The Development and Trend of Research on the Aesthetic Assessment of Multi-Theme Images

Wenjing Cao

***Abstract*— Image aesthetic assessment is a complex and subjective task intended for computers to mimic the process of human visual perception to score the aesthetics of an image. Current research in image aesthetic assessment focuses on learning the aesthetic features of an image through convolutional networks, and then aesthetically scoring the image based on the learned features, and researchers are committed to improving the aesthetic assessment method by considering a more comprehensive set of aesthetic features. From aesthetic dichotomy to aesthetic regression to aesthetic distribution, images can provide more and more rich aesthetic information, but the interpretability is still weak. In recent studies, researchers have found that thematic information of images can effectively improve the interpretability of aesthetic evaluation models. As a research theme that has emerged only in the past two years, the aesthetic assessment of multi-theme images is still in the early stage of research. There are still fewer papers in the research direction of multi-theme image aesthetic assessment, and this paper provides an overview of the multi-theme image aesthetic assessment model at this stage. Firstly, it analyzes the research status and development trend of image aesthetics assessment; then it gives an overview of the multi-theme image aesthetics assessment model at the present stage, and details the research status and future development trend of the multi-theme image aesthetics assessment model at the present stage.**

***Index Terms*— Terms—Multi-theme Image Aesthetic Assessment; Deep Learning; Image Aesthetic Learning**

I. INTRODUCTION

With the rapid development of mobile Internet, people can easily access a large amount of image data through mobile devices in their daily life, which greatly enriches people's visual experience. The beauty and aesthetics of images have become an important part of people's pursuit of spiritual life. Image aesthetic assessment (IAA) has become a hot research issue in the field of image processing and computer vision[1][2]. IAA can be applied to many practical scenarios such as image enhancement[3],image retrieval[4][5],photo album management[6] and recommendation system[7]. For example, when a user enters the word mountain scenery in an image search system, he would like to see colorful and pleasant mountain scenery or well-composed mountain peaks, rather than gray or blurred mountain scenery. At present, image aesthetics assessment has appeared in some practical applications, and achieved some success. For example, Luban system that automatically designs advertisement posters, Meituxiu software that automatically beautifies images, and Tencent video software that automatically selects video covers. Image aesthetics assessment has important theoretical research significance and practical application value. Early images by the equipment imaging technology and image processing technology will introduce different degrees of noise, researchers mainly through the image quality assessment (IQA) method to quantify the degree of image distortion[8]. With the gradual maturation of image imaging and processing technologies, people can not only obtain high-quality images relatively easily, and require images with both high-quality content and aesthetic appeal. For example, when cell phone users take pictures, the images not only require clear content, but also meet the user's aesthetic experience. Since human's aesthetic experience of images is influenced by both the objective content of images and human's own psychological factors, the evaluation of image aesthetics requires the joint support of multiple interdisciplinary disciplines such as psychology, aesthetics, and computer vision, and it is a very challenging research topic.

The current aesthetic assessment model can be divided into two stages: feature extraction and aesthetic decision-making. The key task of the image aesthetic assessment model is to correctly extract the aesthetic features in the image and make a reasonable decision. At the beginning of the aesthetic assessment task, researchers extracted specified aesthetic features by hand-designed methods. With the development of deep learning and further deepening of the technology, researchers introduced deep convolutional neural networks in the image aesthetic assessment task. Convolutional networks have a powerful automatic learning ability and do not require researchers to have a rich knowledge base of image aesthetics to automatically extract image aesthetic features. Convolutional layers of different depths can extract semantic features at different levels, and the extracted aesthetic features become more and more abstract as the network level deepens. Classical photography[9] shows that image aesthetics are closely related to the subject matter. To assess the aesthetics of an image, the first step is to focus on the theme of the image, and then use different evaluation criteria (Image → Theme → Aesthetics) for images with different themes to further extract various types of features of the image, as shown in Figure 1. This leads to the study of the aesthetic evaluation method of multi-theme images.

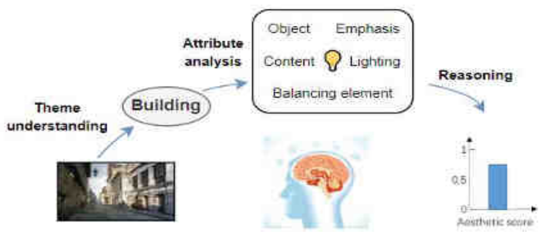

Fig. 1 Schematic diagram of human aesthetic mechanism

Manuscript received March 26, 2024

At present, the relevant review literature on image aesthetics evaluation at home and abroad mainly focuses on the research of generalized aesthetics assessment model[2][10][11]. Jin Xin et al[2] reviewed the development history of image aesthetic assessment, and overviewed the development of key technologies in this field from the perspective of methods, new challenges and database construction; Bai Ruyi et al[11] and Lu Yue et al[10] analyzed the current research status and development of the aesthetic assessment methods of painting images in detail from the perspective of art painting image classification. These reviews mainly discuss image aesthetic assessment methods from the perspective of popular aesthetics, and lack analysis and summarization of research progress related to multi-theme image aesthetic assessment models. In order to further expand and supplement the existing review literature on image aesthetic assessment, this paper summarizes the research progress of the multi-theme image aesthetic assessment model in detail.

II. Image Aesthetic Assessment

A. Research Status

What exactly is "beauty"? This question has long been debated in the fields of philosophy and aesthetics. The Ge--rman philosopher Alexander Gottlieb Baumgarten first put forward the concept of aesthetics in 1750 and called it "Aesthetic", or aesthetics. From the development of aesthetics, although the founder of aesthetics Baumgarten defined aesthetics as "the discipline of sense perception", but he focused on the examination of art, and since then aesthetics gradually limited to the philosophy of art. Subsequent studies of aesthetics have also tended to focus on the attitudes, values, and experiences of the aesthetic subject, and have lacked the study and methodology of the objective aesthetic object. Aesthetics was defined as a philosophical subdiscipline, and it was not until the development of other disciplines and methods in the twentieth century, such as psychology, sociology, neuroscience and the introduction of computational science, that it provided a new basis for the objective study of aesthetics and the revival of one of the concepts of Ancient Greek aesthetics, namely, "Beauty is in Proportion". Computational Aesthetics is one of the most representative research branches, and in the first half of the 20th century, George D. Birkhoff, an American mathematician, proposed that the ratio between order and complexity can be used as a kind of aesthetics measure[12]. Therefore, the main task of computational aesthetics is to develop new scientific methods to quantify beauty and to build models that mimic the process of human aesthetic perception[13]. With the continuous development of statistical physics and network science methods, as well as the exploration of big data collection, computational aesthetics can better quantify the study of what exactly evokes the pleasurable perception of beauty. Visual aesthetics is an important branch of human perception of beauty. Visual aesthetic quality is a measure of visually perceived beauty. The visual aesthetic quality of an image measures how visually appealing an image is to the human eye. The assessment of whether an image is aesthetically pleasing or not often involves emotions and personal tastes, making the assessment of image aesthetics a highly subjective task. However, there is often a consensus that some images are more visually appealing than others, which is one of the principles of computational aesthetics. By exploring how computational techniques can be used to predict human emotional responses to visual stimuli, computers can mimic human perception and cognition of beauty, and thus automatically assess the "aesthetics" of an image.

With the continuous progress of scientific computing methods and the rapid development of artificial intelligence disciplines, more and more researchers are committed to using scientific computational methods to find laws from the human aesthetic perception system. Researchers use objective computation to study subjective aesthetics, trying to derive a set of computer-understandable image aesthetic assessment methods. Therefore, the task of image aesthetic assessment is a highly subjective study. At present, image aesthetics assessment, as a popular research direction in computational aesthetics, has attracted the attention and research of domestic and foreign research institutions. The research results in this research direction have also shown a yearly growth trend in recent years, and these research results have promoted the rapid development of image aesthetics assessment.

B. Research Progress

Image aesthetic assessment task is currently one of the research hotspots in the field of computer vision, researchers for how to make computers learn to use human thinking to aesthetically assess the image to carry out research. Image aesthetic assessment task can be divided into two stages: image aesthetic feature extraction and aesthetic decision making. Initially, traditional manual feature extraction methods combined with expertise in the field of photography focused on the global features of the image.Datta et al[14] combined low-level and high-level features and trained an SVM classifier for high-quality and low-quality binary classification of the aesthetic quality of the image.Aydın et al[15] constructed the image through sharpness, depth, clarity, and hue of aesthetic attributes. Ultimately, the aesthetic quality score of an image is calculated based on the degree of influence of these five aesthetic attributes. Based on focusing on these global features, subsequent studies combined global saliency to compute the visual aesthetic distribution of an image. sun et al[16] used a global saliency map to compute the visual attention distribution and describe an image, and they trained a regressor to output the quality score of an image based on the rate of the focusing attention region in the saliency map. Luo et al[17] extracted clarity, contrast, color, and color tone from the region where the subject matter of an image is represented. The features such as clarity, contrast, lighting, geometric composition and color harmony are extracted from the image to evaluate the image aesthetic score.Wu et al[18] proposed the use of Gabor filters to estimate the position of the photographic subject in the image and to extract low-level HSV color features from the global and central image regions. These features were fed into an SVM classifier to predict words describing the aesthetic quality of the image.

With the continuous development of deep learning, automatically extracted deep image features based on CNNs surpass the performance of manual features, and different depths of convolutional layers can be extracted to different levels of semantic features.Lu et al[19] proposed the RAPID model which can be considered as the first attempt to use convolutional neural networks in visual aesthetics tasks. They used an AlexNet-like architecture to compute aesthetic quality binary classification of images.Tian et al[20] learned effective feature representations from CNNs and the authors proposed a query-dependent model as an aesthetic quality classifier. Specifically, for each input image, a query-dependent training set is retrieved based on predefined rules (visual similarity and image label association). Subsequently, an SVM classifier is trained on this retrieved training set. The results show that the features learned from aesthetic data outperform the general deep features learned in the ImageNet task. Deep convolutional networks can only receive fixed-size inputs, but the aesthetics of an image can be destroyed by operations such as cropping and scaling. Therefore, Mai et al[21] proposed an architecture (Multi-Net Adaptive Spatial Pooling ConvNet) that preserves the original size and aspect ratio of the input image, which consists of sub-networks with different adaptive spatial pooling (Adaptive Pooling) in order to achieve multi-scale feature extraction. At the time of testing, the final result of the model's computation of the aesthetic quality of an image is usually expressed mostly in the form of a high and low quality dichotomy and an aesthetic score, Talebi & Milanfar et al[22] proposed a new way of representing the results of the model's aesthetic assessment, where, for the first time, the computed aesthetic quality score is represented as a probability distribution over the interval of scores. It was found that this way of generating a histogram of scores is more in line with the assessment results as perceived by humans.

III. MULTI-THEME IMAGE AESTHETIC ASSESSMENT

A. Research Status

The key task in the assessment of image aesthetics lies in correctly selecting and extracting aesthetic features in images and making rational decisions. Recently, researchers[23] have suggested that when evaluating aesthetics, human beings either explicitly or implicitly take into account the influence of image themes, and that different thematic images focus on different aesthetic features. The current aesthetic assessment model directly learns the aesthetics of all thematic images without differentiation and ignores the correlation between themes and aesthetics hindering the further development of image aesthetics assessment.

In earlier studies, generic aesthetic assessment studies[24][25] also pointed out that the unconventionality of subject matter or style has a direct impact on aesthetic scores, but did not explicitly propose a solution for the impact of image theme interdependence on the aesthetic assessment model.Cui et al[24] proposed an improvement based on the VGG16 by developing a hybrid fully convolutional network that utilizes object and image scene semantic cues to predict their perceived aesthetic quality; Fu et al[25] proposed an effective solution to improve the accuracy of image aesthetic assessment by utilizing composite features generated by deep pre-trained convolutional neural networks, the proposed training-free method considers local, global and scene-aware information of an image and utilizes off-the-shelf deep learning models in the feature extraction process; in the most recent research, the He[23] et al. pointed out that existing IAA dataset labels generally do not consider that different themes have different scoring criteria, created a theme-oriented aesthetics dataset, TAD66K, and established a baseline model, TANet, which effectively extracts thematic information and adaptively establishes perceptual rules to evaluate images with different themes. The article demonstrates that TANet achieves state-of-the-art performance through large-scale testing. However, the complexity of multi-branching model and the difficulty of unifying the branching network parameters also have an impact on the model performance.Yang et al[26] proposed a MetaMP-based IAA method, which trains the network based on meta-learning to obtain content-oriented aesthetic representations. The meta-knowledge learned by the model from different short-term goals can be used to update the parameters of the long-term goals to quickly adapt to various thematic tasks. Meta-learning can assist the model in obtaining general initialization parameters related to the topic. For evaluation networks, initialization is usually performed by pre-trained weights, which are obtained based on a large amount of data, and then fine-tuned for the target IAA task. The obtained model weights are not accurate.

B. Aesthetic assessment model for multi-theme images

Theme and Aesthetics Network (TANet) He et al[23] formally proposed for the first time that images with different themes correspond to different assessment criteria. Learning aesthetics directly from images while ignoring the impact of theme changes on human visual perception hinders the further development of image aesthetics assessment, which is a challenge for image aesthetics assessment. In He et al.'s study, they constructed the first theme-oriented image database and proposed a benchmark model TANet for different themes based on the theme dataset.TANet consists of three parts, namely, Theme-aware Network (TUNet), RGB Attention-aware Network (RGBNet), and Aesthetic-aware Network (APNet).TANet can be used to predict the aesthetics of an image based on the recognized themes to adaptively learn rules for predicting aesthetics. To further improve the perception of each theme, the model adds an RGB distribution-aware attention network (RGBNet) to help the network perceive the color distribution in RGB space and solve the high complexity problem of standard attention.TUNet uses ResNet18 as the backbone S and is trained on a scene database, achieving a 85.03% top-5 accuracy. The scene database is a repository of 10 million images labeled with more than 400 unique topic semantic categories and environments, which almost covers the TAD66K dataset and topics in daily life. As a result, TUNet ultimately learns parameters that include both basic topic information and the rules that control how that information is perceived.

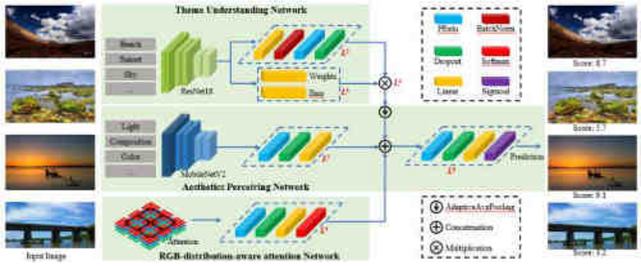

Fig. 2 Framework diagram of TANet model

Complete-information Patch Selection Scheme and a Multipatch Network(Mate MP) Yang et al[26] argued that directly fine-tuned pre-trained networks may not be able to adapt quickly to a variety of topics in an aesthetic assessment task. The performance of different aesthetic themes may be poor, and aesthetic criteria across themes should be established. In the case of data imbalance, the model should maintain its advantages. Therefore the article proposes a meta-learning based IAA method to quickly adapt to various theme tasks. The model trains metalearner by iteratively training images with different themes to obtain content-oriented aesthetic features and solve the problem of poor performance for different aesthetic themes. The generated parameters are then trained and tested with new image types. In addition, the article considers the interaction between the image as a whole and the details, and designs a full-information patch selection method from the image as a whole and the details. Thus, an image patch with rich details and matching the overall impression is obtained. the overall block diagram of the model is shown in Fig. 3.

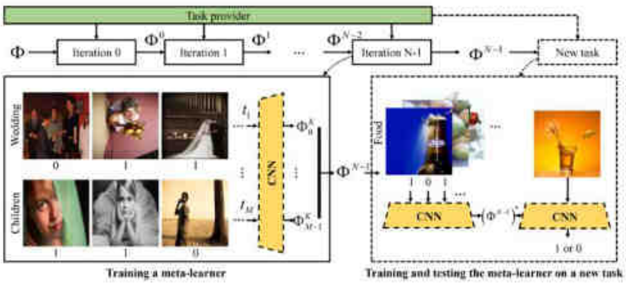

Fig.3 Mate MP model block diagram

IV. Assessment Indicators and Datasets

A. Assessment Indicators

The current research on the aesthetic assessment of multi-theme images is consistent with the research on generic aesthetic assessment. The degree of correlation between variables is measured by the correlation coefficient. A larger correlation coefficient indicates a higher degree of correlation between two variables, and in the multi-subject image aesthetics assessment task it indicates the degree of correlation between the predicted value of the aesthetics scores and the true value, and a larger correlation coefficient indicates a better model performance. These include Linear Correlation Coefficient (LCC) and Spearman's Rank Correlation Coefficient (SRCC).

$$LCC = \frac{\sum_{i=1}^{N}(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^{N}(y_i - \bar{y})^2}\sqrt{\sum_{i=1}^{N}(\hat{y}_i - \bar{\hat{y}})^2}} \#$$

where N denotes the number of images, y_i and $\hat{y}_i$denotes the true value and the predicted value of the ith image, respectively, $\bar{y}$ and $\bar{\hat{y}}$ denotes the average of the true value and the predicted value.

$$SRCC = 1 - \frac{6\sum_{i=1}^{N}(v_i - p_i)^2}{N(N^2 - 1)} \#$$

Where, N is the number of images, v_i and p_i is used to calculate the level difference between the true value and the predicted value.

When assessing the performance of the aesthetic assessment model, there exists a threshold value for the aesthetic score of an image. Generally when the aesthetic score is greater than this threshold, we consider the image to be of high aesthetic quality, and vice versa for low aesthetic quality. Accuracy is also a commonly used performance assessment metric for multi-theme aesthetic assessment tasks.

$$ACC = \frac{I_{Truth}}{I_{all}} \#$$

Where I_{Truth} is the predicted correct image and I_{all} is all images. When larger, it indicates that the model has better prediction performance for the aesthetic quality of the image.

B. Theme-oriented Image Datasets

There are many existing databases established for IAA research, but most of them are constructed for generalized aesthetic assessment tasks, such as AVA (aesthetic visual analysis)[27], AADB (aesthetics and attributes database)[28], etc., which makes the GIAA This makes the research of GIAA relatively mature and fast development. On the theme-oriented image database research, AVA as the most commonly used dataset in aesthetics tasks, the dataset also contains 66 semantic labels. These labels are not in the same dimension, some of them are describing the content of the image, such as water, architecture, and some of them are describing the style of the image, such as black and white.These labels also imply the thematic information of the image, but they are not strictly classified according to the theme in a systematic way.

TAD66K[23] serves as the first theme-oriented image dataset, which consists of 66K images containing 7 major categories and 47 subcategories of popular themes. Each image contains 1200 valid annotations. The researchers collected the most frequently downloaded themes from Flickr website from 2008 to 2021 to ensure the richness of the themes, which are 47 themes in total, and categorized these themes into 7 major categories, which are Plants, Animals, Artifacts, Colors, Humans, Landscapes, and Others. Previous scoring of image aesthetics suffered from long-tailed distributions, such as the AVA dataset, where images with scores of 5-6 were 2,700 times more common than images with scores of 1-10. For this reason, the researchers divided the images into three categories: good, average and bad, and maximized the diversity of the aesthetic scoring of the images by sampling the images in these three categories as evenly as possible. If an image is scored without a reference annotation, it may make the annotator's annotation unstable. For this reason, the researchers set anchor images, i.e., reference labeled images, for images with different scoring ranges.

Moreover, the researchers used the batch labeling method to label 50 images at a time, so that the annotators can see enough samples to make a fair and consistent annotation. Eventually, after manual cleaning, close to 1200 comments per image were collected and the average of these values will be used as the GT of the image.

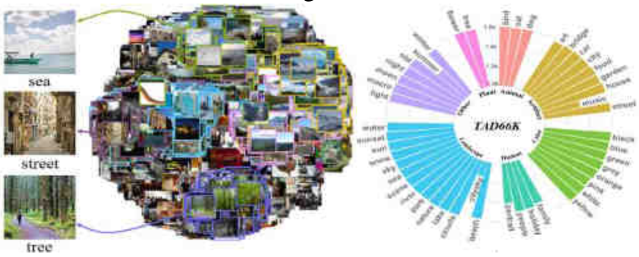

Fig. 4 TAD66K dataset

V. CONCLUSION

Visual aesthetics is an innate human ability, and image aesthetics is an abstract and highly subjective task. The rapid development of deep learning has led to an unprecedented boom in computational aesthetics research as well. Researchers have explored image aesthetics from various aspects and perspectives, continuously expanding and deepening their research, discovering problems in their research, and continuing their research from problems. At present, there are still a series of challenging problems in the field of image aesthetics. The image aesthetics assessment model can be divided into two stages: feature extraction and aesthetic decision-making. How to construct a feature extraction network to extract more comprehensive and reasonable aesthetic features has been the difficulty and focus of the aesthetic evaluation task, and it is also an important research direction at present. From manual annotation to convolutional network extraction, and from bottom layer features to high level semantic features, researchers are committed to obtaining complete aesthetic features of images. The current research development in this field is constantly updated and improved, and shows good performance in applications. However, there are still some development areas to be explored. This paper introduces a new research direction-multi-theme image aesthetic assessment research, mainly from the correlation between image themes and aesthetics. This paper first analyzes the current research status and development trend of image aesthetics assessment, and then gives a detailed introduction to the current research on multi-theme image aesthetics assessment. The current research on multi-theme image aesthetic assessment is still in its infancy, and how to utilize the existing theme dataset for model training and feature learning is still the key to the problem. This paper summarizes the current research status of multi-theme image aesthetics assessment methods, hoping that it can give some inspiration to other researchers and motivate future research to mine more potential applications from it.

REFERENCES

[1] Y. Deng, C. C. Loy, X. Tang. (2017,Jul). Image Aesthetic Assessment: An experimental survey. IEEE Signal Processing Magazine. 34:80-106.

[2] JIN Xin, ZHOU Bin, ZOU Dongqing,et al. (2018,Apr). Image aesthetic quality assessment: A survey. Science & Technology Review. 36(9): 36-45.

[3] Jin YY, Han XW, Zhou SN, et al. (2021,Jun). Review on Image Enhancement Algorithms. Computer Systems and Applications. 30(6): 18-27. Available:http://www.c-s-a.org.cn/1003-3254/7956.html.

[4] Vo Nam, Jiang Lu, Sun Chen, et al.(2020, Jan). Composing Text and Image for Image Retrieval - an Empirical Odyssey. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). 6432-6441.

[5] 柯圣财,赵永威,李弼程,等.（2017）.基于卷积神经网络和监督核哈希的图像检索方法.电子学报.DOI:CNKI:SUN:DZXU.0.2017-01-022.

[6] Kuzovkin, Dmitry.(2019,Jun). Assessment of photos in albums based on aesthetics and context. (Évaluation de photos dans des albums basée sur l'esthétique et le contexte).

[7] HUANG Li-Wei,JIANG Bi-Tao,LV Shou-Ye,et al. (2018). Survey on Deep Learning Based Recommender Systems. Chinese Journal of Computers.41(7):1619-1647

[8] WANG Zhi-Ming.(2015,Jun). Review of No-reference Image Quality Assessment. ACTA AUTOMATICA SINICA. 41(6): 1062-1079.

[9] Barnbaum B.(2017). The Art of Photography: A Personal Approach to Artistic Expression. Rocky Nook.

[10] Lu Yue, Guo Chao, Lin Yi-Lun, et al.(2020). Computational aesthetics of fine art paintings: The state of the art and outlook. Acta Automatica Sinica. 46(11): 2239−2259.

[11] Bai R Y, Guo X Y, Jia C H, et al. (2018, Nov). Overview of research methods of painting aesthetics. Journal of Image and Graphics. 24(11):1860-1881.

[12] Birkhoff, George David. (1933).Aesthetic Measure. Cambridge, MA and London, England: Harvard University Press.

[13] A. Iqbal, H. van der Heijden, M. Guid, et al. (2012). Evaluating the Aesthetics of Endgame Studies: A Computational Model of Human Aesthetic Perception. IEEE Transactions on Computational Intelligence and AI in Games. 4: 178-191.

[14] Datta R, Joshi D, Li J, et al. (2006). Studying Aesthetics in Photographic Images Using a Computational Approach. European Conference on Computer Vision (ECCV).288-301.

[15] Aydin T O, A. Smolic, M. Gross. (2015). Automated Aesthetic Analysis of Photographic Images. IEEE Transactions on Visualization and Computer Graphics. 21: 31-42.

[16] Sun X, Yao H, Ji R, et al.(2009). Photo assessment based on computational visual attention model. 17th ACM international conference on Multimedia. 541-544.

[17] Luo Y, Tang X.(2008). Photo and Video Quality Evaluation: Focusing on the Subject. European Conference on Computer Vision (ECCV).386-399.

[18] Wu Y, Bauckhage C, Thurau C. (2010). The Good, the Bad, and the Ugly: Predicting Aesthetic Image Labels. 20th International Conference on Pattern Recognition. 1586-1589.

[19] Lu X, Lin Z L, Jin H, et al.(2014). RAPID: Rating Pictorial Aesthetics using Deep Learning. 22nd ACM international conference on Multimedia.457-466.

[20] Tian X, Dong Z, Yang K, et al. (2015). Query-Dependent Aesthetic Model With Deep Learning for Photo Quality Assessment. IEEE Transactions on Multimedia. 17: 2035-2048.

[21] Mai L, Jin H, Liu, F, et al.(2016). Composition-Preserving Deep Photo Aesthetics Assessment. IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 497-506.

[22] Talebi H, Milanfar P. (2018). NIMA: Neural Image Assessment. IEEE Transactions on Image Processing.27: 3998-4011.

[23] He S, Zhang Y, Xie R, et al. (2022). Rethinking Image Aesthetics Assessment: Models, Datasets and Benchmarks. Thirty-First International Joint Conference on Artificial Intelligence. 942-948.

[24] Cui C, Liu H, Lian T, et al. (2019). Distribution-Oriented Aesthetics Assessment With Semantic-Aware Hybrid Network. IEEE Transactions on Multimedia.21: 1209-1220.

[25] Doshi N, Shikkenawis G, Mitra S K. (2019). Image Aesthetics Assessment using Multi Channel Convolutional Neural Networks. Computer Vision and Image Processing.15-24.

[26] Yang J, Zhou Y, Zhao Y, et al. (2022). MetaMP: Metalearning-Based Multipatch Image Aesthetics Assessment. IEEE Transactions on Cybernetics. 53: 5716-5728.

[27] Murray N, Marchesotti L, Perronnin F. (2012). AVA: A large-scale database for aesthetic visual analysis. IEEE Conference on Computer Vision and Pattern Recognition. 2408-2415.

[28] Kong S, Shen X, Lin Z, et al. (2016). Photo Aesthetics Ranking Network with Attributes and Content Adaptation. European Conference on Computer Vision. 662-679.