A Survey of Hand Crafted and Deep Learning Methods for Image Aesthetic Assessment

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Abstract—Automatic image aesthetics assessment is a computer vision problem that deals with the categorization of images into different aesthetic levels. The categorization is usually done by analyzing an input image and computing some measure of the degree to which the image adhere to the key principles of photography (balance, rhythm, harmony, contrast, unity, look, feel, tone and texture). Owing to its diverse applications in many areas, automatic image aesthetic assessment has gained significant research attention in recent years. This paper presents a literature review of the recent techniques of automatic image aesthetics assessment. A large number of traditional hand crafted and deep learning based approaches are reviewed. Key problem aspects are discussed such as why some features or models perform better than others and what are the limitations. A comparison of the quantitative results of different methods is also provided at the end.

Index Terms—Image aesthetic assessment, feature extraction, classification, convolutional neural networks, deep learning

I. INTRODUCTION

It may be true that beauty lies in the eyes of the beholder but quantifying the beauty of a photograph is a challenging task for a computer to perform automatically. In computer vision, the task is known as automatic image aesthetics assessment and deals with quantifying the beauty, quality and impression of photographs for the categorization of images into different aesthetic levels. Image aesthetic assessment has diverse applications in many areas of multimedia content generation, processing and communication. For example, it can be used to benchmark image noise removal and image restoration algorithms. It can also be used for quality of service (QoS) monitoring in systems where images are digitally compressed, communicated and then decompressed. Image recognition and classification systems can also benefit from aesthetic assessment techniques [1]. For example, in biometric systems [2], image quality assessment can be used and image enhancement approaches can be applied to improve quality and accuracy in case of low quality image input [3][4][5]. Moreover, image quality assessment can be used in robotics where a robot automatically assess quality of image and change focus and position to recapture the image if quality metric is below some recommended level. Due to its significant application potential in the rapidly increasing digital camera and photography industry, automated image aesthetic assessment has recently gained notable research attention from computer vision and pattern recognition community [6][7][8][9][10].

Automatic image aesthetic assessment has many challenges. For example, the input visual data may contain noise and image artefacts such as illumination and environmental conditions. Focus and pose deflections introduce disparities in images. Images may be subject to variations in color harmony because of sensor resolution issues. Background clutter can also hinder accuracy of aesthetic assessment algorithms. Moreover, visual judgment conflicts of humans also translate to different challenges for image quality rating algorithms.

Over the past couple of decades, many computer vision techniques have been developed for image aesthetic/quality assessment. Both hand crafted features based approaches and deep learning based approaches have been exploited for the task. Hand crafted features based algorithms generally design filters to encode some aspect of the image aesthetics such as photographic rules, image texture, local and global content features etc. The represented aesthetics features are then fed to classical machine learning approaches to classify the image in different aesthetic levels. Deep learning based techniques use powerful deep neural networks to learn and encode the knowledge about image aesthetics from a large number of training images. Deep learning based methods are more accurate as they can model more complex image features and their relationships.

In this paper, we provide a survey of techniques for automatic image aesthetic assessment. Both hand crafted features based methods and the recent deep learning approaches are covered in detail by describing the basic framework of each technique, and discussion about their pros and cons. Experimental results of each technique in terms of accuracy, the dataset used and its size, and depth of each aesthetic rating algorithm are also discussed in the end.

II. HAND CRAFTED FEATURES BASED METHODS

Although hand crafted features are considered a thing of the past but they still provide a good insight into a computer vision task. Hand crafted methods mostly design some kind of pixel filters to extract or encode low level image features. Common features used by the hand crafted methods include color, contrast, saturation, brightness, texture and foreground background statistics, global features and local features ratio statistics [11]. Figure 1 summarizes different techniques based on the features they use to encode the aesthetic information about images. We discuss each of these categories in detail in the next sections.

A. Basic image features based methods

Lo et al. [12] proposed an intelligent photographic interface with on-device aesthetic quality assessment for bilevel image quality assessment on general portable devices and tablets (Fig. 2). In this framework, photographic rules were followed and a three layered structure was designed. The first layer extracted composition, saturation, color combination, contrast and richness features using hand-tuned techniques.
In the second layer, an independent SVM classifier [13] was trained for each feature perspective to obtain the feature index. In last layer, an overall aesthetic SVM classifier is trained to obtain the aesthetic score. This framework is tested on a Core i5 3.4MHz PC with 16GB RAM and on a tablet PC ASUS transformer TF101 with 1MHz CPU and 1GB RAM using CUHK dataset, comprising of 2078 high quality and 7573 low quality images. It provides an overall accuracy of 89% and consumes 82 ms on PC and 288 ms per image on Tablet.

Ditta et al. [15] presented a computational aesthetic algorithm. Region based features are extracted using k-means clustering algorithm. Using connected component technique, color segments are extracted from image. Region based features and texture information is utilized to assess the quality of images. After feature extraction, SVM classifier is trained that categorizes images into high and low aesthetic categories. A regression model [16] is also trained to obtain regression score. Dataset is collected from a photo sharing website consisting of 3581 images.

Mavridaki et al. [17] proposed a system using five basic photography rules: simplicity, colorfulness, sharpness, pattern and composition. Simplicity refers to capturing images with emphasized subjects. For colorfulness, k-means clustering is performed to separate different colors. For sharpness, no blur detection algorithm [18] is employed, and for pattern assessment, SURF point features [19] are extracted. For composition rule, landscape composition [20], and rule of thirds [21] are examined. All these features are combined in the last stage to produce a 1323 element feature vector, which is fed to an SVM classifier. The overall framework of the proposed system is depicted in Figure 4. This framework is evaluated on CUHKPQ, CUHK and AVA datasets. 12000 images are sampled from these datasets to build another dataset. The new dataset contains 6000 high quality and 6000 low quality images. The proposed framework achieves an overall accuracy of about 77.08 % accuracy.
Redi et al. [22] introduced a technique to access quality of digital portraits. The framework is based on features such as composition, scene semantics, portrait specific features, correct perception of signal and fuzzy properties. Five basic features are extracted from images. Composition rules are the essential and basic rules of photography including sharpness, spatial arrangement, lighting, texture, and color. Semantic contents represent overall depiction of photography including high-level features [23]. Correct perception of signals includes noise, contrast quality, exposure quality, and JPEG quality. Portrait specific features are position of face, face orientation, age, gender, eye, nose, and mouth position; contrast of foreground and background. Fuzzy properties are originality, memorability, uniqueness, and emotion depiction. After feature extraction, LASSO regression [24] is applied on composition features. For every feature group, regression parameters are learned and a correlation between predicted score and original aesthetic value is computed. Using regression on all features, an overall aesthetic score is predicted. Training and testing are performed on AVA dataset with 75.76% accuracy. First, the framework is tested on small scale and later it is tested on large scale, classifying the images as beautiful and non-beautiful by SVM classification.

Aydin et al. [25] proposed a photographic rating framework that computes aesthetic signatures using attributes of colorfulness, sharpness, depth, tone, and clarity. Their proposed framework works on 8-bit RGB images. In the first step, their algorithm converts the input image to double precision image and normalizes it. In the second step, an edge pyramid is computed with domain transform applied to each layer of pyramid. In the third step, a multi-scale contrast image is computed. Another data structure is built using detailed contrast images which is known as a focus map. A focus map indicates in-focus regions in the image and inverse of focus map depicts out-of-focus image regions. From this focus map, depth, colorfulness, sharpness, clarity, and tone features are computed. After computing the features, training is performed on 955 images randomly selected from DpChallange [27] dataset. Application domains for this research are HDR tone mapping, automatic photo editing applications, auto aesthetic analysis, and multi-scale contrast manipulation.

Pogacnik Domen et al. [28] proposed a photo aesthetic technique using feature extraction and SVM classifier. They proposed a photo aesthetic technique using feature extraction and SVM classifier. Three basic photography features including simplicity, composition, and color selection are considered for aesthetic assessment. Simplicity is determined by edge features and the ratio of background to image color palette. Composition is determined by rule-of-thirds and golden ratio. For the purpose of classifying image in high aesthetic score and low aesthetic score, SVM classifier is trained on Flicker and DpChallange datasets. 258 images are randomly selected from Flicker dataset and 1048 images are selected from DpChallange dataset with SVM classifier evaluated using 10-fold validation technique. 95% accuracy is achieved by using 73 features from each image.

We provide a comparative analysis of different handcrafted techniques using basic image features in Table I.

B. Texture and Foreground Background Statistics based Methods

In this subsection, we discuss various methods for image aesthetics, based on texture, foreground, and background.

Yang et al. [30] proposed a technique for landscape photo assessment. The basic flow of algorithm is shown in Figure 6. Generally, relation to photographic rules and clear definition (sharpness, clarity, and colorfulness) are basic building blocks of any images aesthetic algorithm. A framework is designed in which an image is displayed on a video display with 5 stimuli of image displayed on other video display in addition to a short task description. The stimuli are separately determined from image for each of five basic attributes: colorfulness, sharpness, depth, tone, and clarity. Task description contains aesthetic rating of image separately for each attribute. Their proposed framework works on 8-bit RGB images. In the first step, their algorithm converts the input image to double precision image and normalizes it. In the second step, an edge pyramid is computed with domain transform applied to each layer of pyramid. In the third step, a multi-scale contrast image is computed. Another data structure is built using detailed contrast images which is known as a focus map. A focus map indicates in-focus regions in the image and inverse of focus map depicts out-of-focus image regions. From this focus map, depth, colorfulness, sharpness, clarity, and tone features are computed. After computing the features, training is performed on 955 images randomly selected from DpChallange [27] dataset. Application domains for this research are HDR tone mapping, automatic photo editing applications, auto aesthetic analysis, and multi-scale contrast manipulation.

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Table I: Comparative analysis of hand crafted techniques using basic image features for image aesthetic assessment.

| Author            | Year | Features                      | Classifiers | Dataset                  | Dataset Size | Categorization | Accuracy |
|-------------------|------|-------------------------------|-------------|--------------------------|--------------|----------------|----------|
| Ditta et al.      | 2006 | Color, Hue, Saturation        | SVM         | PhotoWeb                 | 3,581        | Bilevel        | 71%      |
| Li et al.         | 2010 | Color, Contrast, Brightness   | Linear Regression | Self Collected           | 510          | Multi Level    | 72%      |
| Gadde et al.      | 2011 | Color, Contrast, Brightness   | SVM         | DPChallange              | 12,000       | Bilevel        | 79%      |
| Pogacnik et al.   | 2012 | Color Selection, Simplicity, Composition | SVM         | Flickr, DPChallange      | 1,306        | Bilevel        | 95%      |
| Lo et al.         | 2013 | Color, Contrast, Saturation, Composition, Richness | SVM         | Photo Database           | 9,651        | Bilevel        | 89%      |
| Mavridaki et al.  | 2015 | Color, Sharpness, Composition | SVM         | CUHKPQ, CUHK and AVA     | 12,000       | Bilevel        | 77.08%   |
| Redi et al.       | 2015 | Color, Contrast, Sharpness, Texture | Sparse Coding & SVM | AVA          | 250,000       | Bilevel        | 75.75%   |
| Aydin et al.      | 2015 | Sharpness, Depth, Clarity, Tone, Color | SVM         | DPChallange              | 955          | Bilevel        | -        |

thirds, object of interest must lie at the center of the image. Color harmony is the relative position of each color in spatial domain. Color harmonic normalization \[31\] is performed by hue wheel. After feature extraction by relative foreground position features and color harmony features, support vector regression (SVR) algorithm \[32\] is trained to map the extracted features with the ground real aesthetics. After achieving the composition deviation, a mapping model is learned to predict aesthetic level. Their proposed method is tested on 431 images from Flickr \[33\] and Pconline, and it achieves 84.83% accuracy.

Bhattacharya et al. \[34\] presented a photo quality assessment and enhancement algorithm. Relative foreground position and visual weight ratio features are extracted from image and fed to SVR for training. After computing the aesthetic score between 1 to 5, if appeal factor is lower, than the image is edited. Architecture of their proposed framework is depicted in Figure \[7\]. 632 images are downloaded from Flickr. The dataset consist of 384 single object images and 248 images are scene images. This approach achieves 86% accuracy.

Bhattacharya et al. \[35\] presented an image aesthetic assessment framework for videos. As the algorithm deals with videos, three levels of features are extracted including cell level, frame level and shot level. Cell level features include dark-channel, sharpness and eye sensitivity. For frame level, Sentibank library \[38\] is used to detect 1200 dimensional feature vector. For shot level foreground motion \[39\], \[40\], \[41\], \[42\], background motion and texture dynamics \[43\] are detected from the video. For every specific feature a different SVM is trained. At the end all SVM scores are fused using low rank late fusion (LRLF) \[44\] and the algorithm is evaluated using NHK dataset \[45\] comprising of 1000 videos.

Yen et al. \[36\] proposed an image aesthetic assessment
Table II: Comparative analysis of hand crafted techniques using texture and FG/BG features for image aesthetic assessment.

| Author          | Year | Features                                                                 | Classifiers | Dataset          | Dataset Categorization | Accuracy |
|-----------------|------|---------------------------------------------------------------------------|-------------|------------------|------------------------|----------|
| Yang et al.     | 2015 | Color, Relative Foreground Position                                       | SVR         | Internet         | Five level             | 84.83%   |
| Bhattacharya et al. | 2010 | Foreground Position, Visual Weight Ratio                                  | SVR         | Flickr           | Bilevel                | 87.3%    |
| Bhattacharya et al. | 2013 | Sentibank Features, Foreground background features, Spatio-temporal binary patterns | SVM         | NHK Video Database | Bilevel                | -        |
| Lo et al.       | 2012 | Global Texture, Edge Composition, Layout Composition and Color Palette    | SVM         | CUHK             | Bilevel                | 86%      |
| Wang et al.     | 2010 | Global features, Salient regions features and foreground-background relationship features | SVM         | Photo.net        | Bilevel                | 83.7%    |

algorithm using color palette, layout composition, edge composition and global texture features. Color palette features are extracted by histogram of HSV color components. Layout composition features are determined by computing L1 distance between H, S and V channels. Edge detection filters compute edge composition features and finally global texture features are computed by sum of absolute differences between four channels. In addition to above mentioned features, blur, dark channel, contrast and HSV counts are also computed. An SVM classifier is trained on CUHK dataset. The classifier rates the image in high and low aesthetic levels. This framework provides 86% accuracy in their experiments.

Wang et al. [37] presented an algorithm for image aesthetic level prediction by using saliency enhancement. They use salient region of image to represent objects. Saliency map is computed by Itti’s visual saliency model [47]. After computing saliency map and detecting saliency locations, visual features are extracted from image including global features, features of saliency regions and foreground-background relationship features. Global features extracted for this purpose are texture details, low depth of fields and rule of thirds. Distribution, position and area of salient regions are determined as features of salient regions. Foreground-background relationship is represented by hue count and edge spatial distribution. Images are classified into high and low aesthetic levels by an SVM classifier trained on dataset downloaded from Photo.net [48]. The dataset contains 3161 images. Their proposed framework provides 83.7% accuracy.

In Table II we have presented the comparative analysis for image aesthetics prediction using foreground and background features.

C. Local and Global Features based Methods

Gao et al. [49] explored the multi-label task for assessing aesthetic quality of images based on different aesthetic attributes like aesthetic, memorable and attractive attributes using high level semantic information. The block diagram of their algorithm is shown in Fig. 8. A Bayesian Network (BN) [50] is designed to predict the aesthetic level using multi aesthetic attribute prediction. A three node BN presents each aesthetic attribute including its label, value and measurement. There are two modules of this framework measurement acquisition and multi attribute relation modeling. Measurement acquisitions are obtained by SIFT [51], GIST [52], HOG [53] or self-similarities and finally a support vector regression (SVR) is trained to predict the measurements. In building model, ground truth values are discretized and a hybrid BN

![Figure 8: The framework proposed by et al. [49]](image-url)
structure is learned on both continuous and discrete values. Memorability dataset [54] is used for testing and training, containing 2222 images. Training is performed using 10 fold cross validation. The framework is evaluated on three different metrics, F1-score, Kappa and accuracy.

Yin et al. [55] proposed a scene dependent aesthetic model (SDAM) based aesthetic assessment framework. They take into account both visual content and geo-context by utilizing transfer learning [56] approach. Input images along with their geo-context (online images with similar contents as that of input image) are used. Two types of images are used to learn SDAM. One category is geo contextual images that are location wise similar online images and in other category similar class images from available database (DB) are used. If sufficient number of contextual images are available, machine learning [57] approaches are applied to access the quality of input image. The framework of algorithm is depicted in Figure 9. Contextual image retrieval may contain images of same location but with different objects. These types of irrelevant images are identified by GIST and discarded. To learn SDAM state vector machine, (SVM) is trained. The algorithm is tested on 9600 geo-tagged images and 32000 auxiliary dataset images [BG: and it achieves an accuracy of 81% on famous spots and 73% accuracy on images of less famous locations.]

Wang and Simoncelli [63] presented an image aesthetic assessment framework using wavelet domain natural image statistical model. They provide a distortion measure algorithm for communication systems where images are transferred from one location to other. Input Image is decomposed into 12 wavelet bands including 3 scale and 4 orientations. Six wavelet bands are randomly selected to extract features and minimize KLD [64]. KLDs provide quality score to rate image in different distortion levels. Architecture of the proposed deployment scheme is given in Figure 11. The framework is tested on LIVE database containing 489 images providing 92% accuracy.

Riaz et al. [65] proposed a framework for photo quality assessment using generic features including both global and local features. They extracted SURF features in addition with Wavelet and composition features. Also the basic photographic features, color combination, saturation, contrast, smoothness, intensity, hue and aspect ratios are determined from the input image. In the first step, the online database comprising of 250 images is downloaded from Photo.net. In the second step, images are rated by human professionals and further in third step above mentioned features are extracted. An artificial neural network is trained on these features and scores are calculated. This framework achieves 83% accuracy. Table III presents a comparative analysis of image aesthetic prediction using local and global features.

D. Content Based Methods

Nishiyama et al. [66] use bag-of-color patterns for quality classification of photographs. Aesthetic quality is highly based on local region’s sum of color harmony scores. Sum of color harmony scores is computed by moon and spencer model [67]. Shown in Figure 12. Local regions of images are sampled and hue, chroma and lightness values are evaluated by applying a color model to each local region. These distributions
Table III: Comparative analysis of handcrafted techniques using local and global features for image aesthetic assessment.

| Author       | Year | Features            | Classifiers | Dataset            | Dataset Size | Categorization | Accuracy |
|--------------|------|---------------------|-------------|--------------------|--------------|----------------|----------|
| Gao et al.   | 2015 | SIFT, GIST          | BN, SVR     | Proprietary        | 2,222        | Bilevel        | 72.7%    |
| Yin et al.   | 2012 | GIST, SDAM          | KNN, SVM    | Flickr             | 10,200       | Bilevel        | 73 %     |
| Saad et al.  | 2012 | DCT                 | Bayesian    | LIVE               | 799          | Bilevel        | 91%      |
| Wang et al.  | 2005 | Wavelet             | KLD         | LIVE               | 489          | Bilevel        | 92%      |
| Riaz et al.  | 2012 | SURF, Wavelet &     | ANN         | Photo.net          | 250          | Bilevel        | 83%      |

are then integrated to form a bag-of-features framework. Every local region is described by these features using simple color patterns of color harmony models. Color distribution in a local region is assumed to be simple. Aesthetic rating is classified by calculating histogram of each color pattern. At the end SVM classifier is trained to predict quality of photograph. 124,664 images are collected from DPChallange database and are categorized in high and low aesthetic quality levels. The algorithm is tested in two different scenarios. 1) Whole image and 2304 local regions each of size 32x32, and (2) absolute and relative color values. It provides an overall 77.6% accuracy. In addition to color harmony patterns, saliency, blur and edges features are also taken into consideration which further improves the classification accuracy.

Marchesotti et al. [70] proposed an image descriptor based photo quality assessment algorithm. Fisher vector (FV) [71] and bag-of-visual-words [72] are used in this research for extracting generic descriptors from image. For both descriptors, Scale Invariant Feature Transform (SIFT) is used for gradient information. Input image is divided into patches and for each patch discrete distribution is calculated by BOV and continuous distribution is calculated by FV. SIFT is also applied to each patch and in addition to SIFT, GIST descriptor is also considered, which was initially designed for scene categorization. The algorithm is evaluated on two datasets Photo.net and CHUK dataset. Photo.net dataset consists of 3581 images and CUHK dataset consists of 12,000 images. 32 x 32 size patches are extracted from image and BOV and FV are computed from these patches at 5 different scales. Patches are represented by SIFT features which generate 128 dimensional feature vector for each patch which is reduced to 64 dimensions using PCA. Visual vocabulary Gaussian mixture models are learned by EM algorithm. SVM classifier is learned using hinge loss and stochastic gradient descent algorithm [73], [74]. In their experiments Fisher Vector outperforms all other technique and archives maximum of 78% accuracy.

Tang et al. [75] proposed a content based photo quality assessment algorithm. They deal with both regional and global features. Features are extracted with respect to three different areas including clarity based detection, layout based detection and human based detection. Regional features are extracted from input image are dark channel, clarity contrast, lighting contrast, composition geometry, complexity and brightness. Global features include hue composition and scene composition features. An SVM classifier is trained on CUHKPQ database including 17673 images. The classifier classifies images into high, low and uncertain categories. This algorithm provides 83% accuracy.

Zhang et al. [76] presents a perception guided image aesthetic assessment algorithm. Their proposed model is learned by a sparsity constrained learning algorithm as shown in Figure 13. Different low rank graphlets are created by fusing...
Table IV: Comparative analysis of hand crafted techniques using content based features for image aesthetic assessment

| Author          | Year | Features                          | Classifiers | Dataset          | Dataset Categorization | Size    | Task   | Accuracy |
|-----------------|------|-----------------------------------|-------------|------------------|------------------------|--------|--------|----------|
| Nishiyama et al. [66] | 2012 | Bag-of-Words                      | SVM         | DPChallenge      | Bilevel                | 124664 |        | 77.6%    |
| Marchesotti et al. [70] | 2011 | Fisher Vector, Bag-of-Words       | SVM         | Photo.net, CHUK  | Bilevel                | 15,581 |        | 78%      |
| Tang et al. [75] | 2013 | Dark Channel & Scene Composition  | SVM         | CUHKPQ           | BiLevel                | 17673  |        | 83%      |
| Zhang et al. [76] | 2014 | Sparsity constrained learning & Actively viewing path | GMM         | CUHK, Photo.net, AVA | BiLevel                | 40581  |        | 85.5%    |
| Su et al. [77]   | 2011 | Bag-of-Aesthetics Features        | Adaboost    | DPChallenge & Flickr | BiLevel                | 3000   |        | 92.06%   |
| Sun et al. [78]  | 2015 | Component Layer Features & Global Features | SVM         | CHAED             | BiLevel                | -      |        | -        |

low level and high level features from image. Sparsity of these graphlets is then calculated to generate jointly sparse matrices. These graphlets turned into actively viewing path (AVP) descriptors. Distribution of these aesthetic descriptors are learned by Gaussian Mixture Model. Proposed algorithm is trained and tested on AVA [79], Photo.net and CUHK datasets. CUHK dataset consists of 12000 photos, photo.net consists of 3581 images and AVA contains 25000 images. This algorithm provides 90.59% accuracy on CUHK dataset, 85.52% accuracy on Photo.net and 84.13% accuracy on AVA dataset.

Su et al. [77] proposed a modeling method that uses bag-of-aesthetics preserving library. The algorithm is implemented in two steps. In first step image is decomposed into multiple resolutions followed by extraction of bag-of-aesthetics features. HSV color space, local binary patterns and saliency map are used to extract features from images. The framework of their proposed algorithm is shown in Figure 14. AdaBoost classifier is trained and tested on a dataset of 3000 images downloaded from DPChallenge and Flickr providing 92.06% accuracy.

Rongju et al. [78] explored another problem of artificial intelligence to evaluate quality of Chinese handwriting. Proposed algorithm is composed of three steps. In first step component layout features and global features are extracted from Chinese handwritten image. For component layout features extraction stroke components are extracted by semi-automatic component extraction method. Alignment, stability and distribution of white spaces and gap between strokes are global features which are extracted from input Chinese handwritten image. A novel dataset is built by researchers which they named as CHAED [80] which is used to train SVM classifier.

Table IV presents a comparative analysis for image aesthetic prediction using content based features.

### III. Deep Learning Based Methods

Deep learning uses the power of artificial neural networks to automatically learn complex low and high level features that are useful for the computer vision tasks. In many cases, deep learning has produced results compared to human accuracy or even surpassing humans in many areas. Convolutional neural networks are the back bone of deep learning for image analysis [81][82]. These networks once trained on millions of images can provide outstanding accuracy on image understanding tasks such as image aesthetic assessment. In this section, we discuss various important works for image aesthetics prediction using deep learning methods.

Zhou et al. [83] proposed a deep neural network for photo quality assessment. Their dataset is collected from internet consisting of 28896 images where each image is resized to 160 x 120 resolution and features are extracted from images by converting them to HSV color space. A deep autoencoder
Figure 15: Flowchart of the scheme proposed by Zhou et al. [83].

is designed using a five layer using non recurrent multi-layer perceptron that encodes feature vector of length 56 to a feature vector of length 28. Overall structure of their proposed scheme is depicted in Figure 15. This scheme is tested on an AMD Athlon II PC providing 82.1% accuracy.

Kao et al. [84] proposed a deep learning photo aesthetic assessment algorithm which performs aesthetic rating using semantic information. The algorithm provides both aesthetic and semantic labels as output. A multitask convolutional neural network (MTCNN) [85] is designed that performs both semantic segmentation and quality assessment considering input image size of 227 x 227. The proposed CNN automatically learns relation between semantics and aesthetics. Their CNN consists of five convolutional layers, three pooling layers and three fully connected layers. Proposed Convolutional neural network architecture is shown in Figure 16. Further three representations of the MTCNN are proposed in which different configurations of convolutional layers and pooling layers [86], [87], [88] are designed. Multi task probabilistic framework is applied. Network is trained and tested on AVA dataset and Photo.net dataset. AVA dataset consisting of 255,000 images and photo.net dataset comprising 20,278 images. On AVA dataset, MTCNN achieves up to 77.71% accuracy and on Photo.net it achieves up to 65.20% accuracy.

Figure 16: Architecture of the system proposed by Kao et al. [84].

Bianco et al. [90] used deep learning to predict image aesthetics using aesthetic visual analysis (AVA) dataset. In this model, canonical convolutional neural network architecture is fine tuned to obtain aesthetic scores. Aesthetic quality assessment is treated as a regression problem. Caffe network [91] is selected to be fine-tuned and last fully connected layer of Caffe net is replaced by a single neuron providing aesthetic score between 1 and 10. Another modification is incorporated in Caffe Net to use Euclidean loss [92] instead of Softmax loss [93]. The new network is fine-tuned by stochastic gradient descent back propagation algorithm. The dataset contains 255,000 images, from which 250,129 images are used for training and 4970 images are used for testing. The algorithm achieves 83% accuracy.

Figure 17: Framework of the system proposed by Kao et al. [89].

Kao et al. [89] proposed an aesthetic quality assessment algorithm using convolutional neural network. There are three categories defined for each image: scene, object and texture. For each category there is separate convolutional neural network named as Scene CNN, Object CNN and Texture CNN. In addition another A&C CNN is deployed which performs recognition of quality and aesthetic rating. Each CNN provides aesthetic label in addition to aesthetic scores. Figure 17 shows overall structure of implemented scheme. A SVM classifier prior to CNNs classifies image into scene, object and texture. The algorithm is tested on AVA dataset containing 255,000 images. It achieves 91.3% accuracy. Scene, object and texture CNN are highly dependent on classification accuracy of SVM classifier. If SVM provides wrong classification than wrong CNN gets activated and output wrong results.

Figure 18: Architectures of different models proposed by Kong et al. [94].
Kong et al. [94] proposed a deep convolutional neural network using content adaptation technique. A new dataset is published by these researchers which they named as aesthetics and attributes database (AADB) [95] comprising 10,000 images. AlexNet architecture [96] is fine-tuned on AADB dataset. Softmax loss is replaced by Euclidean loss. Another Siamese network [97], [98] is fine-tuned with content category classification and attribute layers to achieve hybrid performance. An attribute adaptive model and a content adaptive model are designed. Figure 18 shows three different models initially based on AlexNet. Model (a) uses shared low level layers of AlexNet and adopts Euclidean loss and Ranking loss whereas model (b) is an attribute adaptive net that has an additional attribute predictor branch. Model (c) provides a combined approach of content adaptive net and attribute adaptive net. It takes an input image of size 227 x 227 and provides 77.33% accuracy.

Lu et al. [99] proposed a content adaptive aesthetic rating convolutional neural network. A two column novel neural network is proposed that takes into account both style contents and semantic information. Each column is trained on two different crops of single image. Each column consists of three convolutional layers and three pooling layers followed by a fully connected layer. Finally style and semantic features extracted by both columns are fused by two fully connected layers as shown in Figure 19. The network is trained using end to end learning and stochastic gradient descent. A network adaptation strategy is proposed to facilitate content based image aesthetics. This helps improving adaptation of semantic contents of images and hence fewer images from each category are required for training. A regularized double column convolutional neural network (RDCNN) is proposed which includes a style single column convolutional neural Network (Style-SCNN) for style information and a double column convolutional neural network (DCNN) for semantic information. Final structure of the framework is shown in Figure 20. This network is tested on AVA dataset and IAD dataset [100] to categorize images into high and low quality and achieves 71.2% accuracy.

Mai et al. [101] proposed a photo aesthetic algorithm using composition preserving convolutional neural network. The algorithm incorporates concept of image quality degradation by resizing and clipping. multi net adaptive spatial pooling convolutional neural network (MNA-CNN) is designed to rate variable size images. For this purpose, an adaptive spatial pooling layer is introduced that adjusts its receptive size according to output rather than input. There are multiple streams of network [102] where last pooling layer is replaced by adaptive spatial pooling layer. Pre-trained VGG-Net [103] is fine-tuned on Torch Deep Learning package [104] and each sub network is trained separately. Another scene categorization CNN is trained on Places205-GoogleLeNet consisting of 2.5 million images. This framework is shown in Figure 21. Scene categorization network increases aesthetic assessment accuracy to 77.1% accuracy.

Wang et al. [105] fine-tuned a pretrained convolutional neural network for accessing quality of images. AlexNet and VGGNet are fine-tuned to provide output in two categories (high and low). VGGNet is a deeper network as compared to AlexNet; providing high accuracy and requires more training time. AlexNet is composed of five convolutional layers with ReLU non linearity, five pooling layers and three fully connected layers. The last layer is replaced by a fully connected layer for two class classification. VGGNet is a much deeper network consisting of sixteen to nineteen convolutional and pooling layers. The networks are trained by both global and local views. A V A and CUHKPQ datasets are used to fine-tune both AlexNet and VGGNet. Both the networks are trained on both the global and local views. Alexnet achieves 91.20% accuracy CUHKPQ dataset and VGGNet achieves 91.93% accuracy. AlexNet achieves 83.24% accuracy on A V A dataset and VGGNet achieves upto 85.41% accuracy.
Lu et al. [106] proposed an image aesthetic network using deep learning in. They take ResNet-152 network which was trained on ImageNet dataset for object classification and further fine-tuned on AVA, Places and emotion6 datasets. Network is trained for four different categories; scene images, object images, emotion images and general semantic images as depicted in Figure 22. For the scene images 2.5 million images from Places dataset [107] are used to fine-tune ResNet-152. For object images network is trained using AVA dataset and emotion images network is trained on Emotion6 dataset consisting of 1980 images. This network achieves 78.6% accuracy.

Figure 22: Deep semantic aggregation network proposed by Lu et al. [106].

Wang et al. [108] proposed a brain inspired deep neural network (BDN) for image aesthetic assessment. BDN is composed of two parts, first part is an attribute learning via parallel pathways and the second part is a high level synthesis network as shown in Figure 23. Attribute learning via parallel pathways is a combination of deep neural network streams. Different attributes are learned from input images including hue, saturation, value, complementary colors, duotones, high dynamic range, image grain, light on white, long exposure, macro, motion blur, negative image, rule of thirds, shallow DOF, silhouettes, soft focus and vanishing point. Hue, saturation and value are directly computed from image whereas the other attributes are learned using parallel deep neural networks as shown in Figure 24. This network predicts a label 0 or 1 and trained using AVA dataset. Their high level synthesis network is a four layer convolutional neural network. This network predicts overall aesthetic level of image. At this stage entire network is trained end-to-end using AVA dataset. Experiments are performed on 12 CPUs (Intel Xeon 2.7 GHz) and a GPU (nVidia GTX680). Training and fine-tuning takes around 1 day with an accuracy of 76.80%.

For image aesthetic quality assessment, Liu et al. [109] proposed a semi-supervised deep active learning (SDAL) algorithm, which discovers how humans perceive semantically important regions from a large quantity of images partially assigned with contaminated tags.

Fu et al. [110] considered the global, local and scene-aware information of images into consideration and exploits the composite features extracted from corresponding pretrained deep learning models to classify the derived features with support vector machine. They found that deep residual network could produce more aesthetics-aware image representation and

Figure 23: Brain inspired network architecture proposed by Wang et al. [108].

Figure 24: Attribute learning via parallel pathways proposed by Wang et al. [108].

composite features.

Li et al. [111] introduced an end-to-end personality driven multi-task deep learning model to assess the aesthetics of an image as shown in Fig. 25. Firstly, both image aesthetics and personality traits are learned from the multi-task model. Then the personality features are used to modulate the aesthetics features, producing the optimal generic image aesthetics scores.

Figure 25: The architecture of the multi-task learning model by Li et al. [111].

Chen et al. [112] developed an adaptive fractional dilated convolution, which is aspect-ratio-embedded, composition-preserving and parameter-free. The fractional dilated kernel is adaptively constructed according to the image aspect ratios, where the interpolation of nearest two integer dilated kernels are used to cope with the misalignment of fractional sampling.

Li et al. [113] presented a personality-assisted multi-task
Table V: Comparative analysis of deep learning techniques for image aesthetic assessment.

| Author       | Year | Layers                                                                 | Dataset          | Dataset Size | Classification Levels | Accuracy |
|--------------|------|------------------------------------------------------------------------|------------------|--------------|-----------------------|----------|
| Lu et al.    | 2014 | Six Conv layers, six Pool layers and three FC layers                  | AVA              | 255000       | Bilevel               | 71.2%    |
| Zhou et al.  | 2015 | Two Conv layers, two Pool layers and one FC layer                     | Dattrra          | 28896        | Bilevel               | 82.1%    |
| Kao et al.   | 2016 | Five Conv layers, three Pool Layers and one FC layer                  | ATA & Photo.net  | 275278       | Bilevel               | 79.08%   |
| Mai et al.   | 2016 | 12 Conv. layers, 5 Pool layers, 3 FC layers                           | Places205-       | 2.5 million & | High & Low            | 77.1%    |
| Wang et al.  | 2016 | Five Conv layers, Five Pool layers and Three FC layers                | AVA & CUHKPQ     | 272960       | High & Low            | 91.93%   |
| Liu et al.   | 2018 | Semi-supervised active learning                                       | CUHK, Photo.net  | 12000, 3581 &| Bilevel               | 94.65%   |
| Fu et al.    | 2018 | Different deep learning models                                        | AVA              | 250000       | High-low              | 90.01%   |
| Li et al.    | 2019 | DenseNet121                                                            | AVA              | 250000       | Bilevel               | 81.50%   |
| Chen et al.  | 2020 | ResNet-50                                                              | AVA              | 250,000      | Bilevel               | 83.24%   |
| Li et al.    | 2020 | Siamese network                                                        | AVA              | 250,000      | Bilevel               | 83.70%   |
| McCormack and Lomas et al. | 2021 | ResNet-50                                                              | Lomas dataset    | 1774         | Multilevel            | 97%      |
| Zhang et al. | 2021 | InceptionNet                                                           | AVA              | 250,000      | Bilevel               | 86.66%   |

In this section, we provide a comparative performance analysis of both hand crafted and deep learning based methods. We use dimension reduction methods to visualise both genotype and phenotype space in order to support the exploration of new territory in a generative system. Convolutional neural networks trained on the artist’s prior aesthetic evaluations are used to suggest new possibilities similar or between known high-quality genotype-phenotype mappings.

Zhang et al. [115] proposed a multimodal self and collaborative attention network as shown in Fig. 27. The self-attention module finds the response at a position by attending to all positions in the images to encode spatial interaction of the visual elements. To model the complex image-textual feature relations, a co-attention module is used to jointly perform the textual-guided visual attention and visual-guided textual attention.

Table V presents comparative analysis of deep learning methods for image aesthetics prediction.

IV. PERFORMANCE ANALYSIS

In this section, we provide a comparative performance analysis of both hand crafted and deep learning based methods. We provide an overview of how the reviewed techniques are different from each other with respect to features utilized, accuracy, dataset size and classifiers used.

Figure 26: The personality-assisted multi-task learning model by Li et al. [113].

McCormack and Lomas [114] used a convolutional neural network to investigate the relationship between image measures, such as complexity, and human aesthetic evaluation. We use dimension reduction methods to visualise both genotype and phenotype space in order to support the exploration of new territory in a generative system. Convolutional neural networks trained on the artist’s prior aesthetic evaluations are used to suggest new possibilities similar or between known high-quality genotype-phenotype mappings.
A. Performance Analysis of the Hand Crafted Methods

Figure 28 shows accuracy achieved by various hand crafted techniques based on basic image features for image aesthetic assessment. The maximum accuracy is achieved by \[28\]. Figure 29 provides a distribution of classifiers used by basic hand crafted methods. Figure 30 provides a pictorial representation of different features extracted for basic hand crafted techniques.

Figures 31, 32 and 33 provide a comparison of accuracy, dataset size, classifier and features extracted for local and global features based methods.

Figures 34, 35 and 36 provide a comparison of accuracy, dataset size, classifier and features extracted for content based hand crafted methods.

For hand crafted state-of-art methods a large dataset is not required. Most of these techniques use few hundreds or few thousand of images for training of classifiers. Almost 75% of papers discussed in this survey used SVM classifier to classify images into high and low aesthetic levels and around 15% used support vector regression. Regression here
provides a continuous score on which threshold is applied for classification into different aesthetic levels. Hand-tuned approaches mostly rely on low level features. They do not take into account semantic information of images so provide a minimal scoped aesthetic rating.

**B. Deep Learning Methods Analysis**

In this section we present the comparative analysis of deep learning approaches for image aesthetic assessment. Figure 40 shows a comparison of accuracy achieved by various deep learning techniques for image aesthetic assessment. Deep learning techniques provide better accuracy as compared to hand crafted feature based techniques as they focus on broader picture including both low level and high level features. Convolutional neural network requires huge amount of data for training. The graph in Figure 40 depicts that the datasets are
Figure 40: Comparison of Accuracy for Deep Learning Techniques

larger in size as compared to the datasets used in hand crafted techniques. The depth of the network i.e. the number of layer for each paper is also represented in Figure 40. This figure shows that the accuracy may not be directly proportional to the depth of the network. Moreover, deep learning techniques also require more computational resources and time for their training and deployment.

V. CONCLUSION

Images may be degraded due to compression artifacts, illumination or lighting issues, pose or camera angle, sensor problems, background clutter and many other imperfections. Image quality assessment can be used to quantify such degradations which can then be analysed for corrections. With the rapid use of digital photographs in almost every field of life like medical, communication, safety, security, entertainment and sports etc., image quality assessment becomes a basic needed functionality. This paper provides a detailed review of image aesthetic assessment techniques available in the literature along with their strengths and shortcomings. The accuracy, dataset size, classifier selection and the choice of deep learning models used for each respective technique are also presented. Our paper also provides an insight for future research to compare the performance of different image aesthetic assessment algorithms.

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