Journal of Harbin Engineering University
ISSN: 1006-7043

Vol 44 No. 11
November 2023

Assessing The Document Image Quality Metrics for the Camera Captured Printed and Handwritten Documents

Himaan A S

Department of Computer Science
School of Computing
Amrita Vishwa Vidyapeetham, India

Nachappa K M

Department of Computer Science
School of Computing
Amrita Vishwa Vidyapeetham, India

N Shobha Rani

Department of Computer Science
School of Computing
Amrita Vishwa Vidyapeetham, India

Chithra V S

Department of Computer Science
School of Computing
Amrita Vishwa Vidyapeetham, India

***Abstract*-Quality of an image determines whether it can be used for human analysis or any information retrieval process. Document Image Quality Assessment (DIQA) is one such method of quality assessment of documents, which consists of a complex process from data collection to model training g and obtaining the result. This Document Image Quality assessment (DIQA) has gained a prominent need in the human world today as it is used in the medical and education sector. This work aims to develop a model which can be used to access the quality of camera-captured document images (handwritten images) based on different handwriting styles which helps classify the document and predict the image quality. Overall document quality assessment based on the degradation angle of projection of camera based on textual features. The proposed model attains a machine-learning accuracy of 51.15%, and deep-learning model accuracy of 89.42%.**

Keywords-Document Image Quality Assessment, HOG (Histogram of Oriented Gradients), GLCM (Gray-Level Co-occurrence Matrix), Gabor, and Dilation.

I. INTRODUCTION

Computer and digital media use have exploded in practically every industry in the modern world. A representation of a record, whether written, printed, or digital, that acts as an official transcript and offers evidence or data is referred to as a document. A document might degrade during many stages of scanning, printing, transmission, compression, and decompression. As a result, combinations of numerous degradations or a single degradation may appear frequently or in unexpected ways. A record, whether written, printed, or digital, acts as an official transcript Additional stages influence document picture quality owing to environmental or physical variables, such as the quantity and direction of illumination utilized to capture the document. Handwriting is an essential trait for collecting and sending information; it is linked to kinematics and decoding ability, whereas kinematics and legibility are connected to document quality. Existing evaluation methods depend almost exclusively on human labor, which has numerous important limitations, including different assessment norms between individuals, limited competence, and high labor costs. Existing techniques do not provide a clear idea about unified metrics, different researchers use different metrics, which can make it challenging to compare the results of different studies. Numerous currently used techniques for evaluating the quality of photos are created to evaluate particular types of distortions and rely on a reference image to compare to the distorted image. The image has traditionally been examined using conventional processing techniques, which contain metrics or a reference with which the image may be compared. This existing technique consists of three reference techniques namely Full-reference, No-reference, Reduced –reference. In this work, we develop a model which can be used to evaluate the quality of camera-captured handwritten documents with different handwriting styles, and with different resolutions by generating an image readability score to access the quality of the image. General document quality assessment based on camera projection angles involves evaluating the legibility, clarity, and accuracy of document images. We try different textual feature extraction from the images, intensity identification of pixels, and try different machine learning and deep learning models for testing the working correctness of our model.

II. RELATED WORK

Madeed et al,[1] (2014), proposed a methodology that used full reference, no reference, and Reduced Reference techniques. Considered DB's for IQA-CSIQ, TID2013, with Laboratory Images, Corneel A-57, and using State of Art Approach. Data has been trained and applied in all 3 reference approaches and applied Wavelet Transformation. Sara, et al.,[2] (2019), proposed a study that considered the Full Reference and No Reference techniques to measure the image quality. Other techniques considered include MSE, RMSE, PSNR, SSIM, DSSIM, and FSIM. Data sets have been pertained and split into training and testing sets. Choi et al [3] (2009), proposed a model which is used to calculate the blur and noise in a spatial domain, The blur is measured by simple numeric operations on pixel.1. Blur Measurement, 2. Noise Measurement 3. Combination of Blur and Noise Used Pearson linear coefficient for performance accuracy, Mat lab source code for JPEG compressed picture no-reference perceptual quality assessment, which analyzes blocking artifacts and blur of JPEG compressed image, a data set is divided into training and testing to obtain accuracy. Lin [4] (2018), proposed a new NR-IQA's be overcome by using a hallucination-guided quality regression network, which incorporates the perceptual discrepancy information into network learning and dramatically increases prediction precision and robustness. It employs a Quality-Aware Generative Network and a Quality-Aware Perceptual Loss with the assistance of the complementary consideration of both texture attribute similarity and quality feature similarity to generate qualified hallucinated references.

Rajchel et al [5] (2021), describe a set of innovative attributes for images that consider both local and global factors is put forth. Sharpness, the median and mean values of kurtosis, or the ratio of bright to dark pixels are all employed. The foundation of the NR-IQA approach is a set of perceptual features, the applicability of which for the evaluation of naturally distorted images may need more study. The effectiveness of the approach is evaluated using a performance evaluation on the BR picture dataset to determine what happens if a particular property is removed from the feature vector. Kim et al [6] (2017), here ML is adapted in no-reference IQA technique, for sensitivity map prediction using only convolution layers to generate sensitivity without losing any pixels. Here distorted images are normalized using CNN. The suggested method was tested using LIVE IQA, CSIQ, TID2008, and TID2013, four independent IQA datasets. The reference images were split into two independent groups (80% for training and 20% for testing) to ensure there was no overlap between the two sets. Additionally, two subsets of compatible distorted photos were created. Paramesran et al [7], proposed full reference and reduced reference approaches and performed IQA mainly on medical images like MRI images, and ultrasound images. In comprehensive reference methods, they have taken into account variables such as the Double-Stimulus Continuous-Quality Scale (DSCQS), Difference Mean Opinion Score, Perceptual Difference Model, and Mean Structural Similarity (MSSIM). Athar et al [8] (2019), Considered multiple databases like single distortion databases, multiple distortion databases, and other iqa databases. The analysis includes content analysis and distortion analysis. Full-reference image quality evaluation techniques can be divided into four categories: error-based, structural similarity-based, natural scene statistics-based, and mixed strategy-based. Empirical, learning-based, and rank aggregation-based fusion are the three types of fusion used in fusion-based image quality assessment.

FZ Ou et al [9] (2019) Proposed method consists of 4 features based on asymmetrical GGD, 1 feature based on picture entropy, and generalized Gaussian distribution-based features. Six features based on the energy sub-band ratio and 32 features based on Benford's law are included in the feature selection from the transform domain. Results include mean SROCC and PLCC of six NR-IQA methods over 1000 trials, analysis through Box plot demonstrating SROCC distributions of six NR-IQA methods, and more. using the LIVE-C database. Kalatehjari et al [10] (2014), Performed the NIQE method on grayscale images, based on a multivariable Gaussian model. Zero modes asymmetric Gaussian distribution is used to estimate the model neighboring coefficient. NIQE extracts features before 2 scales along 4 directions then NSS features are computed. Approaches used consist of an evaluation of quality and extraction of features in the quaternion space. Analyses are made between the quality assessment of various methods using the linear correlation coefficients, the quality evaluation of various methods using Spearman's rank correlation coefficients, and the comparison of blind iqa methods using Spearman's rank correlation coefficients. Xue et al [11] (2013), Two sorts of blind image quality assessment (BIQA) methods can be distinguished: strategies specific to distortion, and distortion-independent methods, as explained in Blind Image Quality Assessment Training without Human Ratings. The four most typical types of distortions—Gaussian noise, Gaussian blur, JPEG compression, and JPEG2000 compression—are all simulated. Other types of distortion that are considered include TID2008, LIVE, and CSIQ. Pooling of blind quality has been done using Cluster assignment, Blind image quality evaluation results on LIVE, CSIQ, and TID2008 were obtained by patch quality estimation, final pooling, and each of these metrics.

Lao et al [12] (2022) proposed An efficient hybrid architecture to measure image quality that examines Taking into account the relationships between patches and the various contributions from each patch, images at the patch level fill with spatial information and is scored patch by patch. Three distinct functionalities: a patch-wise prediction module, a feature extraction module, and a feature fusion module. Comparison with the State-of-the-art Methods includes Evaluation of Traditional Datasets, Comparisons of performance on the LIVE, CSIQ, and TID2013 databases, On the testing datasets for the ENTIRE 2022 IQA Challenge, assessment of PIPAL, cross-database assessment of performance, and comparison between multiple feature extraction backbones were carried out. Cheon et al [13] (2021), CNN feature extraction backbone network. Here both reference and distorted images are used. Obtained an accuracy of 87.9%. Zhang et al [14] (2021, proposed a model which worked on pre available IQA database, The statistical results on images with multiple-grained quality differences could obscure the full evaluation results on FG-IQA, especially considering that three correlation coefficients for popular IQA models are usually used. Techniques used are FG-IQA on Compressed Images, FG-IQA on Denoised Images, FG-IQA on Retargeted Images, FG-IQA on tone-mapped Images, and FG-IQA on enhanced Images in other ways. Raj et al [15] (2019), Dataset consists of JPEG, BMP, and TIFF, for quality assessment, vessel segmentation, DR classification, AMD classification, OD segmentation, and M-A segmentation. Fundus IQA algorithm is modeled for training for machine learning-based, segmentation-based, and similarity-based. Based on the feature extraction method, Calculated is a summary of segmentation-based fundus IQA techniques, similarity-based fundus IQA techniques, and machine learning-based fundus IQA techniques. Methods based on segmentation can be specific and sensitive, The extraction of features based on structure analysis, extraction of features based on general image statistics, and feature extraction based on CNNs models are a few instances of machine learning-based methodologies.

Kumar et al.,[16], Considered different degradation levels like degradation caused while scanning, highly degraded documents, background, etc. Take into count factors like foreground and background uniformity, transient region density, sharpness, and noise. Fu et al [17] (2018), Using the SIQAD database, experimental findings with higher HSV perceptual consistency have been presented in IQA matrices. The reference and distorted SCIs are first subjected to the multi-scale difference of the Gaussian (MDOG) operator to recover the edge maps at two different scales. The smaller-scale edge map (SEM) is separated from the larger-scale edge map by this operator. By comparing the similarities of the two SEMs, the edge resemblance map is constructed in the second stage. Edge Strength Weighting, Edge Similarity Measurement, and Multi-Scale Difference of Gaussian techniques are employed. Li1 et al [18] (2021), take into account elements like the smartphone's camera's focal length. The paper type and the lighting conditions. the kind of Smartphone and the dataset collected. collected document images of books with various sorts of images or without images, and took pictures with various smartphones. The color orientation on the grading scale was also tested. On our testing set, we computed the SROCC and LCC scores following training until convergence at a TID of 0.780.

Me et al [19] (2021), Objective methodology is capable of providing consistent quality prediction and more accurate classification, texture awareness model comparison model mainly includes 3 types are pre-selected volume of images to form a test-set, a second collection MOS of each image third rank the competing model, other models are MAD, Eigen-distortion analysis. Lahouhou et al [20] (2009), a hybrid solution based on machine learning, feature extraction has been split into two categories: composite indices to directly evaluate the image quality (PSNR, SSIM, SNRWAV), and pre-local statistical statistics The following metrics have been used to assess the quality of images: PSNR, SSIM, MSE, MAX-COVAR, and MAX-MSE. A structural Risk management strategy is used in the estimating model. Nair et al [21](2021), proposed work on a modified version of RESNET that uses five blocks for image binarization and Convolution, Batch normalization, and Relu as one block. For the picture binarization of deteriorated horoscopic palm leaf documents, the suggested Resnet model is a useful technique. The model successfully eliminates noises like irregular lighting, stains, ink bleed, and shades. It involves preprocessing data, enhancing images, and training the RESNET model to provide binarized output utilizing a deep learning technique with a RESNET architecture to binarize palm leaf papers obtaining an accuracy of 95.38%.

III. METHODOLOGY

A. Dataset Collection

Data has been collected manually, with varying handwriting styles, and this image has been captured through the mobile camera with different resolutions, and light conditions at a height of 35 to 40cm respectively. The collected data has been categorized into five categories based on handwriting style, skewness in writing, texture, and considering spacing, and legibility level. The images were taken with a mobile phone camera, making them susceptible to deterioration due to illumination, blur, or compression quality loss. Here category one indicates poor quality of score with poor handwriting whereas category contains good images with better legibility and less skewness.

Fig:1 Images in each category

Each category consists of 280 images with a total of 1472 Images of handwriting that have been divided into training, testing, and validation groups. The collection includes images of student notes, assignments, and exams from various educational institutions. Because the photos in the dataset are of varying sizes, they must be normalized before being assigned to one of the five classes. The photographs in the collection were made and gathered in various contexts, resulting in a wide range of image sizes.

B. Workflow of the Model

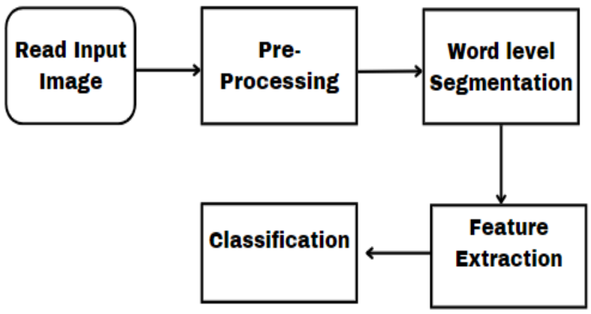

Fig:2 Workflow of the proposed model

The data samples are taken from each category at a time it is preprocessed, word-level segmentation is performed on the images, the edge map feature is identified and the peak intensity concerning black and white pixels is obtained. Textual features such as Gabor, GLCM, and HOG features are obtained for all images, the mean and standard deviation of these extracted features are given to the classifier for appropriate categorization of images, and a quality generation score is developed to predict the overall quality of each image.

We perform image resizing for clear text detection while preserving its aspect ratio, applying a Gaussian blur filter on the image by Gaussian Kernel, and later performing contrast adjustment by linear stretching and non-linear stretching. Thresholding is performed on the image to convert the grayscale image to a binary image where each pixel is either black or white. These images are segmented using the HSV (Hue, Saturation, and Value) color system, and the image boundaries are enlarged using dilation.

C. Word Level Segmentation: In document image analysis, the quality of the text within the document is a crucial factor in overall image quality. Word-level segmentation can be used to identify individual words within the document, which can then be analyzed for quality and legibility. This can be used to identify and extract individual words from images, which can then be recognized and analyzed. The rules that are applied in segmentation are Preprocessing to enhance the quality of the document image, Text detection to locate regions containing text within the document image, Connected component analysis to identify individual text components, Thresholding to separate individual characters within the connected components, Character grouping to group the separated characters into words, Postprocessing to refine the word segmentation results.

D. Feature Extraction: Feature extraction is an important step in DIQA because it allows us to identify and extract important visual features from an image that can be used to assess its quality. The flowing features are being extracted to access the quality.

Histogram features are extracted from the data as they can give a quick and easy approach to capturing the distribution of pixel intensities in an image. The frequency of pixel intensity values in an image is described by histogram characteristics, which can be used to analyze changes in picture contrast, brightness, and saturation that may affect image quality. to compare the intensity distributions of an original image to a distorted image. By comparing the histograms of the two images, it is possible to quantify changes in image contrast, brightness, and saturation that may be caused by distortions such as blurring, noise, or compression artifacts.

Gabor Feature: The Gabor filter feature extraction procedure begins with the application of a two-dimensional Gabor filter on each picture separately. Gabor features are derived from the Gabor filter, a linear filter that is used in image processing to extract features, analyze textures, and detect edges. These features can be used to compare the texture and structural data of two images. This can help identify image distortions, such as blurring or noise, that may affect the quality of an image. Gabor features can also be used to analyze the perceptual quality of images by simulating the response of the human visual system to different spatial frequencies and orientations. The theory also indicates that frequency and spatial measurements must define a rectangle shape in Fourier space with an area >1/4pie. The Gabor function is represented as:

$$G(a, b; k, \theta, \sigma, \gamma) = \exp\left(-\frac{a'^2 + \gamma^2 b'^2}{2\sigma^2}\right)\cos(2\pi f x' + \theta) \qquad (1)$$

where:

a' = a cos(θ) + y sin(θ)

b' = -a sin(θ) + y cos(θ)

a and b are the spatial coordinates of the image

k is the frequency of the filter

θ is the orientation of the filter

σ controls the size of the Gaussian envelope

γ controls the aspect ratio of the Gaussian envelope

GLCM feature: Gray-Level Co-occurrence Matrix feature extraction is a commonly used method in Digital Image Quality Assessment (DIQA) to quantify the textural information in an image. GLCM calculates the second-order statistical properties of an image by analyzing the distribution of its pixels' grayscale values. The GLCM is a matrix that quantifies the frequency with which pairs of pixels in an image possess specific values and spatial connections.

GLCM features can be used to analyze the texture of an image and identify changes in texture due to image distortions They are sensitive to changes in texture and can be used to analyze both local and global image properties. The GLCM matrix function is:

$$G(i, j, d, \theta) = \sum_{a=0}^{X-1}\sum_{b=0}^{Y-1} \delta(I(a, b) = i, I(a + d\cos\theta, b + d\sin\theta) = j) \qquad (2)$$

where G (i, j, d, θ) represents the element of the GLCM matrix corresponding to gray-level i, gray-level j, distance d, and angle θ, I(a, b) represents the gray-level value of the pixel at position (a, b) in the image, δ is the Kronecker delta function, and X and Y represent the dimensions of the image.

HOG Features: Histogram of Oriented Gradients feature extraction is another commonly used method in Digital Image Quality Assessment (DIQA) to extract features from images. HOG analysis can be used to describe the local texture and gradient information in an image, which can be useful for detecting edges and corners, as well as identifying objects. This can be used to compare the structure and shape of objects in an original image to a distorted image. This can help identify changes in image quality due to distortions such as blurring, noise, or compression artifacts. The HOG descriptor is:

$$HOG(d) = \frac{1}{|R|}\sum_{p \in R} w(p) \cdot v(d, p) \qquad (3)$$

where HOG(d) is the HOG descriptor for a single cell at position d, |R| is the number of pixels in the cell, w(p) is a weighting function based on the pixel intensity, and v(d, p) is the gradient vector for pixel p in cell d.

IV. RESULT AND DISCUSSION

The model is trained in the Google Colab and Jupyter Notebook environments, both of which run on Windows 10 systems with GPU memory. The libraries used are Scikit-learn, OpenCV, PIL, matplotlib, and Numpy. The documents are fed into the classifier for appropriate categorization of the documents and the obtained mean and standard deviation of the feature extraction values are taken for this purpose. In the ratio of 80:10:10, the dataset is split up into three categories: training, testing, and validation. In this process, we have taken Random Forest classifiers which can handle large values, with both continuous and categorical values. We obtained an accuracy score of 52.9% for the applied classifiers, we can observe that the accuracy is less for the individual extracted features, and the combination of all the extracted features provides good considerable accuracy. Deep learning models include MobileNet, ResNet 18, CNN, ResNet 50, and EfficientD4. ResNet 34, having 50, 18, and 34 layers respectively.

TABLE 1: Performance of models in Machine learning

Name of the Model	Performance of models in Machine learning		
	Test Accuracy	*Validation Accuracy*	*Loss in Validation*
HOG, GLCM, Gabor	51.15	32.93	2.7525
HOG	26.26	24.07	0.3085
GLCM	25.55	26.85	0.3246
Gabor	26.85	25.55	0.6591

The above table shows the accuracy and loss in validation for various machine learning models, where the combination of HOG, GLCM and Gabor gives high accuracy than when they are taken individually into consideration.

TABLE 2: Performance of models in Deep learning model

Name of the Model	Performance of models in Deep learning model		
	Training Accuracy	*Validation Accuracy*	*Loss in Validation*
MobileNet	46.46	44.95	1.9503
ResNet 34	99.88	86.19	0.5229
ResNet 50	100	84.86	0.543
ResNet18	100	81.23	0.6439
EfficientD4	100	84.86	0.5438
CNN	89.42	87.12	0.4911

The above table shows the accuracy and loss in validation for various Deep learning models. We observe that the MobileNet Model produces low accuracy but CNN gives high accuracy due to its adaptability, effectiveness, capacity to learn features particular to a given domain, and accessibility to pre-trained models.

We observe that the model produces less accuracy and has high loss invalidation in Mobile Net due to the complexity of the task, the size of the dataset, and the choice of hyperparameters. concerning ResNet 34, 50, and 18 have a good validation accuracy above 84% and have significantly less loss in validation ranging below 1, because they offer a good trade-off between model complexity and performance. ResNet-18: is a relatively small ResNet architecture with only 18 layers, which makes it easier and faster to train. In IQA, ResNet-18 is often used as a baseline model because it is simple yet effective. ResNet-34 is often used when higher accuracy is required than what can be achieved with ResNet-18. ResNet-50 is often used when very high accuracy is required, and the computational cost of training and inference is not a concern. Of the all-deep learning model Efficient4 and CNN give high accuracy with less validation loss. CNNs are still widely used due to their flexibility, efficiency, ability to learn domain-specific features and the availability of pre-trained models that can be fine-tuned for IQA tasks. We observe that the deep learning model produces significantly high accuracy as compared to Machine learning models.

The precision vs recall vs f1-score and accuracy of different models can be distinguished as the representation below. The result obtained has been represented below

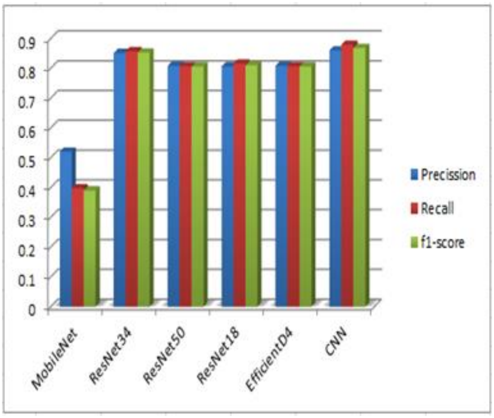

Fig3: Precision vs Recall vs f1-score

The above graph describes the performance of various deep learning models with the parameters of Precision, Recall and f1-score. The proposed deep learning model produces best performance for the CNN Model.

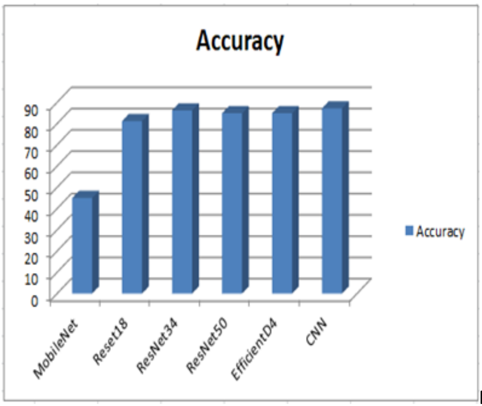

Fig 4: Accuracy of different Models

The above graph shows the accuracy of various deep learning model, with the MobileNet producing a low accuracy of 46.46%, and CNN with a accuracy of 89.42%.

V. CONCLUSION

The system achieves a highly accurate result, which can be improved by fine-tuning and experimenting with newer models, and produces results that are more similar to human perception because DIQA performance is evaluated visually. Each model's performance varies greatly, influenced by the various hyper-parameters, with differences in results ranging from a small proportion to a high number of points. In the future, we want to expand the algorithm for judging quality at the word and character levels. We also want to improve the model so it can work with handwritten text from more scripts, participants, and niches and get better every time it is retrained.

REFERENCE

[1]. Al Madeed, Noor, Zainab Awan, and Somaya Al Madeed. "Image quality assessment-a survey of recent approaches." 8th International Conference on Computer Science, Engineering and Applications. 2018.

[2]. Sara, Umme, Morium Akter, and Mohammad Shorif Uddin. "Image quality assessment through FSIM, SSIM, MSE, and PSNR—a comparative study." Journal of Computer and Communications 7.3 (2019): 8-18.

[3].Choi, Min Goo, Jung Hoon Jung, and Jae Wook Jeon. "No-reference image quality assessment using blur and noise." International Journal of Computer Science and Engineering 3.2 (2009): 76-80.

[4].Lin, Kwan-Yee, and Guanxiang Wang. "Hallucinated-IQA: No-reference image quality assessment via adversarial learning." Proceedings of the IEEE conference on computer vision and pattern recognition. 2018.

[5].Rajchel, Milosz, and Mariusz Oszust. "No-reference image quality assessment of authentically distorted images with global and local statistics." Signal, Image and Video Processing 15 (2021): 83-91.

[6]. Kim, Jongyoo, and Sanghoon Lee. "Deep learning of human visual sensitivity in image quality assessment framework." Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.

[7].Chow, Li Sze, and Raveendran Paramesran. "Review of medical image quality assessment." Biomedical signal processing and control 27 (2016): 145-154.

[8].Athar, Shahrukh, and Zhou Wang. "A comprehensive performance evaluation of image quality assessment algorithms." Ieee Access 7 (2019): 140030-140070.

[9].Ou, Fu-Zhao, Yuan-Gen Wang, and Guopu Zhu. "A novel blind image quality assessment method based on refined natural scene statistics." 2019 IEEE International Conference on Image Processing (ICIP). IEEE, 2019.

[10].Kalatehjari, Ehsanhosein, and Farzin Yaghmaee. "Blind image quality assessment of multi-degraded images." 2014 4th International Conference on Computer and Knowledge Engineering (ICCKE). IEEE, 2014.

[11].Cheon, Manri, et al. "Perceptual image quality assessment with transformers." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2021.

[12].Lao, Shanshan, et al. "Attentions help cnns see better: Attention-based hybrid image quality assessment network." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2022.

[13]. Cheon, Manri, et al. "Perceptual image quality assessment with transformers." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2021.

[14]. Zhang, Xinfeng, Weisi Lin, and Qingming Huang. "Fine-grained image quality assessment: A revisit and further thinking." IEEE Transactions on Circuits and Systems for Video Technology 32.5 (2021): 2746-2759

[15]. Raj, Aditya, Anil Kumar Tiwari, and Maria G. Martini. "Fundus image quality assessment: survey, challenges, and future scope." IET Image Processing 13.8 (2019): 1211-1224.

[16].Kumar, Deepak, and A. G. Ramakrishnan. "Quad: Quality assessment of documents." International Workshop on Camera based Document Analysis and Recognition. 2011.

[17].Fu, Ying, et al. "Screen content image quality assessment using multi-scale difference of Gaussian." IEEE Transactions on Circuits and Systems for Video Technology 28.9 (2018): 2428-2432.

[18].Li, Zhenghao, et al. "A Document Image Dataset for Quality Assessment." Journal of Physics: Conference Series. Vol. 1828. No. 1. IOP Publishing, 2021.

[19].Ma, Kede, and Yuming Fang. "Image quality assessment in the modern age." Proceedings of the 29th ACM International Conference on Multimedia. 2021.

[20]. Lahouhou, Atidel, Emmanuel Viennet, and Azeddine Beghdadi. "Combining and selecting indicators for image quality assessment." Proceedings of the ITI 2009 31st International Conference on Information Technology Interfaces. IEEE, 2009.

[21]. BJ, B. N., & Nair, A. S. (2021, April). Ancient horoscopic palm leaf binarization using A deep binarization model-RESNET. In 2021 5th International Conference on Computing Methodologies and Communication (ICCMC) (pp. 1524-1529). IEEE.