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REVIEW ARTICLE

# Advancements in image quality assessment: a comparative study of image processing and deep learning techniques

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## Abstract

Image quality assessment (IQA) is a crucial field in image processing that ensures optimal performance in various applications such as medical imaging, surveillance, and multimedia systems. The evolution of IQA methods spans from traditional image processing techniques to the incorporation of advanced deep learning algorithms. This literature review aims to provide a comprehensive analysis of the methodologies used in image quality assessment, focusing on both full-reference, reduced-reference, and no-reference approaches. Traditional methods such as peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) are discussed alongside more recent deep learning-based approaches that leverage convolutional neural networks (CNNs), generative adversarial networks (GANs), and transformers for feature extraction and prediction. Deep learning models have demonstrated enhanced performance in complex tasks like noise reduction, image reconstruction, and compression artifacts correction. Additionally, this review highlights the challenges in IQA, including the subjectivity of human visual perception and the limitations of various algorithms in handling different types of distortions. It concludes by suggesting future research directions that integrate hybrid models combining classical techniques with deep learning to achieve more robust and efficient image quality evaluation.

**Keywords:** Image quality assessment, Image processing, Deep learning, Machine learning, Neural networks, Peak signal-to-noise ratio, Structural similarity index measure.

## Introduction

Image quality assessment (IQA) has become a pivotal area of research as the demand for high-quality images continues to expand across various industries, including media, medical imaging, autonomous driving, and surveillance. Traditionally, image quality has been assessed through standard image processing techniques that use hand-crafted algorithms to quantify image distortions like noise, blur, and compression artifacts. While effective to some extent, these methods often fall short in capturing the subtleties of human perception, making it challenging to accurately evaluate images in real-world applications. Recent advancements, however, have introduced deep learning-based techniques that leverage large datasets and neural networks to analyze image quality, offering promising improvements in accuracy, adaptability, and perceptual relevance, Wang, L. (2021).

The evolution of IQA methods can be broadly categorized into two main approaches: image processing-based techniques and deep learning-based methods. Traditional image processing techniques, such as peak signal-to-noise ratio (PSNR) and structural similarity index measure (SSIM), provide an efficient, quantitative assessment of image quality by comparing reference and distorted images at the pixel level. However, they often lack the perceptual sensitivity necessary to handle complex distortions and are inadequate for scenarios where reference images are unavailable. Deep learning, on the other hand, has emerged as a transformative force in IQA, with convolutional neural networks (CNNs) and other neural architectures offering unprecedented capability in understanding complex

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patterns and delivering no-reference (NR) assessments. These models excel in learning perceptual features directly from data, resulting in more robust evaluations that align closely with human subjective assessments, Ma, K., & Fang, Y. (2021, October).

This comparative study aims to explore the strengths and limitations of traditional image processing techniques and modern deep learning-based approaches for image quality assessment. By examining these two paradigms, this paper will provide insights into their respective advancements, evaluate their effectiveness across various image quality scenarios, and discuss emerging trends in the field. The study ultimately seeks to provide a comprehensive understanding of how each approach can be optimally applied to meet the growing demand for accurate and reliable image quality evaluation across diverse applications.

### *Importance of Image Quality Assessment*

IQA plays a critical role across a wide range of fields where accurate and high-quality visual information is essential. From entertainment and communication to medical imaging, autonomous systems, and satellite monitoring, IQA is necessary to ensure that images serve their intended purpose effectively. Traditional IQA relied on basic quantitative methods, but the proliferation of digital content, increased dependence on high-quality visuals, and the evolving complexities of imaging systems have underscored the need for advanced IQA techniques that can replicate or approximate human visual perception, Gao, R., Huang, Z., & Liu, S. (2022).

### *The Foundation of Image Quality Assessment*

The foundational principle of IQA is to evaluate and quantify the quality of an image to ensure it meets the expected standards for its intended application. Quality assessment methods generally fall into two categories: subjective and objective; Ding, K., Ma, K., Wang, S., & Simoncelli, E. P. (2020).

- Subjective IQA involves human evaluators who judge image quality based on visual perception, which is often used as a benchmark for other assessment methods. Although subjective methods provide reliable and accurate results, they are time-consuming, costly, and impractical for large-scale or real-time applications.
- Objective IQA is the alternative, offering automated methods to evaluate image quality based on mathematical models and algorithms. Objective IQA methods are scalable and consistent, providing a viable solution to assess large datasets efficiently. Objective IQA has further classifications, such as full-reference (FR), reduced-reference (RR), and no-reference (NR) methods, depending on whether a pristine reference image is required.

### *The Growing Importance of IQA in Various Fields*

IQA has emerged as a vital component across several fields where high-quality imagery is not only beneficial but often essential, Kim, W., Nguyen, A. D., Lee, S., & Bovik, A. C. (2020), Saeed, S. U., Fu, Y., Baum, Z. M., Yang, Q., Rusu, M., Fan, R. E., ... & Hu, Y. (2021, June).

*Media and entertainment*

In fields such as digital photography, video streaming, and gaming, IQA is crucial for maintaining image fidelity during compression and transmission processes. The quality of images and video streams directly affects user satisfaction, making it necessary for service providers to utilize IQA methods to deliver content that meets user expectations.

*Healthcare and medical imaging*

Medical diagnostics rely on high-quality images for detecting and analyzing conditions such as tumors, fractures, and other anomalies. Poor-quality images can lead to misdiagnosis or missed diagnoses, impacting patient outcomes. Thus, IQA is essential in medical imaging to ensure that images are clear, precise, and diagnostically useful. Techniques like MRI, CT, and X-ray imaging require automated IQA to monitor and maintain high standards.

*Autonomous vehicles and surveillance systems*

Autonomous driving systems, as well as surveillance and security applications, rely heavily on high-quality visual data to operate safely and effectively. In autonomous vehicles, IQA is critical to ensuring that the visual data captured by cameras is reliable for obstacle detection, path planning, and decision-making processes. Surveillance cameras, on the other hand, require good IQA methods to ensure clarity in images used for security and identification purposes.

*Remote sensing and satellite imagery*

Satellite and drone imagery used for monitoring natural resources, disaster management, and urban planning must be clear and accurate for effective analysis. IQA in this field ensures that the images captured are suitable for tasks such as vegetation analysis, land use mapping, and environmental monitoring.

### *Traditional vs. Modern Image Quality Assessment Techniques*

Traditionally, IQA was limited to simpler metrics like peak signal-to-noise ratio (PSNR) and mean squared error (MSE), which focus on pixel-to-pixel comparison between images. While these metrics are computationally efficient, they fall short of aligning with human perception, particularly in complex images with varying lighting, textures, and subtle distortions. Modern IQA techniques leverage more advanced methods to overcome these limitations, Ding, K., Ma, K., Wang, S., & Simoncelli, E. P. (2021), Ou, F. Z., Wang, Y. G., Li, J., Zhu, G., & Kwong, S. (2021):

*Structural similarity index (SSIM)*

SSIM marked a breakthrough in IQA, as it considers structural information in an image to assess quality, resulting in more perceptually aligned evaluations compared to PSNR or MSE.

*Deep learning-based IQA*

Deep learning models, particularly convolutional neural networks (CNNs), have revolutionized IQA by enabling data-driven methods that capture high-level features. These models are particularly effective in no-reference (NR) scenarios, where they learn quality indicators directly from image data, making them robust to various distortions without needing a reference image.

*No-reference IQA (NR-IQA)*

NR-IQA is increasingly important for real-time and large-scale applications where reference images may not be available, such as live streaming, mobile applications, and surveillance. NR-IQA methods use neural networks and machine learning techniques to directly analyze and quantify distortions in an image.

### *Background Study on Image Processing Techniques*

*Image pre-processing techniques*

Pre-processing involves preparing an image for analysis by enhancing its quality and removing unwanted noise. Techniques include Soomro, T. A., Ali, A., Jandan, N. A., Afifi, A. J., Irfan, M., Alqhtani, S., ... & Zheng, L. (2021):

*Noise reduction*

Commonly used filters, such as Gaussian, median, and Wiener filters, help smooth images and reduce noise while retaining important details.

*Image resizing*

Resizing standardizes the dimensions, which is useful for applications needing uniform input sizes (e.g., convolutional neural networks).

*Normalization*

Normalizing pixel intensity levels enhances contrast and uniformity.

*Histogram equalization*

This technique enhances image contrast by redistributing the intensity values for a more visually balanced output.

### *Image Segmentation*

Segmentation divides an image into meaningful regions, helping isolate specific parts for analysis, such as objects in medical imaging or features in satellite images, Ramesh, K. K. D., Kumar, G. K., Swapna, K., Datta, D., & Rajest, S. S. (2021), Jaiswal, S., & Pandey, M. K. (2020).

*Thresholding*

A simple approach that segments images by setting pixel intensity thresholds, separating background and foreground.

*Edge detection*

Algorithms like Sobel, Canny, and Laplacian filters identify the boundaries of objects within an image.

*Region-based segmentation*

Techniques like region-growing and watershed segmentation expand regions based on pixel similarity.

*Clustering methods*

Algorithms like K-means and fuzzy C-means group pixels based on intensity or color for image segmentation.

### *Feature Extraction and Representation*

Feature extraction identifies critical attributes that help in recognizing patterns or objects. Features can be structural, statistical, or transform-based, Kumar, K. K., Chaduvula, K., & Markapudi, B. (2020), Zhang, L., Sui, Y., Wang, H., Hao, S., & Zhang, N. (2022).

*Shape and texture analysis*

Techniques analyze geometrical structures or patterns (e.g., Haralick's texture features, Histogram of Oriented Gradients).

*Color analysis*

RGB and HSV color models enable the extraction of color-based information, particularly in object detection tasks.

*Transform-based features*

Fourier, Wavelet, and Gabor transform extract features in various frequency domains, capturing both spatial and frequency details of images.

### *Image Classification and Recognition*

Classification involves labeling an image or its components, often using machine learning or deep learning models, Chen, L., Li, S., Bai, Q., Yang, J., Jiang, S., & Miao, Y. (2021), Xi, E. (2022).

*Machine learning*

Traditional algorithms like support vector machines (SVM), k-nearest neighbors (k-NN), and decision trees classify images based on extracted features.

*Deep learning*

CNNs have significantly improved image classification accuracy by automating feature extraction and learning complex patterns.

### *Background Study on Deep Learning Techniques*

A background study on deep learning techniques explores the architectures, algorithms, and applications of deep learning, a subset of machine learning. Deep learning models are inspired by the human brain's structure, using layers of neurons to learn representations of data through multiple levels of abstraction, Chen, L., Li, S., Bai, Q., Yang, J., Jiang, S., & Miao, Y. (2021), Xi, E. (2022).

### *Neural Network Foundations*

*Artificial neural networks (ANNs)*

The most basic type of neural network consists of input, hidden, and output layers. Each neuron in a layer is connected to neurons in the next, forming a feedforward structure.

*Backpropagation*

The core of deep learning training involves adjusting weights to minimize error using gradient descent. Backpropagation helps in tuning these weights efficiently across multiple layers.

### *Deep Neural Networks (DNNs)*

- Deep Neural Networks are ANNs with multiple hidden layers, enabling the learning of complex representations. DNNs use hierarchical feature extraction, where each layer extracts features of increasing complexity from the data.
- Applications range from predictive modeling to signal processing, where DNNs provide significant improvements over traditional machine learning models.

### *CNNs*

*Architecture*

CNNs are specialized for processing grid-like data, such as images. They use layers like convolution, pooling, and fully connected layers to extract and downsample features.

*Convolution layers*

Kernels or filters slide over the input image, extracting spatial hierarchies of features.

*Pooling layers*

Pooling reduces the spatial dimensions and computational complexity while preserving important information.

*Applications*

CNNs are dominant in image classification, object detection, medical imaging, and autonomous driving.

### *Recurrent Neural Networks (RNNs)*

*Architecture*

RNNs are designed for sequential data, where the output depends on previous inputs. They use feedback loops in the network, allowing information persistence across time steps.

*Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU)*

LSTMs and GRUs are improvements over traditional RNNs, addressing issues of vanishing gradients by retaining long-term dependencies in sequences.

*Applications*

RNNs and their variants are widely used in natural language processing, time series forecasting, speech recognition, and video analysis.

### *Autoencoders*

*Architecture*

Autoencoders are unsupervised networks that learn efficient data codings by encoding input data into a lower-dimensional representation (latent space) and then reconstructing it.

*Variational autoencoders (VAEs)*

VAEs introduce a probabilistic approach to generate synthetic data and model data distributions, useful for tasks requiring data synthesis.

*Applications*

Autoencoders are used for anomaly detection, image denoising, dimensionality reduction, and data compression.

### *Literature Review*

Ophthalmological pathologies such as glaucoma, diabetic retinopathy and age-related macular degeneration are major causes of blindness and vision impairment. There is a need for novel decision support tools that can simplify and speed up the diagnosis of these pathologies. A key step in this process is to automatically estimate the quality of the fundus images to make sure these are interpretable by a human operator or a machine-learning model. We present a novel fundus image quality scale and deep learning (DL) model that can estimate fundus image quality relative to this new scale, Abramovich, O., Pizem, H., Van Eijgen, J., Oren, I., Melamed, J., Stalmans, I., ... & Behar, J. A. (2023).

The authors presented a multiscale deep blind image quality assessment method (BIQA, M.D.) with spatial optimal-scale filtering analysis. Motivated by the multi-channel behavior of the human visual system and the contrast sensitivity function, we decompose an image into a number of spatial frequency bands through multiscale filtering and extract features to map an image to its subjective quality score by applying a convolutional neural network. Experimental results show that BIQA, M.D. compares well with existing NR-IQA methods and generalizes well across datasets, Liu, M., Huang, J., Zeng, D., Ding, X., & Paisley, J. (2023).

The authors proposed a top-down approach that uses high-level semantics to guide the IQA network to focus on semantically important local distortion regions, named TOPIQ. Our approach to IQA involves the design of a heuristic coarse-to-fine network (CFANet) that leverages multiscale features and progressively propagates multi-level semantic information to low-level representations in a top-down manner. A key component of our approach is the proposed cross-scale attention mechanism, which calculates attention maps for lower-level features guided by higher-level features. This mechanism emphasizes active semantic regions for low-level distortions, thereby improving performance. TOPIQ can be used for both FR and NR IQA, Chen, C., Mo, J., Hou, J., Wu, H., Liao, L., Sun, W., ... & Lin, W. (2024).

The authors aspired to fill these gaps by carrying out the most extensive IQA evaluation study for Magnetic Resonance Imaging (MRI) to date (14,700 subjective scores). We use outputs of neural network models trained to solve problems relevant to MRI, including image reconstruction in the scan acceleration, motion correction, and denoising. Our emphasis is on reflecting the radiologist's perception of the reconstructed images, gauging the most diagnostically influential criteria for the quality of MRI scans: signal-to-noise ratio, contrast-to-noise ratio, and the presence of artifacts. Seven trained radiologists assess these distorted images, with their verdicts then correlated with 35 different image quality metrics (full-reference, no-reference, and distribution-based metrics considered). The top performers– DISTS, HaarPSI, VSI, and FIDVGG16– are found to be efficient across three proposed quality criteria for all considered anatomies and the target tasks, Kastryulin, S., Zakirov, J., Pezzotti, N., & Dylov, D. V. (2023).

A variety of external factors might seriously degrade PET image quality and lead to inconsistent results. The aim of this study is to explore a potential PET image quality assessment (QA) method with deep learning (DL), Zhang, H., Liu, Y., Wang, Y., Ma, Y., Niu, N., Jing, H., & Huo, L. (2023).

The authors developed and externally test deep learning (DL) models for assessing the image quality of three-dimensional (3D) macular scans from Cirrus and Spectralis optical coherence tomography devices. The authors used a 3D version of the residual network (ResNet)-18 for Cirrus 3D scans and a multiple-instance learning pipeline with ResNet-18 for Spectralis 3D scans. Two deep learning (DL) models were further tested via three unseen Cirrus data sets from Singapore and five unseen spectralis data sets from India, Australia and Hong Kong, respectively, Tang, Z., Wang, X., Ran, A. R., Yang, D., Ling, A., Yam, J. C., ... & Cheung, C. Y. (2024).

The authors referred to the framework used to train the two encoders as Re-IQA. For Image Quality Assessment in the Wild, we deploy the complementary low and high-level image representations obtained from the Re-IQA framework to train a linear regression model, which is used to map the image representations to the ground truth quality scores, refer to Figure 1. Our method achieves state-of-the-art performance on multiple large-scale image quality assessment databases containing both real and synthetic distortions, demonstrating how deep neural networks can be trained in an unsupervised setting to produce perceptually relevant representations. We conclude from our experiments that the low and high-level features obtained are indeed complementary and positively impact the performance of the linear regressor, Saha, A., Mishra, S., & Bovik, A. C. (2023).

The authors proposed to solve the problem by a pretext task customized for BIQA in a self-supervised learning manner, which enables learning representations from orders of magnitude more data. To constrain the learning process, we propose a quality-aware contrastive loss based on a simple assumption: the quality of patches from a distorted image should be similar but vary from patches from the same image with different degradations and patches from different images. Further, we improve the existing degradation process and form a degradation space with a size of roughly $2x10^7$. After pre-training on ImageNet using our method, models are more sensitive to image quality and perform significantly better on downstream BIQA tasks, Zhao, K., Yuan, K., Sun, M., Li, M., & Wen, X. (2023).

The objective of this IRB-approved retrospective study was to apply deep learning to identify magnetic resonance imaging (MRI) artifacts on maximum intensity projections (MIP) of the breast, which were derived from diffusion-weighted imaging (DWI) protocols. 2D MIP images were computed and the left and right breast were cropped out as regions of interest (ROI). A DenseNet was trained with a fivefold cross-validation to identify artifacts on these images. In an independent holdout test dataset (n = 350 images), artifacts were detected by the neural network with an area under the precision-recall curve of 0.921 and a positive predictive value of 0.981, Kapsner, L. A., Balbach, E. L., Folle, L., Laun, F. B., Nagel, A. M., Liebert, A., ... & Bickelhaupt, S. (2023).

The authors proposed a novel method to detect the forged faces using Image Quality Assessment (IQA) based features. As far as we know IQA has not been used for detecting AI-generated images. Despite the visual appearance being the same for original and fake images, most of the discriminative information will be available in the frequency domain of those images. With that intuition, we have extracted image quality-based features from the frequency domain and also the spatial domain. The proposed method has achieved the highest accuracy of 99% when different types of experiments were performed on standard datasets. The generalization and explainability of the proposed model have also been discussed by Kiruthika, S., & Masilamani, V. (2023).

The authors proposed two salient structure priors incorporated with a deep convolutional neural network (CNN) to enforce CNN and pay attention to these salient structures. Accordingly, two CNN architectures named Dual-branch SalStructIQA and Single-branch SalStructIQA are designed for the incorporation, respectively, Xu, Z., Zou, B., & Liu, Q. (2023).

The authors surveyed the recent advances in deep learning-based IQA methods, which have demonstrated remarkable performance and innovation in this field. The authors classified the IQA methods into two main groups: reference-based and reference-free methods. Reference-based methods compare query images with reference images, while reference-free methods do not. The authors further subdivide reference-based methods into full-reference and reduced-reference methods, depending on the amount of information they need from the reference images, and reference-free methods into single-input, pair-input, and multimodal-input methods, according to the form of input they use. The advantages and limitations of each category are analyzed and some representative examples of state-of-the-art methods are provided, Yang, J., Lyu, M., Qi, Z., & Shi, Y. (2023).

The authors proposed a large no-reference perceptual image quality assessment (PIQA) dataset. Additionally, different deep learning-based methods have been trained on this PIQA dataset in order to provide benchmarking for developing learning-based low-light assessment methods. Finally, this review paper is concluded with current challenges and suggestions for future work, Rasheed, M. T., Shi, D., & Khan, H. (2023).

This study aimed to evaluate the image quality assessment (IQA) and quality criteria employed in publicly available datasets for diabetic retinopathy (DR). A literature search strategy was used to identify relevant datasets, and 20 datasets were included in the analysis. Out of these, 12 datasets mentioned performing IQA, but only eight specified the quality criteria used. The reported quality criteria varied widely across datasets, and accessing the information was often challenging. The findings highlight the importance of IQA for AI model development while emphasizing the need for clear and accessible reporting of IQA information. The study suggests that automated quality assessments can be a valid alternative to manual labeling and emphasizes the importance of establishing quality standards based on population characteristics, clinical use, and research purposes. In conclusion, image quality assessment is important for AI model development; however, strict data quality standards must not limit data sharing. Given the importance of IQA for developing, validating, and implementing deep learning (DL) algorithms, it's recommended that this information be reported in a clear, specific, and accessible way whenever possible, Gonçalves, M. B., Nakayama, L. F., Ferraz, D., Faber, H., Korot, E., Malerbi, F. K., ... & Belfort Jr, R. (2024).

The authors aimed to develop advanced and training-free full-reference image quality assessment (FR-IQA) models based on deep neural networks. Specifically, we investigate measures that allow us to perceptually compare deep network features and reveal their underlying factors. We find that distribution measures enjoy advanced perceptual awareness and test the Wasserstein distance (WSD), Jensen-Shannon divergence (JSD), and symmetric Kullback-Leibler divergence (SKLD) measures when comparing deep features acquired from various pre-trained deep networks, including the Visual Geometry Group (VGG) network, SqueezeNet, MobileNet, and EfficientNet, Liao, X., Wei, X., Zhou, M., Li, Z., & Kwong, S. (2024).

Deep learning (DL) models have a unique characteristic in that they are specialized to a characteristic training set, meaning that deviations between the input testing data from the training data will reduce prediction accuracy. Therefore, we propose a novel DL-based NR-IQA metric, the model specialization metric (MSM), which does not depend on ground-truth images or labels. MSM measures the difference between the input image and the model's prediction for evaluating the quality of the input image. Experiments conducted on both simulated distorted proton T1-weighted MR images and denoised sodium MR images demonstrate that MSM exhibits a superior evaluation performance on various simulated noises and distortions. MSM also has a substantial agreement with the expert evaluations, achieving an averaged Cohen's Kappa coefficient of 0.6528, outperforming the existing NR-IQA metrics, Yuan, S., Whitmarsh, T., Kessler, D. A., Arponen, O., McLean, M. A., Baxter, G., ... & Kaggie, J. D. (2024).

The authors determined the feasibility of using a deep learning (DL) algorithm to assess the quality of focused assessment with sonography in trauma (FAST) exams. The authors used convolutional neural networks (CNNs), pretrained on the Imagenet dataset and fine-tuned on the FAST dataset. Second, the authors trained a CNN autoencoder to compress FAST images with a 20–1 compression ratio. The compressed codes were input to a two-layer classifier network. To train the networks, each video was labeled with the quality of the exam, and the frames were labeled with the quality of the video. For inference, a video was classified as poor quality if half the frames were classified as poor quality by the network, and an exam was classified as poor quality if half the videos were classified as poor quality, Taye, M., Morrow, D., Cull, J., Smith, D. H., & Hagan, M. (2023).

The authors performed a comprehensive intraindividual objective and subjective image quality evaluation of coronary CT angiography (CCTA) reconstructed with deep learning image reconstruction (DLIR) and to assess correlation with routinely applied hybrid iterative reconstruction algorithm (ASiR-V), De Santis, D., Polidori, T., Tremamunno, G., Rucci, C., Piccinini, G., Zerunian, M., ... & Caruso, D. (2023).

The authors focused on subjective and objective quality assessment of textured 3D meshes. The authors first establish a large-scale dataset, which includes 55 source models quantitatively characterized in terms of geometric, color, and semantic complexity and corrupted by combinations of five types of compression-based distortions applied on the geometry, texture mapping, and texture image of the meshes. This dataset contains over 343k distorted stimuli. The authors proposed an approach to select a challenging subset of 3,000 stimuli for which we collected 148,929 quality judgments from over 4,500 participants in a large-scale crowdsourced subjective experiment. Leveraging the subject-rated dataset, a learning-based quality metric for 3D graphics was proposed. Our metric demonstrates state-of-the-art results on our dataset of textured meshes and on a dataset of distorted meshes with vertex colors. Finally, The authors presented an application of our metric and dataset to explore the influence of distortion interactions and content characteristics on the perceived quality of compressed textured meshes, Nehmé, Y., Delanoy, J., Dupont, F., Farrugia, J. P., Le Callet, P., & Lavoué, G. (2023).

### *Research Problem Statement*

IQA plays a critical role in various applications where the accuracy and interpretability of images significantly impact decision-making processes. Traditional methods in IQA, which rely on hand-crafted features and basic image processing techniques, often fall short in accurately capturing complex degradations and subtle quality nuances, particularly in high-resolution and diverse image datasets. As images are widely used in fields such as medical imaging, remote sensing, security surveillance, and multimedia applications, assessing image quality accurately and automatically has become essential.

With the rise of deep learning, numerous models have demonstrated improved accuracy in detecting and quantifying image quality. However, challenges remain in designing and implementing deep learning-based IQA models that can generalize well across diverse image domains and degradation types, such as noise, blurring, compression artifacts, and color distortions. Additionally, many existing models require substantial labeled data and computational resources, which may not always be feasible in real-world applications. This issue is further compounded when the assessment involves perceptual quality, as human visual system (HVS) characteristics are complex and challenging to replicate computationally.

The research problem, therefore, is to develop an effective, efficient, and generalizable deep learning-based Image Quality Assessment framework that leverages advanced image processing techniques to enhance robustness across diverse image degradation types. This framework should also incorporate methods that can emulate or approximate the HVS to improve perceptual quality evaluation, addressing the limitations of current IQA methods in terms of adaptability, data dependency, and computational efficiency.

### *Future Research Direction*

*Hybrid models integrating deep learning and image processing techniques*

Future research could explore hybrid architectures that combine traditional image processing algorithms with deep learning models to improve model interpretability and robustness. By leveraging pre-processing techniques, such as adaptive filtering or edge enhancement, hybrid models may reduce computational costs and enhance performance, particularly in applications with limited computational resources.

*Human visual system (HVS)-inspired models*

There is a need to design IQA models that better mimic the HVS by incorporating perceptual characteristics like contrast sensitivity, color perception, and attention mechanisms. Incorporating neural attention mechanisms aligned with HVS traits could improve perceptual quality assessment, making models more aligned with human perception.

*Domain adaptation and transfer learning for IQA*

Given the diversity in image datasets and degradation types, models that can generalize across different domains are crucial. Domain adaptation and transfer learning could enable IQA models to learn from limited labeled datasets in new domains, improving applicability to varied fields, such as medical imaging and satellite imagery, without extensive retraining.

*Lightweight and efficient IQA models for real-time applications*

As applications like surveillance and mobile photography require real-time quality assessment, there is a growing need for lightweight deep learning architectures. Techniques such as model pruning, quantization, and knowledge distillation can be further explored to develop efficient IQA models suitable for deployment on edge devices.

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