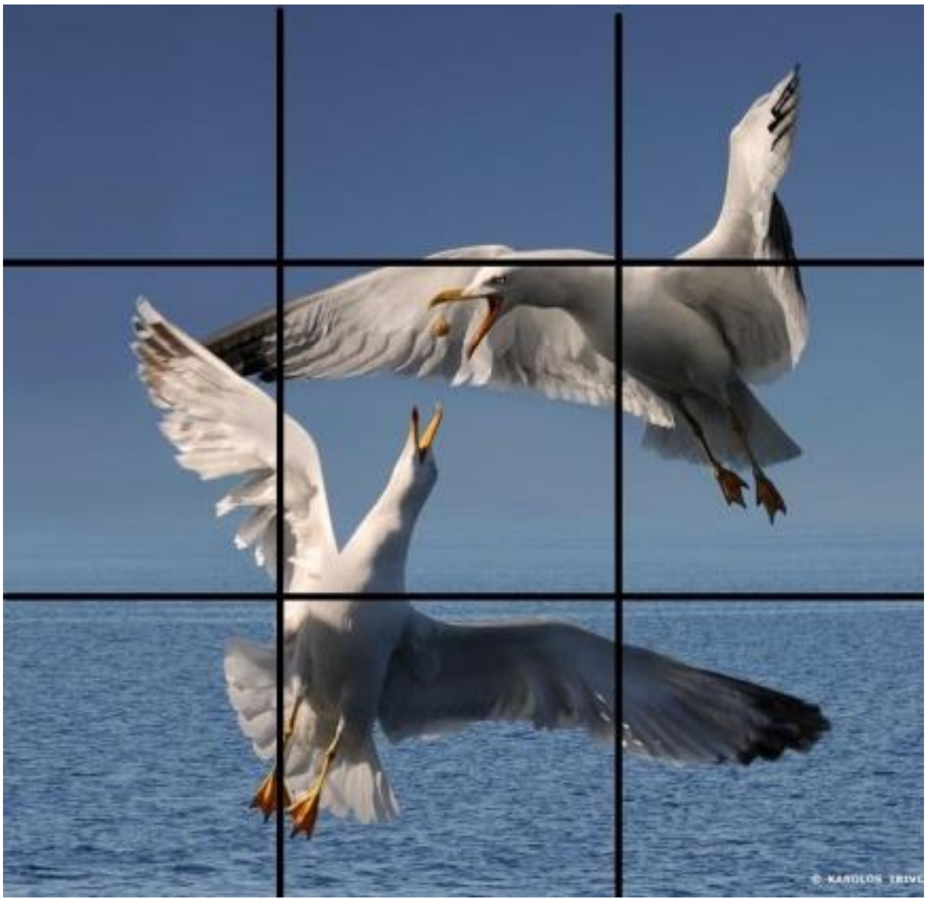


Figure 5.6: Image split by the two horizontal and two vertical lines.

5.3.2 Empirical Study of Photographic Images

In order to carry out the empirical study, we planned to analyze the eleven features of photographic image aesthetics found in the real web pages. The fifty nine real web pages reported in Table 3.12 of Chapter 3 were considered for this study. A group of one hundred and fifty nine photographic images were extracted from the fifty nine web pages. For all the one hundred and fifty nine images, the eleven features' values were computed. The ranges of these features' values were reported in Table 5.5. For the proposed model development, we intended to use a set of photographic images which covers the ranges of the all eleven features observed in the one hundred and fifty nine photographic images. It may be noted that the one hundred and fifty nine images were selected from the real web pages, which are popularly used for different applications. Therefore, the participants may be familiar with the images present on those web pages. It was reported that familiarity of the images may affect the aesthetics. As a consequence, the one hundred and fifty nine images were not considered for the empirical study.

In order to conduct the empirical study, two types of photographic images were considered. One of the data source was *photo.net*. The website was developed for photo sharing, where the peers can view the shared photos. The top ten mostly viewed photographic images for a period of fifteen days, resulting one hundred and fifty photographic images, were considered. As the images were mostly viewed by the users, it is likely to aesthetically pleasing in nature. Therefore, this group of images can be the representative samples of aesthetically pleasing images.

In order to compare the features' ranges of the one hundred and fifty images with the one hundred and fifty nine images (obtained from the fifty nine real web pages), the eleven features of the one hundred and fifty images were computed, as reported in Table 5.5. It may be noted that the ranges of the three features - smoothness, aspect ratio, and sharpness were larger than the one hundred and fifty nine images. However, this is not true for the rest eight features – color contrast, hue, saturation, value, rule of third – hue, rule of third – saturation, and rule of third – value. As a result, there was a necessity to consider more images, suitable for covering the ranges of the rest eight features. In order to carry out this task, we considered more one hundred photographic images, captured by us. Figure 5.7 shows two such images where contrast varied. The range of the eleven features observed on those images are also reported in Table 5.5. It may be noted that except for the colour contrast, the range of the seven features (hue, saturation, value, rule of third – hue, rule of third – saturation, and rule of third – value, number of unique colour) were larger than the ranges of the one hundred and fifty nine photographic images collected from the fifty nine real web pages. However, the combined ranges of the colour contrast of the two hundred and fifty images (one hundred captured images, and the one hundred and fifty images - considered from photo.net) were more than the ranges of the one hundred and fifty nine images. A further analysis of the results (reported in Table 5.5) showed that the ranges of the all eleven features' observed in the two hundred and fifty images were more than the one hundred and fifty nine images, collected from real web pages. Therefore, we planned to develop our proposed model by considering these two hundred and fifty images.

Table 5.5: Range of the 11 features' values in the 159 images (found in the 59 web pages), 150 images (collected from photo.net), and 100 images captured by us, and the combined ranges of the last two groups of images.

#		159 images from the 59 real web pages		150 images collected from [photo.net]		100 images captured by us		combined range 250 images	
	Feature	**min**	**max**	**min**	**max**	**min**	**max**	**min**	**max**
1	CC	0.09	0.43	0.15	0.46	0	0.34	0	0.46
2	H	0.07	0.76	0.24	0.66	0	0.86	0	0.86
3	S	0.11	0.79	0.39	0.61	0	0.87	0	0.87
4	V	0.04	0.82	0.19	0.75	0.04	0.99	0.04	0.99
5	SMT	0.94	7.79	0.04	8.92	1.98	5.23	0.04	8.92
6	AR	0.66	1.25	0.25	1.33	0.25	1.78	0.25	1.78
7	NUC	1163	567650	22156	539609	238	673609	238	673609
8	SRP	10.64	28.20	0.39	38.20	1.36	21.89	0.39	38.20
9	ROT-H	0.03	0.78	0.29	0.63	0	0.81	0	0.81
10	ROT-S	0.11	0.66	0.31	0.68	0	0.96	0	0.96
11	ROT-V	0.09	0.98	0.29	0.75	0.04	1	0.04	1

5.3.2.1 Setup for the Empirical Study

In order to rate those two hundred and fifty image samples, we adopted the same browser-based viewer used in our prior study. All the images were shown to the participants on the PCs having 1.8 *GHz Intel Quad Core i7* processor running *Windows* 10; each had a 17" wide viewing angle color display.

(a)

(b)

Figure 5.7: Two sample images, (a) taken from the internet and (b) captured by us and used in our study, where contrast differed.

5.3.2.2 Participants' Profile

A group of eighty-three participants (*mean age* = 19.5 years, *SD* = 3.2 years; forty-three females and rest are males) was considered to rate all the images on a five-point rating scale; where five denotes most aesthetically pleasing and one denotes the least aesthetically pleasing image. The participants were unaware and not involved in our earlier empirical study (to avoid the learning effects). All of them were regular users of computers, having no screen design concepts. They had normal or corrected to normal vision without color blindness (self-reported).

5.3.2.3 Data Collection Procedure

Before data collection, a small training session was arranged for the participants involved in our study. During this session, participants were familiarised with the five-point rating scale and the browser-based viewer developed by us. After the training session, all the participants rated those two hundred fifty images on the five-point rating scale using the browser-based viewer. To avoid the learning effect, we changed the sequence of the images shown to every participant. All the participants rated those images in four sessions across two days.

5.3.3 Model Development and Validation

The eleven features of the image aesthetics along with the average users rating of the two hundred and fifty images were used to develop and validate our image aesthetics model. The proposed model was developed by using the *Support Vector Regression* analysis. The regression analysis was performed by using the *regression learner apps* of *MATLAB 2017*. *Five-fold cross-validation* technique was adopted to validate the proposed model. The validation result shows that the *coarse Gaussian* kernel outperforms (*MAE* = 0.51) the other five kernels - *linear, quadratic, cubic, fine Gaussian, and medium Gaussian*, as shown in Table 5.6. As a consequence, the same was considered for the development of our proposed image aesthetics model. Experimental results of the proposed model is shown in Figure 5.8, where the dark bar represents the average users' ratings and the light colored bar (orange color) symbolize the ratings predicted by our model for the twelve out of the two hundred and fifty samples, used in our study (details are reported in Appendix C).

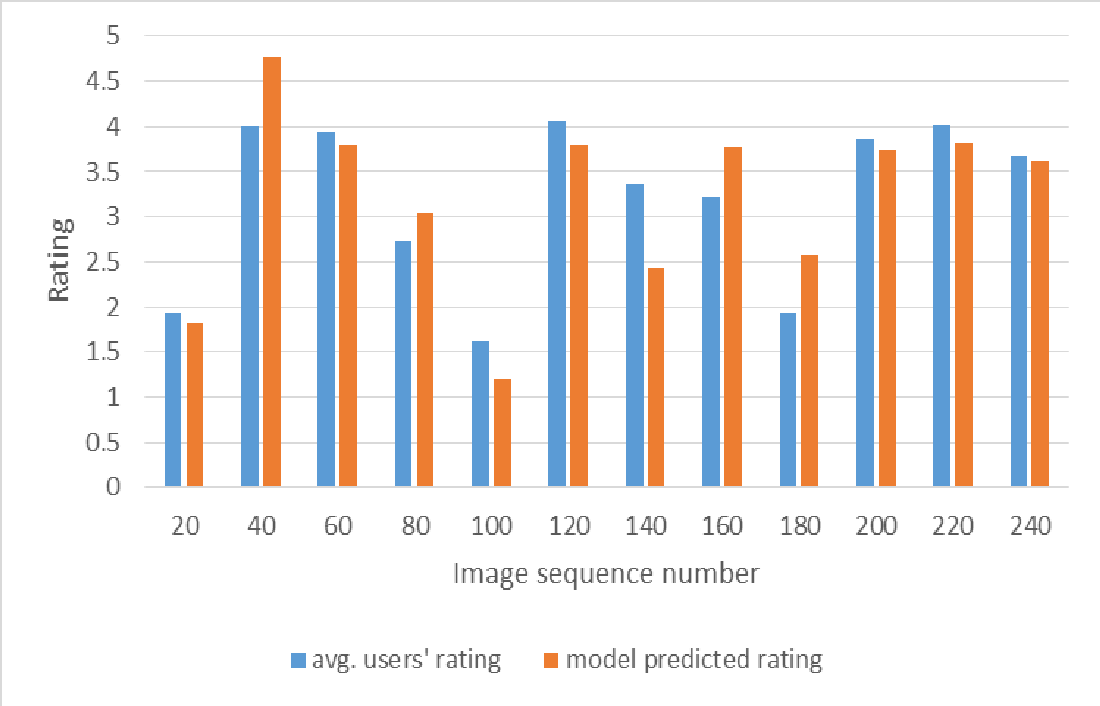


Figure 5.8: Average users' rating (dark color - blue) and model-predicted ratings (light - orange) of the twelve image samples used in our study.

Table 5.6: Comparative study of different kernels of *SVM* for image aesthetics.

	SVM					
	Linear	Quadratic	Cubic	Gaussian		
				Fine	Medium	Coarse
MAE	0.59	0.54	0.59	0.73	0.52	0.51

5.4 Discussion

In this work, we proposed another computational model to predict the aesthetic quality of the photographic images found in a web page. The eleven features - Colour Contrast, Hue, Saturation, Value, Smoothness, Aspect Ratio, Unique Colour, Sharpness, Rule of Third –Hue, Rule of Third- Saturation, and Rule of Third- Value of image aesthetics were considered for the proposed model development. Coarse Gaussian kernel of Support Vector Regression was used to develop our proposed model. The five-fold cross-validation technique shows that the model can measure image aesthetics with a MAE is 0.51 on a five point rating scale. We already discussed in Section 5.3.1.6 that the maximum absolute error in a five-point rating scale is four. This is true for image aesthetics model also and happens when the original rating of an image is one but predicted as five, or vice versa. As a result, we can conclude that our image model can predict the aesthetics of image components with an accuracy of 87.25% as mentioned in the following equation, Equation 5.12.

$$Accuracy_{photographic\_image} = \left(1 - \frac{MAE}{MAE_{\max}}\right)\% = \left(1 - \frac{0.51}{4}\right)\% = 87.25\% \tag{5.12}$$

The proposed model was developed by considering two types of images – (i) ranked images (from photo.net), and (ii) unranked images (captured by us). The one hundred and fifty ranked images were collected based on the number of views in photo.net, whereas the rest one hundred images were captured by us. The ranges of all the eleven features found in the two hundred and fifty images (one hundred and fifty ranked and one hundred unranked) were larger than the ranges of the one hundred and fifty nine images. It may be noted that the one hundred and fifty nine images were obtained from the fifty nine real web pages. These web pages are popularly used to serve the different applications in our daily life. Therefore, these web pages may be considered as the representative samples of all the real web pages. Similarly, the one hundred and fifty nine images taken from those fifty nine web pages may also be considered as the representative image samples found in any real web page. As the proposed model was able to predict the aesthetics of these two hundred and fifty images with a high accuracy = 87.25%, we may claim that the model is suitable for computing the aesthetics of any photographic image, found in a real web page.

5.5 Chapter Summary

In this chapter, we developed two computational models to predict the aesthetics of the image elements present in a web page. Our first model is suitable for the aesthetics measurement of artificial images. The model was developed by considering five images related and fifteen geometry related features. In order to develop the proposed model, *Support Vector Regression* was used. The validation result shows that the proposed model can measure aesthetics of the artificial images with an accuracy of 93.75%. However, as most of the images found on a web page are photographic in nature, another computational model of image aesthetics, suitable for photographic images was proposed. The eleven features of image aesthetics, found in the literature are considered for the model development. The *Support Vector Regression* was used to develop this model. *Five-fold cross-validation* technique on the empirical data of two hundred fifty images shows that the model can predict image aesthetics with an accuracy of 87%. In the next chapter, we integrated both the artificial and photographic image aesthetics models with the model of the wireframe and text aesthetics.

Chapter 6

Combined Model of Web Page Aesthetics

6.1 Introduction

Aesthetics of a web page refers to the perceived beauty of the different contents present in it. Morville and Rosenfeld [2006] - the information architect of WWW, defined web content as “the stuff in your website.” Image, text, video, short animation, table, link, icon, menu, and white spaces are the different elements often found in a web page. The aesthetic appeal of all these web page elements is a vital factor for determining the overall aesthetics of a web page. It was already reported in Section 1.2 of Chapter 1 that the initial impression of a web page, by which the aesthetics is judged [Lindy, 2016], can be represented by the three basic web page elements – image, text and white spaces. In the previous chapter, we reported two computational model for image aesthetics. The first model can predict the aesthetics of artificial image, whereas the other is suitable for computing the aesthetics of the photographic image. Another computational model of text aesthetics was discussed in Section 4.6 of Chapter 4. In this chapter, we proposed a computational model by combining the two models of image aesthetics, and the model of text aesthetics. In order to develop this model, there was necessity to develop a computational model of white space aesthetics, as white space is an important part of any web page. As a consequence, a computational model of white space aesthetics was developed.

The proposed model of white space aesthetics was combined with the two models of image aesthetics, and the SVR based computational model of text aesthetics. The combined model is termed as the *Combined Content Model* (CCM). The model was developed by using the weighted average of the three elements –text, image (artificial and photographic), and white space. The combined content model was validated with empirical data for one hundred fifty web pages, which were developed by us. It was observed that the proposed model can predict the aesthetics with a MAE of 0.42 in a five point rating scale.

In the proposed CCM, the structural organizations of the web page objects were not considered. However, it was reported [Ngo et al., 2003] that the structural organization (wireframe) has an effect on the aesthetics of a web page. In order to further explore the effect of the wireframe geometry on the overall aesthetics of a web page, the proposed model of wireframe aesthetics (as reported in Section 3.6 of Chapter 3) was integrated with the CCM, and another model was developed. The model was termed as the *Combined Wireframe-Contents Model* (*CWCM*). The CWCM works based on the support vector regression. The one hundred and fifty web pages used to validate the CCM were also used to validate the CWCM. The fivefold cross validation result shows that our model can predict the aesthetics with a MAE of 0.31 on a five point rating scale. Finally, using all the computational models developed by us namely,

a) Wireframe based model (Section 3.6 of Chapter 3)

b) Text aesthetics model (Section 4.6 of Chapter 4)

c) Artificial Image aesthetics model (Section 5.2 of Chapter 5)

d) Photographic image aesthetics model (Section 5.3 of Chapter 5)

e) Combined Contents Model (CCM)

f) Combined Wireframe- Contents Model (CWCM)

we developed a framework for web page aesthetics prediction. In this chapter, the proposed framework, the CCM, and the CWCM are discussed.

Rest of the chapter is organized as follows. In Section 6.2, the combined content model is reported. The combined wireframe contents model is presented in Section 6.3. A brief discussion of the CWCM is reported in Section 6.4. In Section 6.5, the proposed framework for web page aesthetics is discussed. Section 6.6 summarizes the contents presented in this chapter.

6.2 Combined Content Model (CCM)

The objective of this model development was to predict the aesthetics of a web page based on the contents present within it. In order to develop the CCM, we proposed a model of white space aesthetics, as white spaces are often found in a web page. The detailed development of the white space aesthetics model is reported in the following section.

6.2.1 White Space Aesthetics Model

The white spaces observed in a web page can be categorized [White space] in the following two types –

- Micro : small spaces between design elements (letter spacing, word spacing, spaces between grid images)
- Macro : large spaces between major layout elements, and the surrounding space of a web page layout

Figure 6.1 shows an example of the IMDB web page[1], where the micro white space was used to distinguish the two different grid images, whereas macro white spaces are the surrounding spaces of the web page layout. Both the micro and macro white spaces are shown using two directed lines in Figure 6.1. It may be noted that micro white spaces observed within a text namely the letter spacing, and the word spacing, were already considered as the two features to develop the computational model for text aesthetics. However, the effect of micro spaces between the grid image elements, and the macro white spaces on web page aesthetics needs to be investigated further.

[1] https://www.imdb.com/

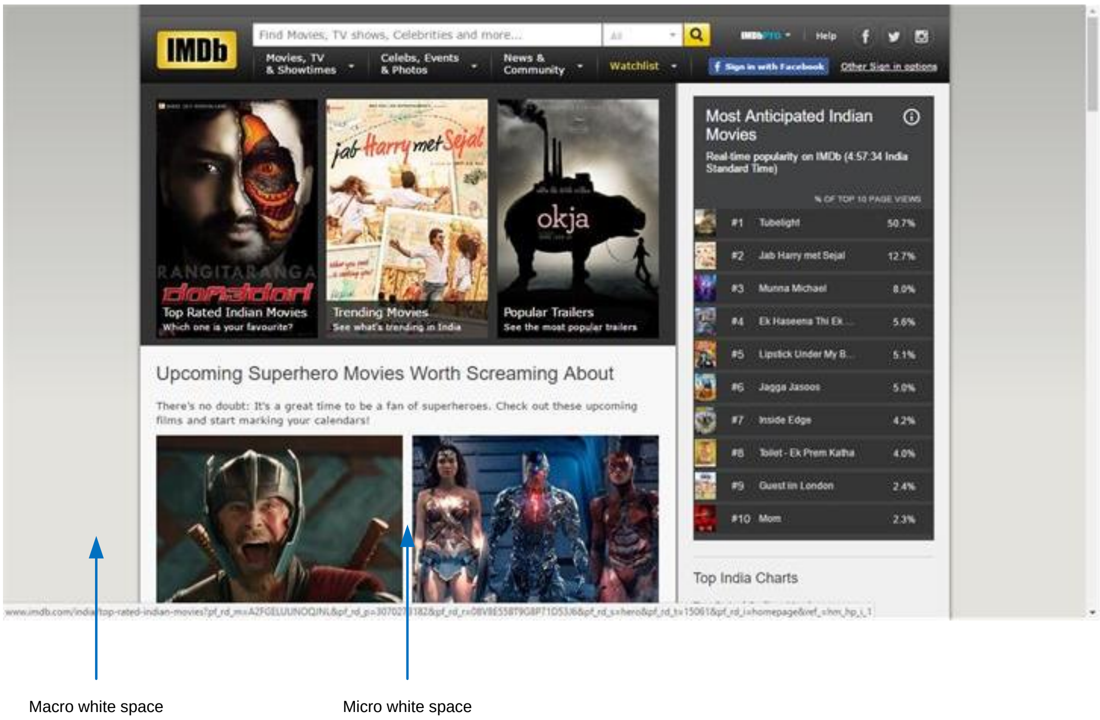


Figure 6.1: Macro and micro white spaces in the web page of IMDB (*https://www.imdb.com/*).

The standard design guideline suggests to use white spaces for elegance and ensuring a quality user experience [White space guidelines]. Unfortunately many web page users believe white space as a wasted area [Lindy, 2016]. They also think instead of using white spaces, different web page elements – text, image, icon, video, tables, and links may be used to enrich a web page. However it was reported [White space guidelines] that the white spaces help to distinguish different web page elements, provides resting point for eyes. Therefore, the role of the white space cannot be ignored to judge the aesthetics of a whole web page. We constructed this model by collecting and analyzing empirical data on white space aesthetics. In order to carry out this study, a research question was formed, as mentioned below.

Research Question:

Rate the effect of white space aesthetics to determine the overall aesthetics of a web page on a five point rating scale.

The study was conducted with a group of forty participants (average age = 20.25, SD = 3.54). They were regular users of web pages and not involved in our earlier studies. A small training session was organized to familiarize the participants with the white spaces found in real web pages. The participants were also acquainted with the five-point rating scale. The training session was conducted with the fifty nine real web pages (Table 3.12 in Chapter 3). After the training session, we asked the participants to respond the research question with the rating scale, where five denotes that the white spaces *significantly* affect the aesthetics of a web page, whereas four, three, two and one indicate – *moderately significant, no direct effect but helps to distinguish the web page objects*, *moderately insignificant*, and *insignificant*, respectively. The experimental result reported in Table 6.1 shows that most of the participants (thirty four out of forty) believed that the white spaces have no direct effect but helps to distinguish the web page objects (rating three in a five-point scale) on aesthetics. As a consequence, we considered the median for modelling the aesthetics of white space. In this study, we used a five point rating scale where the median value is three. Similarly the median value would be two, if a three point rating scale is used. It may be noted that our finding – "no direct effect but helps to distinguish the web page objects" matches with the standard guidelines of white space aesthetics [White space guidelines].

Table 6.1: Empirical study result on white space.

Response	**Number of users**
significant (5)	0
moderately significant (4)	0
no direct effect, but helps to distinguish the web page objects (3)	34
moderately insignificant (2)	3
insignificant (1)	3

6.2.2 Proposed CCM

The model works based on the weighted averages of the different web page elements – text, image (artificial, and photographic) and white space, as shown in Equation 6.1.

$$AS_{combined-contents} = \frac{\sum_{i=1}^{m}(PAS^{i}_{artificial\_image} \times Area^{i}_{artificial\_image}) + \sum_{j=1}^{n}(PAS^{j}_{photographic\_image} \times Area^{j}_{photographic\_image}) + \sum_{k=1}^{p}(PAS^{p}_{text} \times Area^{p}_{text}) + 3 \times Area_{white\_space}}{Area_{webpage}} \quad (6.1)$$

The $AS_{combined\text{-}contents}$ denotes the computed aesthetic score by using the proposed model. The $PAS^{i}_{image\_artificial}$, and $Area^{i}_{image\_artificial}$ represent the predicted aesthetics score, and the area of the artificial image *i*. Similarly, the $PAS^{j}_{image\_photographic}$, and $Area^{j}_{image\_photographic}$ denote the predicted aesthetics score, and the area of the photographic image *j*. The predicted aesthetics score and the area of the text *k* are represented by the PAS^{k}_{text}, and $Area^{k}_{text}$ respectively. It may be noted that the predicted aesthetics scores of $PAS^{i}_{image\_artificial}$, $PAS^{j}_{image\_photographic}$, and PAS^{k}_{text} are predicted by the artificial image aesthetics model, photographic image aesthetics model, and text aesthetics model respectively. The *m*, *n* and *p* denote the number of artificial image, photographic image and text component present in the web page respectively. The white space area was computed by subtracting the images and text area from the layout area, as mentioned in the following equation, Equation 6.2.

$$Area_{white\_spcae} = Area_{webpage} - (Area_{artifical\_image} + Area_{photographic\_image} + Area_{text}) \quad (6.2)$$

Based on the model of white space aesthetics, the aesthetics score of the white space is considered as the median, which was three on a five point rating scale. The $Area_{web\ page}$ and $Area_{white\_space}$ denote the area of the web page and white space respectively.

6.2.3 Validation of the CCM

To validate the proposed model, we conducted another empirical study, by considering the two hundred and nine web pages, as reported in Section 3.3.4 of Chapter 3. It may be recalled that out of these two hundred and nine web pages, fifty nines are real, and the rest one hundred fifty were developed by us. All the two hundred and nine web pages (one hundred and fifty developed by us, and fifty nine real web pages) were rated on a five-point rating scale. Five denotes the most aesthetically pleasing web page, whereas one denotes the least. It may be noted that unlike the wireframes of these web pages (used for the wireframe model development), the original web pages were shown here. The same browser-based viewer (used for the empirical study on images and text) was used to collect the users' ratings. PCs of 1.8 *GHz Intel Quad Core i7* processor running *Windows* 10; each had a 17" wide viewing angle color display were used for this study.

In order to differentiate the performance of the proposed model, with the model of wireframe geometry, all the one hundred fifty participants involved in the empirical study of wireframes (as reported in Section 3.6.3 of Chapter 3), were considered here. As fifty nine real web pages were considered for this study, the participants might be familiar with them. It was expected that the familiar web pages may get higher ratings than the unfamiliar one hundred and fifty web pages developed by us. In order to find out the effect of the familiarity, we analyzed the empirical data of the fifty nine real web pages. The average users' ratings, and the statistical mode of these web pages were reported in Table 6.2. It was observed that all most all (except the *reddit* web page) were rated with the rank four or five (aesthetically most pleasing). The probable reason of high ratings may be the familiarity of the participants with the web pages.

Table 6.2: The average ranking, and statistical mode of the 59 real web pages.

Area	web no	Website	website link	avg.	mode
Education	169	IIM, Ahmedabad	iima.ac.in	4.52	5
	170	IIM Kolkata	iimcal.ac.in	4.29	4
	171	IIT Kharagpur	iitkgp.ac.in	4.72	5
	172	IIT Bombay	iitb.ac.in	4.48	5
	181	NPTEL	nptel.ac.in	4.88	5
	204	IIT Guwahati	iitg.ac.in	4.58	5
	200	CIT, Kokrajhar	cit.ac.in	4.9	5

Social networking and Entertainment	173	IMDB	imdb.com	4.51	5
	175	Instagram	instagram.com	4.47	4
	178	Linkedin	linkedin.com	4.52	5
	180	MSN	msn.com	4.49	4
	182	OZEE	ozee.com	4.49	4
	183	Reddit	reddit.com	3.31	3
	184	Rediff	rediff.com	4.51	5
	194	Twitter	twitter.com	4.49	5
	196	Wikipedia	wikipedia.org	4.54	5
	198	Yahoo	in.yahoo.com	4.5	4
	201	Facebook	facebook.com	4.53	5
	207	Sound Cloud	soundcloud.com	4.5	5
	209	Youtube	youtube.com	4.46	4
E- commerce	154	Apple India	apple.com/in	4.62	5
	155	AXIX bank	axixbank.com	4.52	5
	158	Big Bazaar	bigbazaaar.com	4.54	5
	162	Ebay	ebay.in	4.54	5
	167	Honda	hondacarindia.com	4.36	4
	168	ICICI	icicibank.com	4.15	4
	185	Samsung	Samsung.com	4.53	5
	186	Sony	sony.co.in	4.49	5
	189	Tata Car	tatamotors.com	4.55	5
	202	Flipkart	flipkart.com	4.73	5
	203	Amazon	amazon.com	4.77	5
	206	State Bank of India	onlinesbi.com	4.51	5
News	153	Anandabazar	anandabazar.com	4.43	4
	157	BBC	bbc.com	4.15	4
	190	Telegraph	telegraphindia.com	4.51	5
	191	Times of India	timesofindia.indiatimes.com	4.56	5
	205	NewsLive	newslivetv.org	4.45	4
Corporate	179	Microsoft	microsoft.com	4.52	5
	208	TCS	tcs.com	4.56	5
Weather	151	Accuweather	accuweather.com	4.48	4
Travel	152	Air India	airindia.in	4.59	5
	160	British Airways	britishairways.com	4.17	4
	174	Indigo	goindigo.in	4.49	5

	176	Irctc	irctc.co.in	4.31	4
	187	Spicejet	spicejet.com	4.51	5
	192	Travelocity	travelocity.com	4.52	5
	193	Trivago	trivago.in	4.47	4
	199	Yatra	yatra.com	4.19	4
Search	156	Baidu	baidu.com	4.13	4
	159	Bing	bing.com	4.31	4
	166	Google	google.com	4.67	5
Research	161	DRDO	drdo.gov.in	4.53	5
	177	ISRO	isro.gov.in	4.45	5
	195	UCCN	iitg.ernet.in/cseweb/uccn	4.59	5
Sports	163	FOX sports	foxsports.com	4.21	4
	188	Starsports	www.hotstar.com/sports	4.53	5
Job	164	Freshersworld	freshersworld.com	4.54	5
Mail	165	Gmail	gmail.com	4.53	5
	197	Windows Live	live.com	4.38	4

In order to check the familiarity, we informally asked few participants to report the factors (if any) which influenced them for providing higher ratings. Most of them reported that the *familiarity* with real web pages had encouraged them to provide a higher rating. Consequently, we may claim that the familiarity affected the study. The objective of this thesis is to develop a computational model for the new web pages. Such models can be useful for determining the productivity of a new design. Therefore, we left the fifty nine real web pages for our model validation, and tested with the remaining one hundred and fifty web pages developed by us. It may be noted that the one hundred and fifty web pages are new to the participants. Hence, the familiarity had not affected the aesthetic judgement.

The average ratings for the one hundred and fifty web pages were considered as the ***true*** rating. For all these web pages, the ***predicted*** ratings were computed using the CCM. The true ratings of all the one hundred and fifty web pages were compared with the predicted rating to validate our proposed model. It was observed that the proposed

CCM can predict the aesthetics of a web page with a MAE of 0.42 in a five point rating scale.

Therefore, we can claim that our proposed CCM can compute the aesthetics with a high accuracy of 89.5%, as reported in Equation 6.3.

$$Accuracy_{CCM} = \left(1 - \frac{MAE}{MAE_{\max}}\right)\% = \left(1 - \frac{0.42}{4}\right)\% = 89.5\% \tag{6.3}$$

6.2.4 Discussion

In this work, we developed a computational model for predicting web page aesthetics by considering the three components of a web page, along with their areas. Our proposed model can predict web page aesthetics (predicted rating) on a five-point rating scale based on the weighted average (aesthetics score and area) of the three components (image, text and white space). In this scale, the maximum error is four, which may happen when the predicted rating of a web page is one, whereas the original rating is five or the vice-versa. In the proposed model, we observed a MAE of 0.42 (in a five point rating scale), which indicates the accuracy of 89.5% {(1-0.42/4)×100%}. As a result, the proposed model may be a suitable choice for the web page designers to measure web page aesthetics.

In order to develop the proposed CCM, we developed four computational models for predicting the aesthetics of - texts, artificial images, photographic images, and white spaces present in a web page. All the models of text and image aesthetics were developed using the *Support Vector Regression* technique [Cortes and Vapnik, 1995]. The non-linear kernel of *SVM*, namely the *RBF* (*Gaussian*) was used for the regression modeling. The nonlinear kernel in Support Vector Regression helps to map non-linear data to linear data in higher dimensional space. In the higher dimensional space, a linear model is constructed, which performs better than those models developed in the lower dimensional space, where data may not be separated linearly.

In any web page, overlapping components can be observed as shown in Figure 6.2, where the text components labelled as – HORIZON.COM, login, register, flight, train, buses, hotels, holidays overlapped with the background image. For all the text components, the aesthetic scores were computed using the text aesthetics prediction model. Similarly, we computed the aesthetics of the background image. The active area of the images was computed by subtracting the text area from the original image area. This active area was considered for the aesthetics computation. The proposed technique is suitable for the aesthetics computation of the web pages, as an accuracy of 89.5% was observed in the proposed model. However, further study may be carried out to improve the performance of the CCM by considering the overlapped objects together.

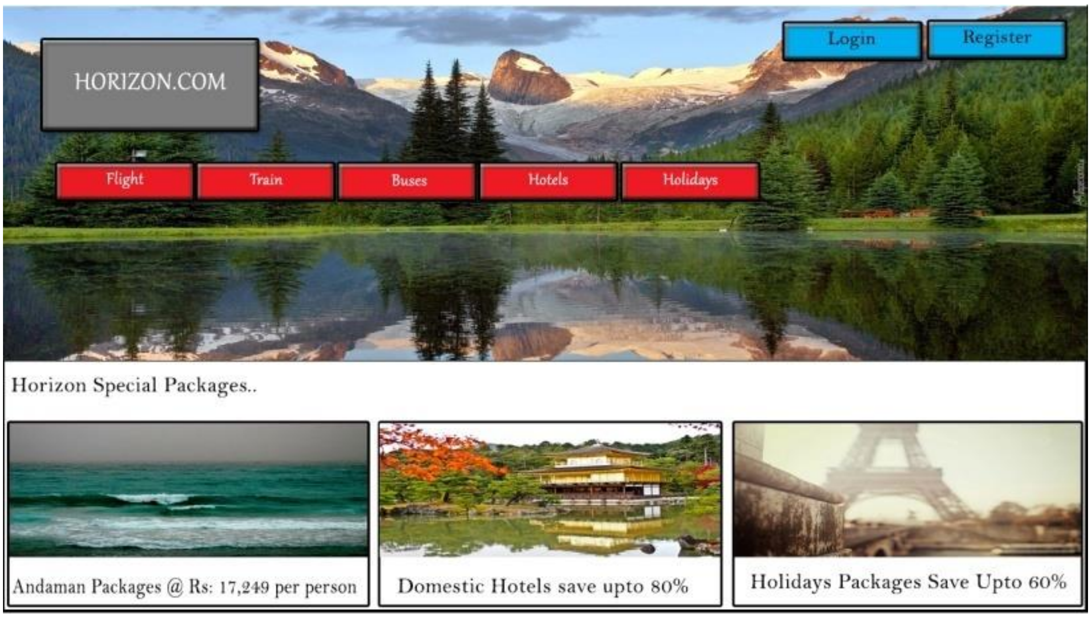


Figure 6.2: A web page with the overlapping objects.

The proposed model can predict the aesthetics of a web page based on the contents present in it. However, the structural organization (wireframe) of these contents is also important to determine the aesthetics of a web page [Ngo et al., 2003]. As a consequence, there is a necessity to develop a computational model of aesthetics by considering the contents of the web page objects, as well as the wireframe geometry. We also developed a model to compute web page aesthetics by combining the CCM, with the model of wireframe geometry (The wireframe geometry model was reported in Section 3.6 of Chapter 3). The proposed model is termed as the Combined Wireframe-Contents Model (CWCM).

6.3 Combined Wireframe-Contents Model (CWCM)

The one hundred and fifty web pages used to validate the CCM were considered for the development of the proposed model. For each web page, we already computed a predicted rating ($AS_{combined\text{-}contents}$) by using the Combined Contents Model. Similarly, the aesthetics of these one hundred and fifty web pages ($AS_{wireframe}$) were predicted by the computational model of wireframe geometry, as reported in Section 3.6, of Chapter 3. Both these predicted ratings - $AS_{combined\text{-}contents}$, and $AS_{wireframe}$ of the one hundred and fifty web pages were used as the two predictors of the proposed CWCM.

In order to develop the proposed model, the Support Vector Regression (SVR) was used. The average users' ratings of the one hundred and fifty web pages, collected from the empirical study (mentioned in Section 6.2.3), were used to validate the proposed model. The model was developed and validated by the MATLAB 2018a regression learner app. The six different kernels of SVR – linear, quadratic, cubic, and three different Gaussian (fine, medium, and coarse) were explored to build the model. The two parameters of the kernel (*Box constraint*, *Epsilon*) were set to *Automatic*. Experimental results presented in Table 6.3 shows that the *linear* kernel outperforms the other kernels (MAE = 0.31). As a consequence, the linear kernel of the SVR was considered for the model development. The users' ratings (denoted by the dark (blue) colour bar), and the model predicted rating (denoted by light colour (orange) bar) of the fifteen samples, out of the one hundred and fifty samples used in our study, are shown in Figure 6.3.

Table 6.3: Comparative study of different kernels of SVR for the CWCM.

	SVR					
	Linear	Quadratic	Cubic	Gaussian		
				Fine	Medium	Coarse
MAE	0.31	0.35	0.38	0.34	0.34	0.33
Time(sec)	33.174	32.057	33.174	32.92	32.756	32.144

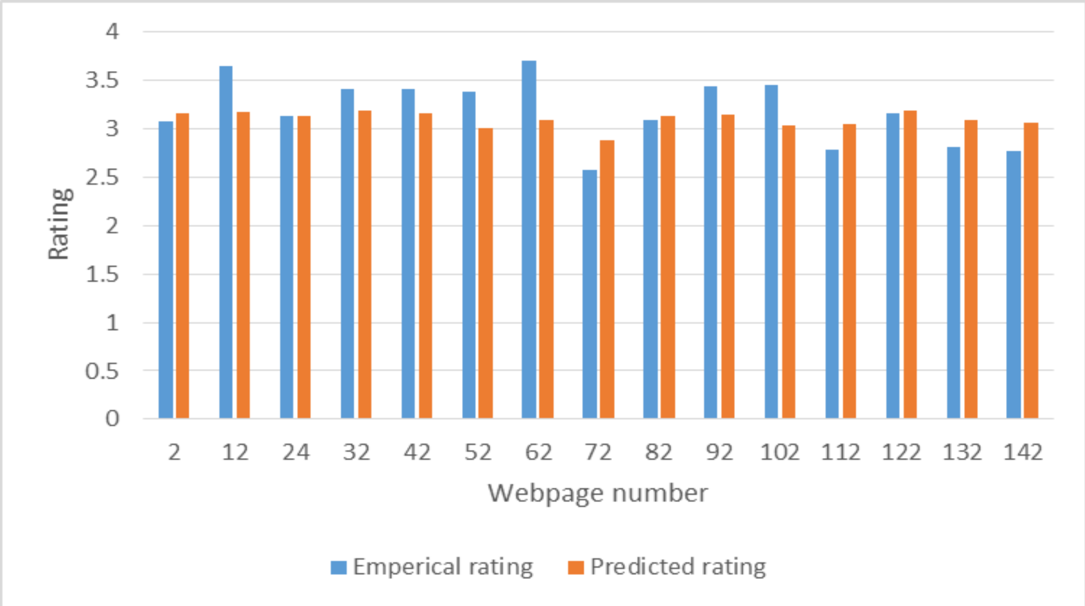


Figure 6.3: The users' average ratings (denoted by dark colour (blue) bar), and the model predicted rating (denoted by light colour (orange) bar), of the 15 samples used in our study.

6.4 Discussion

The proposed model was able to predict the aesthetics of a web page with a MAE of 0.31, on a five point rating scale. Therefore the accuracy of the proposed model should be 92.25%, as shown in Equation 6.4.

$$Accuracy_{CCWM} = \left(1 - \frac{MAE}{MAE_{\max}}\right)\% = \left(1 - \frac{0.31}{4}\right)\% = 92.25\% \tag{6.4}$$

In order to compare the proposed CWCM with the other two models of aesthetics prediction, namely, the wireframe model, and CCM, we considered the data collected with the one hundred and fifty web pages developed by us. The MAE, and the accuracy of the three models are reported in Table 6.4. It may be noted that the proposed CWCM out performs the others with an accuracy of 92.25%. The CWCM's accuracy was 2.75% better than the CCM, and 0.75% better than the wireframe model. Although, the observed differences were small, it could still help us to conclude about the proposed CWCM, if we can determine the nature of the difference. The nature of the difference may be one of the following two types –

- By chance
- Statistically significant.

Table 6.4: Comparative study of the wireframe model, CCM, and CWCM of web page aesthetics.

	MAE	**Accuracy**
Wireframe based model	0.34	91.5%
CCM	0.42	89.5%
CWCM	0.31	92.25%

In order to find out the nature of the differences, we considered the three predicted ratings – wireframe model's rating, Combined Contents model's rating, and the Combined Wireframe-Contents Model's ratings of all the one hundred and fifty web pages. A non- parametric significance test[2] – *friedman* test was conducted using the MATLAB 2018a. It was observed that the *p* value was less than 0.001 (*2.74e-15*). Therefore, it may be concluded that the better result of CWCM was not obtained by chance, rather it is statistically significant. Therefore, the proposed CWCM is likely to perform better than the other two models of aesthetics prediction for any web page.

In order to validate the proposed model (CWCM), the five-*fold cross-validation* technique was adopted. This technique always helps to overcome data overfitting during the training procedure. Therefore, we can claim that our proposed model is also effective for overcoming the problem of data overfitting.

A web page designer can use the propose model in the following way. During the design process, a designer has to provide the content details to our model. The details must include the four features – font size, line height, word spacing, letter spacing, text colour (RGB), and background colour (RGB) of all the text components. From the text colour, and background colour, the text aesthetics model can compute the Colour Contrast, and Luminance Contrast. The proposed text aesthetics model can predict the aesthetics of the text component using the six features values. In order to compute the aesthetics of an image component, a designer has to mention the image type – artificial, or photographic image. Our image aesthetics models (as reported in Chapter 4) can compute their respective features' values. Except the images and text components, a designer has to provide the size of the all images, texts, and the layout. The white space aesthetics model can compute the areas of white space by subtracting the images and texts areas from the layout area. Similarly, the wireframe model of a

[2] Non parametric test does not depend on the distribution of data

web page must be provided as an input to the computational model of wireframe geometry developed by us.

Our Combined Contents-Wireframe Model can help designer to refine his/her design. For a particular design, a low predicted aesthetics score (one and two in five point rating scale) by the CWCM means there is some problem in the design, and a correcting measure must be taken by the designer. In order to refine the design, a designer may look at the two predicted aesthetics scores - $AS_{wireframe}$, and $AS_{combine\_contents}$. A low score of $AS_{wireframe}$ means there is some problem with the placement of web page objects in the layout, which must be corrected. On the other hand a low predicted score of $AS_{combine\_contents}$ means the contents must be refined to improve the aesthetics. Furthermore the designer can check the scores of all the artificial, and photographic images - $PAS_{artificial\_image}$, $PAS_{photographic\_image}$ and text components - PAS_{text} predicted by our artificial images, photographic images, and text models respectively. The low predicted image, and text components may be refined in order to improve the aesthetics of a whole web page.

The proposed model was developed with data collected using one hundred and fifty web pages. These web pages were developed based on the web page object organizations, their sizes found in fifty nine real web pages. These fifty nine web pages popularly used for different applications, and they can be considered as the representative samples of all the real web pages. As the proposed model was developed by using the one hundred and fifty images, which are constructed based on the fifty nine real web pages, the proposed model is likely to be effective for predicting the aesthetics of any real web page.

The proposed CWCM can predict the aesthetics of a web page with a high accuracy of 92.25%. The CWCM was developed using the Support Vector Regression. It was reported [Bajaj et al., 2014] that the Support Vector Regression is a time intensive process, when faced with a large, structurally complex data set. We also observed 33.174 Seconds of response time[3] (as reported in Table 6.3), during the development and validation of the CWCM. A longer period of waiting time (due to the model development and validation) may discourage a web page designer not to use the

[3] Intel(R) Core(TM) i7-4500U, 64 bit CPU running at 1.8 GHz, having 4GB RAM

proposed CWCM. It may be noted that the 33.174 seconds include the model development and validation time. However, it was observed that the validation of a web page needs less than of five seconds. As the web page designers will validate their design during the development period, we believe, the proposed CWCM is suitable for web page aesthetics validation.

In this work, we developed all the models based on the features found in the literature. For example, the wireframe model was developed based on the ten features reported in [Ngo et al., 2003]. However, there may be other factors that may affect aesthetics. Our automated approach can help a webpage developer to evaluate aesthetics during the early stages of development and saves a lot of time. An aesthetically pleasing webpage found by our model, may be further subjectively evaluated in order to finalize its design. Although an accuracy of 92.5% was achieved in our proposed CWCM, other techniques – for example artificial neural network, popularly used for image processing, character recognition may be explored further in order to improve the accuracy.

Based on the CWCM, and the other computational models, a framework for the aesthetics prediction of a web page was developed. In the following section, the proposed framework is reported.

6.5 Framework for Web page Aesthetics

A framework is defined as – "a real or conceptual structure intended to serve as a support or guide for the building of something that expands the structure into something useful"[4]. In this section, we describe a framework for predicting the aesthetics of a web page. In order to develop this frameworks, the wireframe aesthetics model (discussed in Section 3.6 of Chapter 3), the SVR based text aesthetics model (reported in Section 4.6 of Chapter 4), the model of artificial image aesthetics (presented in Section 5.2 of Chapter 5), photographic image aesthetics (discussed in Section 5.3 of Chapter 5), the CCM, and the CWCM were considered. The proposed framework is shown in Figure 6.4. For a particular web page, the component aesthetics can be predicted by their corresponding model. For example, the predicted aesthetics (PAS_{text}) of the text elements can be computed with the help of the text model. Similarly, the predicted aesthetics score of the artificial

[4] https://whatis.techtarget.com/definition/framework

($PAS_{aritificial\_image}$) and photographic images ($PAS_{photographic\_image}$) can be obtained with the models for the artificial, and photographic image aesthetics, respectively. The CCM considers the three predicted ratings - PAS_{text} , $PAS_{aritificial\_image}$ and $PAS_{photographic\_image}$ as inputs. The median of a rating scale is also considered as an input to the CCM. The predicted rating of the CCM is shown in Figure 6.4 as $AS_{combined\_contents}$. The wireframe model can predict the aesthetics of the web page ($AS_{wirefrmae}$) based on the wireframe geometry based model. Finally, the CWCM predicts the aesthetics of the web page by considering the predicted rating of wireframe ($AS_{wirefrmae}$), as well as the predicted rating of the CCM - $AS_{combined\_contents}$. The framework is suitable to predict the aesthetics of any web page.

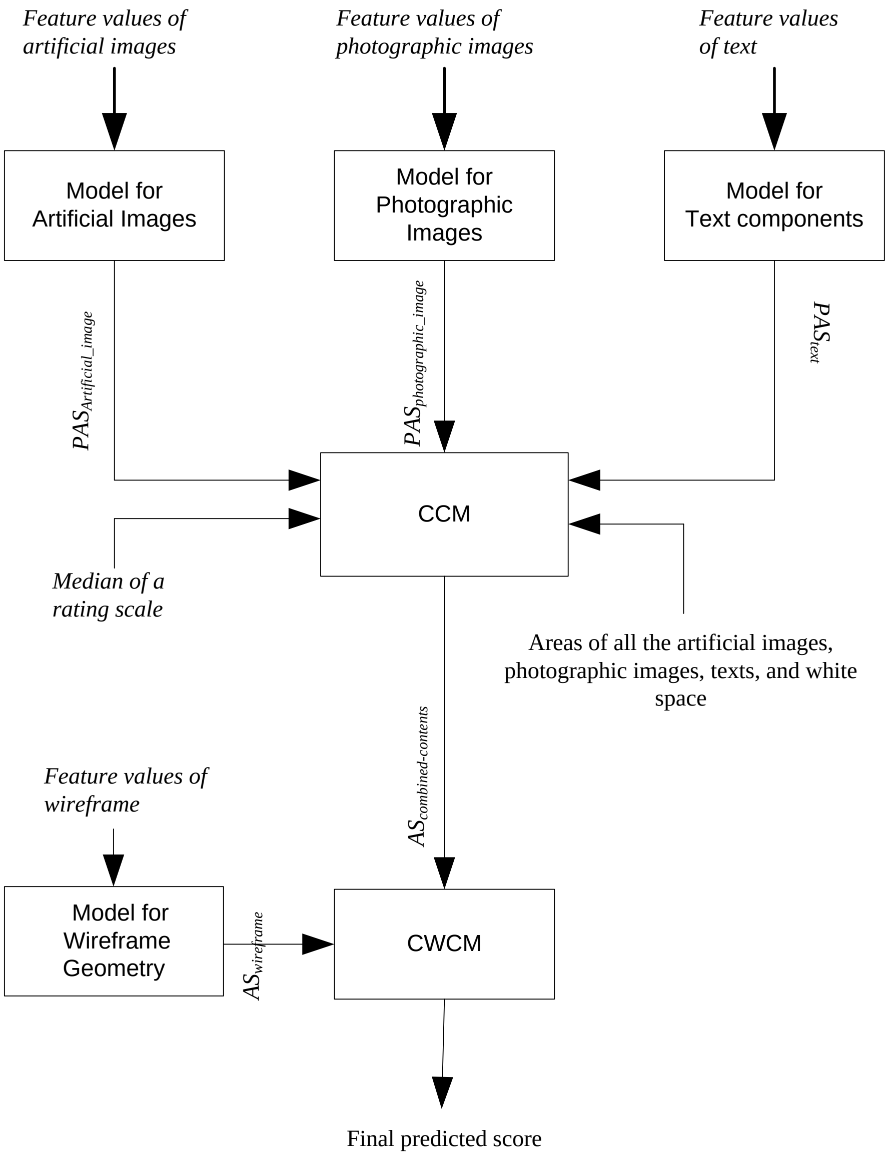


Figure 6.4: Framework for web page aesthetics.

6.6 Chapter Summary

In this chapter, we proposed a computational model of white space aesthetics by considering the median value (three in a five point rating scale) used for empirical study. Using this model, and the two models of image aesthetics and text aesthetics (as reported in Chapter 4, and Chapter 5 respectively) a Combined Contents Model was developed. The model works based on the weighted average of the three different components – text, image and white space. The model was validated using one hundred fifty web pages. The proposed model can measure web page aesthetics with an accuracy of 89.5%. In order to consider the layout geometry, the model was integrated with the model of wireframe geometry and our final model (CWCM) was developed. The *linear kernel* of Support Vector Regression was used to train and validate the model. Experimental result shows that our CWCM can measure web page aesthetics with an accuracy of 92.25%. A comparative study of the three models – wireframe model, CCM, and CWCM showed that the CWCM performed better than the others. Even it was also observed that this betterment is statistically significant.

Chapter 7

Conclusions and Future Work

In this thesis, a framework to predict the aesthetics of a web page has been proposed. In order to predict the aesthetics of a web page, the proposed framework considers six computational models – the wireframe based model, text aesthetics model, artificial image aesthetics model, photographic image aesthetics model, the Combined Contents Model (CCM), and the Combined Wireframe Contents Model (CWCM). The wireframe based model, the Combined Contents Model (CCM), and the Combined Wireframe Contents Model have the capability to predict the aesthetics of a whole web page, whereas the text aesthetics model, artificial image aesthetics model can compute the aesthetics of the parts of a web page. These models can also help a web page designer to compute the aesthetics of his/her design, without empirical study, which in turn can help to speed up the design process.

In this thesis, several contributions have been made to predict the aesthetics of a web page. These contributions are enlisted in the following.

(a) Computational Model of Wireframe Geometry:

In this work, we reassessed the best-known positional geometry features related to web page aesthetics. Using the statistical significant features, a computational model of web page aesthetics based on the wireframe geometry was developed. Therefore, the contribution extend the existing work.

(b) Computational Model of Text Aesthetics:

With the best of our knowledge, aesthetics computation of the textual contents was not reported till date. In this work, we proposed a computational models for text aesthetics prediction. As a consequence, the work is an original contribution of the research.

(c) **Computational Model of Images:**

Two computational models suitable for – artificial, and photographic images are reported in this thesis. Both the model of the artificial image aesthetics, and photographic image aesthetics were developed by us, and can be considered as two original works.

(d) Combined Contents Model (CCM):

The CCM was developed by considering the text, photographic image, artificial image, and white space. With the best of our knowledge, we did not find any such work. Therefore, the CCM is also an original contribution of this thesis.

(e) Combined Wireframe-Contents Model (CWCM):

By combing the wireframe model, and CCM – the CWCM was developed. The CWCM is suitable to model the aesthetics of any web page. This work is also an original contribution of the research.

(f) Framework of Web page Aesthetics Computation:

Using the models of – wireframe aesthetics, text aesthetics, artificial image aesthetics, photographic image aesthetics, the CCM, and the CWCM, a framework for computing the aesthetics of a web page was developed, which is another original contribution of the thesis.

Along with these achievements, there are few short-comings as well. Further investigations on these problems may strengthen our work. Moreover, such investigations open up new directions for future research. In the following, we discuss about those areas where future research can be carried out.

7.1 Refinement of the Text Model

In order to develop the text aesthetics model, we considered six features that affects text aesthetics – Font Size, Line Height, Letter Spacing, Word Spacing, Luminance Contrast, and Chromatic Contrast. Except these six features, there are some more features that can be found in the literature, which may characterize a text. These include *alignment*, *widow* and *orphans*. However, as per our understanding of the literature, these features are not dominant in determining *readability* and *legibility* (and consequently, aesthetics) of a piece of text, as compared to the features we considered. Consequently, we did not consider those as our objective was to capture *most* with *least*, a standard practice in any engineering (otherwise, the model would be bulky without much extra gain in performance, but with increased cost of implementations). It was reported in the literature that there is no single *font family* (example - Arial, Times New roman), *font styles* (Bold, Italics, Underlined) that has better readability than the others. However, there may be an effect of font family, and font styles to determine the aesthetics, which requires further investigation.

7.2 Relating Text Aesthetics with Readability

In this work, two computational models of text aesthetics were proposed. Both the models were developed by the aesthetics or the visual appeal of the text elements. However, the readability of the text elements was not taken into consideration. There may be a relationship of aesthetics with the readability. A future study may be carried out to establish the relations between aesthetics with readability.

7.3 Refinement of CCM and CWCM

The Combined Content Model (CCM) was developed by considering the three major components of a web page – text, image, and white space. All the other elements of a web page are represented by means of these three components. However, in the literature, we found a computational model for the short animations [Bansal and Bhattacharya, 2013], which may be combined with the proposed CCM.

The CCM was developed by using the weighted average of the different components. The assumption of this model was a large component contributes much to the aesthetics than that of a smaller component, and two components of same size contributes equally to the overall aesthetics. However, an image component having the same size of a text block may be more aesthetically pleasing. Further investigation is required to analyze the effect of the different components (having same size) on the aesthetics.

The CWCM model the aesthetics of a web page by considering the structural organizations of the web page objects, as well as the contents present within it. As the model performs with a high accuracy of 92.25%, the refinement of this model for better aesthetics prediction seems difficult. However, further study may be carried out to improve the performance of the proposed model.

7.4 Empirical Study by broader group of Participants

All the empirical studies reported in this thesis were carried out by the Indian participants. The participants involved in this study were taken from the different parts of the country, having different gender, culture, and demographical locations. As a consequence, it can be claimed that the empirical studies were not biased by a group of people from same area, culture, and gender. However, further investigations using the participants across the globe may strengthen our claims.

7.5 Effects of the Overlapping Objects

In the proposed Combined Contents Model, the active area of a partially hidden object (due to the overlapping of others) was computed by subtracting the areas of those objects (for which it was hidden) from its original area. This active area was considered for the aesthetics computation of the partially hidden object. However, such objects are always visually perceived together with those objects, for which it has been overlapped. Therefore, further investigations on web page aesthetics may be conducted to identify the effect of such overlapping.

7.6 Development of an Automated Tool

Our proposed model might be used to create an automated tool in any design environment (for example *Adobe Photoshop*). In the beginning, a web page has only white spaces. As a result, the tool can initialize the aesthetics by the median score (which suits for white space aesthetics). The tool can measure the aesthetics of the different components of a web page, as well as the whole web page during the design process. Like speedometer (always inform the speed of a car), an *aesthometer* (which would show the predicted aesthetics score of an web page) may be added to the proposed tool, which will help the designers to monitor the aesthetics during all the time in the design process. As a result, no extra effort would require in determining the aesthetics. Thus, designers could save a lot of time during the design process.

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Appendix A

Ratings of the Web Pages

Table A.1 shows the average users ratings of the two empirical studies conducted by the two hundred and nine web pages, and their wireframe based models. The predicted ratings of the wireframe model, the CCM, and the CWCM are also reported in this table.

Table A.1: Average users' ratings and the wireframe, CCM, and CWCM predicted ratings.

#	Avg. users' ratings with wireframe	Avg. users ratings with contents	Predicted by Wireframe	Predicted by CCM	Predicted by CWCM
1	3.25	3.42	3.23	2.94	3.05
2	2.02	3.07	3.33	3.10	3.15
3	2.66	3.54	3.24	2.89	3.05
4	3.28	3.36	3.19	3.36	3.11
5	3.32	3.45	3.17	3.46	3.13
6	2.79	3.30	3.20	2.91	3.03
7	3.26	3.23	3.18	2.87	3.01
8	2.41	3.64	3.23	3.62	3.20
9	3.58	3.49	3.19	3.11	3.07
10	3.76	3.29	3.26	2.85	3.05
11	3.84	3.92	3.27	3.56	3.21
12	3.56	3.65	3.14	3.77	3.17
13	3.01	3.49	3.02	2.37	2.80
14	3.33	3.94	3.23	3.35	3.14
15	3.21	4.25	3.23	3.59	3.19
16	4.20	3.42	3.18	2.95	3.02
17	3.42	3.11	3.34	3.05	3.15
18	3.92	2.62	3.07	2.94	2.95
19	3.55	3.33	3.32	3.09	3.14
20	3.18	3.59	3.24	3.89	3.26
21	3.25	2.27	3.02	2.86	2.92
22	4.00	3.57	3.30	2.72	3.05
23	3.62	3.45	3.18	3.52	3.14
24	3.11	3.13	3.30	3.06	3.12

25	3.29	2.87	3.15	2.50	2.91
26	1.97	3.00	3.19	3.04	3.05
27	3.02	3.15	3.27	2.70	3.03
28	3.02	3.54	3.29	3.26	3.16
29	3.07	2.86	3.11	3.68	3.13
30	3.06	3.52	3.29	3.20	3.15
31	2.64	3.34	3.21	3.35	3.12
32	3.18	3.41	3.33	3.24	3.18
33	3.28	3.66	3.24	2.05	2.87
34	3.25	3.69	3.40	3.37	3.25
35	3.04	3.35	3.32	3.49	3.23
36	3.09	2.70	3.30	2.83	3.07
37	3.07	3.89	3.30	3.19	3.15
38	3.08	3.50	3.31	2.65	3.04
39	3.41	3.05	3.21	2.89	3.03
40	3.31	4.09	3.33	2.98	3.12
41	3.04	3.62	3.12	3.11	3.02
42	2.54	3.41	3.23	3.46	3.16
43	3.73	3.58	3.19	2.67	2.97
44	3.17	2.88	3.13	3.43	3.09
45	2.21	2.83	3.16	3.48	3.12
46	3.87	3.21	3.27	3.90	3.28
47	3.23	2.52	3.30	2.93	3.10
48	3.32	3.60	3.33	3.63	3.27
49	3.58	3.77	3.25	2.16	2.90
50	1.61	3.53	3.23	2.53	2.97
51	3.39	3.41	3.20	3.04	3.06
52	3.22	3.39	3.37	2.32	3.01
53	3.67	3.43	3.38	2.82	3.13
54	2.61	3.45	3.34	2.88	3.12
55	2.89	3.00	3.22	3.09	3.08
56	3.60	3.51	3.34	3.38	3.22
57	3.60	1.89	3.34	2.91	3.12
58	2.84	3.70	3.28	3.57	3.22
59	3.14	3.04	3.29	3.14	3.13
60	3.29	3.42	3.19	3.43	3.13
61	3.39	3.31	2.97	3.55	3.02
62	3.08	3.70	3.14	3.36	3.09
63	2.90	3.12	3.30	3.06	3.12
64	3.64	3.08	3.09	2.77	2.93
65	2.93	3.00	2.99	3.72	3.07
66	2.96	3.20	2.95	3.62	3.02
67	3.90	1.67	2.99	2.44	2.79
68	2.84	2.14	3.11	3.13	3.01

69	2.78	3.02	3.35	3.00	3.14
70	3.50	3.35	3.35	3.32	3.21
71	3.05	3.08	3.27	3.37	3.17
72	3.33	2.58	3.26	2.01	2.88
73	3.52	3.30	3.43	3.28	3.25
74	4.18	2.16	3.21	3.00	3.05
75	2.87	3.15	3.32	3.17	3.16
76	3.12	2.93	3.25	3.51	3.19
77	3.47	2.52	3.28	2.95	3.09
78	3.19	2.70	3.29	3.175	3.14
79	3.12	1.93	3.18	2.537	2.94
80	2.64	3.21	3.18	3.62	3.17
81	3.63	3.07	3.31	2.77	3.07
82	3.28	3.08	3.26	3.19	3.12
83	3.32	2.87	3.34	4.10	3.37
84	3.11	2.87	3.41	3.10	3.20
85	3.22	3.15	3.09	3.16	3.01
86	3.70	3.07	3.24	3.04	3.08
87	2.76	2.93	3.15	3.24	3.06
88	3.04	3.33	3.18	3.75	3.19
89	3.06	3.22	3.21	3.38	3.14
90	3.66	3.32	3.26	3.53	3.20
91	3.04	3.57	3.22	3.96	3.27
92	3.06	3.44	3.29	3.14	3.14
93	3.74	3.11	3.09	3.46	3.07
94	3.45	2.69	3.10	3.44	3.077
95	3.04	2.62	3.12	3.05	3.01
96	3.22	3.16	3.04	4.21	3.20
97	3.54	2.98	3.04	3.65	3.08
98	3.30	2.98	3.27	2.94	3.08
99	3.33	2.68	3.13	3.15	3.04
100	3.22	3.79	3.22	3.45	3.15
101	3.14	3.20	3.19	2.86	3.01
102	3.54	3.45	3.09	3.26	3.03
103	2.66	3.21	3.26	3.15	3.12
104	2.81	3.18	3.22	3.53	3.18
105	2.78	3.02	3.22	3.87	3.25
106	3.52	3.12	3.06	3.69	3.10
107	3.20	3.25	3.11	3.71	3.14
108	3.29	2.99	3.14	3.35	3.08
109	3.21	2.61	3.04	1.69	2.67
110	3.00	2.49	3.22	3.63	3.19
111	2.74	2.97	3.25	3.00	3.08
112	3.09	2.79	3.19	3.03	3.05

113	2.67	2.61	3.16	2.79	2.98
114	2.54	2.96	3.21	3.52	3.17
115	3.26	2.56	3.18	3.14	3.06
116	4.18	2.84	3.13	3.37	3.08
117	3.14	2.67	3.12	2.64	2.92
118	2.76	2.88	3.21	2.65	2.98
119	2.66	3.45	3.17	2.99	3.03
120	3.86	3.16	3.19	3.69	3.19
121	3.06	2.93	3.32	3.55	3.24
122	3.35	3.15	3.34	3.22	3.18
123	2.67	2.62	3.30	3.15	3.14
124	2.82	2.97	3.24	3.06	3.08
125	3.59	3.02	3.29	2.46	2.99
126	2.90	3.21	3.27	3.27	3.15
127	3.83	2.92	3.28	3.02	3.10
128	3.57	2.87	3.41	3.50	3.29
129	3.38	2.54	3.35	3.28	3.20
130	2.68	3.62	3.24	3.27	3.13
131	3.51	3.12	3.15	3.70	3.16
132	3.38	2.80	3.28	2.96	3.09
133	3.34	2.59	3.22	3.32	3.13
134	3.60	2.84	3.20	2.68	2.98
135	3.23	2.77	3.30	3.51	3.22
136	3.68	3.04	3.24	2.99	3.07
137	3.00	2.89	3.25	3.50	3.19
138	2.57	2.93	3.29	3.04	3.11
139	3.59	2.57	3.30	2.48	3.00
140	1.68	3.20	3.24	3.00	3.07
141	3.22	2.92	2.86	2.24	2.67
142	2.74	2.77	3.23	2.99	3.06
143	3.29	2.75	3.30	2.54	3.01
144	2.96	2.92	3.18	2.63	2.95
145	3.56	2.88	3.40	3.27	3.23
146	3.38	3.00	3.20	2.90	3.02
147	3.17	2.30	3.15	2.75	2.96
148	3.37	3.47	3.23	2.57	2.97
149	2.85	3.08	3.24	3.69	3.22
150	2.55	2.71	3.28	2.89	3.07
151	3.14	4.48	3.33	Not used	Not used
152	2.13	4.59	3.14	Not used	Not used
153	3.33	4.43	3.30	Not used	Not used
154	4.09	4.62	3.23	Not used	Not used
155	3.06	4.52	3.19	Not used	Not used
156	3.22	4.13	2.88	Not used	Not used

157	2.66	4.15	3.38	Not used	Not used
158	3.10	4.54	2.62	Not used	Not used
159	3.06	4.31	3.18	Not used	Not used
160	3.09	4.17	3.06	Not used	Not used
161	2.85	4.53	3.05	Not used	Not used
162	3.21	4.54	3.05	Not used	Not used
163	3.41	4.21	3.19	Not used	Not used
164	3.58	4.54	3.12	Not used	Not used
165	3.66	4.53	3.39	Not used	Not used
166	2.88	4.67	3.10	Not used	Not used
167	3.14	4.36	3.20	Not used	Not used
168	3.38	4.15	3.29	Not used	Not used
169	3.20	4.52	3.24	Not used	Not used
170	3.32	4.29	3.16	Not used	Not used
171	3.98	4.72	3.29	Not used	Not used
172	3.05	4.48	3.03	Not used	Not used
173	3.64	4.51	3.07	Not used	Not used
174	4.02	4.49	3.00	Not used	Not used
175	3.10	4.47	3.03	Not used	Not used
176	2.58	4.31	3.13	Not used	Not used
177	3.11	4.45	3.33	Not used	Not used
178	3.16	4.52	3.26	Not used	Not used
179	3.03	4.52	3.32	Not used	Not used
180	2.92	4.49	3.15	Not used	Not used
181	3.20	4.88	3.15	Not used	Not used
182	3.06	4.49	3.32	Not used	Not used
183	3.22	3.31	3.08	Not used	Not used
184	3.09	4.51	2.82	Not used	Not used
185	3.08	4.53	3.25	Not used	Not used
186	2.64	4.49	3.09	Not used	Not used
187	3.30	4.51	2.95	Not used	Not used
188	4.12	4.53	3.14	Not used	Not used
189	4.00	4.55	3.18	Not used	Not used
190	3.13	4.51	3.36	Not used	Not used
191	3.21	4.56	3.35	Not used	Not used
192	3.25	4.52	3.08	Not used	Not used
193	3.13	4.47	3.24	Not used	Not used
194	3.22	4.49	3.25	Not used	Not used
195	3.79	4.59	3.19	Not used	Not used
196	3.99	4.54	3.01	Not used	Not used
197	3.24	4.38	2.98	Not used	Not used
198	3.39	4.5	3.13	Not used	Not used
199	3.36	4.19	3.17	Not used	Not used
200	2.59	4.9	3.26	Not used	Not used

201	3.32	4.53	3.05	Not used	Not used
202	3.42	4.73	3.20	Not used	Not used
203	3.12	4.77	3.30	Not used	Not used
204	3.32	4.58	3.18	Not used	Not used
205	2.99	4.45	3.17	Not used	Not used
206	2.64	4.51	3.23	Not used	Not used
207	3.66	4.5	3.29	Not used	Not used
208	3.93	4.56	3.28	Not used	Not used
209	3.40	4.46	3.43	Not used	Not used

Appendix B

Ratings of the Text Samples

Table B.1 shows the average users ratings of the ninety five text samples, and their predicted ratings by using the SVR based text model as reported in Section 4.6.

Table B.1: Average users' ratings and the model predicted ratings (text).

#	1	2	3	4	5	6	7	8	9	10	11
Average	2.66	4.44	3.03	1.89	3.75	3.66	3.1	3.5	1.93	1.66	1.8
predicted	2.57	4.13	3.79	3.60	4.14	3.90	2.85	3.99	1.99	2.18	2.08
#	12	13	14	15	16	17	18	19	20	21	22
Average	4.04	3.83	2.26	1.81	3.9	3.63	2.92	2.86	1.81	2.21	2.44
predicted	3.84	2.57	2.84	2.84	3.42	3.14	4.14	2.69	3.14	2.15	2.80
#	23	24	25	26	27	28	29	30	31	32	33
Average	4.01	2.3	4.09	3.23	2.21	3.69	2.32	4.03	3.96	3.46	3.56
predicted	3.41	3.04	4.10	3.11	3.10	3.75	2.45	3.85	4.04	3.71	2.41
#	34	35	36	37	38	39	40	41	42	43	44
Average	3.75	1.86	1.66	3.29	3	2.47	4.15	2.41	2.18	1.53	2.18
predicted	3.84	3.73	2.43	3.49	3.14	2.79	3.84	2.46	2.19	3.12	1.88
#	45	46	47	48	49	50	51	52	53	54	55
Average	1.97	3.88	4.06	1.97	3.56	1.91	2.44	2.48	4.06	1.29	1.44
predicted	2.00	3.78	3.86	1.83	3.75	1.85	3.51	2.81	3.88	1.09	1.14
#	56	57	58	59	60	61	62	63	64	65	66
Average	1.71	2.88	4.06	1.59	1.26	1.65	4.03	1.88	1.26	1.68	3.79
predicted	1.59	2.82	3.84	1.17	1.06	1.24	3.48	2.15	1.43	2.05	3.72
#	67	68	69	70	71	72	73	74	75	76	77
Average	3.19	3.9	2.17	4.2	4.24	2.93	1.17	3.48	4.1	3.36	1.37
predicted	3.14	3.84	2.84	4.04	4.18	2.97	1.39	3.57	4.03	3.39	2.05
#	78	79	80	81	82	83	84	85	86	87	88
Average	2.86	2.6	2.48	3.06	2.73	3.91	1.97	2	2.61	3.12	1.45
predicted	2.84	2.70	2.53	3.14	2.91	3.84	2.02	2.30	2.69	3.77	3.57
#	89	90	91	92	93	94	95				
Average	4.12	2.06	3.64	4.36	3.09	3.18	2.39				
predicted	3.79	2.14	3.61	3.89	3.89	3.38	2.48				

Appendix C

Ratings of the Photographic Images

Table C.1 shows the average users ratings of the two hundred and fifty photographic image samples, and their predicted ratings by the model reported in Section 5.3.

Table C.1: Average users' ratings and the model predicted ratings of the photographic images.

#	1	2	3	4	5	6	7	8	9	10
average	4.02	2.08	1.91	3.85	4.17	4	2.82	3.22	3.82	3.5
predicted	2.87	3.64	3.64	4.05	4.10	4.78	3.02	3.40	3.34	3.77
#	11	12	13	14	15	16	17	18	19	20
average	4.22	4	3.68	3.25	2.61	4.03	3.91	4.07	2.13	1.94
predicted	3.73	3.72	2.40	3.06	3.25	4.77	4.66	3.68	1.66	1.83
#	21	22	23	24	25	26	27	28	29	30
average	3.49	4.16	2.83	2.86	2.48	2.25	4.18	3.77	3.21	2.13
predicted	4.22	3.65	1.95	3.68	3.20	2.81	3.47	3.52	4.55	3.67
#	31	32	33	34	35	36	37	38	39	40
average	3.17	2.21	3.45	3.36	4.04	4.15	4.15	2.57	3.64	4.01
predicted	0.53	3.60	4.11	3.50	4.56	3.65	4.23	2.71	3.56	4.77
#	41	42	43	44	45	46	47	48	49	50
average	2.97	2.83	1.31	3.69	1.86	4.15	4.04	4.41	3.84	1.81
predicted	4.5	1.84	2.65	3.43	2.69	4.22	3.77	4.24	4.25	2.32
#	51	52	53	54	55	56	57	58	59	60
average	1.68	3.17	2.55	2.1	3.93	2.52	4.05	4.2	3.95	3.94
predicted	1.69	2.70	2.27	2.81	3.36	2.91	2.75	4.07	4.12	3.78
#	61	62	63	64	65	66	67	68	69	70
average	4.13	2.93	3.87	3.77	1.94	3.75	3.64	1.99	1.6	3.38
predicted	3.25	3.29	4.17	3.39	1.40	3.87	4.01	1.75	2.31	3.95
#	71	72	73	74	75	76	77	78	79	80
average	4.09	3.91	3.68	4.25	4.27	3.76	3.88	3.61	3.52	2.73

predicted	3.61	4.10	3.43	3.85	3.66	4.12	3.12	4.20	3.51	3.04
#	81	82	83	84	85	86	87	88	89	90;
average	1.64	1.37	1.51	3.56	2.36	2.55	2.91	3.14	4.17	4.24
predicted	2.32	2.65	2.69	4.17	2.13	1.99	2.54	3.07	4.70	3.82
#	91	92	93	94	95	96	97	98	99	100
average	3.81	2.72	2.46	2.5	2.33	3.6	4.11	4.19	1.99	1.62
predicted	3.70	2.62	2.91	2.23	2.13	3.04	2.77	3.95	2.46	1.19
#	101	102	103	104	105	106	107	108	109	110
average	3.77	3.82	3.8	3.27	3.98	3.83	1.77	1.65	1.56	1.49
predicted	2.58	3.55	3.24	1.99	3.98	2.46	1.56	1.22	2.36	1.94
#	111	112	113	114	115	116	117	118	119	120
average	3.18	1.6	1.64	1.31	1.47	3.63	3.81	4.21	4.22	4.06
predicted	2.30	3.37	1.97	1.04	1.22	3.47	3.67	3.67	3.39	3.79
#	121	122	123	124	125	126	127	128	129	130
average	3.59	1.88	3.76	2.64	3.54	1.9	2.74	2.21	2.06	2.78
predicted	2.86	2.10	3.82	2.37	3.95	3.81	2.66	2.81	2.66	2.72
#	131	132	133	134	135	136	137	138	139	140
average	2.14	2.47	2.79	3.5	3.79	3.81	2.61	3.58	3.19	3.36
predicted	3.35	2.58	3.42	3.12	4.38	3.77	2.28	4.36	3.22	2.43
#	141	142	143	144	145	146	147	148	149	150
average	2.68	3.91	3.15	4.05	4.06	4.23	4.03	3.84	3.01	2.85
predicted	3.13	4.14	3.46	2.39	3.72	3.66	4.38	4.00	3.12	3.04
#	151	152	153	154	155	156	157	158	159	160
average	3.42	3.82	3.72	2.57	3.18	3.78	3.99	4.3	4.16	3.22
predicted	3.01	3.24	4.07	2.53	4.59	3.45	3.77	4.00	3.41	3.77
#	161	162	163	164	165	166	167	168	169	170
average	3.75	3.19	3.03	2.56	3.21	2.27	1.93	3.79	4	4.12
predicted	3.51	2.39	3.03	3.59	3.49	3.53	2.88	4.12	3.56	3.28
#	171	172	173	174	175	176	177	178	179	180
average	3.98	4.08	3.62	3.92	2.63	2.01	2.14	2.84	2.62	1.94
predicted	3.82	3.98	4.29	3.35	2.34	2.62	1.99	3.64	2.13	2.57
#	181	182	183	184	185	186	187	188	189	190
average	1.71	1.75	2.4	3.56	1.81	1.96	1.48	3.95	3.93	1.93
predicted	2.09	2.64	3.81	4.86	1.54	3.11	0.75	3.53	3.63	2.23

#	191	192	193	194	195	196	197	198	199	200
average	1.73	2.84	3.59	3.85	3.57	3.9	3.97	4.29	3.62	3.87
predicted	2.71	3.94	3.40	3.53	4.05	4.15	4.67	4.47	4.03	3.73
#	201	202	203	204	205	206	207	208	209	210
average	3.39	2.52	1.84	4.06	4.19	3.88	1.37	1.36	3.59	1.78
predicted	2.75	2.34	2.27	3.21	3.62	3.12	2.30	3.79	3.99	1.54
#	211	212	213	214	215	216	217	218	219	220
average	1.6	1.56	1.56	1.74	3.56	2.34	4.07	3.47	3.43	4.03
predicted	1.29	0.92	1.16	2.38	4.30	3.14	4.20	3.61	4.42	3.81
#	221	222	223	224	225	226	227	228	229	230
average	4.02	3.76	1.78	1.75	3.05	2.34	4.12	4.37	4.12	4.18
predicted	4.61	4.15	2.22	1.44	4.41	2.90	3.54	4.62	3.64	2.94
#	231	232	233	234	235	236	237	238	239	240
average	3.07	3.19	3.39	3.98	2.33	3.24	2.66	3.62	3.28	3.68
predicted	3.63	3.89	3.41	4.09	2.45	2.75	3.59	4.39	3.17	3.62
#	241	242	243	244	245	246	247	248	249	250
average	2.65	4.07	4.26	3.93	3.65	2.56	4.16	3.17	3.3	3.11
predicted	3.22	3.76	3.57	4.04	3.86	2.46	3.80	4.01	3.43	3.32

Curriculum Vitae

Ranjan Maity is a research scholar in the Department of Computer Science and Engineering of Indian Institute of Technology, Guwahati since July 2014. Before this, he was awarded with the MS (by research) degree from the School of Information Technology (presently Department of Computer Science and Engineering), Indian Institute of Technology, Kharagpur in 2007, and B. Tech degree from Murshidabad College of Engineering and Technology, University of Kalyani, West Bengal, India in 2002.

He served IIT Kharagpur as a Program Facilitator, and Junior Project Officer. He also worked as a Lecture in Netajji Subhas Chandra Bose and College of Engineering and Management Kolaghat. From September 2011, he is working as an Assistant Professor in the Department of Computer Science and Engineering of Central Institute of Technology, Kokrajhar, BTAD, Assam, India (cit.ac.in) – a centrally funded institute under the Ministry of Human Resource Development, India.

His current research interest includes human computer interaction, user and cognitive modelling, and architectural design of integrated circuits.

Publications out of this work

Publications from Chapter 3

1. Maity R, and Bhattacharya S, *A Model to Compute Webpage Aesthetics Quality based on Wireframe Geometry*, 16th IFIP TC 13 International Conference on Human-Computer Interaction (INTERACT 2017), 3, 85-94, Mumbai, India, (2017).
2. Maity R and Bhattacharya S, *Computational Model for Webpage Aesthetics using SVM*, 31st British Human Computer Interaction (BHCI 2017), 1-5, Sunderland, UK, (2017).
3. Maity R, and Bhattacharya S, *A Quantitative Approach to Measure Web page Aesthetics*, International Journal of Technology and Human Interaction, 16 (2), (accepted).

Publications from Chapter 4

4. Maity R, Madrosiya A, and Bhattacharya S, A *Computational Model to Predict Aesthetic Quality of Text Elements of GUI*. 7th International Conference on Intelligent Human Computer Interaction (IHCI 2015), published in Procedia of Computer Science**,** 84, 152–159, Allahabad, India, (2016).

Publications from Chapter 5

5. Maity R, Verma G, Uttav A, and Bhattacharya S, *A Non-Linear Regression Model to Predict Aesthetic Ratings of On-Screen Images*, 27th Australian Conference on Human-Computer Interaction (OzCHI 2015), 44-52, Melbourne, Australia, (2015).

Publications from Chapter 3, 4, 5 and 6

6. Maity R, and Bhattacharya S, *Is My Interface Beautiful? – A Computational Model-based Approach*, IEEE Transaction on Computational Social System, 6 (1), 149-161 (2019).
7. Maity R, and Bhattacharya S, *A Framework to Measure Webpage Aesthetics*, ACM Transaction on Management Information Systems (TMIS), (submitted).

Full List of Publications

Publications in the Journals

1. Maity R, and Bhattacharya S, *A Quantitative Approach to Measure Web page Aesthetics*, International Journal of Technology and Human Interaction, 16 (2), (accepted).
2. Maity R, and Bhattacharya S, *Is My Interface Beautiful? – A Computational Model-based Approach*, IEEE Transaction on Computational Social System, 6 (1), 149-161 (2019).
3. Maity R, and Bhattacharya S, *A Framework to Measure Webpage Aesthetics*, ACM Transaction on Management Information Systems (TMIS).

Publications in the Conferences

4. Maity R, Verma G, Uttav A, and Bhattacharya S, *A Non-Linear Regression Model to Predict Aesthetic Ratings of On-Screen Images*, 27th Australian Conference on Human-Computer Interaction (OzCHI 2015), 44-52, Melbourne, Australia, (2015).
5. Maity R, Madrosiya A, and Bhattacharya S, A *Computational Model to Predict Aesthetic Quality of Text Elements of GUI*. 7th International Conference on Intelligent Human Computer Interaction (IHCI 2015), published in Procedia of Computer Science**,** 84, 152–159, Allahabad, India, (2016).
6. Maity R, and Bhattacharya S, *A Model to Compute Webpage Aesthetics Quality based on Wireframe Geometry*, 16th IFIP TC 13 International Conference on Human-Computer Interaction (INTERACT 2017), 3, 85-94, Mumbai, India, (2017).
7. Maity R and Bhattacharya S, *Computational Model for Webpage Aesthetics using SVM*, 31st British Human Computer Interaction (BHCI 2017), 1-5, Sunderland, UK, (2017).
8. Maity R and Bhattacharya S, *Relating Aesthetics of the GUI Text Elements with Readability using Font Family*, Companion Proceedings of the 2018 ACM International Conference on Interactive Surfaces and Spaces (ISS 2018), 63-68, Tokyo, Japan, (2018).