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A Computational Model to Predict the Memorability of Web-pages

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Abstract— In today's digital world, websites are the main point of interaction for a wide range of online activities. As a result, website memorability has become an important topic of discussion. In order to stand out in a highly competitive environment where users are constantly bombarded with information, a website's ability to be memorable is crucial to its success. This study focuses on the development of an automatic computational model for predicting the memorability of a web page. To achieve this, the objects within a web page were identified and their memorability scores were calculated using the ResNet-18 convolutional neural network. The final memorability score of the web page was computed by taking a weighted sum of the areas occupied by these objects on the web page, along with their memorability scores. For the empirical study, 30 web pages from different applications were used to train and test our proposed model. Our model can predict web page memorability with a mean absolute error of 0.077 on a normalized scale of 1.

Keywords- Memorability; Deep Learning; Web-page Design; Empirical Study.

I. INTRODUCTION

In today's digital world websites serve as the principal interface for numerous online activities. However, the memorability of web pages has drawn very little attention. The capacity of a website to create a lasting impression on users, allowing them to recall and recognize the website quickly, is referred to as memorability. A memorable website increases user engagement, aids information retention, and encourages return visits. The memorability of a website is critical to the success and efficiency of online platforms. When consumers come upon a memorable website, they have a favorable user experience, which boosts their happiness and chance of returning. Furthermore, such websites are more likely to be shared with others, resulting in greater traffic and new commercial prospects [1].

Website memorability may be influenced by a variety of design aspects, content qualities, and user interactions. Visual aesthetics, layout, color scheme, and typography are all design factors that may greatly influence how memorable a website is. Memorability can also be enhanced by content features such as relevancy, clarity, distinctiveness, and storytelling aspects [2]. User interactions, such as ease of navigation, engagement, and personalization, can add to a website's overall memorability. Nielsen [3] defined memorability as - "The system should be easy to use and remember so that the casual user can return to it after not using it for a time and still know how it works."

The memorability of any interface is generally considered subjective in nature [4]. In other words, the memorability of an interface may differ from person to person. Consequently, measuring or predicting web page memorability turns out to be a difficult task. Memory Turk games are generally used by researchers [5, 6] for this purpose. These games were played by the Mechanical Turk workers. Initially, a group of long-stream images - termed target images is shown to them. Following this, a group of other images - filler images were added to the target images. After several days, all the target and filler images are again shown to the participants. Generally, these images were shown for 1 second. In between two images, a blank gap of 1.4 seconds was used as shown in Figure 1. Participants were to press the space bar each time they identified an image. Finally, the memorability of an image, in terms of a score is computed with the help of the following equation –

$$MEM_I = M_I / N_I \tag{1}$$

In the above equation, MEM_I denotes the memorability of image I, whereas M_I and N_I denote the number of participants who identified image I, and the total number of participants who viewed image I, respectively. **SUN2012** [7] is popularly used for the memorability computation of images.

Over the years, several works have been reported to measure the memorability of an image. Any interface including a web page can also be considered as an image. However, unlike an image, a web page is composed of many web page objects [8]. These objects are comprised of different images, texts, and short animations. Therefore, there is a necessity to check whether the traditional image memorability prediction is suitable for web page memorability, or there is a need to develop a computational model for predicting the memorability of a web page.

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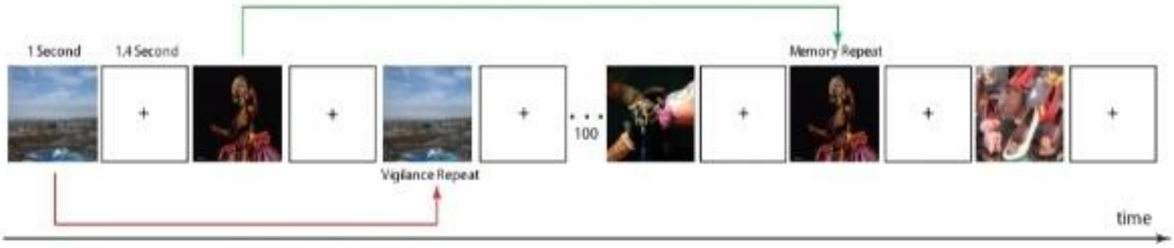

Figure 1. Memory Turk Game.

In this work, we proposed a computational model to predict the memorability of a web page in terms of a score. In order to do this, thirty web pages from different applications were considered. ***ResNet 18*** was used to predict their memorability score. It was observed that our proposed model can predict the memorability of a web page with a low Mean Absolute Difference (MAD) of only 0.08.

II. RELATED WORK

From the psychological point of view, the topic of image memorability and its interaction with numerous aspects of human cognitive function has been studied exhaustively over the years. Among them, Isola et al. [9], in particular, reported an image memorability score which indicates a likelihood that viewers would recognize multiple images during the stream of photos. Their study involved measuring memorability scores for 2222 images, revealing that object and scene semantics, including labeled object counts, areas, multi-scale object areas, object label presences, and scene categories, play a significant role in image memorability. They conducted a study to measure memorability scores for 2222 pictures. The study revealed that objects and scene semantic factors such as object counts, areas, multi-scale fields, and the presence of labels or categories play a significant role.

Khosla et al. [10] labeled memorability scores for a huge set of pictures containing more than 58,000 images. They established the relationship between memorability and high image qualities such as popularity, emotion, saliency, or beauty. According to their findings, image memorability is negatively influenced by feelings of anxiety and saliency but does not affect popularity or beauty. More memorable were images that contained a negative emotion, like disgust, fear, or anger, than those with positive emotions such as joy, excitement, amazement, and satisfaction.

A. Hand-crafted Features for Image Memorability

Image memorability prediction models have been developed by researchers using hand-crafted features. The first-ever dataset of image memorability was created by Isola et al. [11]. Using these hand-crafted features, they developed prediction models to determine the likelihood of an image being remembered. Support vector regression (SVR) was utilized to map a combination of global image features with memorability scores. They also labeled images with different visual properties, including visual emotions, spatial layout, location, aesthetics, image dynamics, and the presence of a person.

Another probabilistic model was proposed by Khosla et al. [12] that predicts image memorability patterns by integrating both local and global image features. Instead of identifying regions of an image that may be remembered, their approach focuses on determining which local regions may be forgotten.

B. Deep Learning Method for Image Memorability

Convolutional Neural Networks (CNNs) have shown exceptional performance in several computer vision tasks. Based on this, recent studies have explored CNN-based models for predicting the memorability of images. ***MemNet***, introduced by A. Khosla et al. [12], is a CNN-based model for image memorability prediction using transfer learning. They refined the CNN model on the LaMem dataset consisting of over 58,000 images. The initial weights of the CNN model were pre-trained on the ILSVRC 2012 and Places datasets.

Baveye et al. also utilized deep CNN models for predicting image memorability by fine-tuning MemNet and GoogleNet on the image memorability dataset created by [11]. Their model includes various high-level factors such as the semantics of objects, depth cues, and motion cues. These types of CNN-based approaches leverage the power of deep learning to automatically identify task-specific features and have displayed promising results in predicting the legibility of images.

Image memorability predictions using depth and motion cues were also reported in [13]. In [14], a deep CNN-based model was used to predict image memorability. Basavaraju et al. also proposed object memorability using deep learning in [15]. Besides these, there are works [16, 17] on image memorability. Comprehensive reviews on image memorability and its prediction techniques are reported in [18].

Although several works have targeted measuring the memorability of images over the years, the memorability of interfaces and web pages has received almost no attention to date. To the best of our knowledge, we did not find any such work. Hence there is a need to explore whether traditional image memorability models are suitable for web page memorability. In this work, we considered web pages as images and computed their memorability using traditional deep-learning models. We observed that the accuracy of those models decreases for web pages. As a result, we developed a weighted average-based web page memorability algorithm. Our proposed approach outperformed other models. We report our proposed approach in the following section.

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Table 1: Thirty websites used in our empirical study.

Sl. No	Educational	Health	Entertainment	Travel	Sports	Others
1	academicearth	mayoclinic	indiamart	skyscanner	sports.yahoo	calendly
2	meritnation	webmd	justwatch	travelguru	sportskeeda	clickindia
3	Internet archive	drugs	shoppersstop	Tripit		magicbricks
4	powerschool	cdc	vocal.media			sulekha
5	sporcle	TATA1mg	soundcloud			pacdora
6			parade			yummly
7			greatist			printfriendly
8						Webnode

III. MATERIALS AND METHODS

To the best of our knowledge, there is no dataset for web page memorability. Consequently, there is a necessity for web page memorability data. Therefore, we conducted an empirical study with the home pages of thirty websites. In the following, we discussed our proposed study.

A. *Empirical Study*

The thirty websites are picked up from six different categories - education, entertainment, health, travel, sports, and others. In Table 1, we reported those thirty websites. The websites were chosen in such a way that they were not familiar with the participants used in our study. The thirty participants were considered from three different age-based groups: ***G1***: 20-30 years, ***G2***:31-40 years, and ***G3***: 41-50 years. Each group consisted of five male and five female participants, ensuring gender diversity within the study. All the participants viewed the thirty web pages as long as they wanted to continue on a computer with a resolution of 1440×900, 59.89 Hz, 8-bit depth RGB color format.

In order to compute the memorability of a web page, we used a low-fidelity-based approach [19]. In this approach, we took the color printout of the web pages without affecting their view size. Following this, the components of a web page in puzzle form and a cardboard template that replicated the size of our screen were provided to the participants as shown in Figure 2. Participants were asked to correctly assemble the web page components (the puzzle pieces) in their respective positions based on the given layout as reported in Figure 3. For a given web page W_i the memorability score of participant *j* is computed with the following equations –

$$Memorability(i, j) = CSA\,(i,j) \,/\, TA(i) \tag{2}$$

In the above equation, *Memorability(i, j)* denotes the memorability of web page *I* of the participant *j*. The *CSA (i,j)* denotes the properly identified area of web page *i* by the participant *j*, whereas *TA(i)* denotes the total area of the web page *i*. It may be noted that the *Memorability(i, j)* score is a normalized score that varies from zero to one. This calculation provided a quantitative measure of the accuracy of the recreations, with higher values indicating a closer resemblance to the original website. We collected memorability scores for each web page two times. Once, they viewed the image samples (termed as short-term memorability) and again after twenty days (termed as long-term memorability). This allowed us to examine the consistency and stability of participants' memorability performance over time. Along with this, participants' profiles - age, and gender were also collected.

Altogether, nine hundred data points (30 participants × 30 web pages) were assembled for further analysis.

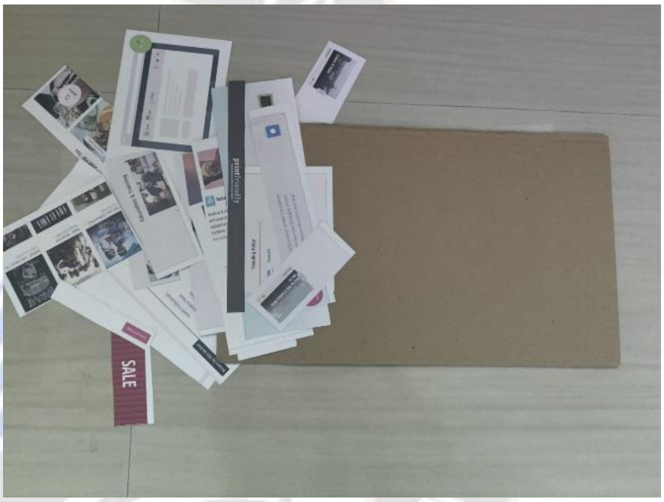

Figure 2: Components of the webpage (low fidelity approach)

Figure 3: Participant recreating a web page.

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Table 2: ANOVA results of short-term memorability.

Sources of Variations	SS	df	MS	F	P- value	F-critical
Between Groups	0.017	2	0.009	1.719	0.185	3.101
Within Groups	0.434	87	0.005			
Total	0.450	89				

Table 3: ANOVA results of long-term memorability.

Sources of Variations	SS	df	MS	F	P- value	F-critical
Between Groups	0.179	2	0.089	14.488	3.707E-06	3.101
Within Groups	0.537	87	0.006			
Total	0.716	89				

B. Short and Long Term Memorability Analysis with Age

To judge the effect of memorability across the three different age groups - **G1**: 20-30 years, **G2**:31-40 years, and **G3**: 41-50 years, we performed a one-dimensional ANOVA (Analysis of Variance) test on both sets of empirical data (short-term, and long-term memorability). The ANOVA test is a tool that compares the means of three or more groups to see whether there are any significant differences. The *F-statistic* or *F-ratio*, which indicates the amount of difference between the means of the different samples, was one of the criteria employed in our study for the ANOVA test. A lower F-ratio shows that the sample means are more similar. The null hypothesis for the test was formed as follows –

H0: The means of the short-term memorability scores among the different age groups have no significant difference.

$$\mu STM_{G1} = \mu STM_{G2} = \mu STM_{G3} \tag{3}$$

In the above equation, μSTM_{G1}, μSTM_{G2}, and μSTM_{G3} denote the mean of the short-term memorability of three different age groups - *G1*, *G2*, and *G3*, respectively.

Using the different age groups' data, we performed 1D ANOVA. Experimental results of the ANOVA are reported in Table 2. The *F* value observed in our study 1.179 is less than the critical value of *F* (3.101) and thus accepts our null hypothesis. In other words, the initial memorability among different age groups is statistically equal in nature. As a result, we refrain from computing the model of short-term memorability.

After the study on short-term memorability, we focused on judging long-term memorability among different age groups. In the following, the null hypothesis formed for this analysis is reported.

H0: The means of the long-term memorability scores across different age groups have no significant difference.

$$\mu LTM_{G1} = \mu LTM_{G2} = \mu LTM_{G3} \tag{4}$$

In the above equation, μLTM_{G1}, μLTM_{G2}, and μLTM_{G3} denote the mean of the long-term memorability scores for the three different age groups - G1, G2, and G3, respectively. Using the long-term memorability data, we performed again 1D ANOVA test again. Experimental results of the test are reported in Table 3. It may be noted that the observed *F* value of 14.488 is greater than the *F* critical value of 3.101. Hence, the null hypothesis was rejected. Consequently, we may conclude that age is an important factor for long-term memorability.

Based on this observation, we planned to develop a computational model for long-term memorability, as reported below.

C. Proposed Computational Model

This proposed model works in the following way. The input to our model is the picture of the thirty web pages considered in our study, as reported in Table 1. A web page can be considered as an image. The web page is then passed through different pre-trained deep-learning models trained on the ***Lamem*** dataset. There are a number of different deep learning models. Among them, ***ResNet*** is used in different works of memorability computation. In this study, we considered three different versions of ResNet - ***ResNet18***, ***ResNet34***, and ***ResNet50***. These models predict the memorability score of the given input web page using the ingested patterns and attributes. The experimental results of these models are reported in Table IV. It may be noted that out of the three versions of ResNets, ResNet18 performs better than the others with a mean absolute error of 0.14 (14% error or 86% accuracy).

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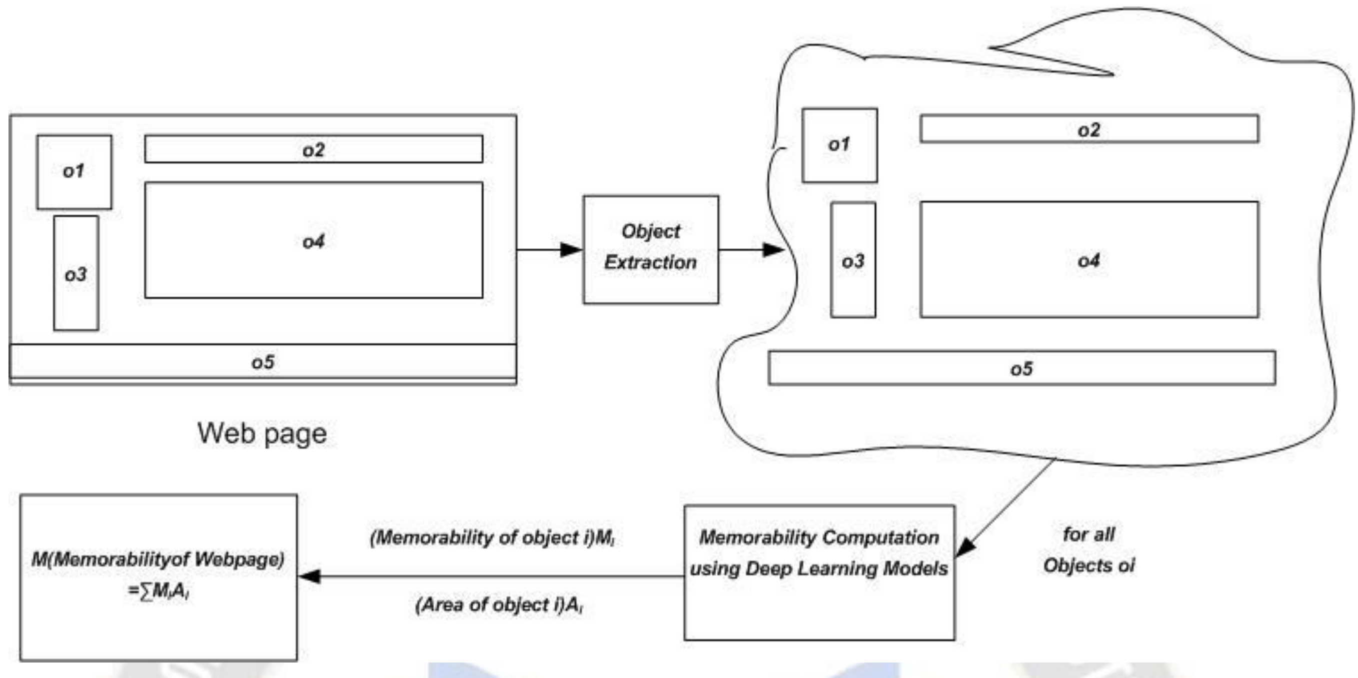

Figure 4: Object extraction based deep learning model.

Table IV: Memorability score without extraction.

#	Ground value	Resnet18	Resnet34	Resnet50
1	0.732	0.690	0.870	0.787
2	0.627	0.619	0.711	0.795
3	0.663	0.548	0.660	0.807
4	0.570	0.624	0.699	0.904
5	0.550	0.716	0.825	0.812
6	0.470	0.592	0.798	0.798
7	0.448	0.679	0.662	0.832
8	0.479	0.764	0.866	0.898
9	0.560	0.767	0.750	0.862
10	0.613	0.738	0.654	0.783
11	0.595	0.762	0.908	0.897
12	0.666	0.775	0.885	0.839
13	0.619	0.720	0.645	0.721
14	0.616	0.876	0.923	0.920
15	0.545	0.606	0.679	0.833
16	0.658	0.728	0.671	0.885
17	0.647	0.663	0.802	0.891
18	0.642	0.613	0.676	0.853
19	0.539	0.703	0.752	0.727
20	0.563	0.695	0.854	0.624
21	0.567	0.669	0.563	0.756
22	0.533	0.878	0.657	0.854
23	0.603	0.813	0.773	0.757
24	0.602	0.875	0.736	0.962
25	0.645	0.733	0.822	0.744
26	0.519	0.843	0.747	0.828
27	0.669	0.883	0.771	0.770
28	0.661	0.695	0.898	0.926
29	0.619	0.687	0.808	0.669
30	0.703	0.616	1.000	0.784
	MAE	0.140	0.172	0.220

Following this, we planned to check whether the extraction-based method is much more suitable for the memorability of web pages. Accordingly, we proposed our web page object-based extraction algorithm as shown in Figure 4. The webpage shown in Figure 4 has five objects inside it - ***o1, o2, o3, o4***, and ***o5***. Using the object extraction technique, the five objects are extracted and passed through the pre-trained deep learning models trained on the ***LaMem*** dataset. These models predicted the memorability scores of those five objects. A weighted sum using their memorability scores and normalized areas was used to compute the final memorability of the web page

Algorithm1	**Compute memorability of a web page.**
Input:	Web page W_I
Output:	Memorability M_I of Web page W_I
	Extract all objects of W_I
	N = number of objects present in W_I
	A_K = normalized area of the object K
	$M_I = 0$
	$K=1$
while ($K<=N$)	
	Compute the memorability of the objects K, *and* M_K using *ResNet*.
	$M_I = M_I + M_K \times A_K$
	$K=K+1$
end while	
	Print M_I

. The normalized area is computed with the following equation –

$$normArea_i = Area_i / TotalArea_i \quad (5)$$

Consider a web page with a size of 200 × 100 pixels has an object (K) with a size of 10 × 8 pixels. Then the normalized area of K is computed as –

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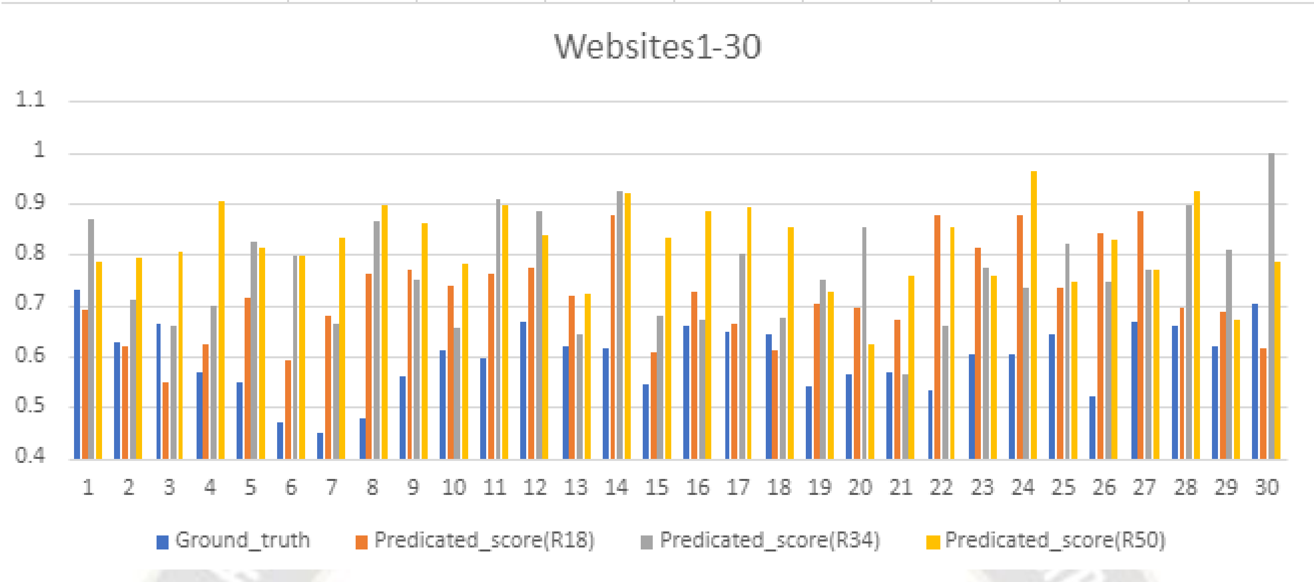

Figure 5: Memorability scores of thirty web-pages without extraction.

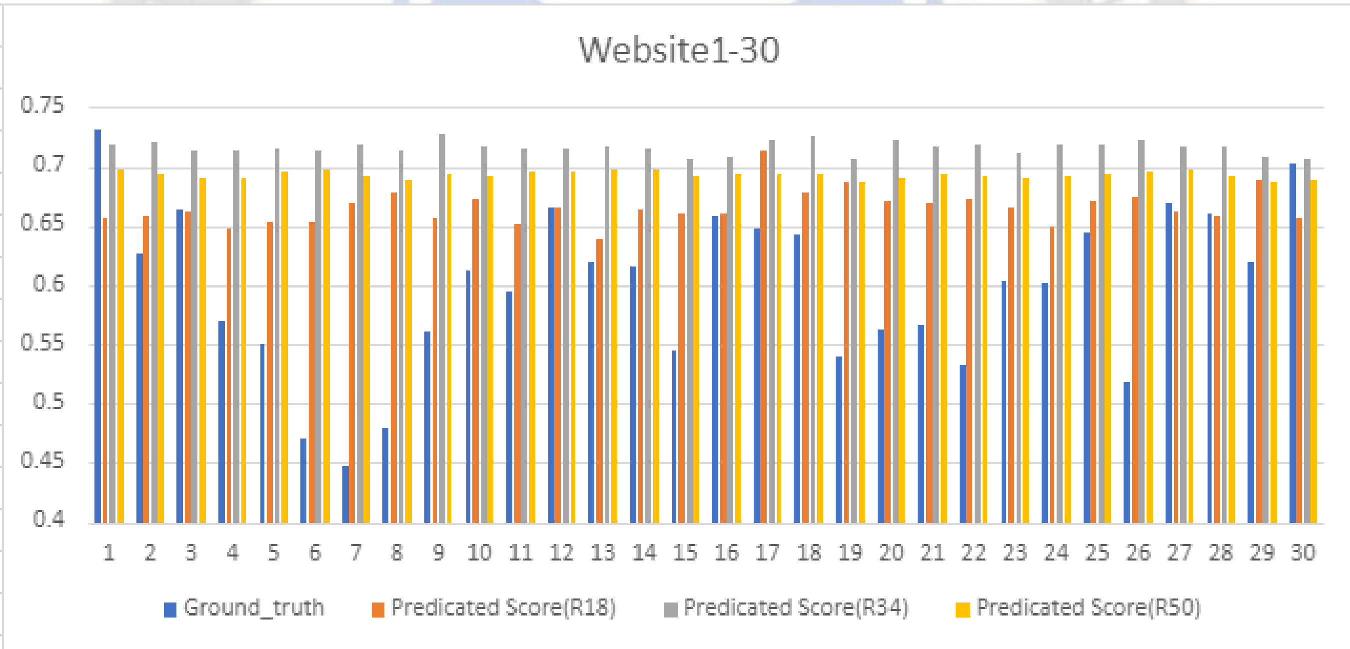

Figure 6: Memorability scores of thirty web-pages with extraction.

$$normArea_K = (10 \times 8)/(200 \times 100)$$
$$= 80/20000$$
$$=0.04 \quad (6)$$

Our proposed algorithm is reported in Algorithm1. The experimental results of our proposed model using three deep-learning models are reported in Table V. In our proposed model a low mean absolute error (MAE) of 0.077 was observed for the ResNet18 model on a normalized scale of 1. In other words, the accuracy was 92.30% which is 6.20% better than the without extraction-based model.

Table V: Memorability score with extraction.

#	Ground value	Resnet18	Resnet34	Resnet50
1	0.732	0.656	0.719	0.697
2	0.627	0.659	0.721	0.695
3	0.663	0.662	0.713	0.690
4	0.570	0.647	0.713	0.691
5	0.550	0.654	0.716	0.695
6	0.470	0.654	0.714	0.697
7	0.448	0.669	0.720	0.693
8	0.479	0.678	0.714	0.688
9	0.560	0.658	0.728	0.695
10	0.613	0.673	0.716	0.692
11	0.595	0.652	0.716	0.695
12	0.666	0.666	0.715	0.696
13	0.619	0.638	0.716	0.698
14	0.616	0.664	0.715	0.697
15	0.545	0.661	0.706	0.693
16	0.658	0.660	0.708	0.694
17	0.647	0.713	0.723	0.695
18	0.642	0.678	0.727	0.694
19	0.539	0.687	0.706	0.687
20	0.563	0.671	0.722	0.691
21	0.567	0.669	0.717	0.693
22	0.533	0.673	0.718	0.692
23	0.603	0.666	0.713	0.690
24	0.602	0.650	0.720	0.693
25	0.645	0.672	0.719	0.693
26	0.519	0.674	0.722	0.696
27	0.669	0.663	0.717	0.698
28	0.661	0.659	0.716	0.693
29	0.619	0.689	0.708	0.687
30	0.703	0.657	0.707	0.689
	MAE	0.077	0.120	0.099

IV. CONCLUSION AND FUTURE WORK

In this work, we developed a computational model for web page memorability prediction. It was observed that the existing models of memorability work on an image. Unlikely, web pages follow a different structure. This includes the different objects which may include text, images, and other web page components. During this study, we observed that our proposed approach of object-based extraction gives a clue to thinking about the web-page memorability problems in a different way.

Unlike the traditional image memorability computation, we used a low-fidelity approach in our work. The reason was not only to identify the correct web page objects but also to check how they are organized in nature. During our empirical study, we observed all the participants enjoyed this game-based low-fidelity approach. This type of low-fidelity approach helps us to get our desired memorability scores quickly as well at almost no cost.

The suggested model for predicting website memorability has demonstrated results and substantial potential for improving user experience and interface design. The model effectively identified components from input pictures depicting website interfaces by employing the bounding box technique. The model predicted the memorability scores for each extracted component after training with the Lamem dataset using pre-trained deep learning models ResNet18, ResNet34, and ResNet50. This enabled a thorough examination of the different aspects' effects on user memory retention and overall interface memorability. The model's performance can vary depending on the scenarios, dataset, task requirements, and specific characteristics of the websites being evaluated. Overall, the findings of this study show that the suggested approach can estimate the memorability of website interfaces. The findings offer useful insights for interface designers and optimization procedures, allowing for the identification of highly memorable aspects and improving user experience and memory retention.

Future study and improvement of the model can improve its accuracy and application in website design and human-computer interaction.

- Some aspects to further enhance the model’s performance and application in Website Design and Human-Computer Interaction can focus on - Data set Expansion: Including a wide range of Website interfaces with different design styles, content types, and targeted audiences can enhance the performance of the model’s ability to predict memorability across different contexts.
- Component Importance Weighting: Finding and developing different methods to determine the importance of each component based on some parameters, categorizing design styles, or user studies can help refine the scoring mechanism.
- Including Temporal Factors: When users interact with a website taking into account the order and duration of exposure of the components can provide a more comprehensive understanding of the memorability process.
- Deploying in Real Time setting: Collecting Data and monitoring user behavior by deploying the model on live websites can provide practical insights and enable improvements.

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