

Unleashing the Power of Image Preprocessing: A Comprehensive Review of Techniques and Applications

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Abstract—Image preprocessing is crucial for enhancing image quality and ensuring their relevance in advanced analysis across multiple domains, including medical diagnostics, remote sensing, biometric recognition, and autonomous vehicles. This paper explores essential preprocessing methods like noise removal, contrast enhancement, edge detection, and segmentation, all of which contribute to refining image clarity and overall quality. It also highlights the significance of these techniques in ensuring better performance of downstream tasks, particularly in deep learning models. The paper highlights the challenges associated with preprocessing, such as balancing the removal of noise while preserving important image details and managing the computational overhead. Furthermore, it examines emerging trends, including AI-driven preprocessing methods, real-time image processing for video applications, and the development of Integrated approaches that merge multiple methods for more effective outcomes. The paper concludes by identifying the open challenges and potential avenues for future research that may result in more adaptive, efficient, and accurate preprocessing techniques across diverse domains.

Index Terms—Gaussian filter, noise reduction, contrast improvement, Histogram equalization, feature extraction, CLAHE, image segmentation, edge detection, grayscale conversion, image denoising, AHE, bilateral filter, Canny edge detection, Prewitt filter, convolutional neural networks, deep learning.

I. INTRODUCTION

Image preprocessing is a crucial step in the image analysis process that involves applying various techniques to raw images to enhance their quality and prepare them for subsequent processing. These techniques help in reducing noise, adjusting contrast, normalizing intensity values, and refining the

structural details of images. The main goal of image preprocessing is to enhance the visual quality of images while retaining crucial details, enhancing their suitability for computer vision and machine learning applications. Preprocessing ensures that the provided data is optimized, facilitating more effective feature extraction along with improving model performance. Key benefits of image preprocessing include noise reduction, contrast improvement, edge detection, image normalization, geometric transformation, image registration, segmentation and others. These methods are crucial for enhancing image quality and enabling accurate analysis. Preprocessing is extensively applied in domains like medical imaging for MRI and CT scans, satellite imagery for environmental monitoring, and biometric recognition for secure authentication. It is also vital for autonomous systems, aiding self-driving cars, robotics, and surveillance with real-time image analysis. Additionally, preprocessing supports industrial quality control, agricultural analysis, and sports analytics.

This review paper examines various image preprocessing techniques, focusing on their application across different domains. These methods are classified into noise removal, contrast enhancement, geometric transformations, segmentation, and feature extraction. Methods like Gaussian blur, median filtering, and wavelet transforms are utilized for noise removal. For contrast improvement, histogram equalization and adaptive contrast adjustment are discussed. Geometric transformations, like resizing, rotation, and scaling, are explored for their effects on image structure, while segmentation techniques like thresholding and edge detection are evaluated. Additionally, feature extraction methods are studied to enhance deep

learning models in computer vision.

This paper also highlights the challenges faced in image preprocessing and reviews emerging trends in the field. This review offers a comprehensive insight into preprocessing techniques, highlighting their benefits and drawbacks, making it a valuable reference for researchers and professionals in image analysis and computer vision.

II. LITERATURE REVIEW

Image preprocessing methods are intended to remove noise, enhance contrast, and optimize image quality, all of these play a role in enhancing the efficiency and accuracy of automated systems. Classical image preprocessing methods, including Gaussian filtering and histogram equalization, have long been utilized to improve image clarity. However, in recent years, AI-powered preprocessing methods, such as convolutional neural networks and deep learning-based filters, have emerged, providing more advanced and adaptive solutions for complex medical imaging tasks. These AI techniques represent a significant leap forward, offering improved performance, particularly in situations where conventional methods may prove insufficient especially in tasks that involve intricate patterns [1][2][3].

A. Overview of Existing Research on Image Preprocessing Techniques

Classical methods like Gaussian filtering and histogram equalization are used in medical imaging. Gaussian filtering smooths images to reduce noise but can blur edges, making it less effective for applications demanding accurate edge detection, such as tumor identification [4].

The Gaussian filter is represented by the following equation:

$$G(x, y) = 1/(2\pi\sigma^2) e^{-(x^2+y^2)/(2\sigma^2)}$$

Where:

- σ is standard deviation (controls the extent of smoothing)
- x and y are spatial coordinates relative to the pixel being processed

Histogram equalization improves image contrast by redistributing intensity levels, which is beneficial for images with poor contrast, like X-rays and MRIs. The histogram equalization formula is given as

follows:

$$s_k = (L - 1) \sum_{\{j=0\}}^{\{k\}p(r_j)}$$

Where:

- s_k is new intensity value
- L are total intensity levels
- r_j is number of pixels with intensity level j

However, excessive equalization can cause over-enhancement, losing important details for diagnosis [5][6]. Conversely, AI-powered preprocessing methods, including GANs and CNN-based filters, leverage deep learning to automatically identify and enhance important features in images. These methods are adaptive, improving results for complex medical images. For example, Li and Li developed a denoising method that removes noise while preserving important edges, surpassing traditional Gaussian filtering [7]. Additionally, AI techniques like U-Net have been effective in automating segmentation tasks, such as tumor detection and organ delineation in MRIs and CT scans, outperforming classical methods in accuracy [8][9].

B. Comparative Analysis of Existing Works

Recent studies show that AI-powered techniques generally outperform traditional methods, particularly in applications such as noise removal, image enhancement, and segmentation. Deep learning techniques are particularly effective in preserving key details, such as edges and textures, crucial for accurate diagnosis. In the research paper [9] highlights the success of histogram equalization and preprocessing for improving disease detection in medical images like X-rays and MRIs [12][13]. Despite the advantages of AI, classical methods remain valuable due to their simplicity and computational efficiency, especially in real-time scenarios. However, they might face challenges with complex images or maintaining important details needed for accurate diagnosis.

AI-powered preprocessing techniques offer improved performance and flexibility but come with challenges. They demand substantial computational resources and extensive datasets for training, which

can pose a barrier in low-resource settings. Additionally, their complexity can hinder real-time use in urgent medical situations that require fast processing. Despite these drawbacks, AI techniques generally perform better, particularly in complex tasks involving noise and intricate patterns. However, there is a gap in addressing the computational needs of these techniques in real-time environments [14][15]. Additionally, standardized metrics are needed to compare different preprocessing methods across various imaging types like MRIs, X-rays, and CT scans [16][17]. AI models also face challenges in generalizing across diverse medical images, emphasizing the necessity for more resilient models [18][19][20].

In conclusion, although considerable progress has been achieved in image preprocessing techniques, both classical and AI-based, challenges remain in real-time processing, generalization across diverse image types, and the computational demands of deep learning models. Addressing these issues will be key to enhancing the efficiency of these methods, particularly in critical applications.

III. CATEGORIES OF IMAGE PREPROCESSING TECHNIQUES

A. Low-level preprocessing

Low-level preprocessing improves image quality and prepares it for further analysis, such as feature extraction, object detection, or classification. These techniques remove noise, standardize data, and emphasize prominent characteristics that are crucial for higher-level tasks. Listed below are several of the low-level preprocessing techniques: Noise reduction techniques, such as median, Gaussian, or adaptive filters, remove irrelevant noise while retaining essential image details. Yan Li and Hongqiao Li (2024) emphasize the significance of edge-preserving denoising in medical imaging [1]. Resizing normalizes image dimensions for machine learning models, promoting consistency and better model convergence [2]. Grayscale conversion reduces complexity by removing colour, making images easier to process, especially in medical imaging. Normalizing pixel values improves model performance by scaling them to a consistent range [3]. Edge detection identifies object boundaries, aiding in recognition and segmentation [9].

Histogram equalization enhances image contrast, improving detail visibility, crucial for diagnostic purposes [4]. Cropping focuses on relevant image regions, reducing computational load. Thresholding converts images into binary formats, isolating specific features. Image augmentation expands datasets by applying transformations like rotations or flips, improving model generalization and robustness, especially when data is limited [8]. A heatmap shows noise reduction, histogram equalization, and image augmentation with balanced performance and moderate complexity (Fig. 1).



Fig. 1. Comparison of Low-Level Image Preprocessing Techniques

B. Mid-level preprocessing

Mid-level preprocessing extracts structured information from images, transforming raw data into a useful form for applications such as pattern recognition, object detection, or feature extraction. It serves as a link between basic image cleaning (low-level) and advanced decision-making tasks (e.g., classification). Listed below are some of the mid-level preprocessing techniques:

Feature extraction methods focus on identifying and extracting relevant patterns from the image that are essential for higher-level tasks such as classification or object recognition. Scale Invariant Feature Transform (SIFT) is particularly useful for detecting distinct patterns or objects in images that may appear at different scales or orientations [1]. The gradient magnitude calculation in SIFT is characterized as follows:

$$f(x, y) = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

Histogram of Oriented Gradients (HOG) method captures edge and gradient information, making it ideal for applications such as object detection, particularly for human shapes and patterns [2]. Colour space transformation, such as converting from RGB to HSV or LAB, helps when colour information plays a crucial role in the task [3]. Image segmentation divides the image into multiple regions, isolating specific objects or features based on criteria like colour, intensity, or texture [4]. Contour detection detects object boundaries, making it valuable for shape analysis and object identification [5]. Template matching compares a small template against a larger image, beneficial for identifying specific objects or patterns [6]. Blob detection identifies regions in an image that distinguish themselves from the surrounding area, aiding in the detection of specific objects or anomalies [7]. Edge linking connects disjointed edges or contours into a continuous boundary, helping to form coherent shapes and structures [8]. Key point matching finds corresponding points between two or more images, useful in tasks like panorama stitching or object recognition [9]. Principal Component Analysis (PCA) reduces the dimensionality of image data by projecting it onto the principal components, which helps to retain important features while simplifying the data [10].

$$Y = XW$$

Where:

- X is original data
- W is projection matrix of principal components
- Y is transformed data in reduced dimensions

Finally, image denoising techniques reduce noise in images while preserving critical details like edges, especially in noisy images [11]. These preprocessing techniques help extract valuable information from images, making it easier for high-level models to perform complex tasks like object recognition, segmentation, or classification [12].

A heatmap comparing effectiveness, complexity, and performance shows SIFT and HOG as highly effective, while PCA offers good performance with lower complexity. (Fig. 2).

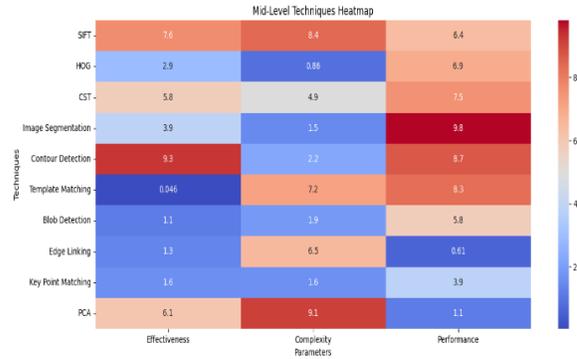


Fig. 2. Comparison of Mid-Level Image preprocessing Techniques

C. High-level preprocessing

High-level preprocessing involves advanced techniques to refine and enhance raw image data, making it more suitable for methods such as classification, segmentation, object detection, and identification. These techniques are designed to enhance image quality, structure, and clarity, ensuring improved performance and accuracy in machine learning models. Listed below are some of the high-level preprocessing techniques:

Noise reduction is one such technique that removes unwanted noise while retaining crucial features such as edges and textures, typically using methods like Gaussian blur, median filtering, or wavelet transforms [1]. Image normalization scales pixel values to a standardized range (e.g., [0, 1] or [-1, 1]), ensuring uniformity across images and reducing the effect of lighting or contrast variations [2]. Histogram equalization improves image contrast by adjusting pixel intensity distributions, making features more distinguishable, particularly in images with low contrast [3]. Morphological operations, including dilation and erosion, refine geometric structures in images, helping to clean small imperfections and enhance object boundaries [4]. Edge detection and enhancement using filters like Sobel or Canny highlights object boundaries, which are essential for applications such as object recognition, segmentation, and scene interpretation. [5]. Data augmentation increases dataset size by applying transformations like rotation, flipping, or scaling to the original images, which improves model generalization by providing diverse examples [6]. Colour space conversion from RGB to other spaces like HSV or LAB can reveal features less visible in the original

colour space, like object edges or gradient variations [7]. Image segmentation divides an image into meaningful regions based on criteria like intensity, texture, or colour, with techniques like Watershed or deep learning-based methods used for complex structures [8]. Feature scaling and selection helps reduce computational complexity and improve model performance by focusing on significant features, such as key points or descriptors [9]. Finally, Contrast Limited Adaptive Histogram Equalization (CLAHE) enhances local contrast without over-amplifying regions, making it a more sophisticated method of contrast adjustment, particularly in preserving details [10]. These preprocessing techniques collectively help optimize images for accurate analysis in various computer vision tasks.

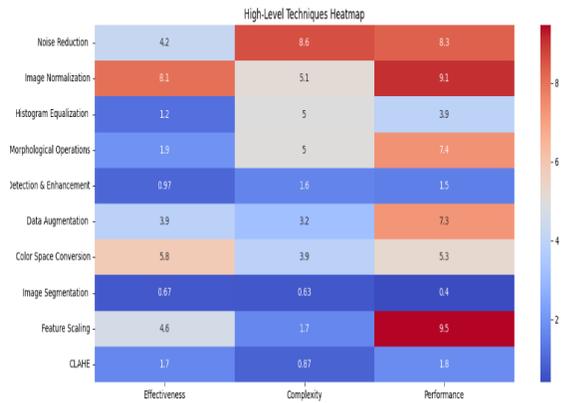


Fig. 3. Comparison of High-Level Preprocessing Techniques

A heatmap shows data augmentation and CLAHE as highly effective, while feature scaling is less impactful (Fig. 3).

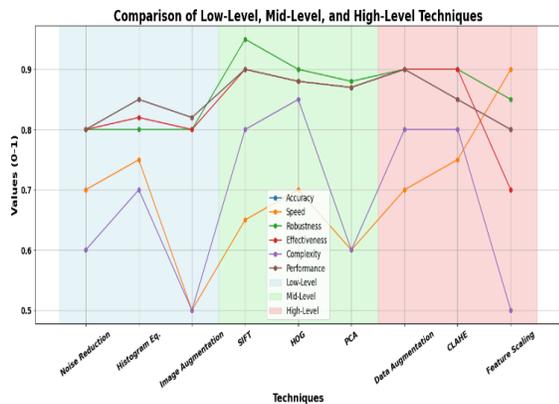


Fig. 4. Technique Comparison Across Different Levels

The graph compares techniques based on accuracy, speed, robustness, effectiveness, complexity, and performance. Low-level methods offer stable performance, mid-level techniques excel in accuracy and robustness, while high-level methods show strong effectiveness with some complexity trade-offs (Fig. 4).

IV.COMMON IMAGE PREPROCESSING TECHNIQUES

Image preprocessing is a vital step in the preparation of raw image data for higher-level analysis tasks such as feature extraction, object detection, or classification. This step ensures that the images meet the necessary quality standards and are in the right format for optimal use in machine learning models. Below are some of the widely used image preprocessing techniques aimed at improving image quality:

Noise Reduction: Images often suffer from noise, which can obscure important details. Noise reduction techniques are essential to smooth the image without compromising its quality.

The Bilateral filter is effective at reducing noise while preserving edges by smoothing the image based on pixel intensity differences and spatial proximity.

$$I_{filtered}(x) = \frac{1}{W_p} \sum_{x_i \in \Omega} I(x_i) f(|I(x_i) - I(x)|) g(|x_i - x|)$$

Where, f is the intensity difference function, W_p is the spatial proximity function, and is a normalization factor.

comparing similar pixels in the image, averaging them to remove noise, making it effective in noisy environments and low-quality images [1].

$$NL(x) = \frac{1}{C(x)} \sum_{y \in I} I(y) e^{-\frac{|I(x) - I(y)|^2}{h^2}}$$

Where $C(x)$ is the normalizing constant and h is the decay parameter.

Contrast Enhancement: Contrast enhancement techniques are critical for enhancing the visibility of features within an image. Adaptive Histogram

Equalization (AHE) is widely used to enhance local contrast by adjusting the intensity values based on local pixel neighbourhoods, which is particularly helpful in images with uneven lighting or low contrast areas. This method ensures that both bright and dark regions become more distinguishable, improving overall visibility [2].

Edge Detection: This technique is used to identify boundaries or changes between objects within an image. It serves as a crucial method for tasks such as object recognition and segmentation. The Prewitt filter detects edges by calculating gradients in both horizontal and vertical directions, helping identify areas of rapid intensity change. The Roberts filter focuses on diagonal gradients, while the Canny filter, a more refined technique, applies a multi-step process involving gradient thresholds and non-maximum suppression to precisely detect edges [3][4].

Resizing and Interpolation: Images often need to be resized to meet the input dimensions required by machine learning models. Resizing involves adjusting an image's size, and interpolation determines how to calculate new pixel values. Bilinear interpolation calculates pixel values by averaging the four nearest pixels, providing smoother transitions. Bicubic interpolation uses the nearest 16 pixels, resulting in even smoother outcomes. Nearest Neighbor interpolation is simpler and computationally efficient but may create a blocky appearance due to assigning pixel values from the nearest neighbor [5][6].

Normalization: For machine learning models to perform well, images are often normalized or standardized. Normalization scales the pixel values to a specific range, typically [0, 1] or [-1, 1], ensuring all input data is comparable and preventing bias toward higher or lower pixel values. This process also helps accelerate training by improving the model's convergence rate [7].

$$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}}$$

Geometric Transformations: Geometric transformations alter the spatial arrangement of images.

Rotation is often used for aligning images or generating augmented data to help models recognize objects from different perspectives.

$$I_{rot}(x', y') = I(x \cos \theta - y \sin \theta, x \sin \theta + y \cos \theta)$$

Scaling changes the size of the image, either enlarging or reducing it, to meet specific model input requirements or to focus on relevant details.

$$I_{scaled}(x', y') = I(sx, sy)$$

Cropping extracts specific regions of significance within an image, such as focusing on a particular object. These transformations, especially when applied as data augmentation, increase the robustness of machine learning models by presenting varied perspectives of the same image, improving accuracy and generalization [8][9].

V. COMPARATIVE ANALYSIS OF PREPROCESSING TECHNIQUES

A. Performance Comparison of Various Techniques

Image preprocessing methods play a crucial role in enhancing the quality of medical images. For noise reduction, Bilateral Filtering efficiently reduces noise while maintaining edge details, though it requires significant computational resources [1]. Gaussian Blur, while faster, may blur important details like edges, making it less ideal for tasks that demand high accuracy [2]. Regarding contrast enhancement, CLAHE is generally preferred over Adaptive Histogram Equalization (AHE) because it prevents over-enhancement of noise while improving local contrast, making it more reliable for medical imaging [3]. For edge detection, methods like Canny Edge Detection provide accurate results, but they are computationally expensive and sensitive to noise, whereas simpler methods such as Prewitt and Roberts filters are faster but offer lower accuracy in complex images [4]. Bicubic Interpolation provides smooth image resizing with better quality than Bilinear or Nearest Neighbor, though it requires more computational resources [5].

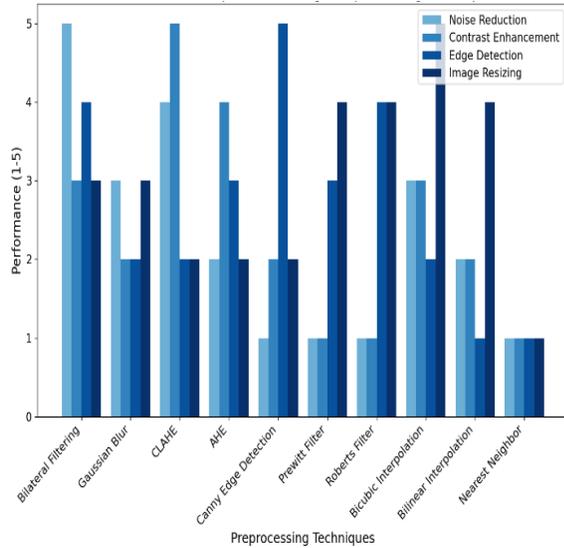


Fig. 5. Performance comparison of Image Preprocessing Techniques

The bar graph compares preprocessing techniques: Bilateral Filtering (noise reduction), CLAHE (contrast), Canny (edge detection), and Bicubic Interpolation (resizing) (Fig. 5).

B. Strengths and Weaknesses of Different Methods

Each preprocessing method has specific strengths and challenges based on the application. Bilateral Filtering works well for reducing noise in images where edge retention is crucial, such as MRI scans, although it may require significant computational resources [6]. Gaussian Blur is efficient but not well-suited for tasks that require precise edge detection, such as diagnostic imaging [7]. Techniques like CLAHE and AHE improve visibility in low-contrast areas, with CLAHE being superior for medical imaging owing to its capability to prevent noise amplification [8]. For edge detection, Canny remains the gold standard for accuracy but may not be the ideal option for real-time applications due to its processing demands, while Prewitt and Roberts filters offer faster alternatives with some trade-offs in precision [9]. Bicubic Interpolation provides a balance of resizing quality however; it is slower compared to simpler methods [10]. Nearest Neighbor is the quickest but introduces jagged edges, which can degrade image quality for medical analysis [11].

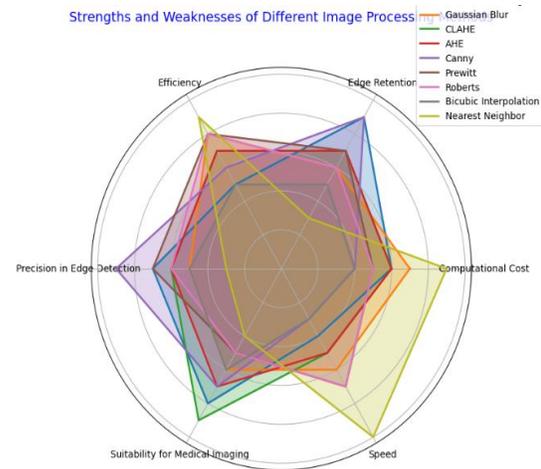


Fig. 6. Strengths and weakness of different Image Preprocessing Techniques

This radar chart compares various image processing methods based on attributes like computational cost, edge retention, efficiency, precision in edge detection, suitability for medical imaging, and speed (Fig. 6).

C. Suitability for Different Image Types

Medical images, particularly MRI and CT scans, benefit from noise-reduction methods like Non-Local Means and Bilateral Filtering, which are effective in maintaining essential details for accurate diagnoses [12]. CLAHE is widely used in these contexts to enhance local contrast without exacerbating noise issues [13]. In satellite imaging, where lighting conditions can vary, techniques like Global Histogram Equalization and Bilateral Filtering help improve contrast and visibility, which are essential for terrain and land classification [14]. For biometric applications such as fingerprint recognition, Edge Detection methods and Bilateral Filtering are crucial for extracting fine details, with the latter aiding in noise reduction without sacrificing detail [15]. Bicubic Interpolation is frequently used in these applications to resize images while minimizing quality loss [16].

VI. IMAGE PREPROCESSING IN AI AND DEEP LEARNING

Image preprocessing plays a crucial role in enhancing the effectiveness of deep learning models, especially in Convolutional Neural Networks (CNNs). By transforming the raw data into a more suitable

format, preprocessing techniques help deep learning models extract relevant features more effectively and efficiently.

A. Role in CNNs and Deep Learning Models

In In deep learning, CNNs are built to automatically extract features from images using multiple layers. However, the efficiency of these models heavily depends on the clarity of the input images. Image preprocessing improves input quality by minimizing noise and highlighting essential features, enabling CNNs to concentrate on meaningful patterns rather than irrelevant details. This is particularly crucial in fields like object detection, facial recognition, and medical image analysis.

Preprocessing techniques such as edge detection, noise reduction, and contrast improvement improve feature extraction by accentuating critical elements (such as edges and textures) while minimizing irrelevant details. Additional methods like Gray-scaling, resizing, and cropping help standardize image dimensions, ensuring uniformity when inputting data into CNNs, thereby optimizing the feature extraction process [1][2].

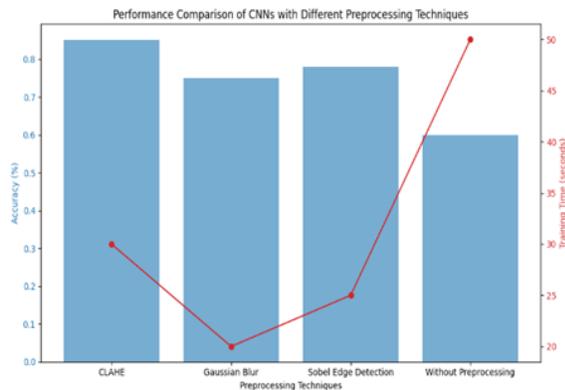


Fig. 7. Performance comparison of CNNs with Different Preprocessing Techniques

The chart compares CNN performance with and without preprocessing, showing improved accuracy and reduced training time with techniques like CLAHE and Sobel Edge Detection (Fig. 7).

B. Preprocessing for Improving Model Accuracy and Performance

Data augmentation is a commonly used preprocessing technique that improves model

generalization by artificially expanding the dataset. Techniques like rotation, flipping, scaling, and cropping introduce changes in the input, helping the techniques learn better representations and avoid overfitting. In healthcare imaging, for example, data augmentation enables models to train on a larger set of examples without requiring an extensive dataset [2].

Normalization ensures consistent pixel value scales, preventing CNNs from struggling to converge during training. Popular methods like Min-Max Scaling, Z-score Normalization, and Global Contrast Normalization (GCN) standardize pixel values, leading to smoother training and stable convergence [3].

C. Recent Advancements in AI-Driven Preprocessing Techniques

Generative Adversarial Networks have transformed image preprocessing by generating high-quality images from noisy or low-resolution inputs. In medical imaging, GANs enhance MRI or CT scan images, improving resolution and reducing artifacts, facilitating the identification of abnormalities such as tumors [4]. GANs also excel in image-to-image translation, converting low-resolution images into high-resolution ones.

Super-resolution methods, including Deep Learning Super Resolution (DLSR) and Single Image Super-Resolution (SISR), leverage deep learning to enhance image resolution while preserving details. These approaches are especially useful in medical diagnostics and satellite imagery, where high resolution is crucial for precise analysis [5].

VII. IMAGE PREPROCESSING ACROSS DIFFERENT FIELDS

A. Medical Imaging

Preprocessing methods improve the quality of medical imaging by minimizing noise and enhancing contrast. Methods like Gaussian filtering and Wavelet Denoising refine clarity, while Histogram Equalization and CLAHE enhance contrast for better anomaly detection. Normalization standardizes pixel intensity, ensuring consistent diagnostic results. These techniques aid disease detection and image segmentation for accurate treatment planning.

B. Remote Sensing

In remote sensing, preprocessing is essential for rectifying distortions and aligning satellite images with accurate geographic data. Techniques like geometric correction and radiometric calibration remove these distortions, while Contrast Stretching enhances important features in the images. This aids in tasks like land cover classification and object detection, allowing for improved identification of urban areas and vegetation. Enhancing these features improves the accuracy of satellite image analysis [2][3][19].

C. Biometric Recognition

In biometric systems, preprocessing enhances image quality for applications like facial recognition, fingerprint identification, and iris recognition. Techniques like skin color filtering and contrast enhancement improve facial feature visibility, while ridge sharpening enhances fingerprint minutiae for better identification accuracy. Iris localization and edge detection help isolate distinct patterns for iris recognition. These techniques enhance biometric system performance by optimizing image clarity and improving feature extraction [12][13][20].

D. Autonomous Vehicles

In autonomous vehicles, preprocessing techniques are crucial for enhancing object detection and road recognition. Image normalization and noise reduction help the vehicle's sensors better identify obstacles, pedestrians, and other objects. Edge detection and semantic segmentation methods aid in recognizing road boundaries and surfaces, assisting with lane detection. By improving sensor data quality, preprocessing enables real-time decision-making, contributing to safer navigation, especially in complex or low-visibility environments [10][16][18].

VIII. LIMITATIONS AND CHALLENGES

A. Computational Overhead: Balancing Efficiency and Performance

Traditional image preprocessing methods, such as Gaussian filtering, are computationally less demanding but might not yield optimal results for complex image types, such as medical imaging [1]. Conversely, AI-based methods, like deep learning,

can produce more precise and detailed outcomes but demand considerably higher computational power and processing time. Balancing computational overhead and performance is particularly challenging in applications where processing time is crucial, such as in real-time medical diagnostics [2][4].

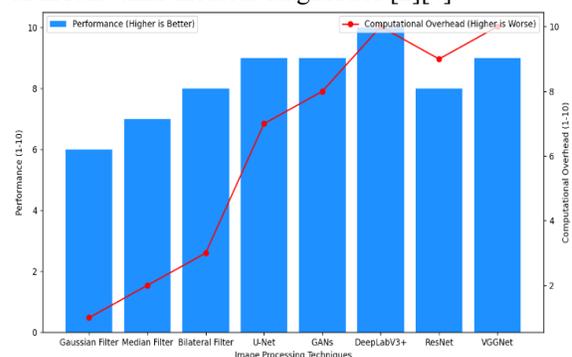


Fig. 8. Comparison of computational overhead and performance

The graph shows that traditional techniques like Gaussian filters offer lower computational overhead but moderate performance, while AI-driven methods excel in performance with higher computational demands (Fig. 8).

B. Trade-off Between Detail Preservation and Noise Removal

In image preprocessing, removing noise without affecting the image's important details, like edges, is a crucial challenge. Classical methods like Gaussian filtering are effective in noise removal but can blur significant details. AI methods, including CNNs, often retain more intricate details but may also preserve unwanted features or noise, making them less suitable for specific applications. Achieving an optimal equilibrium between noise reduction and detail retention is essential for effective preprocessing outcomes [5].

C. Limitations of Traditional Techniques vs. AI-Driven Methods

Traditional techniques like histogram equalization are simple and computationally efficient but struggle with intricate image processing tasks. AI-powered methods, such as deep learning-based models, are more flexible and can accommodate a diverse range of images, offering improved results. However, these methods require huge datasets and significant

computational power, this can pose difficulties in resource-constrained settings. Hence, traditional techniques may still be preferred for simpler tasks due to their lower computational cost [8][9].

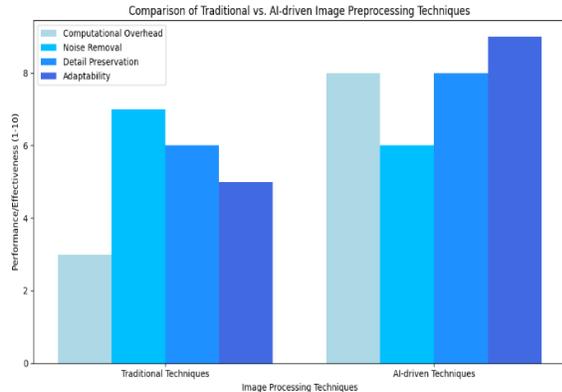


Fig. 9. Comparison of Traditional vs. AI-driven Image Preprocessing Techniques

The graph compares Traditional and AI-driven techniques in image preprocessing. Traditional methods excel in efficiency and noise removal, while AI-driven methods offer better detail preservation and adaptability despite higher computational demands (Fig. 9).

D. Need for Adaptive and Real-Time Preprocessing Techniques

A key limitation is the requirement for preprocessing methods that can adjust to different image conditions. For instance, medical images can differ greatly in terms of resolution, noise, and quality, posing challenges for static preprocessing techniques to perform effectively. AI methods, while more adaptive, often face challenges when applied to real-time scenarios because of their computational demands. A requirement exists for preprocessing methods that can efficiently handle these variations while maintaining high performance in real-time applications [10][11].

IX. FUTURE TRENDS AND RESEARCH DIRECTIONS

A. AI-Powered Preprocessing Methods

AI, especially deep learning, is increasingly being used to improve image preprocessing. Deep learning architectures, such as Convolutional Neural Networks (CNNs), can autonomously refine images

by reducing noise and enhancing quality. Future advancements will aim to optimize these models for efficiency and adaptability across various image types, including medical and satellite imagery. Additionally, cutting-edge approaches like Generative Adversarial Networks (GANs) hold promise for further improving image enhancement techniques [1][7].

B. Real-Time Preprocessing for Video Applications

With the rise of video applications in areas like security and healthcare, there's a growing need for real-time image preprocessing. Deep learning methods are being explored to process video frames instantly while maintaining high quality. However, achieving fast processing with minimal delays is challenging. Using technologies like edge computing and hardware acceleration (e.g., GPUs) will help make real-time processing possible [2][5].

C. Hybrid Techniques Combining Multiple Methods

There's interest in combining traditional image processing methods with deep learning for better results. Hybrid methods use classical techniques for tasks like noise reduction and deep learning for advanced tasks such as feature enhancement. This approach aims to balance speed and accuracy, and future research will aim to seamlessly integrate these methods across different applications, enhancing their adaptability and efficiency. [8][9].

D. Edge AI and Low-Power Devices

Edge AI refers to processing images on devices themselves, rather than relying on cloud servers. This approach is important for mobile and embedded devices, where resources are limited. Researchers are working on making deep learning models more efficient for such devices using techniques like model compression. Specialized hardware, like AI accelerators, will also help make edge AI possible for real-time image processing on low-power devices [4][6].

X. CONCLUSION

In conclusion, image preprocessing plays a vital role in improving image quality across multiple applications, such as medical imaging, remote sensing, biometric recognition, and autonomous

vehicles. This review provided a summary of various of different preprocessing techniques, categorized into low-level and mid-level methods, and examined their impact on deep learning and AI. Despite the advancements, obstacles such as computational overhead and the necessity of adaptive preprocessing methods remain. Future research is expected to focus on AI-driven preprocessing techniques, real-time applications, and hybrid methods that combine various techniques. Overcoming these challenges will drive the ongoing advancement and refinement of image preprocessing across various fields [1]-[20].

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