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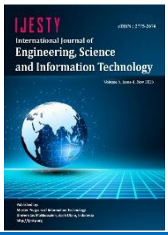

# An Improvement of License Plate Detection Under Low Light Condition Using CLAHE and Unsharp Masking

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## Abstract

The rapid increase in vehicle numbers has rendered traditional manual traffic monitoring approaches inefficient and unreliable, thereby emphasizing the need for intelligent, automated systems to assist in traffic management and law enforcement. Among these, Automatic License Plate Recognition (ALPR) systems play a crucial role in detecting and tracking vehicles. However, their performance often deteriorates under low-light or poor visibility conditions, leading to reduced detection accuracy. To address this limitation, this study proposes a two-stage image enhancement pipeline that integrates Contrast Limited Adaptive Histogram Equalization (CLAHE) and Unsharp Masking (USM) techniques with the advanced YOLOv11 object detection model. The dataset utilized comprises 1,496 images extracted from Electronic Traffic Law Enforcement (ETLE) video footage captured in Makassar, Indonesia. These images were systematically divided into training, validation, and testing sets in a 70:20:10 ratio to ensure balanced model evaluation. Four experimental scenarios were conducted to assess the contribution of each enhancement method. The results revealed that the combined application of CLAHE and USM significantly improved detection accuracy, achieving a Precision of 0.945, Recall of 0.977, and a mean Average Precision (mAP@0.5:0.95) of 0.830—outperforming all other configurations. These findings confirm that the synergistic use of contrast enhancement and edge sharpening effectively mitigates the challenges posed by low-light environments. Consequently, the proposed approach enhances the robustness, clarity, and reliability of ALPR systems, offering a practical solution for real-world intelligent transportation applications and automated traffic law enforcement.

***Keywords***: *Vehicle Plate Detection, Low-Light Condition, YOLOv11, CLAHE, Unsharp Masking.*

## 1. Introduction

Vehicles are one of the main necessities for society, and as the population in an area increases, the demand for vehicles also rises. Every vehicle, whether two-wheeled or four-wheeled, must have a license plate as an official registered identity. The license plate number serves as a distinguishing feature or identifier for a vehicle, assigned by the police. Each vehicle's identity in the form of a license plate is unique, consisting of a combination of numbers and letters used only by that specific vehicle. This identity is crucial for distinguishing one vehicle from another.

As the number of vehicles on the road increases, monitoring and controlling vehicles becomes very difficult to do manually, as performed by traffic police [1]. Intelligent systems can be used to address this issue efficiently. License plate detection plays an important role in various traffic management fields. License plate detection is not only necessary for traffic monitoring, but also for traffic law enforcement [2].

Although automatic license plate recognition technology has made significant progress, developing methods that can reliably operate under complex environmental conditions is still required. Currently, most existing approaches are less effective when facing changes in lighting, and generally only work optimally during daylight hours [3]. Automatic license plate recognition systems play a very important role in urban traffic management and are a key component of the smart city concept. The process of license plate recognition is usually divided into two stages: license plate location detection and license plate character recognition [4].

The detection or localization stage of the license plate is a critical component in an automatic vehicle license plate recognition system. The overall accuracy of the system greatly depends on the model's capability in accurately locating the position of the license plate within the vehicle image. Without robust detection, the system will have difficulties distinguishing the text on the license plate from other elements around the vehicle, such as signs, shop boards, or advertisements, since license plates often only occupy a small part of the image and may be overlooked. Therefore, accurate detection becomes the main foundation for the success of the subsequent stages, such as segmentation and character recognition (OCR) [4][5].

Extensive research has been conducted on vehicle license plate detection, with a prevalent approach involving the integration of object detection models, such as You Only Look Once (YOLO), and Optical Character Recognition (OCR) techniques. The study by [6] underscores the significance of automated systems for the detection and recognition of vehicle license plates. This necessity arises from the increasing number of vehicles on the roada, which contributes to a rise in traffic violations, accidents, and criminal activities. Consequently, there is a demand for an automatic vehicle license plate recognition system that operates with speed and precision to aid in traffic monitoring. However, in practice, these systems encounter several challenges, including slow image processing and reduced accuracy, particularly when license plate images are blurred or tilted. This research endeavors to address these issues by integrating two technologies, YOLOv8 and EasyOCR. The findings indicate an accuracy rate of 84%, with real-time observation tests yielding a detection accuracy of 86%.

In the study conducted by [7], it was elucidated that a primary challenge in vehicle license plate recognition systems is the occurrence of blurry images, which are often caused by fast-moving vehicles and varying camera angles, particularly in real-time traffic monitoring scenarios. This results in unclear captured images, complicating the segmentation and recognition of license plate characters. Moreover, the application of conventional OCR engines, such as Tesseract, is deemed suboptimal under these conditions, as their performance deteriorates when confronted with distortion and low image quality.

In the study conducted by [2], a license plate detection and recognition system utilizing CNN achieved high accuracy through the implementation of super-resolution methods to address low image quality. Nonetheless, this approach still exhibits limitations in enhancing local contrast in license plate images, especially under poor lighting conditions. In the study by [8], a method was proposed that integrates the YOLOv8 algorithm for license plate detection with an Adaptive Gabor Filter to enhance the image prior to recognition by the OCR system. Experimental results indicated that the use of the Adaptive Gabor Filter can reduce the character reading error rate from 7.5% to 4.98%. This demonstrates the method's efficacy in improving license plate reading accuracy, particularly when images are captured under uneven lighting conditions or from challenging angles.

Based on this review, this study proposes the utilization of YOLOv11, the latest advancement in the YOLO object detection model series, which is engineered for superior performance in complex environments and for identifying small objects. To address the primary challenge of low-light conditions, it is proposed to incorporate a preprocessing pipeline consisting of the Contrast Limited Adaptive Histogram Equalization (CLAHE) filter to adaptively enhance local contrast without excessively amplifying noise, and Unsharp Masking (USM) to sharpen the edge details of the license plate [9].

The performance of deep learning models such as YOLO is highly contingent upon the quality of the input image. In low-light conditions, the visibility of license plates diminishes significantly[10][11], potentially decreasing detection accuracy. Therefore, preprocessing steps such as CLAHE and USM become essential. CLAHE aims to enhance the clarity of local features on the plate, while USM is intended to sharpen the object boundaries that may be blurred due to low lighting.

This study aims to address existing limitations, particularly the challenges associated with license plate detection in low-light conditions. Although previous research has utilized preprocessing techniques, many approaches have inadequately enhanced local contrast or have predominantly concentrated on improving recognition (OCR) accuracy. This research focuses exclusively on the detection stage, which is a critical foundation for the entire system. The primary contributions of this study are as follows:

a. Proposing a two-stage preprocessing pipeline that incorporates Contrast Limited Adaptive Histogram Equalization (CLAHE) and Unsharp Masking (USM) to significantly enhance the quality of low-light images prior to processing by the detection model.
b. Conducting an empirical analysis of the performance improvements of the state-of-the-art object detection model, YOLOv11, following the application of the proposed preprocessing pipeline, particularly in the context of low-light license plate datasets.
c. Presenting an ablation study to assess the individual and combined effects of CLAHE and Unsharp Masking, thereby demonstrating the synergistic effectiveness of these two filters in enhancing license plate detection accuracy.

By integrating CLAHE and Unsharp Masking image enhancement techniques with the YOLOv11 detection model, this research seeks to provide a more robust and accurate solution for license plate detection in low-light conditions, which are frequently encountered in real-world traffic surveillance applications.

## 2. Literature Review

### 2.1. Vehicle License Plate Recognition Systems

Automatic License Plate Recognition (ALPR), also referred to as Automatic Number Plate Recognition (ANPR), is a computer vision–based system designed to identify vehicles through their license plates using image processing and pattern recognition techniques. The system plays a vital role in intelligent transportation systems (ITS), smart city initiatives, and modern traffic management frameworks, where automation, speed, and accuracy are crucial for handling large volumes of vehicles efficiently [12][13].

Generally, an ALPR system consists of three main stages: (1) image acquisition, (2) license plate detection or localization, and (3) character segmentation and recognition. In the image acquisition stage, vehicle images are captured using surveillance cameras installed at traffic intersections, toll booths, or parking facilities. The detection stage then identifies the exact region of the license plate within the image. This step is critical since the overall recognition accuracy depends largely on the model's capability to localize the plate region precisely. Finally, the Optical Character Recognition (OCR) stage extracts alphanumeric characters from the detected region and converts them into digital data for subsequent storage, analysis, or enforcement [14][15].

The accuracy of ALPR systems can be affected by several factors such as lighting variations, camera angle, motion blur, weather conditions, and plate design differences. These environmental and operational constraints often lead to detection or recognition errors, particularly in real-world deployments involving low-light or night-time conditions [16][17]. Consequently, recent studies have introduced advanced preprocessing and deep learning–based models to improve robustness and accuracy in complex environments [18].

ALPR technology has found applications in diverse domains, including traffic law enforcement, automated toll collection, vehicle access control, urban surveillance, and smart parking management. In the broader context of smart cities, the integration of ALPR with IoT and cloud-based analytics supports real-time traffic monitoring, violation detection, and intelligent transportation planning. These wide-ranging applications highlight the critical importance of accurate license plate detection as the foundation for the entire recognition process.

## 2.2. Evolution of License Plate Detection Techniques

The development of automatic license plate recognition (ALPR) systems has undergone several methodological transitions over the past two decades. Early approaches primarily relied on conventional image processing techniques, while recent advancements have leveraged machine learning and deep learning to achieve higher accuracy, robustness, and real-time performance.

In the early stages of ALPR research, detection methods were dominated by classical image processing techniques such as edge detection, color segmentation, and morphological operations. These methods typically employed algorithms like Sobel, Canny, or Laplacian edge detectors to extract potential plate regions based on rectangular edge patterns and aspect ratios [14]. Color-based methods exploited the difference between the plate background and characters, while morphology-based filters were used to isolate regions with high edge density [12].

Although these approaches were computationally lightweight and effective under controlled environments, they demonstrated poor performance under variable lighting, shadows, occlusions, or camera angles. Additionally, their dependency on manually tuned parameters limited their adaptability to diverse plate formats and environments [19]. Consequently, researchers began to explore learning-based algorithms that could better generalize across different scenarios.

The introduction of machine learning algorithms marked the second phase of ALPR evolution. Techniques such as Support Vector Machines (SVM), AdaBoost, and Haar-like feature classifiers were used to train models capable of identifying license plate regions [20]. The Viola–Jones framework, initially designed for face detection, was adapted for plate detection due to its ability to perform rapid object localization [21].

However, despite their improved robustness compared to classical methods, these approaches still relied heavily on handcrafted features such as Histogram of Oriented Gradients (HOG) or Local Binary Patterns (LBP). As a result, they struggled to maintain accuracy in complex urban environments characterized by diverse vehicle types, backgrounds, and illumination conditions [22].

The advent of Convolutional Neural Networks (CNNs) revolutionized the field by enabling end-to-end learning from raw image data. Deep learning–based object detection models eliminated the need for manual feature engineering and demonstrated superior generalization and adaptability [23]. The development of frameworks such as Region-based CNN (R-CNN), Faster R-CNN, Single Shot MultiBox Detector (SSD), and You Only Look Once (YOLO) established new benchmarks for accuracy and speed in ALPR applications [24].

Among these models, the YOLO family has gained widespread adoption for license plate detection due to its real-time processing capability and high detection accuracy for small objects. Studies such as those by [6][18] demonstrated that integrating YOLO-based detectors with Optical Character Recognition (OCR) systems significantly enhances performance compared to conventional pipelines. YOLO's single-stage detection mechanism directly predicts bounding boxes and class probabilities in one forward pass, making it particularly suitable for real-time traffic surveillance.

Recent research has focused on optimizing deep learning models for complex environments, including low-light, blurry, and angled license plate conditions. Techniques such as image enhancement, super-resolution, and adaptive filtering have been incorporated to address visibility challenges before detection [15][17]. However, despite these advancements, achieving consistently high detection accuracy under night-time or uneven lighting remains difficult.

This ongoing evolution—from rule-based systems to deep neural networks—illustrates the increasing sophistication and adaptability of license plate detection technologies. The next generation of models, such as YOLOv11, aims to further improve detection precision for small and low-contrast objects, making them particularly relevant for real-world deployment in smart city and traffic monitoring applications.

# 3. Methods

The research methodology is designed to develop and evaluate a vehicle license plate detection system optimized for low-light conditions. The general workflow of the system is illustrated in Fig. 1.

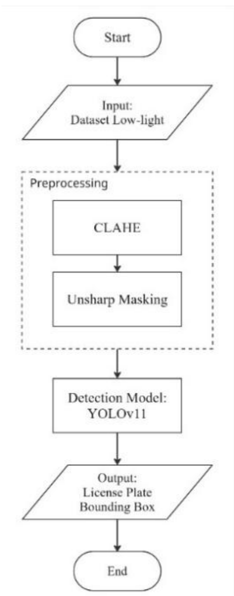


**Fig 1.** Flowchart of the proposed research methodology

The system consists of two main stages. The first stage is Image Preprocessing, which aims to enhance the visual quality of low-light input images so that the features of the license plate become clearer. The second stage is Object Detection, where the processed images are fed into a YOLOv11-based object detection model to detect license plates.

## 3.1. Dataset

The dataset used in this study is primary data specifically collected to evaluate vehicle license plate detection performance under low-light conditions. The data was obtained from video recordings of Electronic Traffic Law Enforcement (ETLE) cameras installed on Jalan A.P. Pettarani, Makassar, precisely in front of the Ministry of Religious Affairs office. This data collection location is situated under an elevated toll road, resulting in consistently low lighting conditions, even during the day. From the video recordings, image frames were extracted to produce a static image dataset. A total of 1,496 images were successfully extracted.

For model training and evaluation purposes, this dataset is divided into three subsets based on the sequence of frames in the video, with proportions of 70:20:10 as follows:

a. Training Set: 70% of the total data, allocated as 1,050 images.
b. Validation Set: 20% of the total data, allocated as 300 images.
c. Testing Set: 10% of the total data, allocated as 146 images.

This division aims to train the model on most of the data, adjust hyperparameters using the validation data, and finally measure the model's generalization performance on previously unseen testing data.

## 3.2. Contrast Limited Adaptive Histogram Equalization (CLAHE)

Contrast Limited Adaptive Histogram Equalization (CLAHE) is a more advanced image contrast enhancement technique. Unlike the global Histogram Equalization (HE) method, which can lead to excessive noise amplification in homogeneous areas, CLAHE operates adaptively [25]–[27]. This technique divides the image into several small blocks and performs local histogram equalization on each block to improve contrast and clarify image details. Unlike Adaptive Histogram Equalization (AHE), which tends to excessively amplify noise, CLAHE limits the level of contrast enhancement through specific parameters, thereby preventing over-enhancement in areas with high intensity [27][28].

In this study, CLAHE was independently applied to each color channel (B, G, R). This per-channel methodology has demonstrated advantages under low-light conditions, as it enhances the contrast of local features pertinent to the plate edges and characters [29].

The process commences by dividing the image on each channel into (8x8) patches. For each patch (t) with a pixel domain (Ωt), a 256-bin discrete histogram (L=256) is computed:

$$h_t(k) = |x \in \Omega_t | I_c(x) = k|, k \in 0, \dots, 255 \quad \text{.....(1)}$$

To mitigate the amplification of excessive noise, the histogram ($h_t(k)$) is subjected to clipping at a predetermined threshold ($C$), thereby producing a clipped histogram:

$$h'_t(k) = min(h_t(k), C) \quad \text{.....(2)}$$

The excess mass ($E_t$), defined as the total number of pixels surpassing the threshold $C$, is subsequently redistributed uniformly across all histogram bins.

$$\tilde{h}_t(k) = h'_t(k) + \left\lfloor \frac{E_t}{L} \right\rfloor \quad \text{.....(3)}$$

The assignment of new pixel values is determined by the Cumulative Distribution Function (CDF) of the redistributed histogram ($\tilde{h}_t(k)$), where $N_t$ represents the total number of pixels within the block.

$$CDF_t(k) = \sum_{i=0}^{k} \tilde{h}_t(i)\,, N_t = |\Omega_t| \quad \text{.....(4)}$$

The mapping function ($\phi_t(k)$) normalizes the CDF to generate new intensity values ranging from 0 to 255.

$$\phi_t(k) = round\left(\frac{(CDF_t(k) - CDF_t(0))}{(N_t - CDF_t(0))}, (L-1)\right) \quad \text{.....(5)}$$

To mitigate pronounced block artifacts at the boundaries between blocks, the final output intensity value at each pixel ($I\ c$^"clahe" ) is computed using bilinear interpolation from the four nearest neighboring blocks.

## 3.3. Unsharp Masking

The second stage entails the enhancement of image detail sharpness through the application of the Unsharp Masking (USM) technique. Unsharp Masking is a well-established image sharpening method that functions by isolating high-frequency details, such as edges, from an image. Conceptually, this technique involves generating a blurred (unsharp) version of the original image, which is then subtracted from the original to produce a mask containing only edge details. This mask is subsequently added back to the original image to augment visual sharpness [30]. The Unsharp Masking process is a highly effective approach for improving sharpness and refining images, particularly for scanned images that may lack sufficient sharpness.

This process is applied to the input image ($I\ \ c$^"$input$" ) to sharpen the edges of the license plate, thereby facilitating easier recognition by the detector. Initially, the image is smoothed using a low-pass filter in the form of a Gaussian kernel ($G\ \ \sigma$) with a size of (9x9) and a standard deviation ($\sigma = 10$).

$$B_c = I_c^{\iota\nu\pi\upsilon\tau} * G_\sigma, G_\sigma(\boldsymbol{u}) = \left(\frac{1}{2\pi\sigma^2}\right) exp\left(\frac{-(|\boldsymbol{u}|^2)}{2\sigma^2}\right) \quad \ldots\ldots(6)$$

The process results in a blurred version ($B_c$) of the image. Subsequently, a high-boost combination is applied by utilizing a weighted combination of the original image ($I\ \ c$^"$input$" ) and its blurred version ($B\ \ c$).

$$I_c^{\sigma\eta\alpha\rho\pi} = \alpha I_c^{\iota\nu\pi\upsilon\tau} + \beta B_c + \gamma, \alpha = 1.5, \beta = -0.5, \gamma = 0 \quad \ldots\ldots(7)$$

This can equivalently be written as:

$$I_c^{\sigma\eta\alpha\rho\pi} = I_c^{\iota\nu\pi\upsilon\tau} + 0.5(I_c^{\iota\nu\pi\upsilon\tau} - B_c) \quad \ldots\ldots(8)$$

The selection of these parameters (λ=0.5, σ=10) effectively enhances mid-to-high frequency content, such as plate edges and character strokes, while mitigating the amplification of noise typically observed in low-light images.

## 3.4. YOLOv11 Detection Model

The detection model employed in this study is You Only Look Once version 11 (YOLOv11), a single-stage object detector architecture designed to optimally balance accuracy and inference speed[31]. YOLOv11 represents an advancement over YOLOv8, incorporating significant enhancements in the feature extraction backbone, neck structure, and decoupled detection head, thereby increasing its adaptability to variations in scale and lighting conditions of target objects. The primary architecture of YOLOv11 comprises three essential components: Backbone, Neck, and Head [32].

In the Backbone section, YOLOv11 utilizes the C3k2 block architecture, an evolution of CSPNet (Cross Stage Partial Network), which features the innovative Partial Convolution Layer and Dynamic Expansion Ratios. The aim is to extract critical semantic features from the input image while preserving significant spatial details. In this study, the input size is set to 640×640 pixels to maintain a balance between detection accuracy and speed [32].

The neck component of YOLOv11 integrates features from various levels (ranging from low-level to high-level) using a combination of Path Aggregation Network (PAN) and Feature Pyramid Network (FPN), referred to as PAN-FPN, along with Bi-directional Cross-scale Fusion. This mechanism facilitates more reliable detection of license plates with varying sizes and brightness levels. Additionally, the Neck employs C2PSA (Convolutional block with Parallel Spatial Attention) to enhance global context and strengthen spatial attention [32].

For the final detection process, YOLOv11 utilizes a decoupled head that separates the classification and regression paths. This approach enhances convergence stability during training and reduces errors in bounding box regression. The sigmoid activation function is applied for class prediction, while Complete IoU (CIoU) loss is used to update the bounding box coordinates.

The Total Loss ($\mathcal{L}$) function employed during the YOLOv11 training phase is delineated as a synthesis of three principal components:

1. $\mathcal{L}\_bbox$ (Regression Loss), utilizing Complete IoU (CIoU) loss to quantify the error in the position and dimensions of the predicted bounding box.
2. $\mathcal{L}\_obj$ (Object Loss), employing Binary Cross-Entropy loss to evaluate the confidence or presence of an object within the predicted box.
3. $\mathcal{L}\_cls$ (Classification Loss), applying Focal Loss for classification, which is efficacious in addressing class imbalance issues.

Mathematically, the Total Loss function is expressed as in the equation below.

$$\mathcal{L} = \lambda_1 \mathcal{L}_{bbox} + \lambda_2 \mathcal{L}_{obj} + \lambda_3 \mathcal{L}_{cls} \quad \ldots\ldots(9)$$

The image produced following the preprocessing stages of CLAHE and Unsharp Masking is subsequently input into the YOLOv11 model. Within this model, the image is partitioned into a grid, with each cell containing multiple anchor boxes that predict the parameters of the center, width, height, and the object confidence score C. The confidence score for each anchor is determined using the sigmoid activation function and is multiplied by the Intersection over Union (IoU) between the prediction and the ground truth, as illustrated in the equation below.

$$\mathit{Χονφιδενχε\ Σχορε} = \sigma(C) \times \mathit{IoY}(\mathit{πρεδιχτιον,\ γρουνδ–τρυτη}) \quad \ldots\ldots(10)$$

## 3.5. Experimental Design

This research aimed to assess the influence of CLAHE and Unsharp Masking preprocessing on the efficacy of the YOLOv11 detection model for vehicle license plate images in low-light environments. All experiments were conducted utilizing the PyTorch framework.

The YOLOv11 model was initialized with pre-trained weights from the COCO dataset and subsequently fine-tuned on the vehicle license plate dataset specific to this study. Training was executed using the Adam optimizer with learning rate $2 \times 10^{-3}$. A batch size of 16 was employed, and the training spanned 100 epochs. Input images were resized to 640x640 pixels. The preprocessing parameters were configured as follows: for CLAHE, clipLimit=2.0 and tileGridSize=(8,8), for Unsharp Masking, $\sigma = 10$ dan $\lambda = 0.5$ ($\alpha = 1.5, \beta = -0.5$).

To isolate the effect of each preprocessing technique, we conducted an ablation study with four experimental scenarios:

a. Scenario 1 (Baseline): YOLOv11 model trained and tested directly on original images without preprocessing.
b. Scenario 2 (YOLOv11 + CLAHE): Images were processed with CLAHE before detection by YOLOv11.

c. Scenario 3 (YOLOv11 + Unsharp Masking): Images were processed with Unsharp Masking before detection by YOLOv11.
d. Scenario 4 (Proposed Method: YOLOv11 + CLAHE + Unsharp Masking): Input images were processed sequentially, first using

CLAHE and then Unsharp Masking. The resulting images from this combined preprocessing were then inputted into the YOLOv11 model. All scenarios were trained and evaluated using the same dataset to ensure a fair comparison.

### 3.6. Evaluation Metrics

The performance of each experimental scenario is evaluated using standard metrics pertinent to object detection tasks, with the aim of assessing the model's accuracy and reliability. These metrics are predicated on the counts of True Positives (TP), False Positives (FP), and False Negatives (FN), defined as follows:

1. True Positive (TP): Denotes a correct detection, wherein the model predicts a vehicle license plate bounding box that significantly overlaps with the ground truth license plate bounding box, as determined by the Intersection over Union (IoU) threshold.
2. False Positive (FP): Denotes an incorrect detection, wherein the model predicts a vehicle license plate bounding box in a region devoid of a ground truth plate, or where the overlap falls below the IoU threshold.
3. False Negative (FN): Denotes a ground truth license plate object that the model fails to detect.

a. **Precision (P)**
Precision is defined as the ratio of true positive detections (TP) to the total number of positive detections generated by the model (TP + FP). This metric serves as an indicator of the accuracy of the model's positive predictions. A high precision value signifies a minimal occurrence of false positives [33].

$$P = \frac{TP}{TP+FP} \quad \text{.......(11)}$$

b. **Recall (R)**
Recall quantifies the proportion of true positive detections (TP) relative to the total number of ground truth objects that should have been identified (TP + FN). This metric reflects the model's capability to identify all pertinent target objects. A high Recall value signifies a minimal occurrence of False Negatives [33].

$$R = \frac{TP}{TP+FN} \quad \text{.......(12)}$$

c. **Mean Average Precision (P)**
Mean Average Precision (mAP) serves as a comprehensive metric that encapsulates the overall performance of object detection systems by evaluating the Precision-Recall curve across various confidence thresholds. This metric is extensively utilized as the primary evaluation standard in the field of object detection. The mAP is computed as the mean of the Average Precision (AP) values for each object class under consideration [33]. Mathematically, mAP is defined as follows:

$$mAP = \frac{1}{C}\sum_{(i=1)}^{C} AP_i \quad \text{.......(13)}$$

$AP_i$ represents the Average Precision value for the $i$-th class, while $C$ denotes the total number of classes evaluated. Given that this study focuses exclusively on detecting a single class, namely vehicle license plates ($C = 1$), the AP and mAP values are effectively equivalent to the AP value for that specific class.

In this study, two variants of mean Average Precision (mAP) are employed as follows:
1. mAP@0.5 (mAP50): This metric calculates mAP using a single Intersection over Union (IoU) threshold of 0.5, thereby assessing general detection capability without imposing stringent requirements on localization accuracy [33].
2. mAP@0.5:0.95 (mAP50-95): This metric computes mAP as the average of Average Precision (AP) values across 10 different IoU thresholds, ranging from 0.5 to 0.95 in increments of 0.05. This approach is more rigorous and exhibits heightened sensitivity to the precision of bounding box localization [33].

## 4. Results and Discussion

This section delineates the experimental outcomes of the performance assessment of the YOLOv11 vehicle license plate detection model, both with and without the implementation of CLAHE and Unsharp Masking preprocessing techniques, under low-light conditions. The analysis emphasizes a quantitative comparison utilizing the previously described evaluation metrics to ascertain the efficacy of the proposed methods.

### 4.1. Results of Experimental Performance Comparison

The quantitative evaluation results from the four experimental scenarios conducted on the test dataset, comprising 146 images, are summarized in Table 1. This table presents the Precision (P), Recall (R), mAP@0.5, and mAP@0.5:0.95 values for each model configuration.

**Table 1.** Detection Performance Results on Low-Light Datasets

| Method | Metrics Evaluation | | | |
|---|---|---|---|---|
| | ***Precision*** | ***Recall*** | ***mAP50*** | ***mAP50-95*** |
| YOLOv11 | 0.943 | **0.990** | 0.974 | 0.828 |
| YOLOv11 + CLAHE | 0.931 | 0.988 | **0.978** | **0.830** |
| YOLOv11 + Unsharp Masking | **0.945** | 0.983 | 0.975 | 0.828 |
| YOLOv11 + CLAHE + Unsharp Masking | **0.945** | 0.977 | **0.978** | **0.830** |

According to Table 1, the baseline YOLOv11 model (without preprocessing) exhibits a relatively robust initial performance. With a very high Recall (0.990) and commendable Precision (0.943), this base model effectively detects most license plates with minimal classification errors. Although the mAP@0.5 is also high (0.974), the lower mAP@0.5:0.95 value (0.828) suggests potential for enhancing bounding box localization accuracy under low-light conditions.

The application of preprocessing techniques individually yielded varying results. Unsharp Masking alone succeeded in elevating Precision to the highest level (0.945), indicating its capacity to reduce False Positives. However, this metric did not significantly improve mAP@0.5:0.95 (remaining at 0.828), implying that sharpening without contrast enhancement is insufficiently effective and likely only accentuates noise. In contrast, CLAHE alone had the most pronounced impact on mAP, achieving the highest values for mAP@0.5 (0.978) and mAP@0.5:0.95 (0.830). These results underscore the critical role of local contrast enhancement in improving detection and localization, albeit with a slight reduction in Precision (0.931), which may be attributed to noise amplification.

The method combining CLAHE and Unsharp Masking demonstrated the best overall performance balance. This combination successfully maintained the highest mAP improvements achieved by CLAHE (0.978 and 0.830), while also restoring Precision to the highest level (0.945). This indicates a synergistic effect: CLAHE enhances feature visibility, while Unsharp Masking sharpens relevant details, enabling YOLOv11 to detect more accurately with fewer errors. Although there was a slight further decrease in Recall (0.977), this value remains very high and is considered an acceptable trade-off for overall improvements in localization accuracy and precision.

## 4.2. Analysis of Results and Discussion

Experimental findings consistently indicate that the application of image preprocessing techniques, particularly the integration of Contrast Limited Adaptive Histogram Equalization (CLAHE) and Unsharp Masking (USM), significantly enhances the license plate detection performance of the YOLOv11 model under low-light conditions compared to the baseline model. The most pronounced improvement is observed in the mAP@0.5:0.95 metric, suggesting that preprocessing not only aids the model in detecting plates but also in localizing them more accurately with bounding boxes.

Technically, this enhancement occurs because CLAHE effectively corrects the local contrast distribution without excessively amplifying noise. In low-light images, the edge information of the plate and characters is often obscured by a limited brightness range and low gradients. CLAHE operates by equalizing the histogram in small local areas, thereby making critical features such as plate boundaries and characters more prominent against the dark background. This contrast enhancement enables the YOLOv11 feature extractor to identify spatial patterns that were previously indiscernible, resulting in higher objectless and confidence scores. Consequently, the number of True Positives increases while False Negatives decrease, directly contributing to higher Recall and mAP@0.5.

The greatest effectiveness is achieved when both methods are applied sequentially in a CLAHE + USM pipeline. This sequence is crucial because CLAHE initially improves the image's signal-to-noise ratio (SNR) and highlights relevant features, before USM sharpens the plate contours that have already been clarified. Thus, USM does not sharpen noise but instead reinforces meaningful edge structures. This combination produces a synergistic effect, enhancing all evaluation metrics: Precision increases due to a reduction in False Positives (the model is less likely to detect non-plate objects), Recall remains high as more plates are detected, and mAP@0.5–0.95 increases due to reduced localization errors.

A slight decrease in Recall (from 0.990 in the baseline to 0.977) can be considered an acceptable trade-off for a significant improvement in Precision and mAP. In real-world applications such as Electronic Traffic Law Enforcement (ETLE) systems, high Precision is prioritized over perfect Recall because incorrect detection of non-plate objects can lead to wrongful legal identification. Thus, the resulting model is not only more accurate but also more reliable for real-world traffic surveillance situations.

These results underscore the substantial benefits of implementing a real-time Automatic License Plate Recognition (ALPR) system, where computational efficiency and reliability under various lighting conditions are critical factors. Overall, this study demonstrates that integrating traditional image enhancement methods with state-of-the-art detection models is an effective and adaptive approach that can significantly enhance license plate detection performance in challenging lighting environments.

# 5. Conclusion

This study seeks to address the challenge of diminished license plate detection accuracy by the YOLOv11 model under low-light conditions. To enhance image quality prior to the detection stage, we propose the integration of a preprocessing pipeline comprising Contrast Limited Adaptive Histogram Equalization (CLAHE) and Unsharp Masking (USM).

Experimental results on a real-world low-light image dataset demonstrate that the proposed method (YOLOv11 + CLAHE + USM) achieves superior performance compared to the baseline model (YOLOv11 alone) as well as the individual application of CLAHE or USM. The proposed method attains the highest Precision value (0.945), the highest mAP@0.5 (0.978), and the highest mAP@0.5:0.95 (0.830). Ablation studies confirm a synergistic effect between CLAHE, which effectively enhances local contrast to reveal plate features, and USM, which sharpens those feature details, thereby reducing ambiguity and False Positives. The significant improvement in mAP@0.5:0.95 particularly underscores the proposed method's capability to enhance bounding box localization precision.

These findings underscore that relatively lightweight, classical image preprocessing techniques remain relevant and can significantly enhance the performance of modern deep learning object detection models in challenging imaging conditions. The proposed solution offers a practical approach to improving the reliability of ALPR systems in low-light environments without necessitating complex changes to detection model architectures. Future research may focus on exploring optimal preprocessing parameters, testing on more diverse low-light datasets (for example, nighttime settings with headlight glare), as well as conducting computational cost analyses to evaluate feasibility for real-time applications such as ETLE.

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