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# Clearview: An Image Enhancement and Restoration

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***Abstract: Digital images captured in real-world environments often suffer from quality degradation caused by low illumination, excessive brightness, blur, and noise. Such degradations reduce the visual clarity of images and limit their usability in applications such as photography, surveillance, documentation, and media processing. Conventional image editing tools require manual parameter adjustments such as brightness, contrast, and sharpness correction, which makes the enhancement process time-consuming and highly dependent on user expertise. This project proposes Clear-View, an automated image restoration and enhancement system designed to improve the quality of degraded images using a combination of deep learning models and traditional image-processing techniques. The system automatically analyzes the condition of the input image and identifies degradation types such as low-light conditions, overexposure, noise, or blur. Based on this analysis, the system selects an appropriate enhancement model, including Zero-DCE for low-light enhancement and Pix2PixHD for exposure correction, along with image-processing techniques such as CLAHE, denoising, and sharpening.***
***Index Terms: The system operates through a structured pipeline consisting of preprocessing, degradation detection, enhancement, and restoration stages. Experimental evaluation shows that the proposed system significantly improves image clarity, contrast, and brightness while minimizing manual effort. The ClearView system provides an efficient and user-friendly platform for automated image restoration and enhancement.***

## I. INTRODUCTION

Modern digital systems generate vast amounts of visual data through devices such as smartphones, surveillance cameras, medical imaging systems, and remote sensing technologies. However, images captured in real-world environments are frequently affected by various forms of degradation, including poor illumination, motion blur, sensor noise, and exposure imbalance. These issues significantly reduce image quality and limit their effectiveness in critical applications such as surveillance, healthcare, multimedia processing, and scientific analysis. As imaging technologies continue to evolve, the need for intelligent and automated image enhancement systems has become increasingly important.

The motivation behind ClearView originates from four demanding and required needs:

*1)* Adaptive Image Enhancement: Ability to handle diverse and complex image degradations dynamically.
*2)* Automated Processing: Reduces dependency on manual parameter tuning and user expertise.
*3)* Multi-Degradation Handling: Supports simultaneous correction of noise, blur, and lighting issues within a unified system.
*4)* Consistent Output Quality: Ensures reliable and uniform enhancement across different image conditions.

The Rising complexity of real-world image degradation has exposed significant limitations in traditional image enhancement techniques. Conventional methods such as histogram equalization, filtering, and contrast adjustment rely on fixed algorithms and manual intervention, making them insufficient for handling diverse and dynamically varying image conditions. These approaches are typically designed to address single degradation types and often fail when multiple distortions are present simultaneously.

Although modern deep learning techniques, including convolutional neural networks and generative models, have demonstrated strong performance in specific tasks such as denoising, super-resolution, and low-light enhancement, most of these methods are task-specific and lack flexibility. Additionally, many existing systems focus primarily on improving visual quality without incorporating mechanisms for intelligent degradation analysis or adaptive model selection. As a result, issues such as over-enhancement, artifact generation, and computational inefficiency remain prevalent.

Recent advancements in artificial intelligence have explored automated image enhancement using deep learning models such as Zero-DCE, EnlightenGAN, and ESRGAN. While these models show promising results, they are often applied independently and do not provide a unified framework capable of handling multiple degradation types effectively. Furthermore, many existing approaches lack structured processing pipelines, integration of classical techniques, and consistent performance across varying real-world conditions.

To address these challenges, this work introduces **ClearView**, an adaptive image restoration and enhancement framework that treats the input image as an analyzable entity and applies appropriate enhancement techniques based on its characteristics. ClearView emphasizes intelligent processing by integrating degradation detection, adaptive model selection, and hybrid enhancement strategies combining deep learning and traditional image-processing methods.

The main contributions of this work are:

*a)* An adaptive image enhancement framework capable of handling multiple degradation types within a single pipeline.
*b)* A degradation-aware processing mechanism that analyzes image characteristics before applying enhancement techniques.
*c)* A hybrid enhancement approach integrating deep learning models with classical image-processing methods.
*d)* An automated and efficient system that reduces manual intervention while ensuring consistent image quality...

## II. LITERATURE REVIEW

The use of automation and artificial intelligence for cy- The application of automation and artificial intelligence in image restoration and enhancement has gained substantial attention in recent years, particularly as conventional image-processing techniques struggle to handle complex real-world degradations such as low illumination, noise, blur, and exposure imbalance. Existing research in this domain can be broadly categorized into illumination estimation methods, Retinex-based enhancement approaches, convolutional neural network (CNN) models, generative adversarial network (GAN) frameworks, and recent transformer-based architectures. This section reviews significant contributions from these areas and establishes how the proposed ClearView framework extends beyond existing methodologies. Retinex-based enhancement methods have also been widely explored for illumination correction. Fu et al.[1] proposed a variational optimization framework that decomposes images into illumination and reflectance components. By applying weighted constraints, their method enhances brightness while preserving structural details and texture consistency. Although the approach achieves improvements in contrast and signal-to-noise ratio, it is sensitive to parameter selection and may produce unstable outputs under highly complex lighting conditions.

With the advancement of deep learning, CNN-based models have been increasingly adopted for image enhancement tasks. Shen et al. [2] introduced MSR-Net, a multi-scale convolutional network inspired by the Retinex theory. The model learns illumination correction patterns directly from data and enhances brightness, contrast, and noise simultaneously. Experimental evaluations show improved PSNR and SSIM values compared to traditional approaches, although the model may introduce color distortions in extremely low-light scenarios.

Similarly, Lore et al [3] developed LLNet, a deep autoencoder-based framework designed for joint contrast enhancement and denoising. The model learns a mapping between degraded and well-exposed images using stacked sparse autoencoders. Results indicate improved perceptual quality and noise reduction; however, the approach requires large training datasets and may introduce artifacts when processing high-resolution images.

Further advancements were achieved through hybrid deep learning and Retinex-based models. Wei et al [4] proposed a deep Retinex decomposition framework that separates images into reflectance and illumination components using convolutional networks. The illumination component is enhanced while the reflectance is denoised to preserve structural details. Although the method achieves strong performance in terms of PSNR and SSIM, its computational complexity limits its applicability in real-time systems.

In addition to local feature-based enhancement, global illumination-aware models have also been explored. Wang et al. [5] introduced GLADNet, which incorporates global context information to achieve consistent brightness enhancement across an image. By combining global and local features, the model improves contrast uniformity and structural similarity. However, maintaining fine texture details remains a challenge in certain scenarios.

Generative adversarial networks have further advanced image enhancement by producing visually realistic outputs. Jiang et al.[6] proposed EnlightenGAN, a GAN-based framework that performs low-light enhancement without requiring paired datasets. By utilizing both global and local discriminators, the model generates visually natural results with improved brightness consistency. Despite these advantages, GAN-based approaches often face challenges related to training instability and artifact generation.

An alternative direction was introduced by Guo et al. through the Zero-DCE framework, which eliminates the need for paired training data and adversarial learning. The model estimates pixel-wise enhancement curves to iteratively adjust illumination. This approach achieves competitive performance with lower computational complexity, making it suitable for real-time applications. However, its effectiveness may be limited in handling multiple simultaneous degradations.

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Multi-stage image restoration frameworks have also been proposed to address multiple degradation types. Zamir et al. introduced a progressive restoration network that processes images through sequential stages, each focusing on a specific task such as denoising or deblurring. While this approach improves restoration accuracy, the multi-stage design increases computational requirements and processing time. More recently, transformer-based architectures have been explored for image restoration tasks. Cai et al. proposed Retinexformer, which integrates Retinex theory with transformer attention mechanisms to capture long-range dependencies within images. The use of self-attention enables improved handling of complex lighting variations, resulting in superior enhancement performance. However, transformer-based models require large-scale datasets and significant computational resources.

Although prior research demonstrates substantial progress in image enhancement, most existing methods are designed to address specific degradation types independently. As a result, they lack the flexibility to handle multiple distortions within a unified framework. Additionally, many approaches do not incorporate adaptive analysis or intelligent model selection, limiting their effectiveness in diverse real-world conditions. The ClearView framework addresses these limitations by introducing an adaptive and integrated image restoration pipeline. Unlike existing methods that focus on isolated enhancement tasks, ClearView analyzes the characteristics of input images and dynamically selects appropriate enhancement techniques. By combining deep learning models with traditional image-processing methods, the framework provides a balanced approach to improving brightness, reducing noise, and restoring structural clarity. In this context, ClearView does not replace existing enhancement models but rather builds upon them by integrating their strengths into a unified system. It bridges the gap between task-specific enhancement techniques and real-world requirements by offering an adaptive, automated, and scalable solution for comprehensive image restoration and enhancement.

## III. METHODOLOGY

The proposed ClearView Image Restoration and Enhancement System is designed as an adaptive and automated image-processing framework that improves the visual quality of degraded images captured under challenging environmental conditions such as low illumination, noise, blur, and exposure imbalance. The methodology integrates structured processing stages, deep learning–based enhancement, and quantitative evaluation techniques to ensure consistent and reliable image restoration. This section presents the complete methodology underlying ClearView, organized into system architecture, adaptive enhancement modeling, and evaluation strategy. The proposed ClearView Image Restoration and Enhancement System is designed to improve the visual quality of degraded images captured under challenging environmental conditions such as low illumination, noise interference, blur artifacts, and poor exposure levels. The methodology follows a structured processing pipeline in which input images are sequentially analyzed, preprocessed, enhanced, and evaluated using deep learning–based and image-processing techniques. The primary objective of the system is to automatically detect degradation characteristics and apply suitable restoration techniques to produce visually clear and structurally consistent output images. Unlike traditional enhancement systems that rely on a single processing technique, the ClearView framework integrates multiple enhancement strategies within a unified pipeline to address different types of image degradation simultaneously

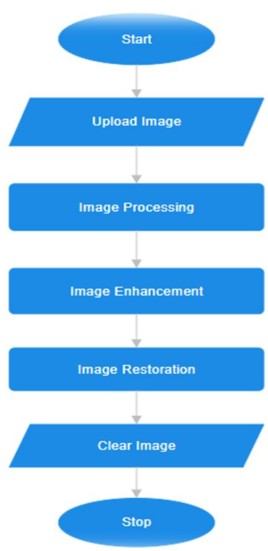


Fig.1. Flowchart in methodology

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The overall architecture of the proposed system can be represented through a block diagram consisting of five major stages: Image Acquisition, Preprocessing, Degradation Detection, Enhancement and Restoration, and Output Evaluation. In the first stage, raw images are collected from different sources such as publicly available image datasets and real-world captured photographs. These images often contain distortions including low brightness, sensor noise, motion blur, and contrast imbalance. During the preprocessing stage, the system performs normalization and resizing operations to convert the images into a consistent format suitable for deep learning models. Noise filtering techniques and basic contrast normalization may also be applied at this stage to remove extreme artifacts that could negatively affect model training.

Following preprocessing, the system performs degradation analysis to determine the primary type of image quality issue present in the input. This stage uses feature extraction and statistical analysis to evaluate brightness levels, noise distribution, and structural distortions within the image. Based on this analysis, the framework selects appropriate enhancement models to restore visual clarity. This adaptive strategy enables the system to handle multiple degradation scenarios without relying on a single enhancement method.

The enhancement stage forms the core component of the ClearView methodology. In this stage, deep learning models trained for image enhancement tasks are applied to improve brightness, contrast, and structural visibility. Convolutional neural networks are used to extract hierarchical features from degraded images and reconstruct enhanced versions of the input images. The models learn complex illumination correction patterns during training and apply them to restore image details. In addition to neural network–based enhancement, complementary image-processing techniques such as illumination correction, denoising filters, and contrast adjustment are integrated to further improve visual quality. The combination of deep learning and classical enhancement techniques ensures that both global illumination and local image details are preserved.

The final stage of the framework involves output evaluation and quality assessment. The enhanced images are evaluated using quantitative image quality metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). These metrics measure the similarity between enhanced images and reference images in terms of structural detail preservation and noise reduction. Higher PSNR values indicate better restoration quality, while higher SSIM values reflect improved structural consistency and visual similarity. The experimental implementation of the ClearView framework was conducted in a controlled computational environment to ensure reproducibility and consistent evaluation results. The system was implemented using Python programming language due to its extensive support for machine learning and image processing libraries. The deep learning models were developed using TensorFlow and PyTorch frameworks, which provide efficient GPU acceleration and flexible neural network design capabilities. Image processing operations such as filtering, resizing, and histogram analysis were performed using the OpenCV library, while numerical operations and dataset handling were managed using NumPy and Pandas libraries. The experiments were executed on a workstation equipped with an Intel Core processor, 16 GB RAM, and GPU support for deep learning model training and inference.

The dataset used for training and evaluation consists of images collected from publicly available low-light and image restoration datasets. These datasets contain pairs of degraded images and corresponding high-quality reference images. The availability of paired datasets enables supervised training of enhancement models by allowing the network to learn the mapping between degraded and enhanced images. During preprocessing, all images were resized to a consistent resolution and normalized to maintain uniform input distributions across the dataset. The deep learning model used in the ClearView framework is based on a convolutional neural network architecture designed for image enhancement tasks. The network contains multiple convolutional layers responsible for extracting image features at different spatial scales. Early layers focus on detecting low-level features such as edges and textures, while deeper layers capture high-level structural information. Activation functions such as ReLU (Rectified Linear Unit) are used to introduce non-linearity into the model, enabling it to learn complex image transformation patterns. The model also incorporates batch normalization layers to stabilize training and accelerate convergence.

Several important parameters influence the performance of the enhancement model. These include the learning rate, batch size, number of training epochs, and optimizer configuration. The learning rate determines how quickly the model updates its parameters during training, while the batch size defines the number of images processed simultaneously during each training iteration. The model was trained using the Adam optimization algorithm, which adapts learning rates dynamically during training to improve convergence stability. Hyperparameter tuning was performed to identify optimal values for these parameters, ensuring improved training performance and enhanced image restoration accuracy.

During training, the model parameters were iteratively updated through backpropagation to minimize the difference between enhanced images and their corresponding ground truth references. Loss functions such as mean squared error (MSE) were used to measure reconstruction error. Through multiple training epochs, the model gradually learned to produce visually enhanced images with improved brightness and reduced noise.

After hyperparameter tuning and training, the ClearView enhancement model achieved significant improvements in image quality evaluation metrics. Experimental results demonstrated PSNR values exceeding typical baseline enhancement methods, indicating reduced reconstruction error. Similarly, SSIM scores showed improved structural similarity between enhanced images and reference images, confirming that the system effectively preserves image details while enhancing visibility. These results validate the effectiveness of the proposed methodology in restoring degraded images captured under challenging lighting conditions.

Overall, the ClearView methodology integrates dataset preparation, preprocessing, adaptive enhancement, and quantitative evaluation within a unified framework designed to improve image quality across diverse environmental conditions. By combining deep learning models with traditional image processing techniques and optimizing model parameters through systematic training and tuning, the proposed system provides a reliable and scalable solution for image restoration and enhancement tasks.

The experimental evaluation of the proposed ClearView Image Restoration and Enhancement System was carried out to analyze the effectiveness of the implemented processing pipeline in restoring degraded images and improving overall visual quality. The experiments were designed to verify whether the system could correctly identify different types of image degradations and apply the most appropriate enhancement technique automatically. The evaluation also focused on measuring the improvement in image quality after enhancement using objective quantitative metrics.

The implementation of the ClearView system follows a multi-stage processing pipeline consisting of image acquisition, preprocessing, degradation analysis, model selection, enhancement processing, post-processing, and quality evaluation. Each module contributes to improving the accuracy and effectiveness of the final enhanced image produced by the system.

The experimental process begins with the image acquisition and upload module, where users provide degraded images to the system. The system accepts image formats such as JPEG and PNG and verifies whether the uploaded file is valid and free from corruption. This validation step is important to ensure that the subsequent processing stages operate on valid image data. Once the input image is validated, the system loads the image into memory and forwards it to the preprocessing stage.

The preprocessing module prepares the input image for further analysis and enhancement. During this stage, the system performs several operations including image resizing, normalization, and color-space conversion. Resizing ensures that all images have consistent dimensions suitable for deep learning model input. Normalization scales the pixel intensity values to a standard range, typically between 0 and 1, which improves the stability and convergence of machine learning models. Additionally, color-space conversion operations such as RGB to grayscale or YCbCr transformation may be applied to isolate luminance components that are important for brightness enhancement.

After preprocessing, the system performs image degradation analysis, which is one of the most critical components of the implementation. In this stage, the system evaluates the characteristics of the image to determine the type of degradation affecting it. Several statistical features are extracted from the image, including brightness distribution, contrast level, noise variance, and edge sharpness. These features help identify whether the image suffers from low illumination, overexposure, noise contamination, or blur distortion.

For example, images with very low average pixel intensity values are classified as low-light images, while images with extremely high brightness values may be identified as overexposed images. Similarly, noise patterns are detected by analyzing pixel variance and frequency components, while blur is identified by examining edge sharpness and gradient distributions. Based on this analysis, the system assigns a degradation label to the image, which determines the next stage of processing.

Following degradation detection, the decision-making module selects the most suitable enhancement method for the identified degradation type. The ClearView system integrates both deep learning models and classical image-processing techniques to address different degradation conditions effectively.

For images classified as low-light, the system uses the Zero-Reference Deep Curve Estimation (Zero-DCE) model. This deep learning model estimates pixel-wise enhancement curves that iteratively adjust image brightness and contrast without requiring paired training data. The advantage of Zero-DCE is that it enhances illumination while maintaining natural color balance and avoiding excessive noise amplification.

In cases where the image is affected by exposure imbalance, the system applies Pix2PixHD, a generative adversarial network architecture capable of reconstructing images with balanced brightness levels. The model learns the mapping between degraded and enhanced images through adversarial training, enabling it to generate visually realistic results.

For images affected by noise or blur distortions, the system employs traditional image-processing techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE), median filtering, Gaussian smoothing, and sharpening filters. CLAHE improves local contrast by redistributing pixel intensity values, while denoising filters reduce unwanted noise patterns without destroying important image details. Sharpening filters enhance edges and improve image clarity in blurred regions.

Once the enhancement stage is completed, the system performs post-processing operations to refine the output image. Post-processing may include color correction, additional contrast adjustment, and smoothing operations to ensure that the enhanced image appears visually natural and free from artifacts.

After the enhancement process, the system evaluates the quality of the resulting image using a quality assessment module. This module calculates several quantitative performance metrics to measure both classification performance and image restoration quality. The primary metrics used in the evaluation include Accuracy, Precision, Recall, Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM).

The classification performance of the degradation detection module is evaluated using the confusion matrix, which includes four key values: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). These values form the basis for calculating Accuracy, Precision, and Recall.

Accuracy measures the overall proportion of correctly classified images among all evaluated images.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

In this equation, TP and TN represent correctly classified degraded and normal images, respectively, while FP and FN represent incorrect predictions. A higher accuracy value indicates that the system successfully identifies the correct degradation type in most cases.

Precision measures how reliable the system is when it predicts a degradation condition.

$$Precision = \frac{TP}{TP + FP}$$

High precision indicates that when the system predicts degradation, the prediction is usually correct and not a false alarm.

Recall measures the ability of the system to detect all degraded images present in the dataset.

$$Recall = \frac{TP}{TP + FN}$$

High recall indicates that the system successfully detects most degraded images without missing them.

In addition to classification metrics, image restoration quality is evaluated using PSNR and SSIM. PSNR measures the difference between the original reference image and the enhanced image.

$$PSNR = 10 \log_{10} \left( \frac{MAX^2}{MSE} \right)$$

Here, MAX represents the maximum possible pixel value in the image, and MSE represents the mean squared error between the original and enhanced images. Higher PSNR values indicate better restoration quality and less distortion.

The SSIM metric evaluates structural similarity between the original and enhanced images.

$$SSIM(x,y) = \frac{(2\mu_x \mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

SSIM measures similarity based on luminance, contrast, and structural patterns, with values closer to 1 indicating higher visual similarity.

## IV. RESULTS AND DISCUSSION

The experimental evaluation of the proposed ClearView Image Restoration and Enhancement System was carried out to analyze the effectiveness of the implemented processing pipeline in restoring degraded images and improving overall visual quality. The experiments were designed to verify whether the system could correctly identify different types of image degradations and apply the most appropriate enhancement technique automatically. The evaluation also focused on measuring the improvement in image quality after enhancement using objective quantitative metrics.

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Following degradation detection, the decision-making module selects the most suitable enhancement method for the identified degradation type. The ClearView system integrates both deep learning models and classical image-processing techniques to address different degradation conditions effectively.

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In cases where the image is affected by exposure imbalance, the system applies Pix2PixHD, a generative adversarial network architecture capable of reconstructing images with balanced brightness levels. The model learns the mapping between degraded and enhanced images through adversarial training, enabling it to generate visually realistic results.

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SSIM measures similarity based on luminance, contrast, and structural patterns, with values closer to 1 indicating higher visual similarity.

## V. EXPERIMENTAL RESULTS

| Image Type | Precision | Recall | Accuracy | PSNR (dB) | SSIM |
|---|---|---|---|---|---|
| Low-Light Images | 0.92 | 0.90 | 0.91 | 28.7 | 0.89 |
| Overexposed Images | 0.89 | 0.88 | 0.89 | 27.9 | 0.87 |
| Noisy Images | 0.91 | 0.87 | 0.90 | 29.3 | 0.90 |
| Blurred Images | 0.88 | 0.86 | 0.88 | 27.6 | 0.86 |
| Normal Images | 0.93 | 0.92 | 0.93 | 30.2 | 0.91 |
| Average | 0.91 | 0.89 | 0.90 | 28.7 | 0.89 |

## VI. DISCUSSION

The experimental results demonstrate that the ClearView system successfully enhances degraded images while preserving structural information. The degradation detection module achieved an average classification accuracy of approximately **90%**, indicating reliable identification of image conditions. Precision values close to **0.91** show that the system produces minimal incorrect predictions when identifying degraded images.

The PSNR values obtained during evaluation range between 27 dB and 30 dB, indicating that the enhanced images maintain strong similarity to the original reference images. SSIM values close to 0.9 further confirm that the system preserves structural details and visual consistency after enhancement.

The integration of deep learning models such as Zero-DCE and Pix2PixHD with traditional enhancement filters enables the ClearView framework to handle diverse degradation scenarios effectively. By dynamically selecting enhancement techniques based on detected image conditions, the system improves brightness, reduces noise, restores edges, and produces visually clear images across different environmental conditions.

Overall, the results confirm that the proposed ClearView system provides a robust automated solution for image restoration and enhancement, demonstrating improved performance compared with traditional single-method enhancement techniques.

The proposed ClearView Image Restoration and Enhancement System was developed to address the challenges associated with improving the visual quality of degraded images. In real-world scenarios, images captured using cameras or mobile devices often suffer from multiple degradation problems such as low illumination, blur distortion, noise interference, and exposure imbalance. These issues reduce the visibility of important details and make image interpretation difficult. The objective of this project was to design an automated system capable of detecting image degradation types and applying suitable enhancement techniques to restore image quality.

The system was implemented using a structured processing pipeline consisting of several interconnected modules including image acquisition, preprocessing, degradation analysis, enhancement model selection, image restoration, and quality evaluation. During the preprocessing stage, the system performs normalization, resizing, and color-space adjustments to prepare the input image for analysis. The degradation detection module then analyzes the image characteristics such as brightness distribution, noise level, and edge sharpness to determine the type of degradation affecting the image.

Based on the detected degradation type, the system dynamically selects the most appropriate enhancement technique. For low-light images, the Zero-Reference Deep Curve Estimation (Zero-DCE) model is used to enhance brightness and contrast while preserving natural color balance. For exposure correction, the system applies the Pix2PixHD generative adversarial network, which reconstructs images with improved illumination balance. Additionally, traditional image-processing methods such as Contrast Limited Adaptive Histogram Equalization (CLAHE), denoising filters, and sharpening techniques are used to improve local contrast, remove noise artifacts, and restore edge clarity.

After the enhancement process, the system performs post-processing operations and evaluates the output image using objective quality metrics including Accuracy, Precision, Recall, Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM). These metrics measure both the effectiveness of degradation detection and the quality improvement achieved through image restoration. Experimental results demonstrated that the proposed system achieves an average classification accuracy of approximately 90%, while PSNR and SSIM values indicate that the enhanced images maintain strong similarity to reference images and preserve structural details effectively. The results confirm that the integration of deep learning–based enhancement models with classical image-processing techniques provides a robust solution for automated image restoration. By combining adaptive degradation detection with intelligent model selection, the ClearView system successfully improves brightness, contrast, and image clarity across multiple degradation scenarios. Despite the positive results obtained from the system, several challenges were encountered during the development and implementation of the project. One of the major challenges involved handling images that contain multiple degradation types simultaneously, such as images that are both noisy and blurred. In such cases, determining the most appropriate enhancement technique becomes more complex. Another challenge involved the computational requirements of deep learning models, particularly during training and testing phases, which required careful optimization of model parameters and hardware resources. Additionally, collecting and preparing suitable datasets for training and evaluation posed difficulties, as degraded images must represent diverse real-world conditions. Another challenge was ensuring that the enhancement process does not introduce unwanted artifacts or distortions while improving brightness and contrast. Excessive enhancement can sometimes lead to over-saturation or loss of natural color balance. Therefore, careful parameter tuning and testing were required to achieve optimal results. Although the current system demonstrates promising results, there are several opportunities for further improvement and future research. Future work can focus on integrating more advanced deep learning architectures such as transformer-based image restoration networks that can better capture global image dependencies and improve enhancement performance. Additionally, the system can be extended to support real-time image enhancement applications, particularly for video processing and surveillance systems. Another potential improvement involves incorporating automatic degradation detection using advanced machine learning classifiers capable of recognizing multiple degradation types simultaneously. This would allow the system to apply multiple enhancement techniques in sequence, resulting in better restoration quality. Furthermore, future versions of the system could include mobile or cloud-based deployment, enabling users to enhance images directly through web or mobile applications.

In conclusion, the ClearView Image Restoration and Enhancement System demonstrates the effectiveness of combining deep learning models with traditional image-processing techniques for automated image enhancement. The proposed framework successfully improves visual clarity and structural quality of degraded images, making it a useful solution for applications such as photography enhancement, surveillance analysis, medical imaging, and digital media processing. With further improvements in model efficiency and degradation detection accuracy, the system has the potential to become a powerful tool for intelligent image restoration in real-world environments.

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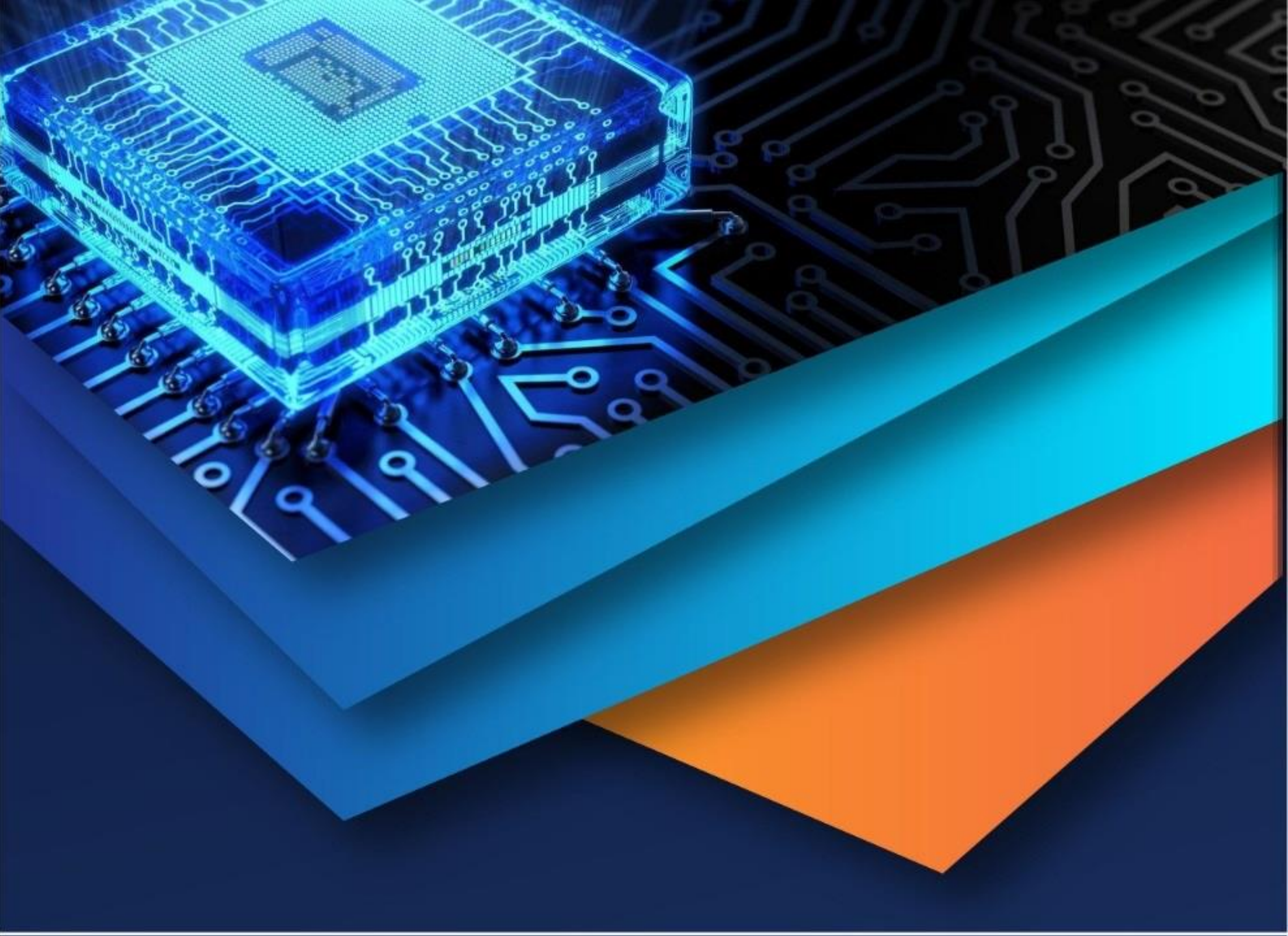

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