

AU-IQA: A Benchmark Dataset for Perceptual Quality Assessment of AI-Enhanced User-Generated Content

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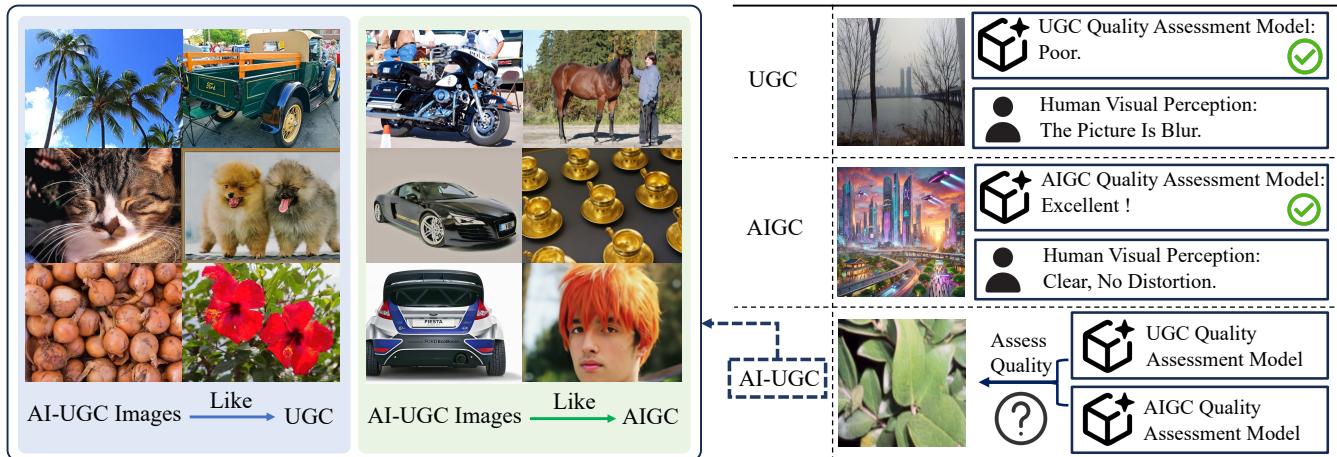


Figure 1: Research significance of AI-UGC quality assessment in practical applications.

Abstract

AI-based image enhancement techniques have been widely adopted in various visual applications, significantly improving the perceptual quality of user-generated content (UGC). However, the lack of

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specialized quality assessment models has become a significant limiting factor in this field, limiting user experience and hindering the advancement of enhancement methods. While perceptual quality assessment methods have shown strong performance on UGC and AIGC individually, their effectiveness on AI-enhanced UGC (AI-UGC) which blends features from both—remains largely unexplored. To address this gap, we construct AU-IQA, a benchmark dataset comprising 4,800 AI-UGC images produced by three representative enhancement types which include super-resolution, low-light enhancement, and denoising. On this dataset, we further evaluate a range of existing quality assessment models, including traditional IQA methods and large multimodal models. Finally, we provide a comprehensive analysis of how well current approaches perform in assessing the perceptual quality of AI-UGC. The access link to the AU-IQA is <https://github.com/WNNGGU/AU-IQA-Dataset>.

CCS Concepts

- Computing methodologies → Image and video acquisition.

Keywords

AI-Enhanced User-Generated Content, Perceptual Quality Assessment

ACM Reference Format:

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1 Introduction

The rapid advancement of generative models [10, 16, 28, 29] and AI-based enhancement techniques [7–9, 13, 14, 31, 56] has led to the widespread emergence of AI-enhanced user-generated content (AI-UGC), such as images that have been super-resolved, denoised, deblurred, or otherwise altered using machine learning algorithms. On multimedia platforms such as Instagram, TikTok, and YouTube, AI-UGC is increasingly common. However, despite their growing popularity, AI-UGC can often suffer from artifacts, over-smoothing, unnatural textures, or hallucinated details—issues that may degrade user experience rather than improve it. As a result, evaluating the perceptual quality of such AI-enhanced content has become an urgent and under-explored problem in both academia and industry.

While AI-enhanced user-generated content (AI-UGC) is becoming increasingly prevalent across multimedia platforms, the methods commonly used to assess its quality still heavily rely on pixel-level metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM). These metrics, while useful for detecting low-level distortions, are insufficient for evaluating the perceptual quality of images that have undergone complex enhancement processes, such as super-resolution, denoising, or generative retouching. In contrast, the field of perceptual quality assessment, designed to align with the human visual perceptual system, has made substantial progress in both traditional user-generated content (UGC) and AI-generated content (AIGC). For these domains, a variety of benchmark datasets [12, 18–20, 41, 54, 58] and learning-based IQA models [36, 51] have been developed, focusing on capturing perceptual quality rather than relying solely on pixel-wise accuracy.

Given that AI-UGC simultaneously inherits characteristics from both UGC and AIGC, such as diverse real-world content and sophisticated generative enhancements, it is plausible that existing perceptual IQA models could be directly applicable to AI-UGC quality assessment. However, as illustrated in Fig. 1, due to the lack of dedicated datasets specifically targeting AI-enhanced user-generated content (AI-UGC), it remains unclear how well current models generalize to AI-UGC scenarios, and whether they can reliably assess the perceptual quality of such content. To address this gap, we introduce the **AU-IQA** dataset, as shown in Fig. 2, a dedicated benchmark specifically designed for perceptual quality assessment of AI-enhanced user-generated content. On this database, we can further explore the performance of existing IQA models on

AI-UGC scenarios, identify limitations about quality assessment on AI-UGC, and fosters the development of AI-UGC perceptual quality assessment methods. The main contributions of our work include:

- A clear definition and scope for AI-enhanced content have not yet to be established. This has greatly impacted the development of AI-enhanced models and user experience. In order to solve this problem, we propose the concept and background of **AI-UGC**.
- We present **AU-IQA** (AI models enhanced User-generated Image Quality Assessment), an AI-UGC quality evaluation dataset with Mean Opinion Score (MOS), comprising 4.8k AI-UGC images enhanced by three types of AI techniques, including super-resolution, low-light enhancement and denoising. Then we test existing UGC and AIGC quality assessment models on our proposed dataset.
- We benchmark a range of existing perceptual IQA models on AU-IQA, systematically analyzing their effectiveness.

2 RELATED WORK

2.1 AI-based Enhancement of User-Generated Content

Apart from direct image generation, recent years have witnessed rapid advancements in AI-based enhancement techniques for user-generated content (UGC) [23], including super-resolution [25, 42, 45, 47], denoising [4] and low-light enhancement [11, 14, 22, 56, 57]. Deep learning models have been widely adopted to improve the perceptual quality of UGC, with various techniques emerging over time. Early approaches were dominated by convolutional neural networks (CNNs), such as DnCNN [49] for image denoising and SRCNN [6] for super-resolution, which demonstrated strong performance on traditional degradation types. Subsequently, generative adversarial networks (GANs) were introduced to further enhance perceptual quality, with notable methods like ESRGAN [38] significantly improving texture recovery and realism. More recently, transformer-based architectures, such as Restormer [48] and Uformer [39], have shown superior capability in handling complex distortions through long-range dependency modeling. Furthermore, diffusion models have started to gain attention for their ability to generate high-fidelity enhancements with controllable quality, as demonstrated by methods like IR-SDE [26] for image restoration and Palette [30] for image-to-image enhancement, marking a new frontier in AI-based UGC enhancement.

As AI-enhanced models become more widely used, it is important for quality evaluation methods to keep up. Developing reliable quality assessment dataset and accurate quality assessment models will help better measure the performance of these AI-enhanced techniques and further improve their results, leading to more realistic and visually appealing content.

2.2 Image Quality Assessment

Image Quality Assessment (IQA) refers to the task of evaluating the quality of images in a way that aligns with human visual perception. Traditional full-reference IQA metrics, such as PSNR and SSIM, assess image quality by comparing pixel differences between the reference and distorted images. While these metrics are widely used, they primarily focus on low-level pixel fidelity and often fail



Figure 2: Our proposed AI-UGC quality assessment dataset, AU-IQA. The dataset consists of three types of AI-UGC generated by nine different AI-enhanced models, totaling 4.8k images.

to capture higher-level perceptual features that align more closely with human subjective evaluations.

Recent developments in image quality assessment [53] have seen the emergence of learning-based no-reference models like NIMA [34], DBCNN [50], and HyperIQA [32] for UGC, followed by models which use visual-textual alignment to improve assessment accuracy such as CLIP-IQA [35], MUSIQ [15] and LIQE [51]. The latest, such as Q-Align [40] and Q-Eval-Score [52] utilize large multimodal models (LMMs) [55] and proposes a discrete-level-based training strategy to better align quality prediction with human perception. As for datasets, UGC-related ones include TID2013 [27] and KADID-10K [24], while AIGC-focused datasets such as AGIQA-3k [20], Pick-A-Pic [17] and HPS v2 [43] are designed to assess AI-generated content. However, existing studies primarily focus on either UGC or purely AIGC scenarios, and there is still a lack of dedicated models and datasets targeting the perceptual quality of AI-generated user content (AI-UGC). To bridge this gap, we propose the dataset **AU-IQA** for AI-UGC quality assessment.

3 Dataset Construction

3.1 AI-based Enhancement Models

To build a comprehensive AI-UGC dataset, we first introduce three typical degradation types commonly encountered in real-world user-generated content: **Low Resolution (LR)**, **Low Light** and **Noise Corruption**. For each type, four representative enhancement models are selected. Specifically, for super-resolution, we adopt DiffBIR [25], OSERdiff [42], PASD [45], and SUPIR [47]. For



Figure 3: The first col of images are UGC with various quality issues, others are AI-UGC generated by different models along with their corresponding MOSs.

low-light enhancement, we employ GLARE [56], LightenDiffusion [14], NeRCo [44], and QuadPrior [37]. For denoising, we apply DiffBIR, MaskedDenoising [4], PASD, and SUPIR. These models, spanning a diverse range of architectures, ensure the generality and diversity of the enhanced UGC content.

3.2 Data Collection and Annotation

Constructing a large-scale AI-UGC dataset poses significant challenges, as real-world UGC images often exhibit uncontrollable quality variations and lack standardized degradation types. To enable

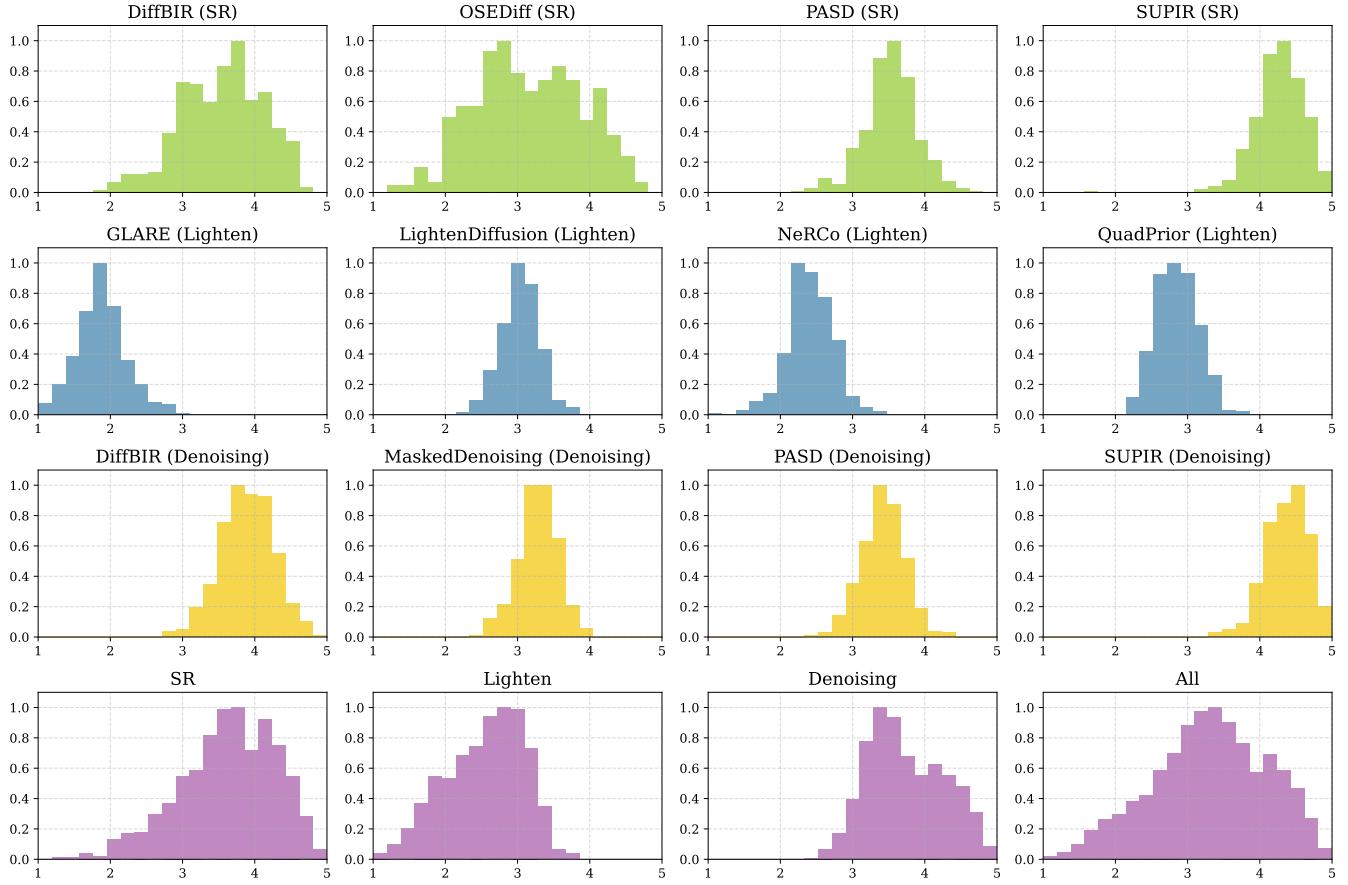


Figure 4: Distribution of MOS Scores for Different Degradation Types and Enhancement Models.

systematic evaluation and controlled analysis, we adopt a synthetic degradation strategy based on high-quality UGC images. Specifically, we select 400 high-quality samples from the KonIQ-10k dataset, based on their subjective quality scores. Three common degradation types—low resolution, low-light conditions, and noise—are then applied to these images through controlled manipulations, including downsampling, brightness reduction, and Gaussian noise addition. Each degraded image is subsequently restored using four different enhancement models corresponding to each degradation type, as introduced in Section 3.1, resulting in a total of $3 \times 4 \times 400 = 4,800$ enhanced images.

For annotation, we adopt the Mean Opinion Score (MOS) approach. Each image is independently rated by five trained annotators following a unified guideline. Annotators assign a quality score from 1 to 5, where higher scores indicate better perceptual quality. Evaluation focuses on four aspects—resolution, brightness, noise, and distortion—with resolution and distortion receiving greater attention. The annotation starts with an initial score of 5, deducting points according to the severity of observed degradations. An illustrative example of the collected data and corresponding annotations is shown in Fig. 3. To ensure the reliability and consistency of the annotations, The annotations are required cross-checked for consistency. In cases where significant discrepancies are found,

the respective annotators are requested to revisit and relabel the samples. After verifying annotation consistency, the final MOS is calculated as the average of all annotators' scores.

3.3 Statistical Analysis

The histograms of the MOS for each AI-based enhancement model and type are shown in Fig. 4. For all three types, the MOS distributions of enhancement models display distinct patterns. **For super resolution (SR)**, DiffBIR and OSEDiff show relatively uniform MOS distributions, while PASD clusters around 3.5 and SUPIR is concentrated above 4, indicating superior performance. **For low light enhancement (LLE)**, all four models yield lower MOS scores, with distributions resembling a normal curve; GLARE centers between 1.5 and 2.5, LightenDiffusion peaks around 3, NeRCo between 2 and 3, and QuadPrior between 2.5 and 3.5. **For denoising**, the MOS distributions are also approximately normal but shift higher, with most scores between 3.5 and 4.5.

The overall MOS distributions across the three AI enhancement types, super resolution, low light enhancement, and denoising highlight the diversity of our AI-UGC dataset. As shown in the histograms, each AI enhancement type exhibits distinct characteristics, reflecting the challenges faced by IQA models in evaluating AI-enhanced content. The MOS distributions for types including

Table 1: Performance of quality assessment models comparison on the each type of AI-UGC. [red: best in each group, red: best in all, PLCC: ↑, SRCC: ↑]

Type	SR				LL Enhancement				Denoising			
	DiffBIR	OSEDiff	PASD	SUPIR	GLARE	LightDiff	NeRCo	QuadPrior	DiffBIR	MaskDN	PASD	SUPIR
Corr	PLCC	SRCC	PLCC	SRCC	PLCC	SRCC	PLCC	SRCC	PLCC	SRCC	PLCC	SRCC
UGC Image Quality Assessment												
TOPIQ	0.164	0.156	0.418	0.384	0.457	0.412	0.246	0.126	0.648	0.611	0.403	0.379
LIQE	0.260	0.271	0.576	0.567	0.395	0.454	0.217	0.185	0.553	0.467	0.408	0.387
ARNIQA	-0.074	-0.092	0.086	0.081	0.103	0.102	0.199	0.179	0.587	0.573	0.255	0.243
HyperIQ	0.382	0.353	0.619	0.626	0.472	0.455	0.347	0.211	0.234	0.217	0.390	0.363
InternVL2	0.288	0.289	0.394	0.363	0.367	0.382	0.230	0.158	0.641	0.650	0.349	0.330
Qwen2-VL	0.292	0.275	0.508	0.428	0.255	0.234	0.122	0.100	0.605	0.580	0.278	0.267
LLaVA-v1.6	0.264	0.284	0.549	0.545	0.380	0.355	0.145	0.100	0.614	0.608	0.418	0.409
Q-Align	0.433	0.429	0.702	0.696	0.479	0.475	0.345	0.190	0.731	0.719	0.474	0.440
Qwen2-VL *	0.342	0.357	0.521	0.467	0.289	0.167	0.254	0.163	0.587	0.492	0.368	0.356
DEQA	0.444	0.433	0.703	0.733	0.467	0.462	0.312	0.136	0.726	0.707	0.498	0.483
AIGC Image Quality Assessment												
MA-AGIQA	0.084	0.090	0.321	0.311	0.008	0.005	-0.021	0.009	0.398	0.375	0.121	0.100
InternVL2	0.333	0.317	0.281	0.251	0.284	0.264	0.213	0.147	0.338	0.330	0.140	0.122
Qwen2-VL	0.261	0.238	0.348	0.314	0.215	0.184	0.244	0.206	0.400	0.423	0.135	0.148
LLaVA-v1.6	0.272	0.256	0.362	0.337	0.225	0.202	0.140	0.133	0.274	0.271	0.138	0.109
Q-Align	0.229	0.248	0.363	0.335	0.178	0.189	0.058	0.073	0.213	0.198	0.087	0.074
Qwen2-VL *	0.225	0.234	0.352	0.252	0.157	0.121	0.100	0.059	0.420	0.397	0.128	0.154
Q-Eval-Score	0.283	0.297	0.161	0.134	0.178	0.205	0.192	0.217	0.224	0.208	0.191	0.173
UGC and AIGC Image Quality Assessment												
InternVL2	0.324	0.334	0.433	0.383	0.357	0.358	0.253	0.178	0.619	0.580	0.333	0.317
Qwen2-VL	0.254	0.238	0.461	0.379	0.200	0.189	0.109	0.098	0.545	0.509	0.179	0.155
LLaVA-v1.6	0.260	0.268	0.453	0.422	0.383	0.363	0.181	0.127	0.660	0.657	0.350	0.322
Q-Align	0.242	0.272	0.491	0.476	0.326	0.277	0.228	0.073	0.661	0.664	0.301	0.291
Qwen2-VL *	0.372	0.362	0.529	0.472	0.243	0.190	0.247	0.150	0.570	0.543	0.307	0.308

super resolution, low light enhancement, and denoising highlight the diversity of AI-enhanced images. For super resolution, the MOS scores range from 2 to 4.5, reflecting varying levels of super resolution enhancement. Scores for low light enhancement are mostly between 1.5 and 3.5, reflecting the difficulties involved in enhancing images captured under low-light conditions. Denoised images achieve MOS scores concentrated between 3.5 and 4.5, suggesting more stable and reliable denoising performance. The diversity of these distributions reflects the realistic nature of AI-enhanced content and ensures the dataset's suitability for evaluating the effectiveness of IQA models across different degradation conditions.

4 Experiments

4.1 Benchmark Models

AI-UGC exhibit characteristics of both UGC and AIGC. To effectively evaluate the capability of current models in assessing such hybrid content and lay the foundation for future research on AI-UGC quality assessment, we select representative models from three categories for benchmarking: UGC IQA models, AIGC IQA models, and large multimodal models (LMMs) that have demonstrated

strong performance in image-text understanding tasks. In our experiments, we finetune LMMs on KADID-10K [24] to serve as UGC quality assessment models, and on AGIQA-3K [20] to serve as AIGC quality assessment models. These models serve as a comprehensive baseline for analyzing the strengths and limitations of existing approaches in the context of AI-UGC image quality assessment. The selected models can be categorized into three groups:

- Traditional image quality assessment models: This group includes TOPIQ [3], LIQE [51], ARNIQA [1], and hyperIQ [33]. These four models are UGC quality assessment models. For the AIGC quality assessment model, since most existing models use the SBS evaluation format, we only selected one model MA-AGIQA[36].
- Large Multimodal Models: This group includes three outstanding LMMs: InternVL2-8B [5], Qwen2-VL-7B-Instruct [2] and LLaVA-v1.6-mistral-7B [21]. Considering the strong task adaptation capabilities of LMMs through fine-tuning, we fine-tune these models to directly output quality scores using the UGC image quality assessment dataset, the AIGC image quality assessment dataset, or a combination of both.

Table 2: Performance of quality assessment models comparison on AI-UGC. The random refers to randomly selecting 1600 images from the dataset. The all refers to the whole dataset. [red]: best in each group, red: best in all].

Type	SR	LLE	Denoising	Random	All
Corr	PLCC SRCC				
UGC Image Quality Assessment					
TOPIQ	0.541 0.501	0.770 0.694	0.120 0.122	0.725 0.668	0.721 0.661
LIQE	0.564 0.505	0.789 0.742	0.051 -0.004	0.648 0.548	0.650 0.549
ARNIQA	0.219 0.190	0.762 0.714	-0.260 -0.284	0.429 0.281	0.416 0.269
hyperIQA	0.410 0.439	0.648 0.542	0.684 0.697	0.720 0.694	0.723 0.695
InternVL2	0.342 0.350	0.660 0.479	0.574 0.610	0.670 0.603	0.671 0.607
Qwen2-VL	0.172 0.129	0.671 0.658	0.183 0.273	0.599 0.539	0.597 0.536
LLaVA-v1.6	0.405 0.374	0.763 0.739	0.458 0.460	0.723 0.664	0.721 0.659
Q-Align	0.551 0.480	0.815 0.751	0.526 0.522	0.795 0.777	0.796 0.771
Qwen2-VL *	0.417 0.366	0.771 0.701	0.556 0.606	0.732 0.687	0.720 0.673
DeQA	0.587 0.523	0.832 0.791	0.383 0.385	0.767 0.746	0.766 0.749
AIGC Image Quality Assessment					
MA-AGIQA	0.159 0.148	0.473 0.418	0.114 0.120	0.429 0.281	0.374 0.321
InternVL2	0.243 0.266	0.395 0.353	0.591 0.598	0.602 0.596	0.606 0.596
Qwen2-VL	0.244 0.206	0.562 0.528	0.304 0.309	0.570 0.510	0.557 0.500
LLaVA-v1.6	0.314 0.299	0.459 0.447	0.400 0.417	0.583 0.576	0.566 0.555
Q-Align	0.143 0.145	0.388 0.367	0.323 0.353	0.530 0.533	0.516 0.519
Qwen2-VL *	0.288 0.303	0.650 0.590	0.570 0.604	0.673 0.634	0.665 0.622
Q-Eval-Score	0.239 0.234	0.250 0.246	0.230 0.240	0.243 0.243	0.258 0.256
UGC and AIGC Image Quality Assessment					
InternVL2	0.305 0.298	0.652 0.398	0.635 0.660	0.689 0.617	0.683 0.616
Qwen2-VL	0.090 0.122	0.664 0.530	0.231 0.330	0.589 0.532	0.568 0.518
LLaVA-v1.6	0.316 0.304	0.658 0.482	0.479 0.490	0.624 0.504	0.624 0.518
Q-Align	0.298 0.269	0.742 0.619	0.329 0.402	0.674 0.635	0.672 0.632
Qwen2-VL	0.367 0.341	0.736 0.665	0.598 0.656	0.733 0.685	0.722 0.674

- LMM-based models for quality assessment: This group includes models Q-Align [40], Qwen2-VL-7B-Instruct* [2] (using the fine-tuning strategy of Q-Align), Q-Eval-Score [52], and DeQA [46], which adapt large multimodal models for the task of image quality assessment. Unlike standard LMMs that directly output scalar quality scores, some of these models are trained to predict discrete quality ratings, which are then mapped to numerical values. This approach enables more stable and interpretable assessments.

4.2 Performance Discussion

The performance on our dataset is presented in Table 1 and Table 2, with the evaluation metrics including Pearson Linear Correlation Coefficient (PLCC) and Spearman Rank Correlation Coefficient (SRCC), which are standard metrics widely used for assessing image quality. From these results, which several key insights can be drawn:

- Performance Comparison in UGC, AIGC, and Hybrid Models:** The UGC quality assessment model performs the best overall. Models capable of assessing both UGC and AIGC images rank second, while models designed specifically for AIGC quality

evaluation perform the worst. This suggests that the features of AI-UGC images are more similar to those of traditional UGC images than to AIGC images.

- Variation Across Different AI-UGC Types:** The performance of the same quality assessment model varies depending on the type of AI-UGC. For example, HyperIQA achieves the best performance on super-resolution enhanced images but performs less well on low-light enhanced images. Overall, the quality assessment of low-light enhanced images appears to be more consistent across two other enhancement types. This indicates that existing quality assessment models exhibit varying effectiveness when applied to different types of AI-UGC, highlighting the need for more specialized approaches tailored to specific content.
- Performance on Larger Datasets:** Models perform significantly better when evaluated on a larger-scale dataset, such as the entire AU-IQA dataset. This suggests that the performance of existing quality assessment models on AI-UGC is unstable, and the observed improvements on larger-scale test sets may result from the increased data volume making it easier for models to fit underlying linear relationships.

In summary, the AI-UGC quality assessment task is more aligned with traditional UGC quality evaluation, possibly because AI-UGC appears visually closer to UGC in terms of perceptual characteristics. However, due to the varying performance of the same model on different types of AI-UGC, while different types of AI-UGC may appear similar to the human eye, they exhibit significant feature differences when assessed by existing quality models. In addition, the performance of models on small-scale datasets is often unstable. Therefore, future research in AI-UGC quality assessment should take these differences into account and consider the unique quality characteristics of each type of AI-enhanced content.

5 Conclusion

The application of AI-UGC is rapidly expanding, yet there is currently no dedicated quality assessment model for these. This gap hampers both user experience and the advancement of AI-UGC technologies. Given that AI-UGC exhibits characteristics of both UGC and AIGC, this paper explores the use of existing quality assessment models and large multimodal models for AI-UGC quality evaluation. We introduce AU-IQA, a benchmark dataset which includes 4.8K AI-enhanced images across three types of AI enhancement for AI-UGC quality assessment, and present a comprehensive evaluation of the performance of current quality assessment models, including traditional models and large multimodal models. The results indicate that UGC-focused models perform the best, achieving satisfactory results on a large-scale test dataset. This suggests that the quality assessment of AI-UGC is more similar to that of UGC. Meanwhile, the result of noticeable performance differences across different test points highlights the limitations and instability of existing models in AI-UGC quality assessment and aim to provide insights for future research in this area.

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References

- [1] Lorenzo Agnolucci, Leonardo Galteri, Marco Bertini, and Alberto Del Bimbo. 2024. ARNIQA: Learning Distortion Manifold for Image Quality Assessment. In *IEEE/CVF Winter Conference on Applications of Computer Vision*.
- [2] Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, Bin Yuan Hui, Luo Ji, Mei Li, Junyang Lin, Runji Lin, Dayiheng Liu, Gao Liu, Chengqiang Lu, Keming Lu, Jianxin Ma, Rui Men, Xingzhang Ren, Xuancheng Ren, Chuanqi Tan, Sinan Tan, Jianhong Tu, Peng Wang, Shijie Wang, Wei Wang, Shengguang Wu, Benfeng Xu, Jin Xu, An Yang, Hao Yang, Jian Yang, Shusheng Yang, Yang Yao, Bowen Yu, Hongyi Yuan, Zheng Yuan, Jianwei Zhang, Xingxuan Zhang, Yichang Zhang, Zhenru Zhang, Chang Zhou, Jingren Zhou, Xiaohuan Zhou, and Tianhang Zhu. 2023. Qwen Technical Report. In *arXiv preprint arXiv:2309.16609*.
- [3] Chaofeng Chen, Jiadi Mo, Jingwen Hou, Haoning Wu, Liang Liao, Wenxiu Sun, Qiong Yan, and Weisi Lin. 2024. TOPIQ: A Top-down Approach from Semantics to Distortions for Image Quality Assessment. In *IEEE Transactions on Image Processing*.
- [4] Haoyu Chen, Jinjin Gu, Yihao Liu, Salma Abdel Magid, Chao Dong, Qiong Wang, Hanspeter Pfister, and Lei Zhu. 2023. Masked Image Training for Generalizable Deep Image Denoising. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition*.
- [5] Zhe Chen, Jianne Wu, Wenhui Wang, Weijie Su, Guo Chen, Sen Xing, Muyan Zhong, Qinglong Zhang, Xizhou Zhu, Lewei Lu, et al. 2024. Internvl: Scaling up Vision Foundation Models and Aligning for Generic Visual-linguistic Tasks. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition*.
- [6] Chao Dong, Chen Change Loy, Kaiming He, and Xiaou Tang. 2016. Image Super-Resolution Using Deep Convolutional Networks. In *IEEE Transactions on Pattern Analysis and Machine Intelligence*.
- [7] Wei Dong, Han Zhou, Yulun Zhang, Xiaohong Liu, and Jun Chen. 2024. ECMamba: Consolidating Selective State Space Model with Retinex Guidance for Efficient Multiple Exposure Correction. In *Advances in Neural Information Processing Systems*.
- [8] Yunlong Dong, Xiaohong Liu, Yixuan Gao, Xunchu Zhou, Tao Tan, and Guangtao Zhai. 2023. Light-VQA: A Multi-Dimensional Quality Assessment Model for Low-Light Video Enhancement. In *ACM International Conference on Multimedia*.
- [9] Kang Fu, Yicong Peng, Zicheng Zhang, Qihang Xu, Xiaohong Liu, Jia Wang, and Guangtao Zhai. 2024. Attentionlut: Attention Fusion-based Canonical Polyadic Lut for Real-time Image Enhancement. In *IEEE International Conference on Acoustics, Speech and Signal Processing*.
- [10] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. 2014. Generative adversarial nets. In *Advances in Neural Information Processing Systems*.
- [11] Jiang Hai, Binhan Guan, Zhen Liu, Xiaohong Liu, Jian Yu, Zheng Liu, Songchen Han, and Shuaicheng Liu. 2025. Learning to See in the Extremely Dark. In *arXiv preprint arXiv:2506.21132*.
- [12] Vlad Hosu, Hanhe Lin, Tamás Szirányi, and Dietmar Saupe. 2020. KonIQ-10k: An Ecologically Valid Database for Deep Learning of Blind Image Quality Assessment. In *IEEE Transactions on Image Processing*.
- [13] Qiang Hu, Qihan He, Houqiang Zhong, Guo Lu, Xiaoyun Zhang, Guangtao Zhai, and Yanfeng Wang. 2025. VARFVV: View-Adaptive Real-Time Interactive Free-View Video Streaming with Edge Computing. In *IEEE Journal on Selected Areas in Communications*.
- [14] Hai Jiang, Ao Luo, Xiaohong Liu, Songchen Han, and Shuaicheng Liu. 2024. LightenDiffusion: Unsupervised Low-Light Image Enhancement with Latent-Retinex Diffusion Models. In *European Conference on Computer Vision*.
- [15] Junjie Ke, Qifei Wang, Yilin Wang, Peyman Milanfar, and Feng Yang. 2021. MUSIC: Multi-scale Image Quality Transformer. In *IEEE/CVF international conference on computer vision*.
- [16] Diederik P Kingma and Max Welling. 2013. Auto-encoding Variational Bayes. In *arXiv preprint arXiv:1312.6114*.
- [17] Yuval Kirstain, Adam Polyak, Uriel Singer, Shahbuland Matiana, Joe Penna, and Omer Levy. 2023. Pick-a-Pic: An Open Dataset of User Preferences for Text-to-Image Generation. In *arXiv preprint arXiv:2305.01569*.
- [18] Tengchuan Kou, Xiaohong Liu, Zicheng Zhang, Chunyi Li, Haoning Wu, Xiongkuo Min, Guangtao Zhai, and Ning Liu. 2024. Subjective-Aligned Dataset and Metric for Text-to-Video Quality Assessment. In *ACM International Conference on Multimedia*.
- [19] Chunyi Li, Tengchuan Kou, Yixuan Gao, Yuqin Cao, Wei Sun, Zicheng Zhang, Yingjie Zhou, Zichao Zhang, Weixia Zhang, Haoning Wu, et al. 2024. AIGIQA-20k: A Large Database for AI-Generated Image Quality Assessment. In *arXiv preprint arXiv:2404.03407*.
- [20] Chunyi Li, Zicheng Zhang, Haoning Wu, Wei Sun, Xiongkuo Min, Xiaohong Liu, Guangtao Zhai, and Weisi Lin. 2023. AGIQA-3k: An Open Database For AI-Generated Image Quality Assessment. In *IEEE Transactions on Circuits and Systems for Video Technology*.
- [21] Feng Li, Renrui Zhang, Hao Zhang, Yuanhan Zhang, Bo Li, Wei Li, Zejun Ma, and Chunyuan Li. 2024. LLaVA-NeXT-Interleave: Tackling Multi-image, Video, and 3D in Large Multimodal Models. In *arXiv preprint arXiv:2407.07895*.
- [22] Wenhao Li, Guangyang Wu, Wenyi Wang, Peiran Ren, and Xiaohong Liu. 2023. FastLLVE: Real-Time Low-Light Video Enhancement with Intensity-Aware Lookup Table. In *ACM International Conference on Multimedia*.
- [23] Xinyue Li, Huiyu Duan, Jia Wang, Xiaohong Liu, Yitong Chen, and Guangtao Zhai. 2025. Situation-adaptive Neural Network for Fast Pre-computing Image Enhancement. In *Science China Information Sciences*.
- [24] Hanhe Lin, Vlad Hosu, and Dietmar Saupe. 2019. KADID-10k: A Large-scale Artificially Distorted IQA Database. In *International Conference on Quality of Multimedia Experience*.
- [25] Xinqi Lin, Jingwen He, Ziyuan Chen, Zhaoyang Lyu, Ba Dai, Fanghua Yu, Wanli Ouyang, Yu Qiao, and Chao Dong. 2024. DiffBIR: Towards Blind Image Restoration with Generative Diffusion Prior. In *European Conference on Computer Vision*.
- [26] Ziwei Luo, Fredrik K Gustafsson, Zheng Zhao, Jens Sjölund, and Thomas B Schön. 2023. Fusion: Enabling Large-Size Realistic Image Restoration with Latent-Space Diffusion Models. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition*.
- [27] Nikolay Ponomarenko, Lina Jin, Oleg Ieremeiev, Vladimir Lukin, Karen Egiazarian, Jaakko Astola, Benoit Vozel, Kacem Chehdi, Marco Carli, Federica Battisti, and C.-C. Jay Kuo. 2013. Image database TID2013: Peculiarities, results and perspectives. In *Signal Processing: Image Communication*.
- [28] Aditya Ramesh, Prafulla Dhariwal, Alex Nichol, Casey Chu, and Mark Chen. 2022. Hierarchical Text-Conditional Image Generation with Clip Latents. In *arXiv preprint arXiv:2204.06125*.
- [29] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. 2022. High-resolution Image Synthesis with Latent Diffusion Models. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition*.
- [30] Chitwan Saharia, William Chan, Huiwen Chang, Chris A. Lee, Jonathan Ho, Tim Salimans, David J. Fleet, and Mohammad Norouzi. 2021. Palette: Image-to-Image Diffusion Models. In *arXiv preprint arXiv:2111.05826*.
- [31] Zhihao Shi, Xiaohong Liu, Kangdi Shi, Linhui Dai, and Jun Chen. 2024. Video frame interpolation via generalized deformable convolution. In *IEEE transactions on multimedia*.
- [32] Shaolin Su, Qingsen Yan, Yu Zhu, Cheng Zhang, Xin Ge, Jingyu Sun, and Yanning Zhang. 2020. Blindly Assess Image Quality in the Wild Guided by A Self-Adaptive Hyper Network. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition*.
- [33] Shaolin Su, Qingsen Yan, Yu Zhu, Cheng Zhang, Xin Ge, Jingyu Sun, and Yanning Zhang. 2020. Blindly Assess Image Quality in the Wild Guided by a Self-Adaptive Hyper Network. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition*.
- [34] Hossein Talebi and Peyman Milanfar. 2018. NIMA: Neural Image Assessment. In *IEEE Transactions on Image Processing*.
- [35] Jianyi Wang, Kelvin CK Chan, and Chen Change Loy. 2023. Exploring CLIP for Assessing the Look and Feel of Images. In *AAAI Conference on Artificial Intelligence*.
- [36] Puyi Wang, Wei Sun, Zicheng Zhang, Jun Jia, Yanwei Jiang, Zhichao Zhang, Xiongkuo Min, and Guangtao Zhai. 2024. Large Multi-modality Model Assisted AI-Generated Image Quality Assessment. In *ACM International Conference on Multimedia*.
- [37] Wenjing Wang, Huan Yang, Jianlong Fu, and Jiaying Liu. 2024. Zero-Reference Low-Light Enhancement via Physical Quadruple Priors. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition*.
- [38] Xintao Wang, Ke Yu, Shixiang Wu, Jinjin Gu, Yihao Liu, Chao Dong, Yu Qiao, and Chen Change Loy. 2018. ESRGAN: Enhanced Super-Resolution Generative Adversarial Networks. In *European Conference on Computer Vision Workshops*.
- [39] Zhendong Wang, Xiaodong Cun, Jianmin Bao, Wengang Zhou, Jianzhuang Liu, and Houqiang Li. 2022. Uformer: A General U-Shaped Transformer for Image Restoration. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition*.
- [40] Haoning Wu, Zicheng Zhang, Weixia Zhang, Chaofeng Chen, Chunyi Li, Liang Liao, Annan Wang, Erli Zhang, Wenxiu Sun, Qiong Yan, Xiongkuo Min, Guangtao Zhai, and Weisi Lin. 2024. Q-Align: Teaching LMMs for Visual Scoring via Discrete Text-Defined Levels. In *International Conference on Machine Learning*.
- [41] Haoning Wu, Hanwei Zhu, Zicheng Zhang, Erli Zhang, Chaofeng Chen, Liang Liao, and Chunyi Li. 2024. Towards Open-ended Visual Quality Comparison. In *European Conference on Computer Vision*.
- [42] Rongyuan Wu, Lingchen Sun, Zhiyuan Ma, and Lei Zhang. 2024. One-Step Effective Diffusion Network for Real-World Image Super-Resolution. In *Advances in Neural Information Processing Systems*.
- [43] Xiaoshi Wu, Yiming Hao, Kegiang Sun, Yixiong Chen, Feng Zhu, Rui Zhao, and Hongsheng Li. 2023. Human Preference Score v2: A Solid Benchmark for Evaluating Human Preferences of Text-to-Image Synthesis. In *arXiv preprint arXiv:2306.09341*.
- [44] Shuzhou Yang, Moxuan Ding, Yanmin Wu, Zihan Li, and Jian Zhang. 2023. Implicit Neural Representation for Cooperative Low-light Image Enhancement. In *IEEE/CVF International Conference on Computer Vision*.
- [45] Tao Yang, Rongyuan Wu, Peiran Ren, Xuansong Xie, and Lei Zhang. 2024. Pixel-Aware Stable Diffusion for Realistic Image Super-Resolution and Personalized

- Stylization. In *European Conference on Computer Vision*.
- [46] Zhiyuan You, Xin Cai, Jinjin Gu, Tianfan Xue, and Chao Dong. 2025. Teaching Large Language Models to Regress Accurate Image Quality Scores Using Score Distribution. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition*.
- [47] Fanghua Yu, Jinjin Gu, Zheyuan Li, Jinfan Hu, Xiangtao Kong, Xintao Wang, Jingwen He, Yu Qiao, and Chao Dong. 2024. Scaling Up to Excellence: Practicing Model Scaling for Photo-Realistic Image Restoration In the Wild. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition*.
- [48] Syed Waqas Zamir, Aditya Arora, Salman Khan, Munawar Hayat, Fahad Shahbaz Khan, Ming-Hsuan Yang, and Ling Shao. 2022. Restormer: Efficient Transformer for High-Resolution Image Restoration. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition*.
- [49] Kai Zhang, Wangmeng Zuo, Yunjin Chen, Deyu Meng, and Lei Zhang. 2017. Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition*.
- [50] Weixia Zhang, Kede Ma, Jia Yan, Dexiang Deng, and Zhou Wang. 2018. Blind Image Quality Assessment Using A Deep Bilinear Convolutional Neural Network. In *IEEE Transactions on Circuits and Systems for Video Technology*.
- [51] Weixia Zhang, Guangtao Zhai, Ying Wei, Xiaokang Yang, and Kede Ma. 2023. Blind Image Quality Assessment via Vision-Language Correspondence: A Multitask Learning Perspective. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition*.
- [52] Zicheng Zhang, Tengchuan Kou, Shushi Wang, Chunyi Li, Wei Sun, Wei Wang, Xiaoyu Li, Zongyu Wang, Xuezhi Cao, Xiongkuo Min, Xiaohong Liu, and Guangtao Zhai. 2025. Q-Eval-100K: Evaluating Visual Quality and Alignment Level for Text-to-Vision Content. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition*.
- [53] Zicheng Zhang, Chunyi Li, Wei Sun, Xiaohong Liu, Xiongkuo Min, and Guangtao Zhai. 2023. A Perceptual Quality Assessment Exploration for AIGC Images. In *IEEE International Conference on Multimedia and Expo Workshops*.
- [54] Zicheng Zhang, Yingjie Zhou, Chunyi Li, Kang Fu, Wei Sun, Xiaohong Liu, Xiongkuo Min, and Guangtao Zhai. 2024. A Reduced-Reference Quality Assessment Metric for Textured Mesh Digital Humans. In *International Conference on Acoustics, Speech, and Signal Processing*.
- [55] Zicheng Zhang, Yingjie Zhou, Chunyi Li, Baixuan Zhao, Xiaohong Liu, and Guangtao Zhai. 2024. Quality Assessment in the Era of Large Models: A Survey. In *ACM Transactions on Multimedia Computing, Communications and Applications*.
- [56] Han Zhou, Wei Dong, Xiaohong Liu, Shuaicheng Liu, Xiongkuo Min, Guangtao Zhai, and Jun Chen. 2024. GLARE: Low Light Image Enhancement via Generative Latent Feature based Codebook Retrieval. In *European Conference on Computer Vision*.
- [57] Xunchu Zhou, Xiaohong Liu, Yunlong Dong, Tengchuan Kou, Yixuan Gao, Zicheng Zhang, Chunyi Li, Haoning Wu, and Guangtao Zhai. 2024. Light-VQA+: A Video Quality Assessment Model for Exposure Correction with Vision-Language Guidance. In *arXiv preprint arXiv:2405.03333*.
- [58] Yingjie Zhou, Zicheng Zhang, Wei Sun, Xiaohong Liu, Xiongkuo Min, Zhihua Wang, Xiaoping Zhang, and Guangtao Zhai. 2024. THQA: A Perceptual Quality Assessment Database for Talking Heads. In *IEEE International Conference on Image Processing*.