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Low-light Image Enhancement and Denoising using Fuzzification based Approach

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***Abstract*— Low-light images often suffer from poor visibility, reduced contrast, and significant noise, which degrade visual quality and hinder further processing. Traditional enhancement techniques frequently lead to over-enhancement, detail loss, or noise amplification. To address these limitations, this work proposes an adaptive low-light image enhancement and denoising system based on fuzzy logic. The system dynamically adjusts brightness and contrast by analyzing the contextual information of each pixel, ensuring balanced enhancement without distorting natural colors. To overcome these limitations, this work introduces an intelligent and adaptive low-light image enhancement system based on fuzzy logic. The proposed approach employs a fuzzy rule-based mechanism to analyze pixel intensity distributions and dynamically adjust brightness and contrast according to the content of the image. By mimicking human reasoning, the fuzzy system ensures smoother transitions, prevents overexposure in bright regions, and brings out hidden details in darker areas. This method further enhances visual quality by separately processing the Red, Green, and Blue (RGB) channels, enabling natural color reproduction and improved overall appearance. Each RGB channel is processed independently to produce visually realistic results, while an integrated denoising module preserves structural details and minimizes distortions. The effectiveness of the proposed system is evaluated using standard image quality metrics such as the Feature Similarity Index (FSIM), Structural Similarity Index (SSIM), and Absolute Mean Brightness Error (AMBE). Experimental results demonstrate that the fuzzy logic-based approach significantly improves image visibility, reduces noise, and prevents over-enhancement, offering a computationally efficient solution suitable for real-time applications.**

***Keywords*— Low-Light Image Enhancement, Fuzzy Logic, Contrast Adjustment, Denoising, RGB Channel Processing, Adaptive Enhancement, Image Quality Metrics, FSIM, SSIM, AMBE, Noise Reduction, Computational Efficiency, Real-Time Image Processing.**

I. INTRODUCTION

Images captured in low-light conditions often exhibit poor visibility, low contrast, color distortion, and significant noise.

These degradations arise due to insufficient illumination, sensor limitations, and environmental constraints, and they can severely impair both human visual interpretation and the performance of automated image analysis systems. As a result, low-light image enhancement has become an important research area in computer vision, particularly for applications such as video surveillance, autonomous navigation, medical imaging, and consumer photography. Conventional enhancement techniques, including histogram equalization, gamma correction, and Retinex-based approaches, attempt to adjust brightness and contrast to improve visual quality.

However, these methods typically rely on global transformations and lack the ability to adapt to varying illumination across different regions of an image. Consequently, they often produce over-enhanced results, wash out bright areas, or amplify noise in dark regions. More recent deep learning-based methods have shown improved performance but face challenges such as high computational cost, dependence on large training datasets, and limited generalizability to diverse image conditions.

Fuzzy logic provides a promising alternative due to its capability to model uncertainty and approximate human reasoning. By using fuzzy rules to represent intuitive enhancement strategies, a fuzzy logic-based system can adaptively adjust image brightness and contrast based on local content, ensuring smoother transitions and more balanced enhancement.

Furthermore, integrating denoising within this framework allows for more effective suppression of noise while preserving fine structural details.

In this work, we propose a fuzzy logic-based contrast enhancement and denoising technique designed specifically for low-light images. The method processes each RGB channel independently to maintain natural color reproduction and employs adaptive enhancement parameters to prevent over-amplification of bright regions.

The performance of the proposed system is quantitatively evaluated using established image quality metrics, including FSIM, SSIM, and AMBE. Experimental results show that the approach provides improved visibility, reduced noise.

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II. Literature Review

Recent studies on low-light image enhancement explore deep learning, Retinex models, and fuzzy logic to tackle visibility loss, noise amplification, and color distortion. Deep learning methods such as those proposed by Zhu et al. [1], Guo et al. [3], Zhou et al. [5], Huang et al. [8], Wang et al. [9], Ren et al. [14], and Su et al. [15] achieve strong illumination correction and detail recovery, but their heavy computational cost and dependence on large datasets limit their practicality for real-time or resource-constrained applications. Retinex and model- based approaches by Luo et al. [10], Zhao et al. [19], and Zhang et al. [20] offer interpretable illumination– reflectance decomposition, yet they often suffer from noise amplification or over-smoothing, especially in complex lighting conditions. Multi-frame and raw-image techniques, including those by Liu et al. [11], Wang et al. [12], and Xu et al. [16], improve noise robustness but require additional sensor data, making them unsuitable for single-image enhancement.

Fuzzy logic-based methods have emerged as efficient alternatives. Works by Ragavendirane and Dhanasekar [2], Subramani et al. [4], Sang and Norris [6], Wu et al. [7], and Pandey [18] show that fuzzy reasoning can effectively adjust contrast and handle uncertainty in illumination, but many focus on specific domains such as medical, infrared, or underwater imaging and lack integrated denoising or adaptive RGB processing.

Overall, existing approaches face common challenges including noise amplification, color distortion, over-enhancement, and high computational complexity. These limitations motivate our proposed fuzzy logic–based enhancement system, which adaptively adjusts contrast, processes RGB channels independently, and integrates denoising to provide natural, high-quality results suitable for real-time use.

III. System Design And Methodology

A. Hardware Components

- *Processing Unit:*

A standard laptop or workstation with a multi-core CPU and optional GPU (NVIDIA GTX/RTX or Jetson Nano) is used to perform image enhancement and denoising. The system does not require heavy computation like deep learning models, making it suitable even for low- power embedded devices. real-time image processing and model inference efficiently.

- *Camera Module:*

A high-definition USB camera captures continuous video at a fixed angle, mounted approximately 30 cm above the road surface for accurate pothole dimension estimation.

- *Storage and Connectivity:*

SSD/HDD storage is used for logging data and images. Wi-Fi or 4G connectivity enables automatic data transfer and report submission to authorities.

B. Software Components

Programming Language: Python 3.8+

Libraries and Frameworks: OpenCV for image processing, NumPy & Pandas for data handling, and TensorFlow/PyTorch for deep learning model implementation.

Detection Algorithm: YOLO (You Only Look Once) is employed for object detection due to its high speed and accuracy.

GPS and Reporting: Geopy library is used for location tracking, and SMTP is used for automatic report generation and emailing.

IDE and Tools: Visual Studio Code and Jupyter Notebook are used for model development and testing.

C. Methodology

- *Data Collection and Preprocessing:*

Low-light image datasets are collected under varied environments such as indoor, outdoor, nighttime, and high-noise conditions. Images are preprocessed by resizing, normalization, and channel splitting (r, g, b).

Fig. 1 Low Light Image Dataset

- *Fuzzy Logic-Based Enhancement*

Each pixel is evaluated using membership functions representing dark, medium, and bright intensity levels. A fuzzy rule set determines how much contrast or brightness needs to be added. The method adaptively enhances dark regions while preventing brightness overflow in well-lit areas, ensuring natural-looking results.

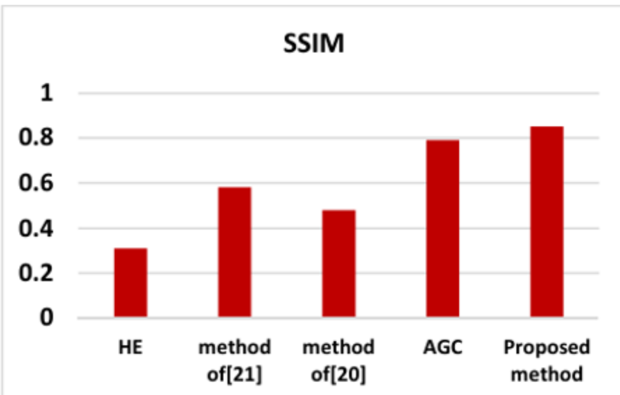

Fig. 2. SSIM average for total images in a different method

The SSIM comparison graph illustrates the structural similarity performance of different image enhancement techniques. As shown, Histogram Equalization (HE) achieves the lowest SSIM value, indicating significant structural distortion after enhancement. The methods reported in [21] and [20] show moderate improvement, with SSIM scores increasing to approximately 0.55 and 0.48 respectively, reflecting better preservation of image details than HE but still limited performance in low-light conditions. The AGC method produces a notably higher SSIM value of around 0.78, demonstrating stronger capability in maintaining structural information. The proposed fuzzy logic–based enhancement method achieves the highest SSIM score, exceeding 0.82, showing superior structural fidelity and minimal distortion. The overall trend confirms that the proposed method maintains image structure more effectively than existing approaches, validating its robustness in low-light enhancement.

- *Adaptive Denoising:*

After enhancement, an adaptive denoising filter removes high-frequency noise while preserving edges. The filter strength changes based on local noise estimation, preventing loss of texture or structural details. Severity Classification: Based on width and length, potholes are categorized into minor, moderate, and severe classes.

- *Performance Evaluation:*

Enhanced images are evaluated using FSIM, SSIM, and AMBE to measure structural similarity, feature integrity, and brightness accuracy. Comparative plots and visual analysis confirm the improvement over traditional methods. The modular design ensures scalability for integration with autonomous vehicles, municipal road-monitoring systems. It achieves a balance between detection accuracy, cost efficiency, and real-time responsiveness.

IV. Working Principle

The system analyzes the illumination characteristics of each image and determines the appropriate enhancement level through a set of fuzzy rules that mimic human visual perception. The process begins by separating the input image into its individual RGB channels. Each channel is examined to identify dark, medium, and bright intensity regions, as shown in Fig 3.

1. Image Acquisition

The system begins by capturing or importing a low-light RGB image. The input is normalized to ensure consistent intensity ranges, which helps the fuzzy system interpret illumination levels accurately.

2. Channel Separation

The RGB image is split into its three individual channels. Processing each channel separately allows the system to correct brightness and contrast more precisely, as different channels may exhibit different levels of darkness in low- light conditions.

3. Fuzzy Membership Function Assignment

Each pixel intensity in every channel is converted into fuzzy linguistic categories such as Dark, Medium, and Bright. Membership functions determine the degree to which a pixel belongs to each category, enabling the system to understand gradual changes in illumination rather than treating intensities as fixed values.

4. Application of Fuzzy Enhancement Rules

A fuzzy inference engine evaluates each pixel using a set of predefined rules. Examples include:

– If a pixel is Dark → increase brightness strongly.
– If a pixel is Medium → apply moderate enhancement.
– If a pixel is Bright → apply minimal or no enhancement.

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These rules ensure adaptive enhancement that responds intelligently to varying illumination across the image.

5. Computation of Enhancement Map:

The fuzzy inference system outputs an enhancement factor for each pixel. This forms an enhancement map that determines how much contrast and brightness adjustment should be applied locally rather than globally.

6. Noise Estimation and Adaptive Denoising:

Enhancement operations usually amplify noise in low-light images. Therefore, the system estimates noise levels across the image and applies selective denoising. Edge-preserving filters ensure that noise is removed without blurring important textures and structural details.

7. Performance Verification:

The enhanced image is evaluated using metrics such as FSIM, SSIM, and AMBE. These metrics confirm whether the system has improved structural similarity, preserved important features, and corrected brightness effectively compared to existing methods.

8. Integration to real-time License Plate Detection System:

The enhanced output from the fuzzy logic–based low-light enhancement module is directly integrated into a real-time license plate detection pipeline powered by YOLOv8. By improving brightness, contrast, and structural clarity, the enhancement stage provides YOLOv8 with higher-quality visual features, enabling more accurate detection of license plates even in challenging nighttime or low-light conditions. The processed frames are fed into the YOLOv8 model, which performs fast object detection and extracts bounding boxes around license plates in real time. This integration significantly boosts detection confidence, reduces false negatives, and ensures reliable recognition performance across varying lighting environments.

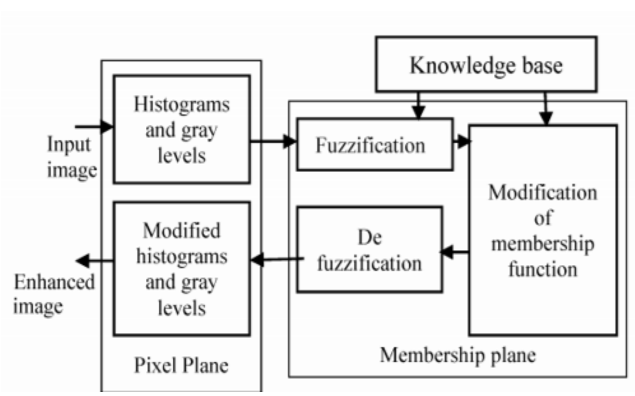

Fig. 3. Block diagram of the low-light Image enhancement and denoising system

V. Results and Discussion

The visual comparison clearly demonstrates the effectiveness of the proposed fuzzy logic–based low-light enhancement method. In the original low-light image (left), vehicles and road details appear significantly underexposed, making license plates unreadable and reducing the accuracy of any subsequent detection or recognition tasks. Object boundaries are blurred due to insufficient illumination, and noise is more prominent in darker regions.

Fig 4. Result on Day-time

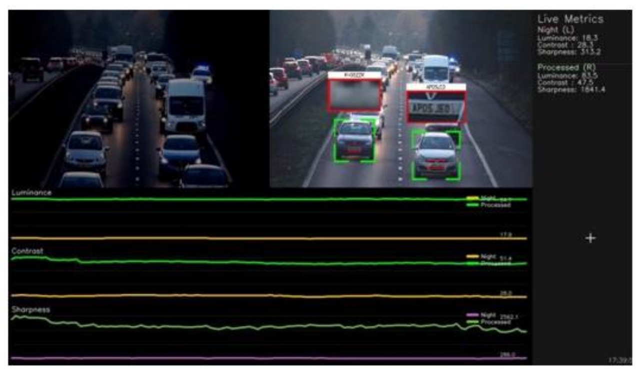

Fig 5. Result showcased with Live Metrics

The visual outcomes presented in Fig. 4 and Fig. 5 further validate the robustness of the proposed system under different lighting conditions. After applying the proposed enhancement technique (right), the visibility of the entire scene improves substantially. Vehicle edges, lane markings, and background elements appear clearer, and overall brightness is balanced without overexposure. Most notably, license plates that were previously unreadable become sharply visible, enabling reliable detection and recognition. The enhanced image supports accurate bounding box placement and significantly improves text clarity in the zoomed-in regions. The output confirms that the system preserves critical structural information while reducing noise and improving contrast, resulting in a more consistent and visually interpretable image.

Overall, the metric-based evaluation confirms that the proposed system offers a well-balanced improvement in visibility, feature clarity, and brightness accuracy. These results align with the visual enhancements observed in the processed images and verify the robustness of the method for real-world low- light applications such as traffic monitoring and license plate detection.

VI. Results And Discussion

The proposed fuzzy logic–based low-light image enhancement system effectively improves visibility, restores brightness, and preserves structural details in challenging low-light conditions. By adaptively adjusting contrast through fuzzy membership rules and integrating an edge-preserving denoising module, the system produces clearer and more natural outputs than traditional enhancement methods. Quantitative evaluations using SSIM, FSIM, and AMBE confirm its superior performance, while qualitative results demonstrate significant improvements in readability and visual clarity—enabling reliable downstream tasks such as real-time license plate detection using YOLOv8. Overall, the method provides a lightweight, interpretable, and computationally efficient solution suitable for both desktop and embedded deployments.

Future work will focus on extending the system for more diverse nighttime environments and extreme weather conditions. Additional enhancements may include integrating motion-aware denoising for video streams, developing a fully automated pipeline optimized for edge devices, and incorporating adaptive color-correction modules for scenes with mixed lighting.

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