Improving low-light image quality for object detection and license plate recognition

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Abstract: Enhancing low-light image quality is crucial for object detection and license plate recognition in surveillance and security applications. Poor illumination degrades image clarity, making accurate recognition difficult. This paper investigates a combination of image enhancement techniques—including Unsharp Masking, Gamma Correction, Gaussian Blur, and Histogram Equalization—to improve visibility and recognition accuracy in low-light conditions. The performance of these methods is quantitatively evaluated using Laplacian variance as a measure of image sharpness and clarity. Experimental results demonstrate that Gamma Correction applied to Unsharp Masking and Histogram Equalization significantly enhances image quality, enabling the accurate extraction and recognition of license plate numbers. The proposed approach successfully extracts and recognizes license plate numbers under poor lighting conditions, demonstrating its effectiveness for real-world surveillance applications.

Keywords: Histogram Equalization, License Plate Recognition, Low-Light Image Enhancement, Object Detection, Surveillance Systems, Unsharp Masking.

1. Introduction

Enhancing the low-light images is essential for various applications, including surveillance, crime detection, and object recognition, where poor lighting conditions hinder the accurate identification of key features. One critical application is for license plate recognition, where low illumination levels reduce visibility, contrast, and sharpness, making it difficult to detect and recognize the text accurately. The traditional object detection and recognition methods struggle under such conditions, necessitating the use of image enhancement techniques to improve visibility without distorting any essential features. Addressing these challenges requires a systematic approach that enhances image clarity while preserving important details for the automated recognition systems.

This paper explores various image enhancement techniques, including Unsharp Masking, Gamma Correction, Gaussian Blur, and Histogram Equalization, each designed to address specific challenges associated with low-light images. Histogram Equalization improves the global contrast, making it particularly useful for object detection, while Unsharp Masking enhances the edge details, improving the clarity of the features. Gamma Correction adjusts brightness non-linearly, making dark regions more distinguishable, and Gaussian Blur aids in noise reduction while preserving the important structures. These enhancement methods are tested to determine their effectiveness in improving the low-light images for the license plate recognition.

The study uses a dataset of locally low-contrast images that closely resemble the real-world low-light conditions encountered in night-time surveillance and security systems. The dataset contains images with naturally reduced contrast, providing a realistic system to evaluate the effectiveness of various enhancement techniques. It includes diverse object types, allowing a broad evaluation across different textures and structures. Additionally, the dataset presents significant challenges in license plate detection and recognition, making it suitable for assessing improvements in text readability and object visibility after enhancement.

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To evaluate the impact of these enhancement techniques, a CNN-SVM-based number plate recognition method is applied to the enhanced images. The effectiveness of these methods is assessed using Laplacian variance, a metric that quantifies image sharpness and clarity. Unlike the traditional measures such as Peak Signal-to-Noise Ratio (PSNR) or Structural Similarity Index Measure (SSIM), which primarily focus on pixel-level intensity differences, the Laplacian variance provides a more meaningful assessment for object detection and text recognition. By analyzing the sharpness improvements, it is possible to determine the extent to which the enhancement techniques contribute to a better object visibility and recognition accuracy.

This paper contributes to the field by analyzing the performance of the multiple image enhancement techniques and demonstrating their impact on the object detection and recognition accuracy in low-light environments. The experimental results show that Gamma Correction, when applied with Unsharp Masking and Histogram Equalization, produces significant improvements in the image quality. The proposed approach successfully extracts and recognizes license plate numbers under poor lighting conditions, demonstrating its effectiveness for the real-world surveillance applications. The findings highlight the importance of enhancing the critical image features to overcome visibility challenges in low-light conditions, enabling the automated systems to operate more efficiently in practical scenarios.

Section 2 of this paper examines earlier studies on low-light image enhancement, explaining the trade-offs between traditional techniques and new learning-based methods. Section 3 then outlines the suggested approach, which combines traditional improvement methods with a CNN-SVM architecture designed for accurate license plate recognition in low light. Experimental results are presented in the Section 4, including visual contrasts and quantitative analyses based on picture clarity. A summary of the main conclusions and reflections on their applicability in actual surveillance situations round out the manuscript.

2. Related works

Low-light image enhancement has garnered significant attention due to its importance in applications such as surveillance, medical imaging, and autonomous systems. The existing methods range from traditional approaches to advanced deep learning models, each with its unique strengths and limitations.

Tao et al. (2017) proposed LLCNN, a convolutional neural network specifically designed for low-light image enhancement. Their approach leverages the hierarchical feature learning to enhance brightness and contrast while preserving fine details. Although effective, the model requires large training datasets and significant computational resources, which limit its usability in real-time and resource-constrained environments.

Nandhini Abirami & Durai Raj Vincent (2021) introduced a generative adversarial network (GAN)-based framework to improve the low-light images. Using the adversarial learning, the model achieves notable improvements in clarity and noise reduction. However, the technique often introduces artifacts in the extremely low-light scenarios and demands substantial computational power, making it less practical for applications that prioritize efficiency.

Jingchun, Eg Su & Shahrizal Sunar (2024) conducted a comprehensive review of the low-light image enhancement methods, classifying them into traditional techniques—such as histogram equalization and Retinex-based methods—and machine learning-based approaches, including CNNs and GANs. The review underscores the trade-offs between efficiency and output quality; while the traditional methods are computationally lightweight and suitable for the real-time applications, they struggle in the extreme low-light conditions. Furthermore, the learning-based models deliver higher-quality results but at the expense of an increased computational complexity.

In contrast, this study focuses on the traditional enhancement techniques, such as Unsharp Masking, Gamma Correction, and Histogram Equalization, to maintain a balance between the processing speed and image quality. These methods are well-suited for real-time applications like the surveillance and crime detection since they do not require heavy training or high computational power. Instead of using enhancement as a standalone process, this study applies these traditional techniques as a foundation to improve the object detection and number plate recognition. By enhancing the visibility and sharpness of the low-light images, these methods significantly help in detecting and extracting the crucial features such as alphanumeric characters on license plates and human characteristics, ensuring a reliable identification even in challenging lighting conditions.

3. Proposed system

3.1. Image enhancement

This section outlines the step-by-step workflow employed to enhance the quality of the low-light images from the dataset. The primary objective of this workflow is to improve visibility and clarity, particularly in detecting the vehicle license plates under challenging lighting conditions. A combination of enhancement techniques, including the unsharp masking, gamma correction, Gaussian blur, and histogram equalization, was utilized alongside the Laplacian variance as the evaluation metric (Jingchun, Eg Su & Shahrizal Sunar, 2024).

For this study, the Kaggle "Locally Low-Contrast Images" dataset was used, which consists of images captured under minimal lighting conditions, such as nighttime scenes and poorly lit indoor environments. The focus was on improving the vehicle license plates, which is critical for applications such as surveillance and crime detection. The dataset’s challenging contrast and brightness levels provided ideal conditions for evaluating techniques such as the unsharp masking, gamma correction, and histogram equalization (Rahman et al., 2016).

In some cases, specific combinations of these techniques were necessary to achieve optimal results. For instance, in the image of a vehicle in a dark alley, the unsharp masking enhanced the edges of the vehicle, while the gamma correction revealed hidden details such as people in the background. This multi-step process was essential for detecting objects that were otherwise difficult to distinguish due to the low-light environment (Arici, Dikbas & Altunbasak, 2009).

3.2. Object detection

The enhanced images, particularly those processed using Histogram Equalization, undergo object detection to identify the license plates, which are visually highlighted in the output images. The comparison between the object detection results in the original and the enhanced images illustrates the effectiveness of the enhancement techniques in improving the detection accuracy (Zheng et al., 2012).

This subsection focuses on the visualization of the original image and its enhanced versions. Each processed image is displayed alongside its corresponding Laplacian variance and entropy values to provide a quantitative assessment of the sharpness and complexity improvements achieved through the enhancement techniques (Lim & Kim, 2021).

3.3. Object recognition - license plate recognition

Following object detection, the CNN-SVM-based number plate recognition method is applied to the detected license plates from the enhanced images. The enhancement process significantly improves the clarity and sharpness of the license plate regions, ensuring a more accurate character extraction and recognition. The workflow for image enhancement, as illustrated in Figure 1, outlines the structured approach used to enhance the low-light images before object detection and recognition.

The Single Shot Detector (SSD) algorithm is employed to localize the number plate region. If a license plate is detected, the recognition pipeline is initiated to extract and process the plate characters (Zheng et al., 2012). The SSD algorithm is used for the accurate number plate localization, and once the bounding box is extracted, the plate characters are segmented using the Canny edge detection. The connected component analysis is applied to isolate individual characters, ensuring a structured approach for the character segmentation. The extracted characters are then processed using a Convolutional Neural Network (CNN) to extract the meaningful features, and a Support Vector Machine (SVM) classifier is used to map these extracted features to corresponding alphanumeric characters. Finally, a post-processing step is performed where a rule-based filtering eliminates the improbable character sequences, and the recognized characters are formatted afterwards into a standard number plate format.

The recognition results from the original and the enhanced images are compared to validate the effectiveness of the proposed enhancement framework. The improved visibility and sharpness of the number plate characters lead to a higher recognition accuracy, demonstrating the practical applicability of this method in nighttime surveillance and crime detection (Tan et al., 2022). The proposed approach successfully extracts and recognizes license plate numbers even under poor lighting conditions, ensuring reliable and accurate object recognition in real-world scenarios.

3.4. Algorithm

This subsection presents the workflow diagram (Figure 1) and the step-by-step algorithm applied to enhance low-light images. The algorithm compares multiple enhancement techniques to improve visibility and clarity, with the Laplacian variance used as the evaluation metric for sharpness.

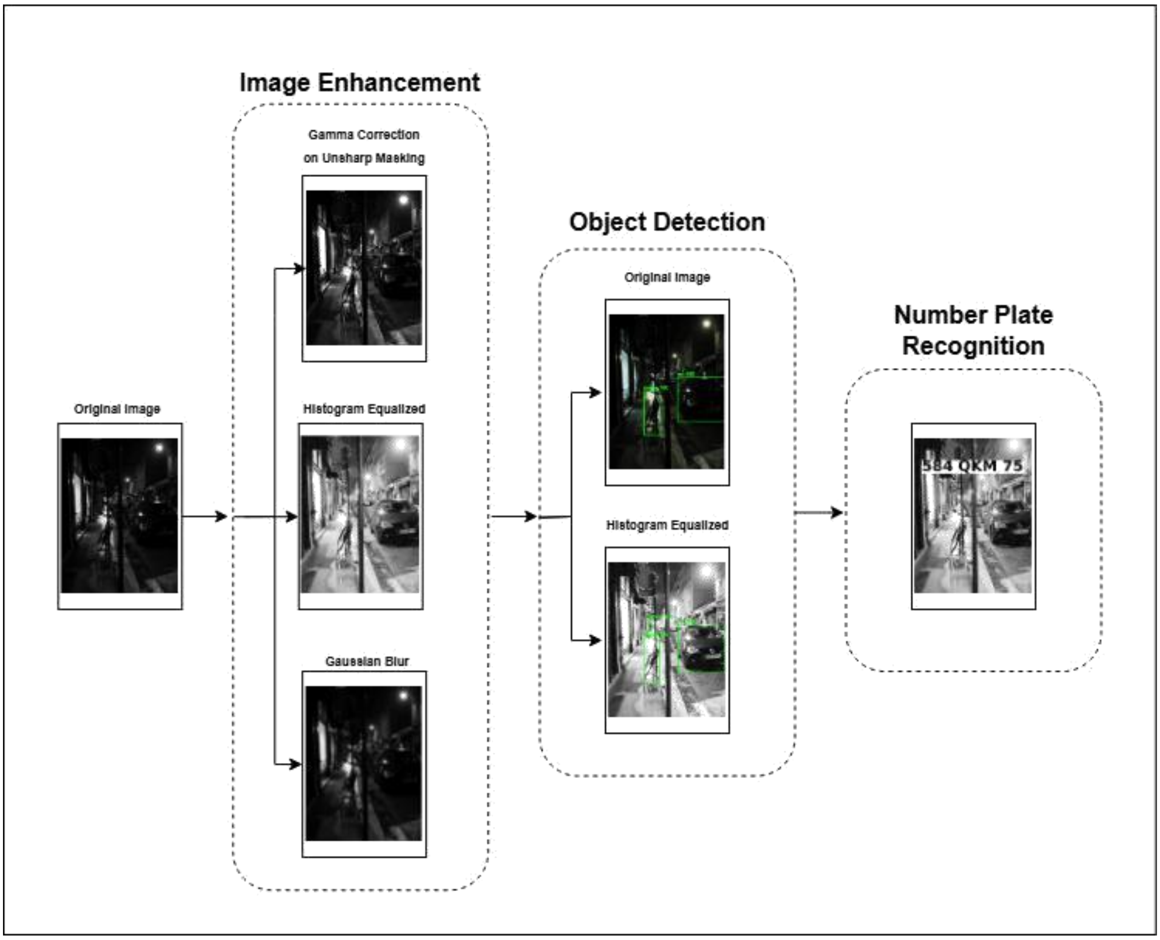

Figure 1. Workflow for image enhancement of low-light images

A detailed analysis was conducted using both the original and enhanced low-light images. The original low-light images were sourced from publicly available datasets on Kaggle. The study found that histogram equalization consistently gave superior results in terms of visibility and clarity, especially for darker images. Among the enhancement techniques tested, the Histogram Equalization stood out by significantly improving the contrast, bringing out previously indistinguishable details such as the license plates and the vehicle outlines. When the outputs were compared side by side, it was evident that the original images lacked edge sharpness and had a poor dynamic range, making detection difficult. In contrast, the histogram-equalized images displayed enhanced sharpness and better separation between the object and its background, which directly improved the object detection accuracy. This improved feature visibility ensured that key objects such as the number plates, pedestrians, or vehicles were more reliably detected and segmented by downstream recognition models, reinforcing the suitability of this method for real-world surveillance tasks.

For the license plate recognition, a two-stage approach, combining the Convolutional Neural Networks (CNN) and the Support Vector Machines (SVM) was used. The CNN architecture consists of multiple convolutional and pooling layers, followed by a flattening layer and a fully connected dense layer, which extracted detailed feature representations from each segmented character. These features were then passed to an SVM classifier, which mapped them to the correct alphanumeric labels. The CNN handled the complex visual patterns, while the SVM provided a strong generalization for classification, especially when trained on limited datasets. This hybrid approach allowed a high recognition accuracy while keeping the model lightweight and efficient for real-time use.

While deep learning models such as the CNNs and GANs had shown impressive results in low-light image enhancement, we intentionally chose the traditional techniques for this work. The main reason is that the deep learning methods typically require large labeled datasets, high computational power, and longer processing times, which makes them less practical for the real-time or resource-limited surveillance systems. In contrast, the traditional methods like the Unsharp Masking, Gamma Correction, and Histogram Equalization are lightweight, easy to apply, and do not rely on data-driven training. These techniques can be tuned manually and still offer significant improvements in image sharpness and contrast, particularly in those situations where the images are heavily underexposed. The experiments conducted showed that combining these methods yielded clear improvements in visibility and detail without introducing excessive noise or artifacts. Moreover, the traditional methods provide a level of transparency and interpretability that is often lacking in the deep learning models. For the security and law enforcement applications, where the ability to explain how an image was processed is critical, and a quicker response is needed, this becomes a major advantage. The ultimate goal was to improve the recognition performance while keeping the system simple, fast, and reliable. The results validated the decision, showing that these classical enhancement techniques can still deliver strong performance when thoughtfully combined and applied.

Algorithm 1 Image Enhancement and Object Detection Algorithm

Step 1: Load the low-light image of dimensions $M \times N$ for enhancement.

Step 2: Calculate the initial Laplacian variance of the input image to assess its sharpness:

$$L_{initial} = Variance\ of\ \ the\ Laplacian\ of\ \ the\ image$$

Step 3: Perform the following image enhancement techniques separately:

1. Apply Gaussian blur to reduce noise while preserving edges.
2. Use histogram equalization to redistribute pixel intensities and improve contrast in light and dark regions.
3. Perform unsharp masking to enhance edges and apply gamma correction to adjust brightness:

$$Unsharp\ Image = Original\ Image + \alpha \times\ (Original\ Image - \ Blurred\ Image)$$

$$I_{out} = I_{in}^{Y}$$

Step 4: Recalculate the Laplacian variance of the enhanced image to evaluate the improvement in sharpness:

$$L_{final} = Variance\ of\ \ the\ Laplacian\ of\ \ the\ enhanced\ image$$

Step 5: Perform object detection on both the original and the histogram-equalized enhanced images using a suitable object detection model to identify the regions of interest.

Step 6: If a number plate is detected, apply the following number plate recognition process:

1. **Number Plate Localization**:

Use the Single Shot Detector (SSD) algorithm to detect and localize the number plate region.

2. **Character Segmentation**:

Use Canny edge detection to identify the boundaries of the number plate.

Perform connected component analysis to isolate individual characters.

3. **Character Recognition**:

Use a Convolutional Neural Network (CNN) to extract features from each segmented character.

Train a Support Vector Machine (SVM) classifier to map the extracted features to character classes.

4. **Post-processing**:

Apply rule-based filtering to remove improbable character combinations.

Format the recognized characters into a standard number plate format.

Step 7: Compare the detection outputs from the original and the enhanced images to validate the improvement in clarity and accuracy.

4. Results and discussions

4.1. Enhanced image quality

In this section, the visual and quantitative results of image enhancement are presented, focusing on two specific examples where the number plates were difficult to detect in the original low-light images. The enhancements are evaluated visually and quantitatively using the Laplacian variance to measure the improvement in the image sharpness.

Figure 2 shows a vehicle in a dim parking lot, with the license plate barely visible due to the shadows and poor contrast. The low-light conditions and uneven illumination pose significant challenges for the automated license plate recognition, which requires targeted enhancement techniques to improve visibility.

Figure 2. Vehicle license plate images in a low-light environment. Column 1: Input images; Column 2: Enhanced images using gamma correction on unsharp masking; Column 3: Enhanced images using Histogram equalization; Column 4: Enhanced images using Gaussian blur

Before Enhancement: In the original image, the license plate is obscured, and the edges are blurred, making any character segmentation difficult. The Laplacian variance was measured at 3297.93, indicating low sharpness and weak edge definition. Additionally, the histogram distribution of the pixel intensities revealed a heavy concentration in the darker regions, confirming the poor contrast.

Enhancement Workflow: To address the challenges posed by the low-light conditions, three separate enhancement techniques were applied independently to analyze their effectiveness in improving the license plate visibility.

- **Gaussian Blur for Noise Reduction:** A Gaussian Blur filter was applied to reduce the high-frequency noise while preserving the overall structural details. This helped smoothen out the noise artifacts that could otherwise interfere with the object detection and recognition.
- **Gamma Correction on Unsharp Masking for Edge Enhancement and Brightness Adjustment:** The Unsharp Masking was applied to enhance the edges by amplifying the high-frequency components, improving the boundary definition and clarity for vehicles, such as cars. The Gamma Correction, with an optimized factor of 2.5, was then applied to adjust the brightness, ensuring a better visibility in the shadowed regions without overexposing the bright areas.
- **Histogram Equalization for Global Contrast Improvement:** To improve the overall contrast, the Histogram Equalization was performed separately, redistributing the pixel intensities and enhancing the details in the dark regions. This method effectively highlighted the critical features, making the license plate more distinguishable.

Each of these techniques was applied independently to compare their individual contributions to the image enhancement. The effectiveness of each method was evaluated based on the sharpness improvements, contrast adjustments, and overall readability of the license plate in the enhanced images.

After Enhancement: The applied techniques effectively improved the brightness, sharpness, and contrast. In particular, the Histogram Equalization achieved the highest Laplacian variance of 16912.66, indicating a substantial improvement in the edge sharpness and overall clarity. The histogram analysis post-enhancement confirmed a more balanced intensity distribution, reducing the over-darkened and washed-out regions. The Visual Results show that in the input images, the license plate was barely visible with blurred edges, making the character recognition difficult. On the other hand, in the enhanced image, the plate is clearly visible with sharp edges and distinct characters, allowing for an improved segmentation and recognition.

Impact on License Plate Recognition: The image enhancement process played a crucial role in improving the visibility of the alphanumeric characters, leading to a better identification and segmentation of the license plates. The workflow involved the grayscale conversion, the Gaussian blurring to minimize noise, and the histogram equalization to enhance contrast (Rahman et al., 2016). A Single Shot Detector (SSD) was used to locate the plate, followed by the Canny edge detection and the connected component analysis for segmentation (Zheng et al., 2012). To ensure an accurate recognition, the features were extracted using a Convolutional Neural Network (CNN) and classified using a Support Vector Machine (SVM), with additional rule-based filtering applied for refinement. The application of the histogram equalization led to a better contrast and sharper details, which contributed to the improved recognition accuracy (Arici, Dikbas & Altunbasak, 2009). Notably, the original image contained only two detected objects—a bicycle and a car—whereas the enhanced image revealed an additional object, a person, demonstrating how the contrast adjustments can uncover previously indistinguishable details.

4.2. Quantitative evaluation of image sharpness and complexity

The Laplacian variance was used as the primary metric to evaluate the effectiveness of the image enhancement techniques. The Laplacian variance measures the sharpness of an image by calculating the second-order derivative of the pixel intensity values. This metric was chosen because it directly assesses the image clarity and the edge definition, which are critical for detecting the number plates in low-light conditions. The traditional metrics such as the Peak Signal-to-Noise Ratio (PSNR) and the Structural Similarity Index (SSIM) are less suitable for this task, as they focus on the overall image quality rather than sharpness, which is essential for the proposed objective. The Laplacian variance is calculated using the following formula:

$$L = \frac{1}{N}\sum(\nabla^2 I(i))^2 \tag{1}$$

Where:

- L is the Laplacian variance,
- N is the number of pixels in the image,
- $\nabla^2 I(i)$ is the Laplacian (second derivative) of the intensity at pixel.

The higher Laplacian variance values indicate a greater degree of sharpness, as sharper images tend to have more pronounced edges, which result in larger second-order intensity derivatives.

4.2.1. Laplacian variance results

Table 1 below shows the Laplacian variance values calculated for each image enhancement technique. A higher Laplacian variance indicates better sharpness and clearer object boundaries.

Table 1. Laplacian Variance for different Enhancement Techniques

Enhancement Technique	Laplacian Variance	PSNR	SSIM
Original Image	3297.93	inf	1.00
Gamma Correction on Unsharp	9232.66	27.36	0.41
Masking	16912.66	27.81	0.15
Histogram Equalization	3.40	32.21	0.66
Gaussian Blur			

4.3. Comparison with Deep Learning-Based Low-Light Enhancement Methods

As compared in Figure 3, the histogram equalization-based method proves sufficient for tasks like license plate recognition, especially in setups with limited computing resources. Unlike the deep learning-based Zero DCE method, which is computationally heavy and slower without dedicated hardware like GPUs, this approach is faster and can run smoothly on regular systems. Although the PSNR and SSIM scores are lower for the Zero DCE output, this is mainly due to its aggressive enhancement which alters the pixel distributions and affects these metrics. Despite that, both methods succeed in making the number plate clearly visible, this method offering a more practical and efficient alternative.

Figure 3. Low-Light Image Enhancement. Column 1: Original image; Column 2: Histogram Equalized image; Column 3: Enhanced image using Zero-DCE

4.4. Laplacian variance analysis

The following figures present the Laplacian variance comparison for 100 enhanced images and 100 original images. The Laplacian variance is used to quantify the sharpness of the images, providing an insight into how effective the enhancement techniques are in improving image clarity.

As shown in Figures 4 and 5, the Laplacian variance values for the enhanced images are significantly higher than those of the original images, indicating an improvement in image sharpness and clarity after enhancement.

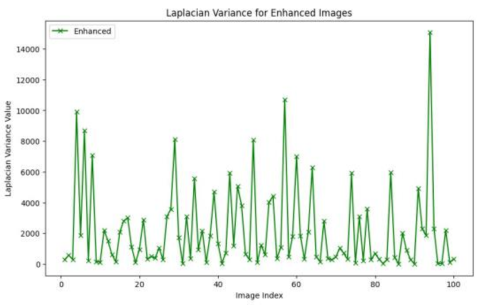

Figure 4. Laplacian Variance for 100 Enhanced Images

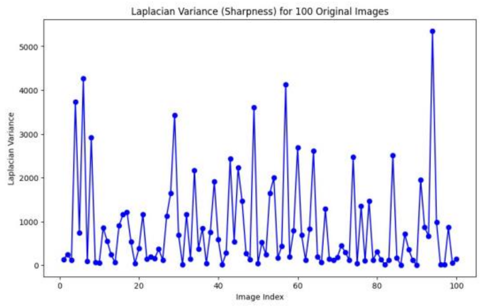

Figure 5. Laplacian Variance for 100 Original Images

4.5. Challenges and limitations

While the image enhancement techniques improved the visibility, several challenges were encountered, particularly regarding the noise introduction and the unnatural color shifts. The techniques such as the histogram equalization and the gamma correction often introduced noise in extremely poor lighting conditions, obscuring finer details on the license plates. In such cases, the noise reduction methods like the Gaussian blur had to be applied carefully to avoid blurring the important edges. These issues have been noted in the previous studies, in which the underexposed images suffer from severe noise and color distortion (Guo et al., 2023). Additionally, converting the grayscale images back to RGB sometimes caused color distortions, particularly after histogram equalization. Although this did not affect the license plate clarity, it introduced artifacts that could mislead the automated systems or manual interpretation. Such color distortion challenges are discussed in the surveys on the low-light image enhancement (Zhao et al., 2024). Furthermore, the enhancement techniques struggled with extremely dark images, where the details in the shadowed areas remained difficult to recover even after the gamma correction or contrast stretching. This limitation is highlighted in the studies addressing noise suppression and structural distortion during brightness enhancement (Tan et al., 2022).

4.6. Effectiveness for object recognition and detection

The Enhancement techniques significantly improved the visibility of the license plates and the critical features in the low-light conditions, particularly for crime identification.

Number Plate Recognition: The Histogram equalization was most effective for enhancing the license plates, improving the edge sharpness and revealing the plates hidden in shadows. This balance between clarity and natural image quality ensured an accurate recognition without excessive noise or distortion.

Balancing Enhancement with Image Quality: The Unsharp Masking and Gamma Correction offered the best trade-off between enhancement and maintaining the natural image quality. Although the Histogram Equalization improved the contrast, it sometimes caused over-enhancement, making the images appear unnatural. Any effective image enhancement should focus on improving the object clarity without altering the image realism. However, in the surveillance applications, prioritizing recognition over natural appearance is a justified trade-off. Overall, these techniques improved critical detail recognition in low-light images, but they must be carefully applied to avoid excessive noise or unnatural color shifts.

5. Conclusions

This proposed work examined the effectiveness of various image enhancement techniques in improving the visibility and clarity of low-light images, particularly for license plate detection. Among the applied methods, the Gamma Correction combined with the Unsharp Masking and the Histogram Equalization proved to be the most effective. The Gamma Correction significantly improved the edge sharpness and enhanced the shadowed areas, making the alphanumeric characters more distinguishable while increasing the overall visibility in the dimly lit environments. The Histogram Equalization, on the other hand, was particularly useful in the extreme low-light conditions by revealing the hidden details and enhancing contrast, though it sometimes introduced noise. These findings emphasize the importance of selecting the appropriate enhancement techniques based on the lighting conditions and application requirements.

These techniques demonstrated their potential to improve the low-light images for crime identification applications, particularly in license plate recognition, where the clarity and contrast are essential.

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