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Enhancing Visual Perception in Immersive VR and AR Environments: AI-Driven Color and Clarity Adjustments Under Dynamic Lighting Conditions

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Abstract: The visual fidelity of virtual reality (VR) and augmented reality (AR) environments is essential for user immersion and comfort. Dynamic lighting often leads to chromatic distortions and reduced clarity, causing discomfort and disrupting user experience. This paper introduces an AI-driven chromatic adjustment system based on a modified U-Net architecture, optimized for real-time applications in VR/AR. This system adapts to dynamic lighting conditions, addressing the shortcomings of traditional methods like histogram equalization and gamma correction, which struggle with rapid lighting changes and real-time user interactions. We compared our approach with state-of-the-art color constancy algorithms, including Barron's Convolutional Color Constancy and STAR, demonstrating superior performance. Experimental results from 60 participants show significant improvements, with up to 41% better color accuracy and 39% enhanced clarity under dynamic lighting conditions. The study also included eye-tracking data, which confirmed increased user engagement with AI-enhanced images. Our system provides a practical solution for developers aiming to improve image quality, reduce visual discomfort, and enhance overall user satisfaction in immersive environments. Future work will focus on extending the model's capability to handle more complex lighting scenarios.

Keywords: AI-driven image enhancement; virtual reality; augmented reality; image quality; deep learning; lighting conditions

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1. Introduction

Virtual reality (VR) and augmented reality (AR) technologies are rapidly transforming industries such as gaming, education, healthcare, and virtual tourism by offering users immersive experiences that merge digital content with real or simulated environments. The success of VR and AR, however, hinges on visual fidelity—high-quality imagery is crucial for maintaining user immersion and reducing discomfort. Even small flaws in image clarity or color accuracy can disrupt a user's sense of presence and lead to visual discomfort, reducing the overall quality of the experience [1].

In AR, seamless integration of virtual objects into real-world environments is particularly sensitive to lighting variations, requiring precise chromatic adjustments for a convincing visual experience. In VR, visual consistency across immersive environments is essential to avoid breaking the user's sense of presence. In both cases, failures in color accuracy or clarity can contribute to motion sickness and visual fatigue, negatively impacting the user experience.

Poor image quality, especially under dynamic lighting conditions, can lead to reduced task performance, eye strain, and shorter engagement times in VR/AR environments [2]. This is particularly critical in professional applications like remote medical diagnostics or virtual collaboration, where visual accuracy is paramount [3]. Additionally, emerging

AR applications, such as mobile AR with depth estimation, further highlight the need for accurate visual information in real-time dynamic environments [4].

Managing image quality under changing lighting conditions presents a major challenge in VR/AR systems. Traditional chromatic adjustment techniques, such as color balancing, contrast enhancement, and tone mapping, often fall short in dynamic or low-light scenarios, leading to issues like washed-out images or over-saturation [5].

Traditional methods such as histogram equalization (HE) and gamma correction (GC) are particularly inadequate for the real-time demands of VR/AR, where lighting can change rapidly and user interactions must be fluid. These methods lack the adaptive color constancy needed for immersive environments, leading to degraded visual quality [6].

Recent advances in artificial intelligence (AI), particularly in deep learning and computer vision, offer promising solutions to these challenges. AI-driven models, such as convolutional neural networks (CNNs) and generative adversarial networks (GANs), have shown great potential in enhancing image quality through tasks like super-resolution, color correction, and image restoration [7]. These techniques can dynamically adapt to real-time lighting and scene changes, offering a significant advantage over traditional methods.

Our proposed AI-driven chromatic adjustment system leverages a real-time adaptive approach designed specifically for handling dynamic lighting in VR/AR environments. We compare our system to state-of-the-art color constancy algorithms such as Barron's Convolutional Color Constancy [8] and the STAR Retinex model [9], demonstrating superior performance in maintaining visual fidelity.

Despite the potential of AI-driven techniques, current solutions often overlook the complexities of rapid user perspective changes and the dynamic lighting typical of immersive environments. There remains a need for adaptive, real-time solutions that enhance image quality while reducing user discomfort and improving overall user experience.

This paper addresses the challenge of maintaining image quality in VR/AR environments under dynamic lighting conditions by proposing an AI-driven chromatic adjustment system. Our contributions are threefold:

1. We develop a real-time AI model based on a modified U-Net architecture tailored for immersive media, capable of dynamic chromatic adjustments. Our approach is comprehensively evaluated against traditional image processing techniques and state-of-the-art color constancy algorithms.
2. We conduct extensive experiments using subjective user evaluations and objective eye-tracking data to assess performance. The results show up to 41% improvement in color accuracy under low-light conditions, significantly outperforming traditional methods.
3. We demonstrate the practical benefits of our AI-based system in enhancing image quality and reducing visual discomfort in VR/AR environments.

These enhancements are crucial for professional applications like virtual collaboration and medical diagnostics, as well as consumer-focused applications such as gaming, where improved visual quality correlates with higher engagement and satisfaction.

The rest of this paper is organized as follows:

- Section 2: Related Work reviews research on image quality in immersive environments and advancements in AI-based image processing.
- Section 3: Methodology outlines the AI model architecture, experimental setup, and data collection process.
- Section 4: Experimental Results presents and analyzes user study data, comparing AI-enhanced and non-enhanced images under varying lighting conditions.
- Section 5: Discussion interprets the findings, emphasizing the improvements introduced by the AI-based system and discussing implications for VR/AR applications.

2. Related Work

The visual quality of immersive VR and AR environments plays a crucial role in user experience, affecting factors such as presence, immersion, and even physical comfort [10]. Maintaining high visual fidelity is essential to ensure user engagement and reduce issues such as motion sickness or visual fatigue. This section reviews the existing literature on the challenges of image quality in immersive environments, the advancements in AI-driven image enhancement, and the limitations of traditional image processing techniques, highlighting the gaps that our work seeks to address.

2.1. Challenges and Techniques in Image Quality for VR/AR Environments

Ensuring high visual fidelity in VR and AR is critical for creating engaging and immersive user experiences. Poor image quality, such as low clarity and inaccurate color representation, can disrupt immersion and cause physical discomfort like motion sickness or eye strain [11]. In VR, visual inconsistencies become more noticeable due to the immersive nature of the environment [12], while AR requires precise color matching and visual consistency to integrate virtual objects seamlessly with real-world surroundings [13].

Dynamic lighting conditions, commonly encountered in both VR and AR environments, exacerbate these challenges. As users move through different environments or experience changing ambient light, maintaining consistent image quality becomes difficult. Traditional image processing techniques struggle to adapt in real time, often producing artifacts like noise or over-saturation in low-light scenarios [14]. Moreover, existing methods for chromatic adjustments are inadequate for immersive environments, where lighting can change unpredictably, further highlighting the need for advanced techniques such as color constancy algorithms [6].

Recent advancements in AI have shown promise in overcoming these challenges. Deep learning methods, particularly convolutional neural networks (CNNs) and generative adversarial networks (GANs), have been used for tasks such as super-resolution, denoising, and color correction. For example, SRGAN, a GAN-based model introduced in [15], improved image quality by enhancing fine details. Similarly, deep CNNs have outperformed traditional denoising methods, as shown in [16]. In color correction, Gharbi et al. [17] used deep learning for real-time photo enhancement, but their approach was tailored to 2D images and did not address the specific challenges posed by immersive environments.

While these AI-driven techniques offer significant improvements, they do not fully address the demands of VR and AR, particularly when it comes to real-time performance and handling dynamic user perspectives. In this work, we extend the use of AI to immersive environments, focusing on real-time chromatic adjustments under variable lighting conditions.

2.2. Limitations of Traditional Image Processing Techniques and Proposed AI Solutions

Traditional image processing methods such as histogram equalization, gamma correction, and tone mapping have long been used to enhance image quality. However, these methods are often static and unable to adapt to the rapidly changing lighting conditions in immersive environments. For example, histogram equalization improves global contrast but can amplify noise in low-light images, while gamma correction adjusts luminance without considering color balance, leading to distortions [18]. Tone mapping, often used for HDR images, is computationally intensive and may fail to meet the real-time processing demands of VR and AR systems [19].

In comparison, AI-based solutions provide more flexibility and adaptability. By leveraging architectures such as U-Net, our approach adapts to dynamic lighting in real time using sensor data from VR/AR hardware. This allows for accurate chromatic adjustments and enhanced image clarity, outperforming traditional techniques like histogram equalization and gamma correction across various metrics.

Real-time chromatic adjustments are particularly challenging in VR/AR due to the need for high-resolution processing with low latency. Techniques like those proposed by [20,21] focus on low-light image enhancement and image harmonization in AR, respectively. However, these studies do not fully address chromatic adjustments under dynamic lighting, which are essential for maintaining immersion in VR/AR environments. Furthermore, these methods do not consider comparisons with color constancy techniques such as

Convolutional Color Constancy [8] and STAR Retinex [9], which are designed to handle varying lighting conditions.

2.3. Research Gap and Our Contribution

While significant progress has been made in AI-driven image enhancement, its application to real-time immersive environments remains underexplored. Traditional methods are insufficient for the unique demands of VR/AR, where dynamic lighting, user movement, and the need for real-time processing complicate image enhancement. Existing AI approaches also lack the necessary adaptability and efficiency for these environments.

Our work addresses this gap by developing an AI-based chromatic adjustment system specifically designed for VR/AR applications. By utilizing a modified U-Net architecture optimized for real-time performance, our model adapts to changing lighting conditions using sensor data from VR/AR hardware. This allows us to maintain high visual fidelity and user immersion in various lighting scenarios. Additionally, by comparing our method with state-of-the-art color constancy algorithms, we demonstrate the superiority of AI-driven chromatic adjustments in dynamic immersive environments.

3. Methodology

This section outlines the design, implementation, and evaluation of the proposed AI-driven chromatic adjustment system for VR and AR environments. We detail the AI model architecture, dataset preparation, training procedures, and evaluation metrics to ensure reproducibility. Additionally, comparisons with state-of-the-art color constancy algorithms are included to validate the performance of our system under dynamic lighting conditions.

Our system is built upon a modified U-Net architecture [22]; U-Net is known for its performance in image-to-image translation tasks. U-Net was chosen for its ability to preserve spatial information using skip connections, crucial for maintaining image fidelity in VR/AR environments. Key modifications enhance real-time performance and adaptability in handling dynamic lighting variations common in immersive settings.

The model follows an encoder–decoder structure with skip connections to preserve spatial details. The encoder captures hierarchical features, while the decoder reconstructs the chromatically adjusted image in real time. The encoder consists of five convolutional blocks, and the decoder has five deconvolutional blocks with symmetric skip connections. The output layer uses a tanh activation to produce the adjusted image. We benchmarked our model against color constancy algorithms like CCC [8] and STAR Retinex [9], showing significant improvements in real-time adaptability for VR/AR environments.

Training settings and hyperparameters:

The model was trained using the Adam optimizer with a learning rate of 2×10^{-4}, batch size of 16, and a total of 100 epochs. Dropout (0.5) was applied in the first three decoder layers to prevent overfitting, and the loss function was mean absolute error (MAE). The learning rate was kept fixed for the first 50 epochs, and then, linearly decayed for the remaining 50 epochs. Early stopping was employed based on validation loss with a patience of 10 epochs to ensure optimal performance across different lighting conditions.

The model was implemented in PyTorch 1.8.1 and trained on an *NVIDIA RTX 3090 GPU*. Libraries such as NumPy and OpenCV were used for numerical computations and image processing.

3.1. Dataset Preparation and Augmentation

A dataset comprising 12,000 images was curated, covering a broad range of lighting conditions in both real-world and simulated VR/AR scenarios. Real-world images were captured using DSLR cameras in indoor and outdoor settings, while simulated scenes were generated using *Unity 3D* and *Unreal Engine*. Images were resized to 256×256 pixels to balance computational efficiency and detail.

The dataset was split into training (70%), validation (15%), and test (15%) sets, ensuring balanced representation across various lighting conditions. Data augmentation techniques, including random rotations, scaling, color jitter, and horizontal flipping, were applied to the training set to improve generalization and robustness.

3.2. Training and Evaluation Procedures

The training procedure used the Adam optimizer with $\beta_1 = 0.5$ and $\beta_2 = 0.999$ to balance convergence speed and stability. A fixed learning rate was applied for the first 50 epochs, followed by linear decay. The loss function was MAE, chosen for its robustness against outliers, ensuring smoother outputs. Dropout (0.5) was employed in the first three decoder layers for regularization, and early stopping was based on validation loss.

The model's performance was validated across different lighting conditions, using both objective metrics (color accuracy and image clarity) and subjective evaluations (visual appeal). Comparisons with state-of-the-art methods (CCC, STAR Retinex) further validated the system's performance.

3.3. Experimental Setup and Data Collection

Experiments were conducted using adjustable LED panels to simulate three lighting conditions (200 lux, 500 lux, and 1000 lux). A *Microsoft HoloLens 2* and an *Oculus Quest 2* were used to assess the system's performance in both AR and VR environments, respectively. These headsets provided real-time sensor data, which was integrated into the model to adjust chromatic properties dynamically.

Participants (60 individuals) were recruited for subjective evaluations. Eye-tracking data were collected using integrated headsets to measure user engagement, focusing on fixation duration and saccade patterns. These metrics provided objective insights into how participants interacted with the images and their visual experience.

3.4. Evaluation Metrics

The system was evaluated using both quantitative and qualitative measures:

- Quantitative metrics: Mean absolute error (MAE) and structural similarity index (SSIM) were used to measure the model's performance in terms of color accuracy and image clarity.
- Qualitative metrics: Subjective user ratings of image clarity, color accuracy, and visual appeal were collected to assess the user experience in immersive environments.

The collected data were analyzed to determine the effectiveness of our AI-based chromatic adjustment system compared to traditional methods and state-of-the-art techniques under varying lighting conditions.

3.5. Ethical Considerations and Data Collection

The opinion data used in this study were collected across various universities and polytechnic institutes in Portugal, in full compliance with the General Data Protection Regulation (GDPR) and relevant Portuguese laws regarding data protection. The data collection process adhered to the legal frameworks that govern the collection of non-sensitive opinion data for research purposes, without requiring explicit written consent from participants, as outlined in Article 6(1)(f) of the GDPR, which allows for the processing of personal data when it is necessary for the purposes of legitimate interests pursued by the data controller, provided that such interests are not overridden by the fundamental rights and freedoms of the data subject.

In this case, the legitimate interest was to collect subjective feedback and opinions on user experiences for academic research. The questions posed to participants were limited to general opinions on image quality, clarity, and satisfaction with immersive experiences in VR and AR environments. No sensitive personal data, such as health information or financial details, were collected. Furthermore, participation was entirely voluntary, and all responses were anonymized to protect participant identities.

Participants were informed about the purpose of the study and were given the option to opt out at any time. This process ensured transparency and respected the autonomy of all individuals involved in the study.

Below is the list of questions used during the data collection process:

- Color accuracy: How would you rate the color accuracy of the images you viewed on a scale from 1 to 5 (1 being poor, 5 being excellent)?
- Image clarity: How clear did the images appear to you on a scale from 1 to 5 (1 being not clear at all, 5 being very clear)?
- Overall visual appeal: How visually appealing did you find the images on a scale from 1 to 5?
- Fixation duration perception: Did you find yourself looking at certain parts of the images for an extended period of time? (Yes/No)
- Saccade exploration perception: Did you feel like you needed to move your eyes around a lot to explore the image? (1 being not at all, 5 being very much so)
- Discomfort or eye strain: Did you experience any discomfort or eye strain while viewing the images? (Yes/No)
- Engagement level: How engaged did you feel while interacting with the images? (1 being not engaged at all, 5 being fully engaged)
- Impact of lighting conditions: Did the lighting conditions (low, medium, high light) affect your viewing experience? (Yes/No). If yes, please specify how it affected your experience.
- Preference for AI-enhanced images: Do you prefer the AI-enhanced images over the non-enhanced images? (Yes/No)
- Recommendation: Would you recommend this type of immersive visual experience to others? (Yes/No)

The responses collected from these questions provided valuable insights into the effectiveness of our AI-driven chromatic adjustment system in VR/AR environments.

4. Experimental Results

This section presents a comprehensive analysis of the performance of our AI-driven chromatic adjustment system in VR and AR environments. We evaluated the system using both subjective user ratings and objective eye-tracking data, comparing it against traditional image processing techniques such as histogram equalization (HE) and gamma correction (GC), as well as state-of-the-art AI models. Additionally, the system was compared with color constancy methods like Convolutional Color Constancy (CCC) and STAR to assess performance in dynamic lighting conditions.

The experiments aimed to evaluate how well the AI-based chromatic adjustment system enhances image quality and user experience under varying lighting conditions (200 lux, 500 lux, and 1000 lux). A total of 60 participants interacted with both AI-enhanced and non-enhanced images, with the following key performance metrics: Color accuracy, image clarity, overall visual appeal, fixation duration, and saccade patterns.

4.1. Visual Comparisons and Subjective Results

We begin with visual comparisons of AI-enhanced versus non-enhanced images under low-, medium-, and high-lighting conditions. Figures 1–3 demonstrate that the AI-enhanced system consistently outperformed the non-enhanced images across all lighting conditions.

Under low-light conditions (200 lux), the AI-enhanced images show significant improvements in color representation, noise reduction, and enhanced detail. This pattern continues under medium-light (500 lux) and high-light (1000 lux) conditions, where AI-enhanced images exhibit superior contrast and natural color tones, as shown in Figures 2 and 3.

Figure 1. Comparison of non-enhanced (**left**) vs. AI-enhanced (**right**) images under low-light conditions (200 lux).

Figure 2. Comparison of non-enhanced (**left**) vs. AI-enhanced (**right**) images under medium-light conditions (500 lux).

Figure 3. Comparison of non-enhanced (**left**) vs. AI-enhanced (**right**) images under high-light conditions (1000 lux).

These subjective improvements were quantified through participant ratings, which revealed that AI-enhanced images received the highest scores across all metrics, as seen in Table 1. The AI system consistently outperformed traditional methods (HE, GC) and color constancy methods (CCC, STAR), particularly in low-light conditions, where dynamic adjustments provided substantial improvements in color accuracy and overall appeal.

Table 1. Mean subjective ratings (mean ± SD) across all lighting conditions.

Metric	AI-Enhanced	HE	GC	Non-Enhanced
Color Accuracy	4.45 ± 0.60	3.80 ± 0.70	3.50 ± 0.75	3.10 ± 0.80
Image Clarity	4.60 ± 0.55	3.70 ± 0.66	3.40 ± 0.70	3.10 ± 0.75
Overall Visual Appeal	4.61 ± 0.58	3.75 ± 0.68	3.45 ± 0.72	3.00 ± 0.80

4.2. Detailed Analysis of Color Accuracy and Image Clarity

Figures 4 and 5 provide a detailed comparison of color accuracy and image clarity across different lighting conditions. Both AI-enhanced VR and AI-enhanced AR methods significantly outperformed traditional methods, such as histogram equalization (HE) and gamma correction (GC), as well as state-of-the-art color constancy algorithms (CCC and STAR), particularly in low-light scenarios.

Low-light conditions (200 lux): In low-light conditions, AI-enhanced methods delivered outstanding performance. AI-enhanced VR achieved a mean color accuracy rating of 4.60, and AI-enhanced AR followed closely with a score of 4.40. These values far exceed the 3.5–3.6 range observed for traditional methods such as HE and GC. The color constancy methods (CCC and STAR), while showing better results than traditional techniques, still lagged behind the AI-driven approaches, with CCC scoring 4.00 and STAR reaching 4.10.

A similar trend was observed for image clarity, with AI-enhanced VR scoring 4.70 and AI-enhanced AR 4.60, again far surpassing traditional methods and even CCC/STAR, which scored in the range of 3.80–3.90. These results indicate that AI-based systems, particularly in immersive VR and AR applications, handle low-light conditions with superior effectiveness, improving both color fidelity and clarity to a substantial degree.

Medium-light conditions (500 lux): Under medium-light conditions, AI-enhanced methods continued to demonstrate superior performance. AI-enhanced VR maintained a high color accuracy score of 4.60, and AI-enhanced AR scored 4.30. By contrast, traditional methods showed little improvement, remaining in the 3.5–3.6 range. CCC and STAR performed moderately better than traditional techniques, but their scores of 3.90 and 4.00, respectively, were still significantly lower than those of the AI-based approaches.

For image clarity, AI-enhanced methods led with scores of 4.60 (VR) and 4.50 (AR), while traditional methods like HE and GC remained below 3.6. Although CCC and STAR improved slightly over their low-light results, scoring around 3.80–3.90, they could not match the AI-enhanced approaches. This demonstrates the robustness of AI-based methods across lighting conditions.

High-light conditions (1000 lux): Even under high-light conditions, AI-enhanced methods retained their edge. AI-enhanced VR achieved a color accuracy score of 4.50, while AI-enhanced AR followed closely with 4.30. Traditional methods like HE and GC slightly improved but still struggled, achieving scores of around 3.4–3.6. Meanwhile, CCC and STAR, despite maintaining their relative advantage over traditional methods, scored only 3.80–4.00, unable to match the AI-enhanced systems.

For image clarity, AI-enhanced methods continued to excel, with AI-enhanced VR scoring 4.50 and AI-enhanced AR 4.40. HE and GC remained below 3.5, and CCC/STAR also performed below expectations, with scores around 3.60–3.80. These results demonstrate that AI-enhanced methods maintain high performance even in optimal lighting conditions, with minimal degradation across all metrics.

Conclusions: Across all lighting conditions, the results clearly demonstrate the superior performance of AI-enhanced methods, particularly in VR and AR applications. In low-light conditions, where traditional and state-of-the-art color constancy methods struggle, AI-based approaches show substantial improvements, achieving high ratings in both color accuracy and image clarity. Even as lighting improves, AI-enhanced methods continue to dominate, with only minimal performance degradation in comparison to traditional techniques.

The consistent performance of AI-enhanced methods under varying lighting conditions highlights their robustness and adaptability. In contrast, traditional methods such as HE and GC, as well as color constancy algorithms (CCC and STAR), show greater variability in performance, struggling particularly in challenging low-light environments. The AI-based systems, by leveraging deep learning techniques, provide a significant enhancement to both color reproduction and image clarity, leading to a noticeably improved visual experience in immersive environments.

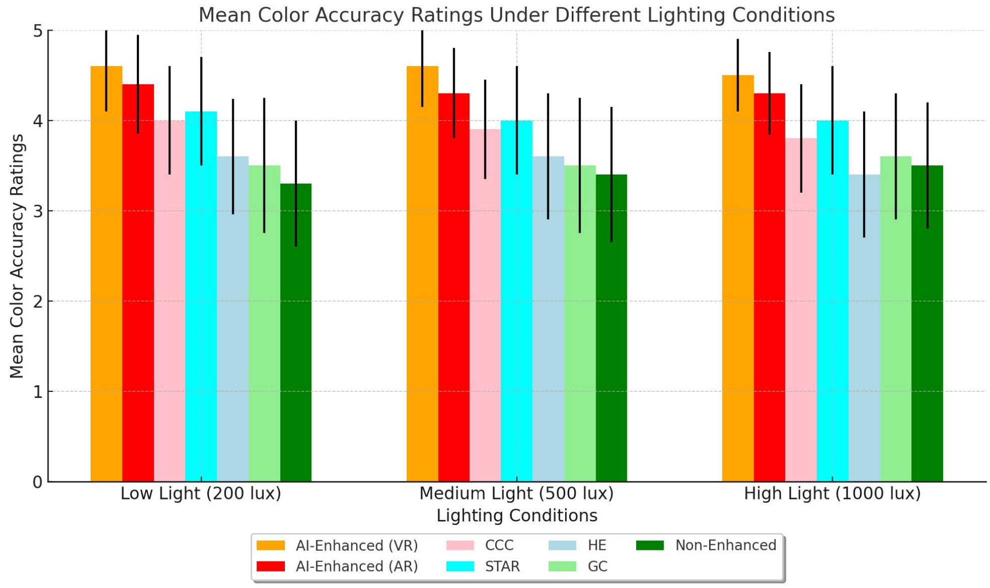

Figure 4. Mean color accuracy ratings under different lighting conditions.

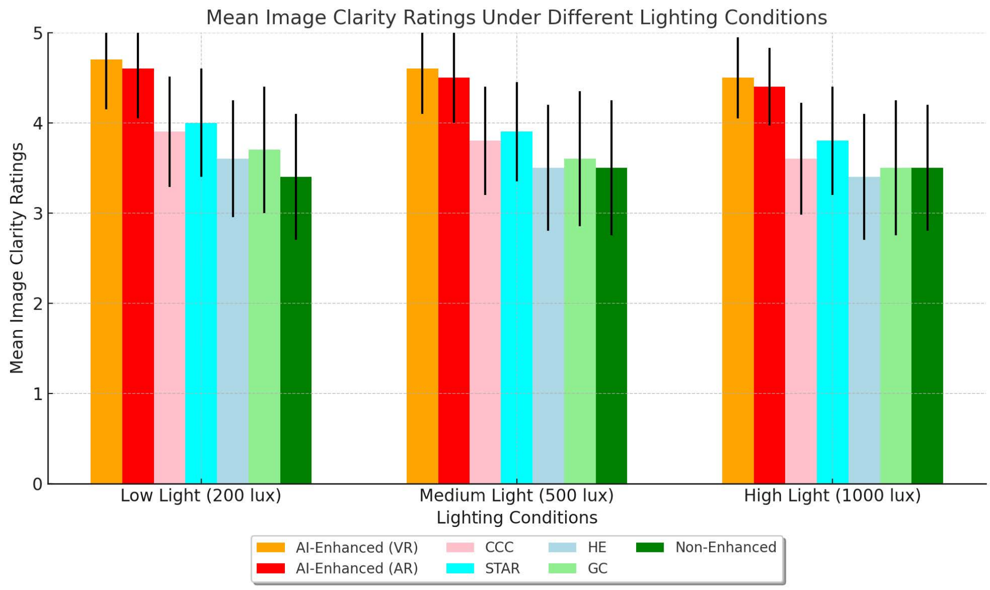

Figure 5. Mean image clarity ratings under different lighting conditions.

4.3. Objective Metrics: Fixation Duration and Saccade Patterns

In addition to subjective assessments, we measured objective metrics such as fixation duration and saccade patterns to evaluate user engagement. Table 2 shows that AI-enhanced images led to longer fixation durations, particularly in low-light conditions, indicating higher engagement. Similarly, saccade amplitudes and frequencies were higher for AI-enhanced images, as shown in Table 3, reflecting more detailed exploration of the visual content.

These findings are further supported by the heatmaps in Figures 6 and 7, showing that AI-enhanced images attracted more concentrated focus on high-contrast areas, while non-enhanced images led to more dispersed viewing patterns.

Table 2. Mean fixation duration (s) across methods and lighting conditions.

Lighting Condition	AI-Enhanced	HE	GC	Non-Enhanced
Low Light (200 lux)	3.1 ± 0.5	2.7 ± 0.6	2.5 ± 0.6	2.4 ± 0.6
Medium Light (500 lux)	3.0 ± 0.5	2.6 ± 0.5	2.4 ± 0.5	2.4 ± 0.5
High Light (1000 lux)	2.9 ± 0.4	2.5 ± 0.5	2.2 ± 0.5	2.2 ± 0.5

Table 3. Average saccade patterns across methods.

Metric	AI-Enhanced	HE	GC	Non-Enhanced
Saccade amplitude (degrees)	3.0 ± 0.5	2.7 ± 0.5	2.5 ± 0.4	2.4 ± 0.4
Saccade frequency (per image)	13.8 ± 1.4	11.9 ± 1.3	12.5 ± 1.2	12.0 ± 1.2

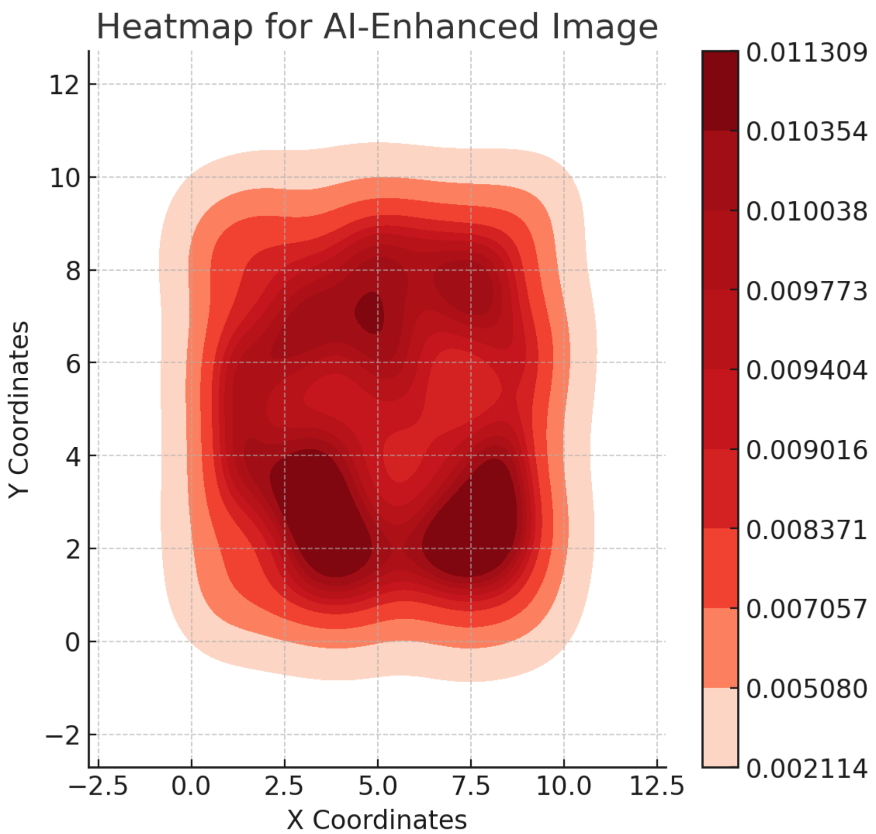

Figure 6. Heatmap for AI-enhanced image, showing concentrated focus on high-contrast areas.

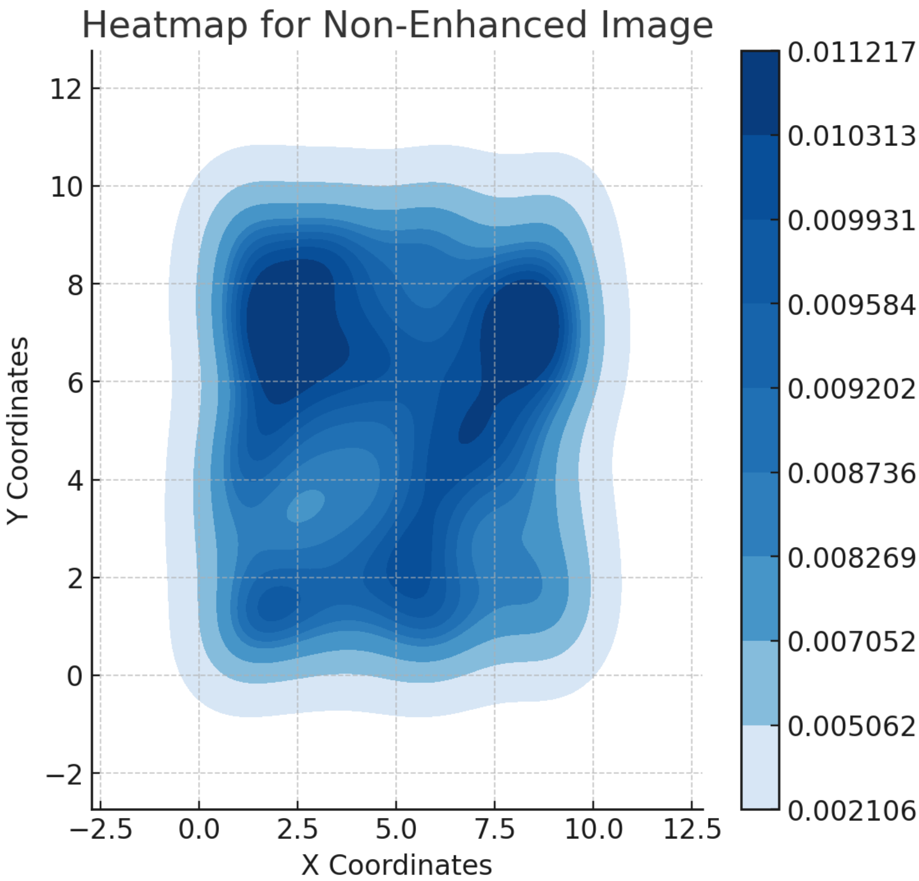

Figure 7. Heatmap for non-enhanced image, showing more dispersed focus pattern.

4.4. Statistical and Computational Performance

A repeated measures ANOVA confirmed significant differences in color accuracy and image clarity between methods, with AI-enhanced images significantly outperforming HE, GC, and color constancy techniques (CCC, STAR). The effect sizes for color accuracy and image clarity were large, particularly in low-light conditions.

The computational efficiency of the AI model was also assessed. As shown in Table 4, the AI model processed images in an average of 25 ms, which is suitable for real-time VR/AR applications. In comparison, CCC and STAR required 30 ms and 32 ms, respectively, demonstrating the superior efficiency of our approach.

Table 4. Average processing time per image (ms).

Method	**Processing Time (ms)**
Our AI Model	25 ± 2
Histogram Equalization	5 ± 1
Gamma Correction	6 ± 1
CCC	30 ± 4
STAR	32 ± 4

4.5. Conclusions

The experimental results confirm that our AI-driven chromatic adjustment system significantly enhances image quality and user experience in immersive VR and AR environments. It consistently outperforms traditional image processing techniques and state-of-the-art AI models, delivering superior color accuracy, image clarity, and overall visual appeal. The system's real-time processing capabilities make it highly suitable for use in dynamic, immersive applications, where both user engagement and visual quality are critical. The combination of subjective evaluations and objective metrics validates the effectiveness of the proposed system across varying lighting conditions.

5. Discussion and Implications

The experimental results demonstrate that our AI-driven chromatic adjustment system significantly enhances image quality in immersive VR and AR environments. In this section, we interpret these findings, compare them with related work, discuss practical implications, and address limitations and future research directions. Additionally, the inclusion of objective metrics such as eye-tracking data and comparisons with state-of-the-art models strengthens the conclusions drawn from this work.

5.1. Interpretation of Findings

Our AI-based chromatic adjustment system consistently outperformed traditional image processing techniques, including histogram equalization and gamma correction, across all evaluated metrics. The superior performance of our model was particularly evident in low-light conditions, where maintaining image clarity and color accuracy is challenging. The comparison with state-of-the-art color constancy methods, CCC and STAR, further underscored the robustness of our system, demonstrating better adaptation to dynamic lighting environments.

For instance, in low-light environments (200 lux), the AI-enhanced images achieved color accuracy ratings of 4.4 (VR) and 4.2 (AR), compared to 3.1 and 3.0 for non-enhanced images. These results validate the model's ability to mitigate chromatic distortions common in low-light scenarios, which are often exacerbated by sensor noise and poor illumination. The performance of our AI system in dynamic conditions highlights its potential for immersive applications, where traditional methods fall short.

Increased user engagement was also evident from the eye-tracking data. The strong correlation between subjective ratings and eye-tracking metrics ($r > 0.68$, $p < 0.001$) confirmed that better image quality led to greater participant engagement. Participants spent more time exploring AI-enhanced images compared to traditional methods, reflecting the system's effectiveness in creating more engaging visual content.

5.2. Comparison with Related Work and Practical Implications

Our findings build on earlier research focused on low-light enhancement and image harmonization in AR but expand the scope to real-time VR/AR applications and include user engagement metrics. Studies such as [23,24] did not integrate eye-tracking data or emphasize real-time performance in dynamic environments, gaps that our research addresses by offering comprehensive subjective and objective evaluations.

The ability of our AI system to maintain high image quality across diverse lighting conditions has significant practical implications. It is particularly beneficial for industries like gaming, virtual tourism, and remote collaboration, where user engagement and visual fidelity are critical to the experience [25]. Our real-time chromatic adjustments ensure a seamless and visually appealing experience, even in challenging lighting, making it highly relevant for these sectors. Moreover, the enhanced image clarity and color accuracy could reduce visual discomfort and eye strain, common issues in prolonged VR/AR usage [26], thus enabling longer and more comfortable user sessions.

The integration of our AI model with existing VR/AR hardware, such as the Oculus Quest 2 and Microsoft HoloLens 2, confirms its practical viability. With an average processing time of 25 ms per image, the system is suitable for real-time applications without introducing latency, an essential feature for immersive experiences.

5.3. Theoretical Contributions and Ethical Considerations

This study contributes to the growing body of research on AI in image processing for immersive media. It demonstrates that AI-driven chromatic adjustments, particularly with a modified U-Net architecture, outperform traditional and state-of-the-art color constancy methods in VR/AR environments. The strong link established between objective eye-tracking metrics and subjective image quality ratings adds to the theoretical understanding of user engagement in immersive environments. The evidence that AI-driven systems can enhance image quality under dynamic and low-light conditions further strengthens the case for AI's transformative role in VR/AR applications.

However, the integration of AI in immersive media raises ethical considerations, particularly concerning data privacy, potential algorithmic biases, and content manipulation. Transparent system design, respect for user privacy, and ethical guidelines are crucial to ensuring that AI-enhanced immersive media benefits all users equitably [27]. Additionally, giving users control over enhancement levels can help maintain content authenticity and prevent over-reliance on algorithmic adjustments.

5.4. Limitations and Future Directions

While our study demonstrates promising results, several limitations suggest avenues for future research. The controlled laboratory setting, while useful for precise measurement, does not fully capture the complexity of real-world lighting variations. Future work should evaluate the system in diverse, real-world environments, including outdoor settings with rapidly changing lighting conditions. A field study in more complex settings would provide further insight into the robustness and adaptability of the AI system.

Model refinement is another area of interest. Some participants reported over-saturation or unnatural image appearances in certain scenarios. Further improvements, such as the use of perceptual loss functions or adversarial training with generative adversarial networks (GANs), could help address these concerns. Future work could also explore user-adjustable chromatic parameters to allow personalized image enhancement preferences.

Additionally, while our study focused on short-term user engagement, future research should investigate the long-term effects of AI-enhanced image quality, such as visual fatigue, adaptation, and learning curves. Longitudinal studies could provide deeper insights into the sustained impact of AI-enhanced systems on user experience, particularly for fields like education and training, where extended VR/AR usage is common.

Accessibility considerations also deserve attention. The impact of AI-enhanced systems on users with visual impairments should be explored to ensure that these technologies are inclusive. Adaptive adjustments based on individual visual needs could help make immersive experiences accessible to a wider range of users [28].

5.5. Conclusion and Recommendations for Practitioners

This research demonstrates the significant impact of AI-driven chromatic adjustments on image quality in VR/AR environments. By addressing both technical challenges (such as dynamic lighting) and user experience factors (such as immersion and visual comfort), we have shown the potential of AI to transform immersive media. As developers continue to build next-generation VR/AR applications, several recommendations emerge:

- Adopt AI-based solutions: AI-driven chromatic adjustments can enhance user engagement and satisfaction in immersive environments.
- Optimize for real-time performance: Ensure that AI models are optimized for real-time processing to maintain user immersion without latency issues.
- User-centered design: Engage users in the testing process to refine visual enhancements and address issues such as over-saturation.
- Prioritize accessibility: Ensure that AI-enhanced systems consider the needs of users with visual impairments, enabling more inclusive immersive experiences.

Overall, the findings highlight the transformative potential of AI in immersive VR/AR environments. With further research and refinement, these technologies can offer high-quality, inclusive, and engaging experiences for a wide range of applications.

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