Classification and Aesthetic Evaluation of Paintings and Artworks

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Classification and Aesthetic Evaluation of Paintings and Artworks

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Abstract— **Painters and Artists have contributed to the field of art over the years with their exceptional talent and skills. The Internet is full of their creativity and imagination where one can find most of their work. Like any other information present on the Internet, paintings are also not well organized. In this paper, a method is proposed to classify paintings with the help of support vector machine classifier using features extracted by a pre trained convolutional neural network-AlexNet. A painting is not only an art on paper but is a medium to arouse emotions and sense of pleasure within the audience. Aesthetic Evaluation aims at evaluation/rating a painting or an artwork on the basis of various parameters like style, topic, emotional engagement etc. which cannot be done by a machine alone. So we cannot leave behind the human inputs while determining the aesthetic value of a painting or an artwork. In this paper we also propose a method to judge or evaluate the aesthetic value of a painting by training a regression model with several image features, like Local Binary Pattern for texture, color histogram for color, Histogram of Oriented Gradients for edges and GIST for scene recognition in the painting, against human ratings for each painting. A dataset constituting of 1225 digital images of paintings of 7 categories is used for classifying and evaluating the aesthetic value. The classification phase was found to have 92.73% accuracy and the evaluation phase performed with an accuracy of 64.15%.**

Keywords–Painting classification; Aesthetic Evaluation; Convolutional neural network; Histogram of oriented gradient; GIST

I. INTRODUCTION

In present Digital Era, the advancement in technology and increase in number of smart phones and computers has eased image retrieval to large extent. Now a user can easily search for an image by giving a simple query on his smart phone device. The concept of aesthetic evaluation will help in retrieving the images based on personal taste and choice on the basis of aesthetic scores.

The objective of the aesthetic assessment is to design methods which can automatically predict the perceived quality of a painting or an artwork. Such methods find great applications in the field of image retrieval. An automatic system that can evaluate painting's aesthetics has many potential applications. Using image retrieval systems, similar images could be ranked using aesthetic properties. They could help a user to select the best pictures from his collection to make photo albums. Also, these models could be deployed directly in photo cameras to make real-time suggestions and give on the spot scores to the photographs clicked. Knowing the aesthetic value of paintings will help in searching a painting and facilitate proper management of paintings. Using the proposed concept a recommendation application can be developed which will show the user a painting of required aesthetic quality. It will also be helpful in easing the process of searching a painting reducing both time and resources.

Figure 1. Painting categories used in this research.

Aesthetic Evaluation of a painting is a complex task. The evaluation not only depends on the theme and style of the artist but also depends upon the likings, disliking, personal taste and views of an individual evaluating the artwork. A piece of art which pleases some portion of a society need not necessarily please others. So we need to develop a system which can mimic the above-said concept efficiently. Fig. 1 shows the categories of paintings considered in this research.

II. LITERATURE REVIEW

Aesthetic Evaluation of images and photographs is a popular topic for research in Computer Vision field. There has been a lot of work done for assessing the aesthetic value of images and photographs, but there are few researches

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done so far that deal with the assessment of aesthetic value of Paintings & Artworks.

AVA dataset [3] is one of the datasets widely used for assessing the aesthetic quality of an image. This large scale dataset containing more than 250,000 images was introduced by Murray et al. In their original work, they formulated a binary classification problem and established the experimental settings. They computed Fisher Vector signatures from SIFT descriptors and trained an SVM which achieved maximum accuracy of 67%.

Extensive research has been done on image classification and aesthetics using convolutional neural networks. Lu et al. [4] used convolutional neural networks on the AVA dataset and achieved classification accuracy between 60.25% and 71.2%. The architecture of convolutional network used by them contained 4 convolutional layers and 2 layers that were fully connected. Bianco et al. [5] used deep Convolutional Neural Network to predict image aesthetics. They fine tuned CNN architecture by casting the image aesthetic prediction as a regression problem and used AVA dataset. Their Experimental results show the robustness of the solution proposed, which outperforms the best solution in the state of the art by almost 17 % in terms (MRSSE). Marchesotti et al. [6] proposed to use generic image descriptors to assess aesthetic quality instead of hand-crafting features which would correlate with best photographic practices and achieved good results. Datta et al. [11] designed special visual features (colorfulness, the rule of thirds, low depth of field indicators, etc.) and used the Support Vector Machine (SVM) and Decision Tree (DT) to discriminate between aesthetic and unaesthetic images. Nishiyama et al. [7] proposed an approach based on color harmony and bags of color patterns to characterize color variations in local regions.

III. PROPOSED METHODOLOGY

The technique proposed for classifying digital images of paintings and evaluating the aesthetic value has been described in this section. Fig. 2 gives a block representation of the proposed approach to classify paintings. Fig. 4 illustrates flowcharts to evaluate aesthetic value of paintings. The dataset used in this research consists of 1225 paintings of 7 categories. The dataset was divided into training and testing data sets. 120 paintings of each category were used to train the algorithm whereas it was tested on 55 paintings of each category. The images were pre-processed as per the requirements of convolutional network.

To extract features of paintings for classification, a pre-trained Convolutional neural network- AlexNet [1] was used. AlexNet is one of the deep ConvNets which competed in the ImageNet Large Scale Visual Recognition Challenge in 2012. AlexNet has 5 convolutional layers, 3 sub sampling layers, 3 fully connected layers.

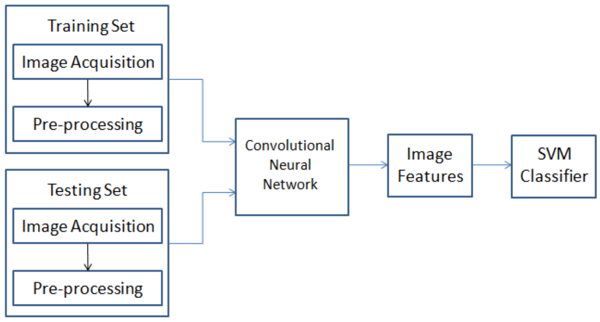

Figure 2. Block representation of proposed approach to classify paintings.

For evaluating the aesthetics of paintings, a survey was conducted and the participants were asked to rate the paintings on a scale of 1 – 10 where a rating close to 1 represents low aesthetic score and rating close to 10 represents high aesthetic score. Total 60 participants rated each of the 1225 paintings. A discussion with the participants revealed that people look for image features like colors, edges and texture in a painting. Keeping in mind the results of discussion following features of each painting were extracted: Colour Histogram, Histogram of Oriented Gradient, Local Binary Pattern and GIST.

A. Histogram of Oriented Gradients

HOG feature descriptors are widely used in Computer Vision for detecting edges. HOG features of the paintings are extracted and stored for further processing. HOG operates on local cells hence it is invariant to geometric transformations.

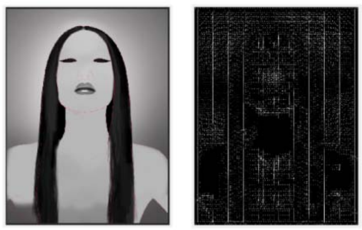

Figure 3. Extraction Of HOG Features
(a) Painting (b) Plot of HOG Features

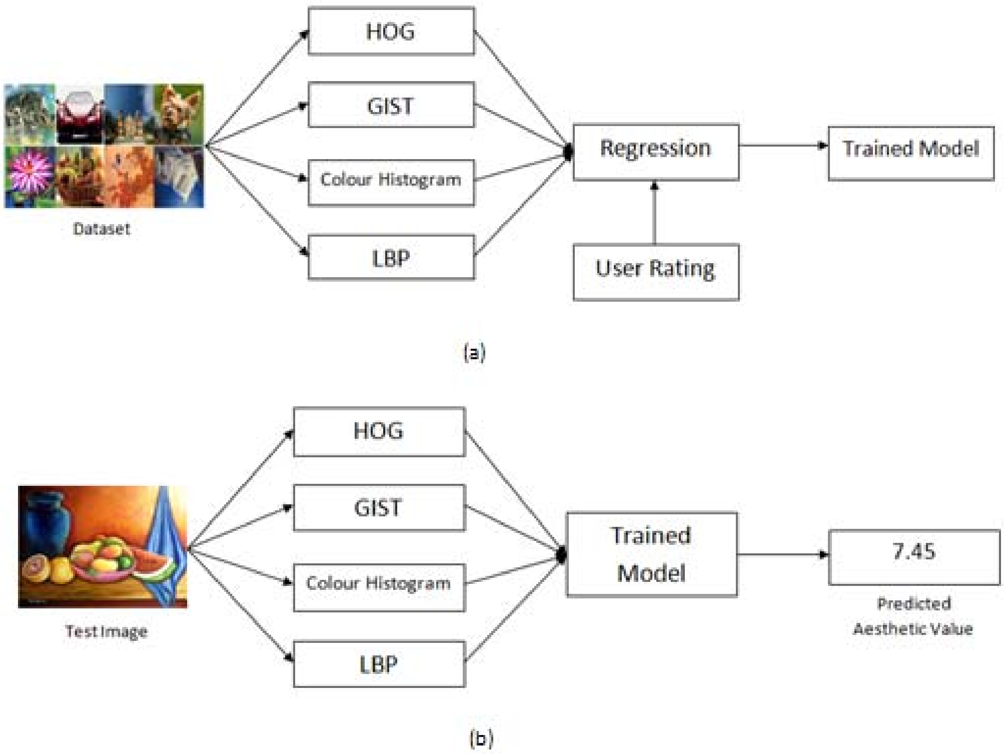

Figure 4. Block representation of proposed method to assess Aesthetic score:
(a) Training a Regression Model (b) Predicting Aesthetic Value using the trained model

B. *Local Binary Pattern*

LBP is a visual descriptor widely used in Computer Vision to classify images based on texture. Discriminative power and computational simplicity of LBP makes it a popular approach in various applications.

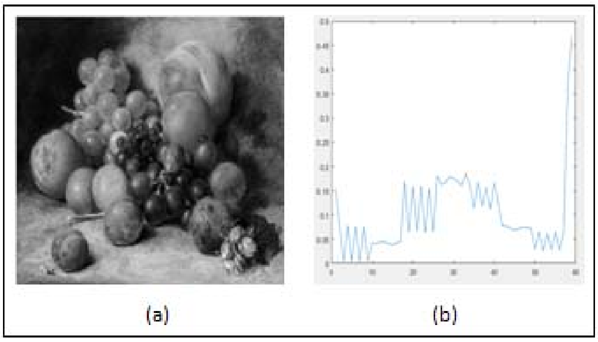

Figure 5. Extraction of LBP Features
(a)Original Painting converted to grayscale (b) LBP Histogram.

C. *GIST*

The GIST descriptor was first proposed for recognition of real world scenes the segmentation and the processing of individual objects or regions. To compute a GIST Descriptor, an image is convolved with 32 Gabor filters at 4 scales, 8 orientations, producing 32 feature maps. Each feature map is divided into 16 regions and the feature values of each region are averaged. Finally, the 16 averaged values of 32 maps are concatenated, giving a 512 GIST descriptor. Fig. 6 shows an example of GIST descriptor.

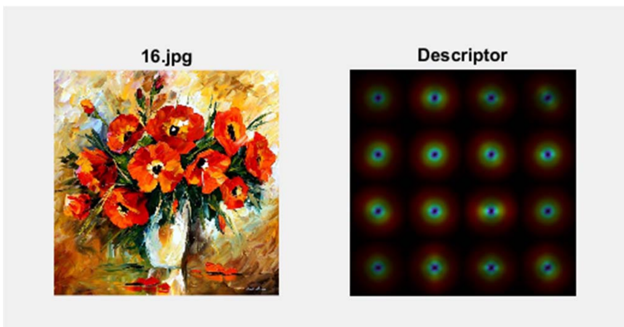

Figure 6. Extraction of GIST Features
(a)Original Painting (b) GIST Descriptor

After extracting the required features, a regression model was trained with image features as predictor variables and user rating as the response variable. Fig. 4 represents the block representation of proposed approach.

IV. EXPERIMENTAL RESULTS

This section describes the results of the proposed algorithms for classifying and assessing the aesthetic score of paintings. The results are described in two sections: first section describes about Classification problem and second section discusses about Evaluation problem.

A. Classification of Paintings

We used 2 layers ('fc6'&'fc7') of pre-trained AlexNet convolutional network for extracting the features of paintings. AlexNet extracted 8192 features (4096 by each layer). These features were then used to train an SVM classifier. Fig. 7 illustrates the confusion matrix obtained after using AlexNet and SVM for classification.

	A	B	C	D	E	F	G
A	**0.927273**	0.036364	0	0.018182	0	0.018182	0
B	0	**1**	0	0	0	0	0
C	0.072727	0	**0.836364**	0.054545	0	0.036364	0
D	0	0	0.054545	**0.854545**	0.054545	0.018182	0.018182
E	0	0	0	0	**0.963636**	0.036364	0
F	0.018182	0	0	0	0.054545	**0.927273**	0
G	0.018182	0	0	0	0	0	**0.981818**

A: Animal B: Car C:Flower D:Fruit
E:Monument F:Mountain G:Portrait

Figure 7. Confusion Matrix.

The model gave excellent results which is evident from the confusion matrix shown above. Paintings of Car, Portrait and Monument gave the best results whereas Paintings of Flower and Fruits gave results with very good accuracy. The proposed method obtained overall **92.73%** accuracy in classifying the paintings.

B. Aesthetic Evaluation of Paintings

After training a regression model, aesthetic scores of test data were predicted and compared with actual ratings given by the participants during the survey. Since prediction of exact aesthetic score of a painting is quiet difficult, following formula was used to determine the accuracy of our predictions:

If **| predicted_rating - average _rating | <= 1,** the prediction is said to be correct. Using described formula, our model was able to predict aesthetic scores of 247 paintings out of 385 test paintings according to the given range, thus giving an accuracy of **64.15%.** Fig. 8 illustrates the results obtained in this phase.

V. CONCLUSION AND FUTURE SCOPE

The experiments and data analysis in this project investigated a machine learning solution to aesthetic evaluation of paintings and artworks. The classification done, using CNN and SVM classifier, performed with an accuracy of 92.73% for over thousand paintings of seven categories. Evaluation of a painting is a complex task which sometimes depends on user's taste and understanding. Accuracy of 64.15% is achieved using image features like HOG, LBP, GIST etc combined with inputs from 60 persons on each painting. From the accuracy achieved it can be concluded that using image features and machine learning approach we can evaluate the aesthetic value of paintings. It is possible to improve the performance of the model by using more features and taking ratings from people of various domains. After improving the performance of the model it may be helpful in optimizing the search engines to show relevant images and paintings to the users. The search engine will show the results based on the aesthetic value input by the user. It would also be helpful in enhanced management of paintings. Art galleries and museums would be highly benefited by the aesthetic evaluation as it will help in attracting the right audience. More complex implementation can enable robots to automatically paint as per the requirement of the users or evaluate and provide guidelines to improve and enhance already existing artworks.

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Figure 8. Result of Aesthetic Evaluation. (a) Correct Prediction (Green) (b) Wrong Prediction (Red)