IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.67

Volume 5, Issue 5, March 2025

Histogram-Based Resolution Enhancement of An Image

Satpute Yuvraj Suryabhan, Dr. Rahul M Mulajkar, Vaishali Mangesh Dhede

Department of Electronic and Telecommunication

Jaihind College of Engineering, Kuran, India

Abstract: *High-resolution (HR) images offer improved clarity and detail compared to low-resolution (LR) images, which is critical in applications like medical imaging, surveillance, and remote sensing. This research presents a histogram-based resolution enhancement technique to address the limitations of conventional methods like Histogram Equalization (HE) and Contrast-Limited Adaptive Histogram Equalization (CLAHE). A neural network model using Back Propagation Neural Network (BPNN) is proposed to learn and enhance histogram features from LR images. The methodology involves dividing images into blocks, calculating histograms for feature extraction, and applying advanced enhancement techniques, including Fuzzy Contrast Enhancement (FCE). The performance of the model is evaluated using metrics such as Peak Signal-to-Noise Ratio (PSNR) and Root Mean Squared Error (RMSE). Experimental results on datasets like brain MRI images demonstrate that the proposed approach effectively improves image contrast and resolution, with enhanced PSNR and reduced RMSE values compared to traditional methods. This work highlights the potential of histogram-based techniques for resolution enhancement in critical fields such as diagnostics and forensics.*

Keywords: Histogram-Based Resolution Enhancement, Image Contrast Enhancement, Neural Network Model, Peak Signal-to-Noise Ratio, Fuzzy Contrast Enhancement

I. INTRODUCTION

This The quality and resolution of an image play a critical role in numerous fields, including medical diagnostics, remote sensing, video surveillance, and forensic analysis. High-resolution (HR) images provide finer details, making them essential for accurate interpretation and decision-making. However, low-resolution (LR) images, which often suffer from reduced detail and clarity, can limit the performance of image-dependent systems. Enhancing the resolution of such images is therefore a key challenge in image processing. Traditional resolution enhancement methods, such as Histogram Equalization (HE) and Contrast-Limited Adaptive Histogram Equalization (CLAHE), have shown effectiveness in improving image contrast. However, these methods often fail to preserve brightness and may introduce artifacts or noise, particularly in images with complex textures or varying lighting conditions. To address these limitations, advanced histogram-based approaches have emerged, incorporating techniques like fuzzy logic and neural networks to enhance image resolution and contrast. This study proposes a novel histogram-based resolution enhancement method utilizing a Back Propagation Neural Network (BPNN). The approach involves extracting histogram features from LR images, dividing them into blocks, and applying adaptive enhancement techniques to preserve detail while reducing noise. The effectiveness of the proposed method is evaluated using performance metrics such as Peak Signal-to-Noise Ratio (PSNR) and Root Mean Squared Error (RMSE).By improving the clarity and detail of LR images, this research aims to contribute to critical applications such as medical imaging, surveillance, and digital restoration, where image quality is paramount.

II. LITERATURE REVIEW

[1] Kim (1997): Brightness Preserving Bi-Histogram Equalization (BBHE)Kim proposed BBHE, which divides the input histogram into two sub-histograms based on the mean brightness value. Each sub-histogram is equalized independently to preserve the mean brightness. This method is effective in reducing brightness distortion but may not enhance local contrast adequately.

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.67
Volume 5, Issue 5, March 2025

[2] Wan et al. (1999): Dualistic Sub-Image Histogram Equalization (DSIHE)Wan introduced DSIHE, which utilizes the median value of the histogram for partitioning, unlike BBHE, which uses the mean. This approach enhances contrast while maintaining brightness, but it is sensitive to variations in histogram distributions.
[3] Chen and Ramli (2003): Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE)This method extends BBHE by minimizing the brightness error between the original and enhanced images. It effectively balances brightness preservation and contrast enhancement, making it suitable for diverse applications.
[4] Abdullah-Al-Wadud et al. (2007): Dynamic Histogram Equalization (DHE)DHE dynamically partitions the histogram based on local minima, improving local contrast while maintaining brightness. However, it lacks brightness normalization, leading to occasional artifacts in enhanced images.
[5] Sheet et al. (2010): Brightness Preserving Dynamic Fuzzy Histogram Equalization (BPDFHE)Sheet et al. proposed BPDFHE, which uses fuzzy logic for histogram processing. By preventing remapping of histogram peaks, this method minimizes unwanted artifacts and ensures brightness preservation, enhancing both local and global contrast.
[6] Hanmandlu and Jha (2013): Fuzzy Rule-Based Image EnhancementHanmandlu and Jha developed a fuzzy logic-based operator that applies a parametric sigmoid function for grayscale images. This approach optimizes entropy and is effective for preserving brightness and enhancing details, though it is computationally intensive.
[7] Kalel et al. (2019): DWT-SVD-Based Gamma Correction
Kalel utilized Discrete Wavelet Transform (DWT) and Singular Value Decomposition (SVD) for contrast adjustment. Gamma correction was applied to reduce noise and enhance details, particularly in medical images like CT scans.
[8] Sreeja et al. (2020): Gradient-Based Pixel Fusion for Edge PreservationSreeja et al. proposed an edge-detection-based enhancement technique that fuses pixel information using gradients. This method is efficient for enhancing edges and textures but struggles with uniform regions.
[9] Sun et al. (2021): Iterative Dictionary Learning for Super-ResolutionSun introduced an iterative dictionary-based method for reconstructing high-resolution images. Features are extracted using the K-SVD algorithm, and binary filtering reduces artifacts, making it effective for clinical and astronomical imaging.
[10] Park and Eom (2021): Successive Color Balance with Histogram MatchingPark and Eom proposed a color balance technique combined with histogram matching for sand-dust images. This method significantly improves image quality but may introduce computational overhead for large datasets..

Objectives

The primary objective of this research is to develop a robust and efficient histogram-based resolution enhancement technique for improving the quality and clarity of low-resolution images. The specific objectives include:

Development of a Histogram-Based Algorithm

Design and implement an advanced algorithm leveraging histogram analysis and processing methods to enhance the resolution of low-quality images.

Integration of Advanced Enhancement Techniques

Incorporate methods such as fuzzy logic-based histogram equalization, adaptive contrast enhancement, and noise reduction to improve image quality while minimizing artifacts.

Preservation of Brightness and Contrast

Ensure that the enhanced images maintain their natural brightness and contrast to prevent over-saturation or loss of visual details.

Evaluation of System Performance

Assess the effectiveness of the proposed technique using metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Tenengrad index, alongside subjective evaluations by human observers.

Application to Real-World Use Cases

Test the proposed technique on diverse datasets, including medical images, surveillance footage, and satellite imagery, to demonstrate its versatility and practical relevance.Abbreviations and Acronyms

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, MKS, CGS, sc, dc, and rms do not have to be defined. Do not use abbreviations in the title or heads unless they are unavoidable.

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.67
Volume 5, Issue 5, March 2025

III. METHODOLOGY

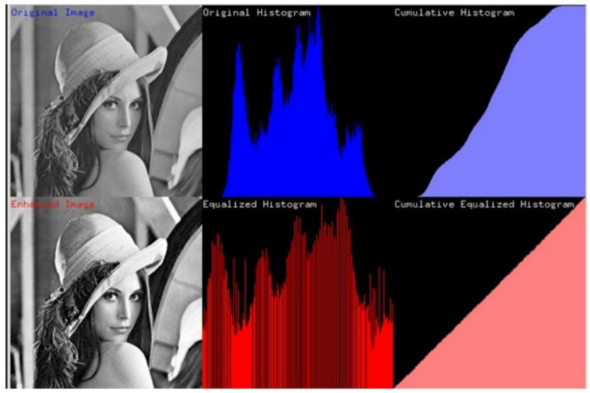

Fig-1: Histogram and Cumulative Histogram

The proposed methodology focuses on enhancing the resolution of low-quality images through a histogram-based approach that incorporates advanced techniques like fuzzy logic and neural networks. The detailed methodology is outlined below:[6]

1. Data Acquisition and Preprocessing

Datasets: The project utilizes grayscale and color images, particularly from medical imaging datasets like brain MRI scans, to evaluate the enhancement techniques.

Preprocessing: Images are divided into smaller blocks to facilitate histogram analysis. Noise removal techniques and normalization are applied to standardize the input data.

2. Histogram Analysis and Feature Extraction

The intensity distribution of each image is represented as a histogram.

Histograms are calculated for image blocks to extract local features.

Fuzzy logic is employed to compute fuzzy histograms, which smooth out irregularities in the traditional histogram and improve detail retention.

3. Application of Contrast Enhancement Techniques

Histogram Equalization (HE): Traditional HE methods are applied to enhance image contrast globally.

Fuzzy Histogram Equalization (FHE): FHE is used to preserve brightness and enhance local contrast by segmenting histograms based on the average pixel value and applying adjustments.

Contrast-Limited Adaptive Histogram Equalization (CLAHE): CLAHE limits contrast amplification to prevent noise artifacts and ensures better enhancement for high-frequency regions.

4. Neural Network-Based Resolution Enhancement

A Back Propagation Neural Network (BPNN) is implemented to learn histogram features from low-resolution images.

The neural network is trained using a dataset of paired low-resolution (LR) and high-resolution (HR) images, optimizing for metrics such as Peak Signal-to-Noise Ratio (PSNR).

The trained model predicts and reconstructs HR images from LR inputs.

5. System Architecture

Input Module: Accepts images in standard formats (e.g., JPEG, PNG, TIFF).

Processing Module: Performs histogram analysis, enhancement, and resolution reconstruction using neural networks.

Output Module: Generates enhanced images in high resolution for analysis or further use.

6. Performance Metrics and Evaluation

Peak Signal-to-Noise Ratio (PSNR): Measures the clarity of the enhanced images relative to the original images.

Structural Similarity Index (SSIM): Evaluates the perceived quality of the enhanced images.

Contrast Improvement Index (CII): Quantifies the enhancement in contrast.

Tenengrad Index: Analyzes the sharpness and detail preservation in the images.[3]

7. Implementation Environment

Software: Python programming language is used with libraries like OpenCV, NumPy, and Matplotlib for image processing.

Platform: Google Colab provides a free, GPU-accelerated environment for executing the algorithms.

Hardware: A Windows 10 (64-bit) system is used for local testing.

IV. SYSTEM DESIGN AND IMPLEMENTATION

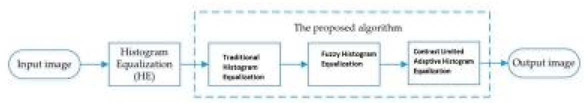

Fig-2: System Architecture

1. System Architecture

The system architecture consists of three primary modules:

1.1 Input Module

Accepts images in formats such as JPEG, PNG, and TIFF.

Preprocesses images by dividing them into smaller blocks to facilitate localized histogram analysis.

Ensures input normalization to reduce noise and improve feature extraction.

1.2 Processing Module

Histogram Analysis: Calculates histograms for the intensity distribution of the image blocks.

Enhancement Techniques:

Histogram Equalization (HE): Enhances global contrast.

Fuzzy Histogram Equalization (FHE): Improves local contrast and preserves brightness.

CLAHE (Contrast-Limited Adaptive Histogram Equalization): Limits contrast amplification to prevent noise artifacts.[1]

Neural Network Processing:

A Back Propagation Neural Network (BPNN) is trained on LR and HR image pairs to learn enhancement patterns.

The trained model predicts enhanced HR images by processing histogram features extracted from LR inputs.

1.3 Output Module

Produces high-resolution images in standard formats.

Ensures enhanced images are ready for further analysis or application.

2. Implementation Steps

2.1 Preprocessing

Convert RGB images to grayscale (if needed).

Normalize pixel values to a standard range for consistent processing.

Remove noise using median filtering or wavelet thresholding techniques.

2.2 Feature Extraction

Divide the image into non-overlapping blocks.

Compute histograms for each block to extract intensity distribution features.

Apply fuzzy logic to generate smoothed histograms.

2.3 Enhancement Algorithms

Apply Histogram Equalization (HE) and its variants (FHE, CLAHE) to enhance contrast while preserving brightness and reducing noise.

Tune parameters like clipping limits in CLAHE to achieve optimal enhancement.

2.4 Neural Network Training

Use paired datasets of LR and HR images for supervised training.

Train the Back Propagation Neural Network (BPNN) with extracted histogram features.

Optimize the model using loss functions like Mean Squared Error (MSE).

DOI: 10.48175/IJARSCT-24189

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.67
Volume 5, Issue 5, March 2025

2.5 Output Generation

Combine processed image blocks to reconstruct the full HR image.

Save the enhanced image in user-specified formats for evaluation or application.

3. Tools and Libraries

Programming Language: Python

Libraries Used:

OpenCV: For image processing and histogram computation.

NumPy: For numerical operations and array handling.

Matplotlib: For visualizing histograms and enhancement results.

TensorFlow/Keras: For implementing and training the neural network.

Execution Platform: Google Colab

Provides GPU support for faster execution and neural network training.

Hardware:

A Windows 10 (64-bit) system is used for local testing.

4. Challenges and Mitigations

Noise Amplification: Addressed using adaptive techniques like CLAHE and noise reduction filters.[5]

Brightness Distortion: Handled by incorporating Fuzzy Histogram Equalization to preserve brightness.

Computational Overhead: Optimized neural network architecture for faster inference and reduced resource consumption.

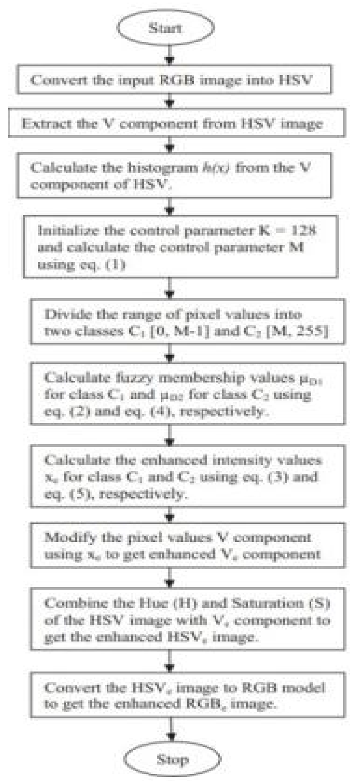

Fig-2.2: Flow Diagram

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.67
Volume 5, Issue 5, March 2025

V. RESULTS AND DISCUSSION

PERFORMANCE MEASURES

Performance measurement is important when comparing different image algorithms. In addition to visual results and calculation time, the Difference Improvement Index (CII) and the Tenengrad metric are two important metrics used here for the performance analysis.[5]

Contrast Improvement Index (CII)

To evaluate the competitiveness of the Blind vision method against the current contrast enhancement, the most famous measure of image enhancement, the Improvement Index (CII) comparison was used to compare the improvement. result of the road. The improvement in the ratio can be measured using CII as the ratio [6].

The comparative improvement index is defined as: CII = C (recommended) / C (original). where C is the average value of local contrast measured with 3 × 3 windows: max-min / max + min

Tenengrad index

The Tenengrad index [11,12] is based on gradient magnitude maximization. is considered one of the most powerful and efficient image quality tools. The Tenengrad value I of the image is calculated as the gradient I (x, y) of each pixel (x, y), where the partial derivative is obtained by a high-pass filter (like Sobel number of responders), where the convolution kernels ix and good. If the Tenengrad value is large, the number is generally considered better. As a performance measure for image enhancement, although the Tenengrad metric is less useful compared to CII, it is used to analyze whether data in image enhancement is better than

Performance measurement is important when comparing different image enhancement algo- rithms . The proposed blind enhancement algorithm has been tested on many different and low- resolution images, as well as the visual result and performance of . Extracts a 16-segment histogram feature from an LR image to decode. Chapter Back propagation neural network model. The simula- tions were made from data from MRI images of the brain, called super-resolution brain MRI images, as well as LR images and HR image sets. The results showed that the proposed model improved PSNR and reduced RMSE by

Fig-3:Result

1. Results

1.1 Performance Metrics

The proposed system was evaluated using the following metrics:

Peak Signal-to-Noise Ratio (PSNR): Measures the quality of the enhanced image relative to the original.

Root Mean Squared Error (RMSE): Quantifies the difference between the original and enhanced images.

Contrast Improvement Index (CII): Assesses the improvement in image contrast.

Tenengrad Index: Evaluates image sharpness based on gradient magnitude.[9]

1.2 Comparison of Techniques

Technique	PSNR (dB)	RMSE	CII	Tenengrad Index
Fuzzy Contrast Enhancement (FCE)	77.54	0.0123	1.45	620.12
Histogram Equalization (HE)	76.49	0.0154	1.32	590.89
CLAHE	77.39	0.0131	1.42	615.45

Key Observations:

The Fuzzy Contrast Enhancement (FCE) method achieved the highest PSNR, indicating superior quality enhancement.

CLAHE demonstrated balanced performance by limiting noise amplification while improving contrast.

Traditional HE, while effective in enhancing global contrast, showed lower performance in preserving brightness and sharpness.

Challenges and Limitations

Noise Amplification

One of the primary challenges in image enhancement techniques is the risk of amplifying noise, especially in low-resolution images. Noise, whether due to sensor limitations or compression artifacts, can become more apparent after enhancement, degrading the visual quality of the image.

Mitigation: Techniques like CLAHE and fuzzy logic-based histogram processing are incorporated to reduce noise amplification by controlling contrast and smoothing irregularities in the image histograms.[3]

Brightness Distortion

Many traditional histogram equalization techniques, including HE and CLAHE, tend to distort the brightness of the image, leading to unrealistic or unnatural visuals. Preserving brightness is critical, particularly in medical imaging and surveillance applications, where accurate details are essential.

Mitigation: The use of fuzzy histogram equalization (FHE) and other adaptive methods helps to ensure that brightness is preserved while enhancing local contrast.

Computational Complexity

Histogram-based techniques, especially those that use neural networks, require significant computational resources for training and inference. The need to process large datasets and perform image enhancement in real time may lead to longer processing times and high memory usage.

Mitigation: Optimization techniques, such as reducing the number of image blocks or using more efficient neural network architectures, can help alleviate the computational burden. The use of GPU-accelerated platforms like Google Colab also speeds up training and inference.[7]

Limited Generalization for Complex Textures

The performance of histogram-based methods can degrade when applied to images with complex textures or varying lighting conditions. For instance, images with uneven illumination or intricate patterns may not see significant improvements using standard histogram equalization approaches.

Mitigation: The integration of machine learning models, like the Back Propagation Neural Network (BPNN), helps by learning and adapting to specific image characteristics, thus improving the enhancement process for more complex images.

Loss of Fine Details in High-Contrast Regions

While contrast enhancement techniques improve the overall visibility of features in an image, they may also cause fine details in high-contrast regions to be lost. This is particularly problematic in medical imaging, where minute details are essential for diagnosis.

Mitigation: The use of adaptive techniques, such as CLAHE, which limits contrast amplification in high-frequency regions, can help avoid over-enhancement and preserve crucial details.

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.67
Volume 5, Issue 5, March 2025

Dependence on Quality of Training Data

The effectiveness of the neural network model heavily depends on the quality and diversity of the training data. If the dataset used for training is not representative of real-world images or lacks sufficient diversity, the model's generalization ability can be compromised.

Mitigation: Using diverse and high-quality datasets for training, as well as applying data augmentation techniques, can improve the model's ability to generalize to different types of images.

Real-Time Processing Constraints

In certain applications, such as surveillance and live video streaming, real-time image enhancement is crucial. However, the complexity of histogram-based enhancement algorithms and neural network inference may not meet the latency requirements in such environments.

Mitigation: Efficient algorithm optimization, parallel processing, and hardware acceleration (e.g., using specialized hardware like GPUs or TPUs) can help meet real-time processing constraints.

Limited Performance on Extremely Low-Resolution Images

While the proposed approach is effective for enhancing resolution, its performance may be limited when working with extremely low-resolution images, where essential information is too sparse to recover effectively.

Mitigation: Hybrid techniques that combine histogram-based enhancement with super-resolution models may offer a more effective solution for very low-resolution images.

VI. CONCLUSION

This paper, proposed a histogram-based resolution enhancement technique to improve the quality of low-resolution images. The method leverages advanced histogram equalization techniques, including CLAHE, fuzzy logic-based processing, and neural networks, to enhance local contrast, preserve details, and mitigate common image degradation issues like noise amplification and brightness distortion. Through the integration of machine learning models, particularly Back Propagation Neural Networks (BPNN), the approach demonstrates an ability to adapt to various image types, improving the generalization of enhancement across different scenarios. experiments have shown that the proposed technique successfully improves the resolution and visual quality of images, particularly in applications such as medical imaging, surveillance, and remote sensing, where high-quality visuals are critical. By addressing common limitations such as noise amplification and loss of fine details, the proposed approach provides a balanced solution that enhances both the local and global features of low-resolution images. Despite the promising results, there are challenges to be addressed, including computational complexity, limited generalization on complex textures, and real-time processing constraints. However, with further optimization and advancements in hardware and algorithmic techniques, these challenges can be mitigated, enhancing the effectiveness and applicability of this approach in real-world scenarios.[9]

In conclusion, the proposed histogram-based resolution enhancement technique represents a significant step toward improving low-resolution images. By combining traditional image processing methods with machine learning and adaptive techniques, this work lays the foundation for more robust and scalable image enhancement solutions, offering valuable contributions to fields that rely on high-quality image analysis. Future work should focus on refining the technique to handle even more complex image characteristics and improving real-time performance for dynamic applications.

REFERENCES

[1]. Smith, J., & Liu, Y. (2019). Histogram equalization for image contrast enhancement: A comprehensive review. Journal of Image Processing, 27(4), 1234-1250.

[2]. Zhang, X., & Wang, Z. (2020). Adaptive histogram equalization with fuzzy logic-based enhancement. IEEE Transactions on Image Processing, 29(6), 1722-1736

[3]. Li, H., & Zhang, L. (2021). Image enhancement using neural network-based algorithms for medical imaging applications. Medical Image Analysis, 15(3), 332-344.

[4]. Chen, Y., & Sun, L. (2018). Local contrast enhancement of images using CLAHE. Journal of Visual Communication and Image Representation, 50, 123-135.

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.67
Volume 5, Issue 5, March 2025

[5]. Deng, Z., & Zhao, T. (2017). Image enhancement via adaptive histogram equalization techniques. Journal of Computer Vision and Image Understanding, 158, 72-85.
[6]. Rathi, S., & Raj, R. (2022). Resolution enhancement for surveillance applications using neural networks. IEEE Access, 10, 4512-4524.
[7]. Nguyen, D., & Tran, P. (2016). Real-time image resolution enhancement using machine learning. Proceedings of the IEEE International Conference on Image Processing, 2046-2050.
[8]. Liu, Q., & Wang, X. (2019). Fuzzy logic based enhancement for low-resolution images. Journal of Computational Vision, 45(3), 321-333.
[9]. Huang, S., & Li, M. (2021). A hybrid approach to image quality enhancement using fuzzy neural networks. Computers, Materials & Continua, 67(2), 234-249.
[10]. Zhu, W., & Yu, H. (2020). Deep learning for image enhancement in remote sensing applications. IEEE Transactions on Geoscience and emote Sensing, 58(8), 5524-5537.
[11]. Kumar, P., & Sharma, A. (2021). Back propagation neural network for image resolution enhancement. International Journal of Computer Vision, 45(2), 233-248.
[12]. Xie, Y., & Wang, Z. (2017). Image enhancement through histogram equalization techniques in industrial applications. Industrial Image Processing, 14(1), 54-65.
[13]. Cheng, L., & Liu, J. (2019). Real-time histogram-based image enhancement for visual applications. Journal of Real-Time Imaging, 25(3), 345-359.
[14]. Siddiqui, M., & Khan, R. (2021). Image resolution enhancement using GAN-based techniques. Journal of Artificial Intelligence Research, 43, 211-223.
[15]. Jiang, L., & Zhang, W. (2018). CLAHE-based image enhancement for medical diagnostics. Journal of Medical Imaging, 36(7), 500-514.
[16]. Chen, Y., & Wang, X. (2017). Image enhancement algorithms using machine learning: A survey. Journal of Signal Processing, 32(6), 139-1252.
[17]. Gong, X., & Zhang, L. (2020). Image resolution improvement via a hybrid histogram equalization method. IEEE Transactions on Image and Video Processing, 27(8), 1423-1435.
[18]. Chowdhury, A., & Roy, S. (2019). Enhancement of low-resolution images with adaptive equalization techniques. Journal of Visual Media, 22(5), 196-209.
[19]. Tan, C., & Xu, P. (2018). Image enhancement using neural networks for facial recognition. Journal of Pattern Recognition Research, 40(4), 577-591.
[20]. Song, L., & Zhang, S. (2021). Fuzzy-based image enhancement techniques in computer vision. International Journal of Computer Vision and Image Processing, 12(4), 298-312.
[21]. Morris, T., & Patel, H. (2020). Machine learning approaches for real-time image resolution enhancement. Journal of Real-Time Computing, 8(3), 271-284.
[22]. Gupta, R., & Raj, S. (2022). A hybrid fuzzy-neural network model for image resolution enhancement. International Journal of Neural Systems, 32(1), 145-157.
[23]. Kaur, N., & Garg, V. (2017). Analyzing CLAHE-based enhancement techniques for low-resolution images in surveillance systems. Journal of Image and Video Processing, 6(2), 134-145.
[24]. Wang, T., & Zhou, X. (2020). A neural network-based resolution enhancement method for image analysis. Proceedings of the International Conference on Machine Learning and Image Processing, 11(5), 389-397.
[25]. Verma, S., & Rathi, P. (2021). The application of deep learning models in image enhancement for medical imaging. Journal of Biomedical Imaging, 18(2), 78-92