A Historical Overview of Image Quality Assessment Methods: Focus on Medical Imaging Applications

Abstract. This paper provides a comprehensive review of Image Quality Assessment (IQA) methods, tracing their historical development from early conventional metrics to modern deep learning-based approaches. First, it describes fundamental subjective and objective techniques, including full-reference, reduced-reference, and no-reference methods. Then, the review examines major advancements across different eras, including HVS-based models, transform-domain and natural scene statistics techniques, and traditional machine learning approaches. Special attention is given to recent deep learning innovations, particularly convolutional neural networks (CNNs), vision transformers, and modern training paradigms such as transfer learning, meta-learning, and self-supervised learning. The survey emphasizes the applications in medical imaging, where accurate and robust IQA is critical for reliable diagnosis and clinical decision-making. Finally, the paper highlights ongoing challenges and outlines future research directions for building medically effective and reliable IQA systems. This paper aims at serving as a comprehensive reference for researchers seeking to understand existing approaches, identify limitations, and develop new solutions tailored to domain-specific needs.

Keywords: Image Quality Assessment (IQA); Medical Imaging; No-Reference (NR) IQA; Full-Reference (FR) IQA; Deep Learning; Convolutional Neural Networks (CNN); Vision Transformers (ViT); Natural Scene Statistics (NSS); Meta-Learning; Transfer Learning; Self-Supervised Learning; Diagnostic Imaging.

1 Introduction

Assessing digital picture quality in a manner that mimics human visual perception is the goal of image Quality Assessment (IQA) . It is generally separated into two categories: objective methods , which employ algorithms , and subjective methods, which depend on human judgments [1] . Depending on whether a reference image is available, objective IQA can be full-reference (FR) , reduced-reference (RR), or no-reference (NR) [2] .The application determines which approach is best, such as the need for aesthetics in photography versus the need for precise diagnosis in medical imaging [1] . This study offers a thorough analysis of IQA techniques, following their development from transform-based and statistical methods to deep learning models such as CNNs and transformers . Particular attention is paid to medical imaging since precise quality evaluation directly affects clinical outcomes .

The remainder of the paper is organized as follows: Section 2 reviews early IQA techniques based on statistical models and the Human Visual System (HVS). Section 3 focuses on transform-domain methods and Natural Scene Statistics (NSS) models. Section 4 presents traditional machine learning approaches for IQA, such as feature-based regression models. Section 5 discusses the advent of deep learning using Convolutional Neural Networks (CNNs). Section 6 introduces transformer-based architectures and their benefits for perceptual modeling. Section 7 explores modern framework-based methods that enhance robustness and generalization using transfer learning, meta-learning, and self-supervised learning. Finally, section 8 concludes the paper and outlines future directions for developing robust IQA systems tailored to medical imaging needs.

2 (Early 2000s) Statistical and HVS-based methods

In the early 2000s, Image Quality Assessment (IQA) methods largely relied on objective statistical metrics and models inspired by the Human Visual System (HVS) [47]. Objective techniques aim to quantify image fidelity through physical measurements and algorithmic predictions. Among these**,** spatial resolution is typically assessed using the Modulation Transfer Function (MTF), which measures the system's ability to reproduce fine image details**.** Contrast resolution, which is critical in distinguishing tissues with similar densities, is often evaluated via the Contrast-to-Noise Ratio (CNR). Noise characteristics are also essential and can be captured using metrics such as the Noise Power Spectrum (NPS) or the Signal-to-Noise Ratio (SNR). Additionally, the presence of artifacts, which are unwanted distortions that may hinder diagnostic interpretation, is a vital consideration in medical imaging quality.

Traditional full-reference (FR) metrics, such as Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR), have been widely adopted due to their mathematical simplicity, computational efficiency, and interpretability [3][4]. However, despite these advantages, such metrics often fail to correlate with human visual perception, particularly in medical imaging, where diagnostic relevance and visual nuance are critical.

To bridge this gap, HVS-based approaches emerged, aiming to better model the perceptual mechanisms of the human visual system. One of the most influential contributions in this area is the Structural Similarity Index Measure (SSIM) which evaluates local structures in pixel intensity patterns while accounting for luminance and contrast [5]. SSIM is based on the idea that structural information aligns more closely with human perception than pixel-wise differences.

In addition to full-reference methods, reduced-reference (RR) techniques were developed to estimate image quality with partial information from the original image. For example, methods introduced by Wang and Simoncelli extract perceptually relevant features from the reference image to reduce the need for full data transmission, which is especially valuable in bandwidth-limited environments [6].

Despite advancements in both statistical and HVS-based methods, the objective metrics often fail to fully capture subjective human perception or clinical utility, especially in domains like medical imaging, where nuanced visual cues can significantly affect diagnostic accuracy.

3 (Mid 2000s-2012) Transform domain and natural scene statistics-based methods

During the mid-2000s to early 2010s, Image Quality Assessment (IQA) research expanded significantly with introducing the techniques that leveraged transform domain representations and natural scene statistics (NSS). These methods aimed to better capture the perceptual characteristics of images by analyzing them in frequency or statistical domains, beyond simple pixel-based comparisons.

3.1 Transform domain methods

Full-reference (FR) IQA techniques in this period began by applying transformations such as the Discrete Cosine Transform (DCT), wavelet transform, or Singular Value Decomposition (SVD) to extract structural features from both reference and distorted images. For example, the method proposed in [7] uses the wavelet domain to quantify changes induced by distortion in wavelet coefficients. Other methods such as SFF [8] and QASD [9] apply sparse representations to model important image features and estimate perceptual quality.

In the no-reference (NR) setting, approaches like BLIINDS-II [10] analyze the statistical distribution of DCT coefficients affected by distortions.

3.2 Natural Scene Statistics (NSS)-based methods

NSS-based approaches assume that undistorted natural images follow specific statistical regularities, and deviations from these patterns can signal quality degradation. As an example, the Information Fidelity Criterion (IFC) [11], which compares the mutual information between reference and distorted images. Another example is the Tone-Mapped Image Quality Index (TMQI) [12], which combines Structural Similarity Index Measure (SSIM) [5] with NSS-based naturalness measures to assess tone-mapped images, frequently used in high dynamic range (HDR) applications.

These methods demonstrate that both frequency-domain transformations and statistical modeling of natural scenes offer powerful tools for capturing perceptual aspects of image quality, particularly when traditional pixel-level metrics fail.

Table 1 and Fig. 1 summarize and represent key statistical, HVS-based, transform domain, and NSS methods along with their citation counts, highlighting their historical impact (data sourced from Google Scholar, April 2025).

Table 1. Stat/HVS/NSS/TD-Methods with citation count (sourced from Google Scholar April, 2025).

Metric	Citation Count	Year	Description
SSIM	58352	2004	Evaluates structural similarity.
MS-SSIM	8043	2004	Multiscale version of SSIM.
IFC	1721	2005	Information fidelity criterion.
PSNR-HVS	433	2006	Perceptual variant of PSNR.
IW-SSIM	1533	2010	Information-weighted SSIM.
FSIM	5512	2011	Uses phase congruency and gradient magnitude.
GSIM	872	2011	Gradient similarity index.
BLIINDS-II	1912	2012	DCT statistics-based method.
TMQI	720	2012	Tone-Mapped image quality index.

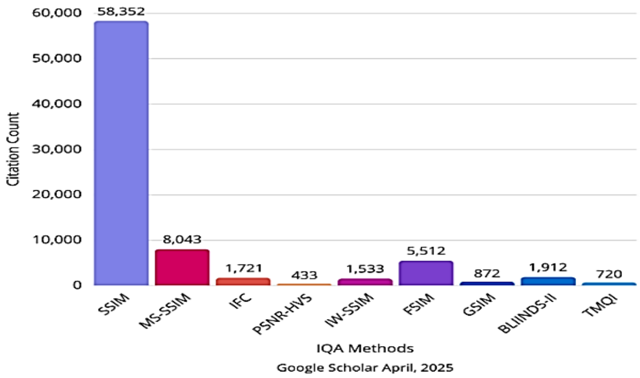

Fig. 1. A representative graph of Table 1.

4 (2011-2015) Traditional machine learning approaches

The period from 2011 to 2015 witnessed the integration of traditional machine learning techniques into Image Quality Assessment (IQA), significantly advancing the field, particularly in medical imaging contexts. Machine learning (ML) models began to offer more flexible, perceptually aligned, and data-driven evaluations of image quality, reducing reliance on hand-crafted metrics or subjective assessments.

In the context of Medical Image Quality Assessment (MIQA), AI-based systems help automate routine image quality checks, reduce noise and artifacts, and ensure consistency across assessments. Rather than replacing radiologists, these tools act as assistive technologies, freeing clinicians from repetitive tasks and allowing them to concentrate on complex diagnostic decisions.

In the FR domain, Multimethod Fusion (MMF) [13] and ParaBoost [14] combined outputs from multiple specialized metrics to capture a broader spectrum of distortions.

For NR IQA, Natural Scene Statistics (NSS) have become foundational. Approaches such as: DIIVINE [15], which extracts NSS features and uses support vector regression for quality prediction; ILNIQE [16], which models multivariate Gaussian distributions over NSS features; and BRISQUE [17], which uses multi-scale NSS features for low-complexity, high-performance quality estimation; all contribute significantly to IQA without requiring a reference image, an essential capability for real-time or clinical use cases.

These models marked a shift from static, handcrafted approaches to more adaptive, learning-based systems that better align with human perception and diagnostic requirements. The ability to operate in blind (NR) conditions made them particularly attractive for deployment in healthcare and mobile imaging systems.

Table 2 and Fig. 2 provide a comparative summary and representation of prominent ML-based IQA methods, including citation counts as of April 2025 (source: Google Scholar).

Table 2. ML-Methods with citation count (sourced from Google Scholar April, 2025).

Metric	Citation Count	Year	Description
DIIVINE	2003	2011	NSS + SVM for distortion classification.
BRISQUE	5733	2012	Multiscale NSS with low complexity.
MMF	216	2012	Multi-method fusion using SVR.
IL-NIQE	1214	2015	MVG model using NSS.
ParaBoost	86	2015	Distortion-adaptive fusion approach.

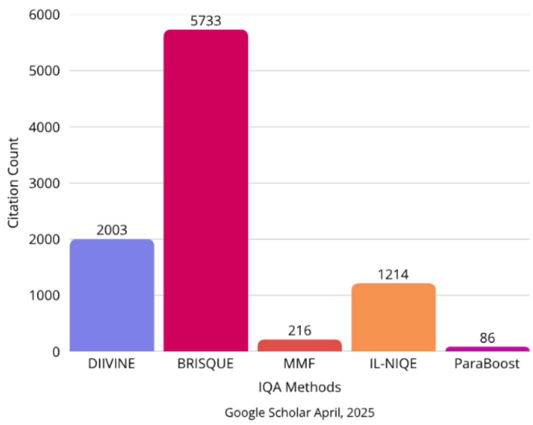

Fig. 2. A representative graph of Table 2.

5 (2014-2022) CNN-based deep learning

Deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized Image Quality Assessment (IQA) by enabling end-to-end learning of complex image features. since the introduction of IQACNN [18], CNN-based models have demonstrated superior performance in both no-reference (NR) and full-reference (FR) settings. Their ability to automatically learn hierarchical representations directly from image data makes them especially effective for tasks like noise reduction, artifact detection, and perceptual quality scoring.

5.1 No-Reference (NR) IQA

In blind IQA, CNNs have enabled accurate quality prediction without reference images. As examples, Bosse et al. [19] introduced a Siamese CNN architecture trained on human opinion scores, and MEON [21] provides an end-to-end quality prediction pipeline. RankIQA [20] uses pairwise ranking with Siamese networks to infer relative image quality. These approaches allow models to learn perceptual differences directly from training data.

5.2 Full-Reference (FR) IQA

In the FR domain, CNNs like SRIF [22] and DR-IQA [23], leverage learned feature embeddings and multi-level descriptors to compare pristine and distorted images. These models improve upon traditional metrics by learning more robust representations aligned with perceptual fidelity.

5.3 Reduced-Reference (RR) IQA

CNNs have also advanced RR IQA. CVRKD-IQA [24] employs knowledge distillation to train networks that are more tolerant of content variations, thus reducing the need for exact reference alignment. Thong et al. [25] proposed content-diverse image pairings to train models that generalize across different scenes and structures.

5.4 Applications in medical imaging

The impact of CNNs on Medical Image Quality Assessment (MIQA) has been particularly significant. CNNs are employed to denoise CT images, enhancing diagnostic clarity, and to detect and classify artifacts in MRI scans, improving their interpretability. CNN-based systems have also been used for automated quality grading in complex modalities like whole-heart MRI, mimicking the visual evaluation performed by expert radiologists. Their ability to bypass manual feature engineering and learn directly from pixel data is a substantial advantage in clinical environments.

5.5 Emerging CNN-based blind IQA

Recent blind IQA models further illustrate the adaptability of CNNs. NIMA [26] adapts popular CNN backbones (e.g., VGG [27], Inception v2 [28], and MobileNet [27]) for perceptual quality scoring. GIQA [29] transforms regression into a set of binary classification tasks under varying thresholds to increase robustness to label noise. Other methods, such as DB-CNN [30] and HyperIQA [31], refine architecture and training processes to specialize in distortion-specific or content-aware quality estimation.

The rapid growth of CNN-based IQA research highlights their critical role in advancing perceptual, consistent, and scalable quality assessment systems across domains. A summary of these approaches and their citation impact is provided in Table 3 and Fig. 3 (based on Google Scholar data, April 2025).

Table 3. CNN-based approaches with citation count (sourced from Google Scholar April, 2025).

Metric	Citation Count	Year	Description
IQACNN	1400	2014	CNNs for no-reference image quality assessment.
IL-NIQE	1214	2015	MVG model using NSS.
RankIQA	500	2017	Learns from rankings for no-reference image quality assessment.
MEON	700	2017	End-to-end blind IQA with a multi-task CNN.
Bosse et al.	1000	2017	Data-driven NR-IQA using a Siamese network.
DB-CNN	700	2018	Uses a custom CNN for artificial distortions and bilinear pooling for NR-IQA.
NIMA	2800	2018	Adapts various CNN networks (VGG, Inception, MobileNet) for NR-IQA.
GIQA	300	2020	Converts regression to binary classification for robust NR-IQA.
HyperIQA	600	2020	Creates a hyper network to adaptively generate weights for NR-IQA.
DR-IQA	200	2021	Trains a degradation-tolerant embedding for FR-IQA.
Thong et al.	30	2022	Content-diverse comparisons improve IQA.
SRIF	100	2022	Multi-level pyramid feature descriptor for FR-IQA.
CVRKD-IQA	100	2022	Uses knowledge distillation for content-tolerant RR-IQA features.

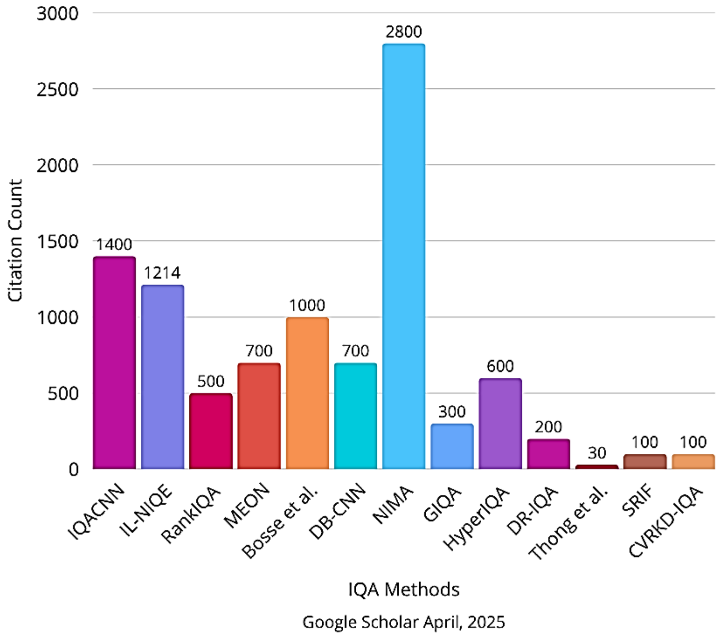

Fig. 3. A representative graph of Table 3.

6 (2021-Now) Transformer-based deep learning

Beyond traditional Convolutional Neural Networks (CNNs), recent deep learning advancements have introduced more sophisticated architectures, such as U-Net, ResNet, and Transformer-based models, that are substantially reshaping the Medical Image Quality Assessment (MIQA) field. While CNNs have achieved significant success by learning hierarchical image features, these new models offer improved capabilities in capturing long-range spatial dependencies and global contextual information, which are critical for robust and perceptually aligned image quality evaluation [48].

U-Net with its variants, originally designed for medical image segmentation, have been successfully repurposed for MIQA tasks. Their symmetric encoder-decoder structure helps preserve spatial resolution, enabling targeted quality assessment in clinically relevant regions such as tumors or organ boundaries [48]. Also, ResNet architectures, known for their use of residual connections, allow deep network training and are effective for extracting fine-grained features. This enhances classification and scoring of subtle variations in medical images [49].

More recently, Transformer-based architectures, particularly Vision Transformers (ViTs) [36], have emerged as powerful alternatives to CNNs for IQA tasks. Unlike CNNs, which are often constrained by fixed input sizes and local receptive fields, Transformers model long-range dependencies and integrate global image context more effectively [49]. In the no-reference (NR) IQA domain, models like TRIQ [32] leverage Transformers for processing images of varying resolutions without losing spatial fidelity. Their multi-head self-attention mechanisms allow precise detection of quality-degrading artifacts that might be missed by local convolutional filters.

Building on this foundation, MUSIQ [37] introduces learnable scale encodings and 2D hashed positional encodings for better capturing multi-scale spatial dependencies. DEIQT [38] improves the quality prediction process by applying quality-aware decoding to Transformer outputs. MANIQA [39] combines Swin Transformer layers to integrate both local attention and global encoding, thereby enhancing its performance on complex distortions.

In the full-reference (FR) IQA domain, Transformer-based models also show strong potential. IQT [33], for example, uses attention mechanisms to refine feature representations after fusing pristine and distorted image inputs. JSPL [34] employs spatial attention to reweight distance maps. AHIQ [35] merges CNNs with ViTs, extracting low-level features using a shallow CNN module and capturing spatial correlations and higher-order dependencies through Transformer layers.

Notably, Transformer-based IQA models, particularly those built on ViT frameworks, have outperformed conventional architectures in benchmark challenges such as the NTIRE 2021 and 2022 Perceptual IQA Challenges [40][41]. These results underscore the growing maturity and effectiveness of Transformer-based approaches in both NR and FR settings. A summary of these methods and their scholarly impact is provided in Table 4 and Fig. 4.

Table 4. Transformer-based approaches with citation count (sourced from Google Scholar April, 2025).

Metric	Citation Count	Year	Description
TRIQ	230	2020	Transformer for resolution-agnostic IQA.
MUSIQ	601	2021	Handles multi-scale and varied aspect ratio images.
DEIQT	50	2021	interpretation task using a Transformer to extract quality-aware features.
IQT	167	2021	Siamese ViT for FR-IQA.
JSPL	57	2022	reweight the distance map between query and reference images.
Maniqa	301	2022	Multi-dimension attention (ViT + Swin).
AHIQ	113	2022	Combining a shallow CNN for details with ViT for capturing spatial correlations.
TRIQ	230	2020	Transformer for resolution-agnostic IQA.

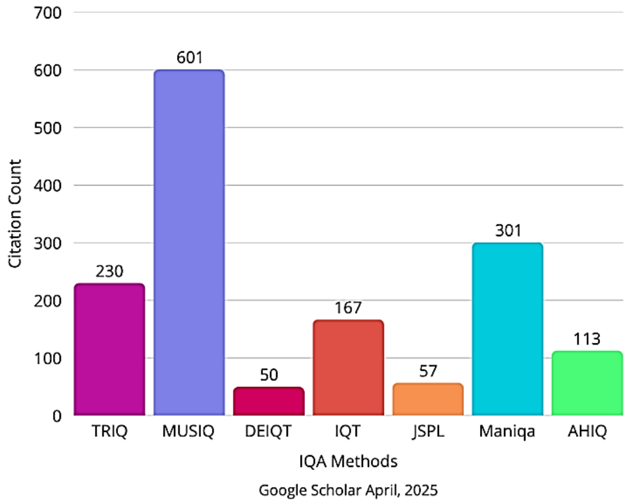

Fig. 4. A representative graph of Table 4.

7 (2021-Now) Framework-based methods

Recent advancements in deep learning have catalyzed the emergence of increasingly sophisticated training paradigms tailored to the unique challenges of Medical Image Quality Assessment (MIQA). Current research focuses on the development of adaptive frameworks that address persistent issues such as data scarcity, domain specificity, and distortion variability in MI. These frameworks are designed to enhance the generalizability, robustness, and clinical applicability of MIQA models. The main methodologies driving this shift include:

- Transfer learning: extensively applied in ultrasound image quality assessment. It involves leveraging features learned from large-scale natural image datasets and adapting them to smaller, domain-specific medical datasets. This strategy improves model performance, especially in scenarios where annotated medical image data is limited [42].
- Meta-learning: introduced in works such as MetaIQA [43], meta-learning trains models to “learn how to learn” across various distortion types. This human-inspired generalization enables models to handle previously unseen or rare distortion patterns, making it particularly valuable for robust MIQA.
- Cross-distortion generalization: Frameworks like UNIQUE [44] address the challenge of distortion diversity by training a single blind IQA (BIQA) model on multiple datasets with varied distortion types. This multi-task learning approach facilitates discovering of shared quality-related features, improving generalization across different imaging conditions and modalities.
- Weakly supervised learning: The DeepFL-IQA framework [45] demonstrates how weak supervision can reduce dependence on extensive subjective

annotations. The model is initially trained using objective image quality metrics (e.g., PSNR, SSIM), and then fine-tuned with a limited number of human-provided scores. This dual-stage approach strikes a balance between computational efficiency and perceptual accuracy.

- Self-supervised learning: CONTRIQUE [46] exemplifies the use of self-supervised learning (SSL) in MIQA. By solving pretext tasks, such as predicting spatial arrangements or transformations, the model learns robust, quality-aware representations without labeled data. These embeddings can be successfully transferred to downstream quality prediction tasks.

These new learning approaches represent a major shift in MIQA , offering scalable and perceptually accurate solutions , especially for no-reference model . By reducing annotation needs and improving adaptability , they enable clinically relevant IQA systems suitable for real-world diagnostics.

Table 5 and Fig. 5 summarize and represent key framework-based approaches and their impact, including citation counts (as of April 2025, sourced from Google Scholar).

Table 5. Framework-based approaches with citation count (sourced from Google Scholar April, 2025).

Metric	Citation Count	Year	Description
CNN-based Medical Ultrasound IQA	21	2021	Transfer Learning
MetaIQA	405	2020	Meta-Learning
UNIQUE	286	2021	Cross-Distortion Generalization
DeepFL-IQA	71	2020	Weakly Supervised Learning
CONTRIQUE	206	2022	Self-Supervised Learning

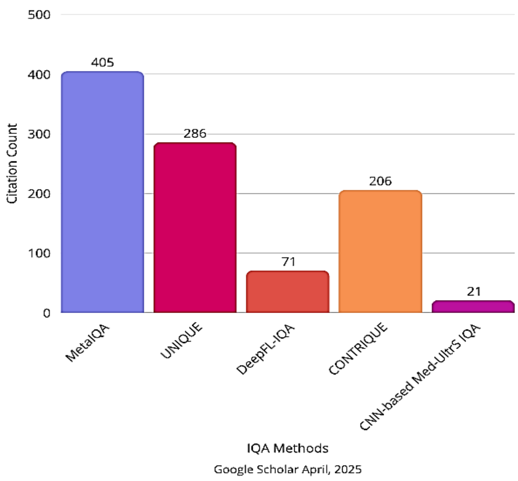

Fig. 5. A representative graph of Table 5.

8 Conclusion

Image Quality Assessment (IQA), especially in the medical domain, is increasingly vital for advancing healthcare outcomes and broader imaging applications. High-quality images are essential for accurate diagnosis, effective treatment planning, and reliable patient monitoring. While traditional objective metrics, such as PSNR and SSIM, have long been favored for their simplicity and interpretability, the emergence of artificial intelligence, particularly deep learning, has transformed the field by enabling faster, more consistent, and scalable assessment techniques.

This survey has systematically reviewed the progression of IQA technologies, highlighting both general-purpose and domain-specific approaches. Although deep learning methods consistently outperform classical ones in terms of predictive accuracy, their deployment is often hampered by challenges such as complex implementation, low interpretability, and dependency on large annotated datasets. Consequently, traditional techniques remain relevant in practical scenarios where simplicity and transparency are prioritized.

In medical imaging, task-specific requirements, such as lesion visibility or organ boundary clarity, are central to quality assessment, unlike in other domains (e.g., facial aesthetics in portrait photography). Therefore, IQA research must evolve in alignment with application-specific needs. For example, dehazing algorithms should prioritize contrast and color fidelity, whereas deblurring models must mitigate artifacts like ringing and ghosting.

The successful integration of AI into IQA workflows also depends on addressing critical issues such as algorithmic bias, ethical decision-making, and standardization across imaging systems. Additionally, the quality, size, and diversity of training datasets remain fundamental to building robust and generalizable models.

Looking ahead, the IQA field is poised for further innovation through the development of more interpretable and efficient models, the integration of multimodal data, and the design of customized quality metrics. Bridging the gap between technical performance, clinical practicality, and user-centered design will be essential to advancing IQA technologies across domains. By embracing these advancements while thoughtfully managing associated challenges, the research and clinical communities can fully harness intelligent image quality assessment to improve outcomes, optimize workflows, and enhance user satisfaction.

Fig. 6 provides a representative timeline highlighting major milestones and trends in the evolution of IQA research and technologies.

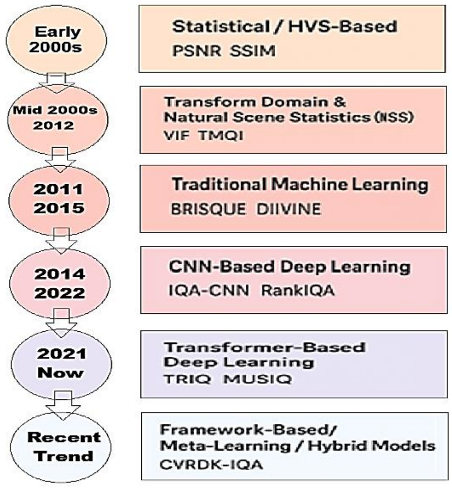

Fig. 6. A representative time-line of IQA

References

1. Ma, C., Shi, Z., Lu, Z., et al.: A survey on image quality assessment: Insights, analysis, and future outlook. arXiv preprint arXiv:2502.08540 (2025).
2. Wang, L.: A survey on IQA. arXiv preprint arXiv:2109.110 (2021).
3. Girod, B.: What's wrong with mean-squared error? In: Digital Images and Human Vision, pp. 207–211 (1993).
4. Wang, Z., Bovik, A.C., Lu, L.: Why is image quality assessment so difficult? In: Proc. 2002 IEEE Int. Conf. on Acoustics, Speech, and Signal Processing, Vol. 4, pp. 3313–3316 (IEEE, 2002).
5. Wang, Z., Bovik, A.C., Sheikh, H.R., et al.: Image quality assessment: From error visibility to structural similarity. IEEE Trans. Image Process. 13(4), 600–612 (2004).
6. Wang, Z., Simoncelli, E.P.: Reduced-reference image quality assessment using a wavelet-domain natural image statistic model. Proc. SPIE 5666, 149–159 (2005).
7. Wang, Z., Simoncelli, E.P.: Reduced-reference image quality assessment using a wavelet-domain natural image statistic model. In: HVEI, Vol. 5666, pp. 149–159 (SPIE, 2005).
8. Chang, H.W., Wang, M.H., et al.: Sparse feature fidelity for perceptual image quality assessment. IEEE Trans. Image Process. 22(10), 4007–4018 (2013).
9. Li, L., Sun, X., et al.: Sparse representation-based image quality index with adaptive sub-dictionaries. IEEE Trans. Image Process. 25(8), 3775–3786 (2016).
10. Saad, M.A., Charrier, C., et al.: Blind image quality assessment: A natural scene statistics approach in the DCT domain. IEEE Trans. Image Process. 21(8), 3339–3352 (2012).
11. Sheikh, H.R., De Veciana, G., et al.: An information fidelity criterion for image quality assessment using natural scene statistics. IEEE Trans. Image Process. 14(12), 2117–2128 (2005).

12. Yeganeh, H., Wang, Z.: Objective quality assessment of tone-mapped images. IEEE Trans. Image Process. 22(2), 657–667 (2012).
13. Liu, T.J., Kuo, C.C.J., et al.: Image quality assessment using multi-method fusion. IEEE Trans. Image Process. 22(5), 1793–1807 (2012).
14. Liu, Y., Rusinkiewicz, S., et al.: A no-reference metric for evaluating the quality of motion deblurring. ACM Trans. Graph. 32(6), 1–12 (2013).
15. Moorthy, A.K., Bovik, A.C.: Blind image quality assessment: From natural scene statistics to perceptual quality. IEEE Trans. Image Process. 20(12), 3350–3364 (2011).
16. Zhang, L., Bovik, A.C., et al.: A feature-enriched completely blind image quality evaluator. IEEE Trans. Image Process. 24(8), 2579–2591 (2015).
17. Mittal, A., Bovik, A.C., et al.: No-reference image quality assessment in the spatial domain. IEEE Trans. Image Process. 21(12), 4695–4708 (2012).
18. Kang, L., Doermann, D., et al.: Convolutional neural networks for no-reference image quality assessment. In: Proc. CVPR, pp. 1733–1740 (IEEE, 2014).
19. Bosse, S., et al.: Deep neural networks for no-reference and full-reference image quality assessment. IEEE Trans. Image Process. 27(1), 206–219 (2017).
20. Liu, X., Bagdanov, A.D., et al.: RankIQA: Learning from rankings for no-reference image quality assessment. In: Proc. ICCV, pp. 1040–1049 (2017).
21. Ma, K., Zuo, W., et al.: End-to-end blind image quality assessment using deep neural networks. IEEE Trans. Image Process. 27(3), 1202–1213 (2017).
22. Zhou, W., Wang, Z.: Quality assessment of image super-resolution: Balancing deterministic and statistical fidelity. In: Proc. 30th ACM Int. Conf. on Multimedia, pp. 934–942 (2022).
23. Zheng, H., Yang, H., Fu, J., et al.: Learning conditional knowledge distillation for degraded-reference image quality assessment. In: Proc. IEEE/CVF Int. Conf. on Computer Vision, pp. 10242–10251 (2021).
24. Yin, G., Wang, W., Yuan, Z., et al.: Content-variant reference image quality assessment via knowledge distillation. In: Proc. AAAI Conf. on Artificial Intelligence, Vol. 36, pp. 3134–3142 (2022).
25. Thong, W., Pereira, J.C., Parisot, S., et al.: Content-diverse comparisons improve IQA. arXiv preprint arXiv:2211.05215 (2022).
26. Talebi, H., Milanfar, P.: NIMA: Neural image assessment. IEEE Trans. Image Process. 27(8), 3998–4011 (2018).
27. Simonyan, K., Zisserman, A.: Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556 (2014).
28. [28] Szegedy, C., Vanhoucke, V., Ioffe, S., et al.: Rethinking the inception architecture for computer vision. In: Proc. 2016 IEEE Conf. on Computer Vision and Pattern Recognition, pp. 2818–2826 (IEEE, 2016).
29. Gu, S., Bao, J., Chen, D., et al.: GIQA: Generated image quality assessment. In: Computer Vision–ECCV 2020, Part XI, pp. 369–385 (Springer, 2020).
30. Zhang, W., Ma, K., Yan, J., et al.: Blind image quality assessment using a deep bilinear convolutional neural network. IEEE Trans. Circuits Syst. Video Technol. 30(1), 36–47 (2018).
31. Su, S., Yan, Q., Zhu, Y., et al.: Blindly assess image quality in the wild guided by a self-adaptive hyper network. In: Proc. IEEE/CVF Conf. on Computer Vision and Pattern Recognition, pp. 3667–3676 (2020).
32. You, J., Korhonen, J.: Transformer for image quality assessment. In: Proc. ICIP, pp. 1389–1393 (IEEE, 2021).

33. Cheon, M., Yoon, S.J., Kang, B., et al.: Perceptual image quality assessment with transformers. In: Proc. IEEE/CVF Conf. on Computer Vision and Pattern Recognition, pp. 433–442 (2021).
34. Cao, Y., Wan, Z., Ren, D., et al.: Incorporating semi-supervised and positive-unlabeled learning for boosting full reference image quality assessment. In: Proc. IEEE/CVF Conf. on Computer Vision and Pattern Recognition, pp. 5851–5861 (2022).
35. Lao, S., Gong, Y., Shi, S., et al.: Attentions help CNNs see better: Attention-based hybrid image quality assessment network. In: Proc. IEEE/CVF Conf. on Computer Vision and Pattern Recognition, pp. 1140–1149 (2022).
36. Dosovitskiy, A., Beyer, L., Kolesnikov, A., et al.: An image is worth 16x16 words: Transformers for image recognition at scale. arXiv preprint arXiv:2010.11929 (2020).
37. Ke, J., Wang, Q., Wang, Y., et al.: MUSIQ: Multi-scale image quality transformer. In: Proc. IEEE/CVF Int. Conf. on Computer Vision, pp. 5148–5157 (2021).
38. Qin, G., Hu, R., Liu, Y., et al.: Data-efficient image quality assessment with attention-panel decoder. arXiv preprint arXiv:2304.04952 (2023).
39. Yang, S., Wu, T., Shi, S., et al.: MANIQA: Multi-dimension attention network for no-reference image quality assessment. In: Proc. IEEE/CVF Conf. on Computer Vision and Pattern Recognition, pp. 1191–1200 (2022).
40. Royat, A., et al.: NTIRE 2021 challenge on perceptual image quality assessment. In: Proc. CVPR, pp. 677–690 (IEEE, 2021).
41. Gu, J., et al.: NTIRE 2022 challenge on perceptual image quality assessment. In: Proc. CVPR, pp. 951–967 (2022).
42. Zhang, S., Hou, W., et al.: CNN-based medical ultrasound image quality assessment. Complexity 2021(1), 9938367 (2021).
43. Zhu, H., Shi, G., et al.: MetaIQA: Deep meta-learning for no-reference image quality assessment. In: Proc. CVPR, pp. 14143–14152 (2020).
44. Zhang, W., Yang, X., et al.: Uncertainty-aware blind image quality assessment in the laboratory and wild. IEEE Trans. Image Process. 30(6), 3474–3486 (2021).
45. Lin, H., Saupe, J.E., et al.: DeepFL-IQA: Weak supervision for deep IQA feature learning. arXiv preprint arXiv:2001.08113 (2020).
46. Madhusudana, P.C., Bovik, A.C., et al.: Image quality assessment using contrastive learning. IEEE Trans. Image Process. 31(7), 4149–4161 (2022).
47. Enhancing radiological diagnosis: A comprehensive review of image quality assessment and optimization strategies. PMC webpage, https://www.ncbi.nlm.nih.gov/pmc/, accessed May 2025 (2025).
48. Deep learning applications in medical image analysis: U-Net for diagnosis. Int. J. Innov. Sci. Appl. Eng., https://ijisae.org/index.php/IJISAE/article/view/5446, accessed May 2025 (2025).
49. A systematic review of medical image quality assessment. J. Imaging, https://www.mdpi.com/2313-433X/11/4/9, accessed October 2024 (2025).