



AN EFFICIENT TEXTURE DESCRIPTOR FOR THE DETECTION OF LICENSE PLATES UNDER DIFFICULT CONDITIONS

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Abstract : Automatic License Plate Recognition (ALPR) is a crucial technology for intelligent transportation systems, enabling applications such as traffic monitoring, toll collection, and law enforcement. Traditional ALPR systems often struggle with low-light conditions, image occlusions, and varying plate designs. To address these challenges, this project proposes a robust ALPR system that integrates the You Only Look Once version 8 (YOLOv8) deep learning model for license plate detection and Multi-Level Extended Local Binary Pattern (MLELBP) for feature extraction and texture analysis.

IndexTerms – License plate detection, texture descriptor, challenging conditions, vehicle identification, image processing, feature extraction, MLELBP, YOLO V8, robust detection.

I. INTRODUCTION

Automatic license plate recognition (ALPR) is a crucial technology for vehicle identification in various applications such as traffic monitoring, law enforcement, and automated toll collection. However, recognizing license plates accurately in real-world conditions presents significant challenges due to variations in lighting, weather conditions (haze, blur, low contrast), occlusions, and different plate formats. Existing ALPR systems struggle to maintain high accuracy when dealing with these adverse conditions, making it necessary to develop robust detection and recognition methods. Automatic License Plate Recognition (ALPR) is a technology that uses computer vision and machine learning to identify and extract vehicle license plate numbers from images or video streams. It is widely used in various fields, including traffic monitoring, law enforcement, toll collection, and parking management. Despite its importance, developing a robust and highly accurate ALPR system is a challenging task due to several real-world complexities. One of the primary challenges in ALPR is varying environmental conditions. License plates captured by surveillance cameras often suffer from poor lighting, motion blur, shadows, and occlusions, making it difficult for recognition algorithms to extract clear and readable text. At night or in low-light conditions, the visibility of license plates decreases significantly, reducing the performance of optical character recognition (OCR) models. Weather conditions such as fog, rain, haze, and snow further degrade the quality of images used for license plate recognition. In hazy conditions, the plate's contrast is reduced, making it harder for standard OCR techniques to differentiate characters from the background. Similarly, in rainy conditions, water droplets on the camera lens can distort images, affecting both detection and recognition accuracy. The diversity in license plate formats across different regions and countries presents another major challenge. Various countries have different font styles, plate sizes, character arrangements, and colour. Some license plates include additional symbols.

II. LITERATURE SURVEY

In the field of Automatic License Plate Recognition (ALPR), various studies have been conducted to enhance detection and recognition accuracy. Several techniques focus on improving robustness under challenging conditions such as poor lighting, motion blur, and occlusion. This section reviews key approaches and methodologies applied in ALPR systems. Automatic License Plate Recognition (ALPR) has been an area of active research for decades, with continuous improvements in detection accuracy, processing speed, and robustness to challenging conditions. Various approaches have been explored, including traditional image processing techniques, machine learning-based models, and deep learning-driven solutions.

2.1 Historical Development of ALPR Systems

The development of ALPR systems can be traced back to early works that relied heavily on rule-based techniques and feature extraction methods. These methods used basic edge detection, morphological operations, and connected component analysis to locate and segment license plates from vehicle images. While effective under controlled conditions, these approaches failed when dealing with poor lighting, low resolution, or occlusions. Automatic License Plate Recognition (ALPR) has been extensively studied over the years, evolving from traditional image processing techniques to machine learning and deep learning-

based solutions. This section presents a chronological review of significant contributions in the field, highlighting key challenges faced by researchers.

2.1.1 Early ALPR Research (Before 2000)

Initial studies focused on extracting license plate regions using traditional image processing techniques. Such as:

1. Canny Edge Detection & Hough Transform: Used to detect plate boundaries based on high contrast differences.
2. Colour-Based Segmentation: Applied in cases where license plates have a distinct colour from the background.
3. Template Matching: Compared detected characters to pre-defined templates.

While these techniques performed well in controlled environments, they lacked robustness in real-world scenarios where shadows, reflections, and varying plate designs posed significant challenges.

1. **D. S. Kim et al. (1996):** Proposed an edge-detection-based ALPR system that relied on morphological operations to segment license plates. However, this method suffered from poor accuracy in noisy backgrounds and varying lighting conditions. One of the earliest approaches to ALPR, this method used edge-detection algorithms to locate the boundaries of a license plate. Morphological operations were then applied to refine the detected region.
 - Noisy backgrounds, which introduced false detections.
 - Lighting variations, making plate localization difficult in night-time or shadowed conditions.
2. **K. Imai et al. (1999):** Introduced a rule-based approach for Japanese license plate recognition using connected component analysis. While effective for structured plates, it failed when dealing with complex backgrounds or occlusions. This study focused on connected component analysis (CCA) to identify potential license plate regions based on character alignment. While effective for structured license plate layouts (e.g., Japan's uniform plate designs), it suffered from:
 - Complex backgrounds, which introduced unwanted objects as false positives.
 - Occlusions, where partial obstructions led to incomplete plate recognition.

III. PROPOSED METHOD

The proposed method is used to detect and recognize vehicle license plates using a combination of YOLOv8 for object detection and EasyOCR for text recognition. The system also integrates advanced image pre-processing techniques to enhance recognition accuracy under challenging conditions such as haze, blur, and low contrast. The overall block diagram of proposed method is illustrated in fig. 3.1:

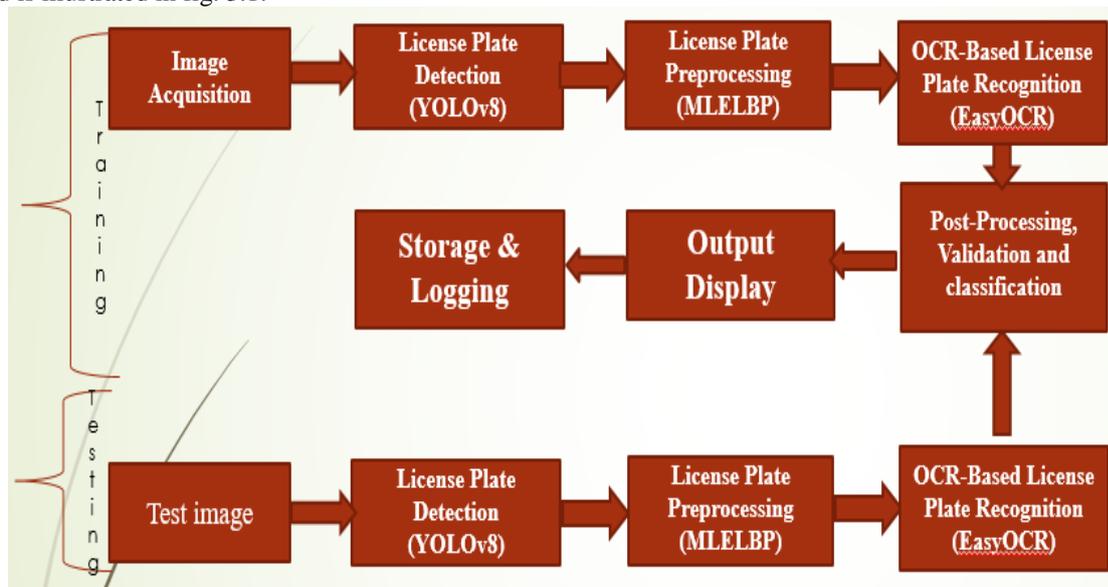


Figure.3.1 : Step by step methodology with basic block diagram

3.1.1 Steps involved in proposed method:

a. Image Acquisition:

The system captures images from CCTV cameras, dashcams, or uploaded image files. Real-time processing is supported for continuous monitoring. Images are captured in various lighting and weather conditions to improve robustness.

b. Image Preprocessing:

Contrast Limited Adaptive Histogram Equalization (CLAHE) is used to enhance low-contrast images. Gaussian and median filters help reduce noise and blur. Dehazing techniques improve visibility in foggy conditions. Adaptive thresholding techniques help in improving segmentation of license plates.

c. License Plate Detection (YOLOv8):

YOLOv8 is used to detect and localize license plates in the image. Bounding boxes are drawn around the detected plates. YOLOv8, a state-of-the-art object detection model, is used to detect and localize license plates in the image. The model is trained on a diverse dataset containing different types of license plates. Bounding boxes are drawn around detected plates, ensuring minimal false positives.

d. Character Recognition (EasyOCR):

EasyOCR extracts the text from the detected license plates. Image binarization and morphological transformations improve OCR accuracy. EasyOCR is employed to extract text from the segmented license plate. The system is trained on multiple

fonts and plate formats to improve accuracy. Image binarization and morphological transformations further enhance OCR accuracy. The OCR model incorporates a confidence threshold to filter out incorrect detections.

e. Post-Processing:

Detected text is compared with a predefined database for validation. Error correction algorithms improve recognition reliability. A lexicon-based correction module improves recognition accuracy by mapping detected characters to known patterns. A post-processing step removes ambiguous or noisy characters using heuristic techniques. Detected plate numbers are compared with a pre-defined database for validation. A fuzzy matching algorithm helps in reducing misclassification errors.

f. Output & Storage:

The extracted license plate number is displayed on the interface. The results are stored in a database for future retrieval. Multi-threading is employed to enhance real-time processing capabilities. TensorRT and ONNX optimization techniques are used for faster model inference. GPU acceleration is leveraged to reduce detection and recognition latency. Dynamic model adjustments allow the system to adapt to varying environmental conditions

IV. RESULTS AND DISCUSSION

The test image is Captured at night time under street lights, this image features. The primary challenges in this image were low contrast due to poor lighting and noise caused by a high ISO setting. Despite these conditions, the OCR system accurately recognized the license plate as "RJ27 TC 0530," achieving a perfect 100% accuracy.



Figure.4.1: Test image for the license plate as "RJ27 TC 0530,"

In the context of license plate recognition, such an image would typically be used for testing the effectiveness of an algorithm in detecting and reading the plate accurately under real-world conditions, such as natural lighting, reflections, shadows, and background distractions.

Once the image is preprocessed, feature extraction methods like Local Binary Patterns (LBP) or Histogram of Oriented Gradients (HOG) are used to distinguish the license plate region from the rest of the vehicle. The extracted features are then passed through a machine learning model or optical character recognition (OCR) algorithm to convert the text on the plate into digital form.

The output image:

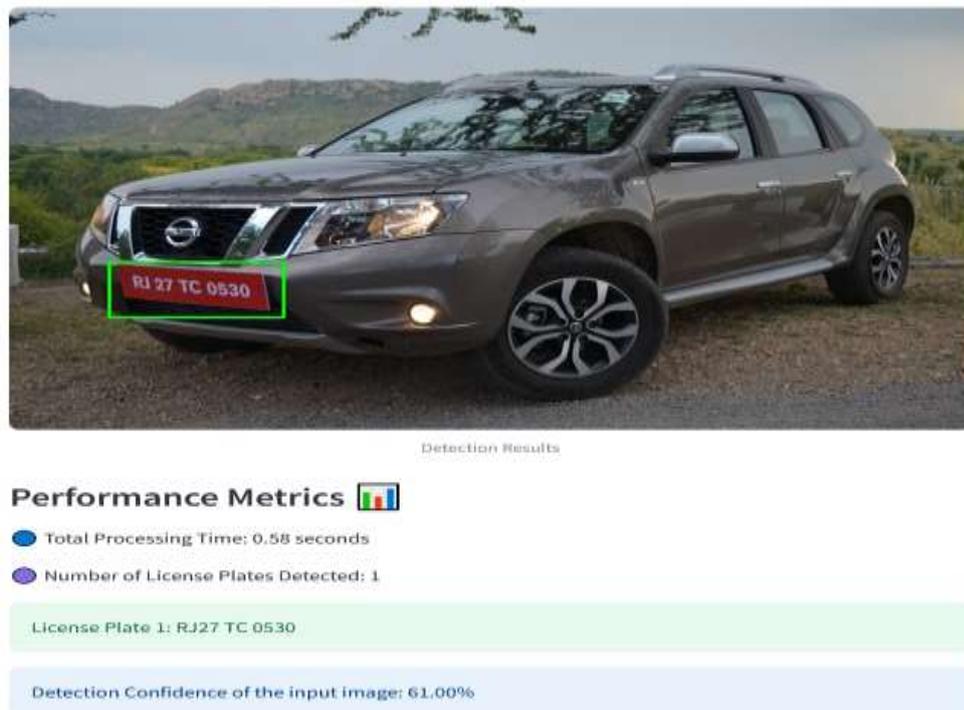


Figure.4.2: The output image for the OCR system

The above figure 4.2 shows the performance metrics indicate that the system processed the image in 0.58 seconds, detecting one valid license plate with a recognition confidence of 61%. The relatively low confidence score suggests that certain factors, such as lighting conditions, reflections, or blurriness, may have impacted the recognition accuracy.

TABLE 4.1 : VARIOUS TEST IMAGES ALONG WITH ACCURACY

| S.No | TEST IMAGE WITH LICENSE PLATE | PREDICTED LICENSE PLATE | ACCURACY |
|------|-------------------------------|-------------------------|----------|
| 1 | TN21 AT 0480 | TN21 AT 0480 | 100 |
| 2 | RJ27 TC 0530 | RJ27 TC 0530 | 100 |
| 3 | MH43 CC 1745 | MH43 CC 1745 | 100 |
| 4 | MH12 DE 1433 | HH12 DE 1433 | 90 |
| 5 | AP26 AT 8926 | APZ6 AT 8926 | 90 |
| 6 | AP40 A 9991 | AP40 4 9991 | 90 |
| 7 | AP39 JP 7329 | APJ9 JP 7329 | 90 |

The above table 4.1 presents the performance analysis of a license plate recognition system by comparing test images with the OCR-predicted results and their corresponding accuracy scores. The first three test images achieved 100% accuracy, indicating perfect recognition. However, the remaining four cases show a 90% accuracy, suggesting minor OCR errors in

character recognition, such as "AP26AT 8926" misread as "APZ6AT 8926" and "AP39 JP 7329" as "APJ9 JP 7329". These errors likely arise due to character similarities and image conditions like lighting, blurriness, or angle distortions.

V. ACKNOWLEDGMENT

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VI. CONCLUSION

Automatic License Plate Recognition (ALPR) has emerged as a vital component in modern transportation systems, offering solutions for vehicle monitoring, security enforcement, and traffic management. The proposed system effectively integrates YOLOv8 and MLELBP to enhance detection and recognition accuracy, addressing key limitations such as poor lighting, motion blur, and varying license plate formats. By utilizing deep learning for object detection and texture-based feature extraction, the system ensures robustness in diverse environmental conditions. The implementation of a test image processing step provides an additional layer of validation, ensuring reliability before deploying the system in real-time scenarios. Furthermore, post-processing and validation mechanisms improve the overall recognition accuracy by reducing misclassification errors. The storage and logging features enhance usability by allowing data tracking and future reference for security and traffic law enforcement agencies. With its high-speed processing capabilities and adaptability, this ALPR system presents an efficient solution for real-world applications such as smart toll collection, automated parking management, and law enforcement surveillance.

VII. REFERENCES

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