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Vehicle Number Plate Recognition using LLM aided OCR

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ABSTRACT

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Automatic Number Plate Detection (ANPD) is essential to contemporary law enforcement and parking management. However, accuracy and efficiency problems plague many of the current ANPD systems. By combining the YOLOv8 object identification model with optical character recognition (OCR) methods and adding a large language model (LLM) for vehicle description, this work presents a sophisticated method. While OCR recovers alphanumeric characters for correct identification, YOLOv8 guarantees quick and accurate plate localization in real time. By offering thorough vehicle descriptions based on identified patterns, like make, model, and colour, the LLM improves the system even more and helps with more thorough vehicle profiling. In addition to increasing accuracy, this combination increases robustness under various circumstances, including variations in lighting, plate orientation, and image quality. Results from experiments demonstrate how well this strategy works in practical situations, enhancing the functionality and performance of ANPD systems for law enforcement and vehicle monitoring.

KEYWORDS: ANPD (Automatic Number Plate Detection), Optical Character Recognition (OCR), You Only Look Once version 8 (YOLOv8), Large Language Model (LLM), vehicle description.

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1. INTRODUCTION

The capacity to swiftly and precisely identify vehicles has become essential in today's fast-paced world, where traffic is always increasing and security concerns are ever-present. By automatically identifying license plates, Automatic Number Plate Detection (ANPD) systems have simplified life by assisting with tasks like parking management, toll collection, and traffic enforcement. These devices are now widely used to guarantee more efficient traffic flow and enhance public safety. But even with their extensive use, a lot of ANPD systems still have trouble with real-world issues including dim illumination, smudged or obscured plates, and various plate shapes. Even if they are proficient at reading license plates, they frequently fail to provide further facts about the car, including its make, model, or colour, which might be very helpful to law enforcement and traffic control.

In order to overcome these drawbacks, this paper presents a more sophisticated system that integrates three state-of-the-art technologies: Optical Character Recognition (OCR) to read the plate numbers, YOLOv5 to swiftly and precisely detect number plates, and a Large Language Model (LLM) to describe the vehicle itself, including its model, color, and brand. Combining these technologies gives the system a more comprehensive picture of the car than just a number, which is useful in real-time scenarios like locating a vehicle that has been involved in an accident or recognizing a fast car.

Even in difficult situations like dim lighting or difficult plate angles, our method seeks to make vehicle identification quicker, more intelligent, and more dependable. These enhancements could make ANPD systems even more effective instruments for maintaining the efficiency and safety of our roads.

2. RELATED WORKS

Deep models and sophisticated algorithms have enabled state-of-the-art developments in ANPR domains. This section lists relevant publications, including approaches and technological advancements connected to the creation of ANPR systems.

Khan et al. (2023)[1] reviews state-of-the-art deep neural network (DNN)-based methods for license plate detection, segmentation, and recognition. The paper delves into the use of convolutional neural networks (CNN), recurrent convolutional neural networks (RCNN), and long-short-term memory (LSTM) networks at different stages of the license plate recognition process. These DNNs demonstrate superior accuracy and adaptability compared to traditional machine learning approaches, as they can manage complex data without requiring handcrafted features. Despite this, the paper emphasizes deep learning models and may under-represent traditional techniques such as OCR.

Dr. R. Kala et al. (2024)[2] present an integrated approach to Automatic Number Plate Detection (ANPD) by combining YOLOv5, a real-time object detection algorithm, with Optical Character Recognition (OCR) techniques. The system involves preprocessing the images, applying edge detection, detecting number plates using YOLOv5, and performing character recognition via OCR. The study reports a high detection accuracy of 95%, making it highly efficient for real-time applications in diverse lighting and environmental conditions.

Fiorita et al. (2024)[3] combine RFID tags embedded in vehicle license plates with computer vision techniques, such as Automatic Number Plate Recognition (ANPR), to enhance vehicle identification and detect illegal vehicles. The study demonstrates increased accuracy in identifying illegal vehicles by reducing errors caused by cloned plates and poor lighting conditions. However, the implementation of this system would require widespread adoption of RFID technology, which may involve significant costs and infrastructure changes. The research verified the system's reliability in identifying vehicles at high speeds and highlighted future work in improving system performance in high-density traffic environments.

Abhishek Tiwari et al. (2024)[4] present a method for Automatic Number Plate and Speed Detection using YOLOv8 and Convolutional Neural Networks (CNN). Their approach involves detecting and extracting license plates with YOLOv8, enhancing image quality with CNN, and utilizing Tesseract for Optical Character Recognition (OCR) to extract text. The system achieves impressive accuracy rates of 98.5% for license plate detection and 96% for speed recognition, although performance may decline under extreme lighting conditions or with heavily distorted plates.

Kumaran et al. (2024)[5] leverage a combination of YOLO for real-time vehicle detection and Haar Cascade for precise number plate identification to enhance Automatic Number Plate Recognition (ANPR) for high-speed vehicles. The study involves collecting and preprocessing images through resizing, normalization, and augmentation to ensure consistency and robustness. This approach achieves a detection accuracy of 97%, making it effective in high-speed scenarios. However, the system faces challenges related to high memory consumption and sensitivity to environmental conditions, highlighting the need for further optimization and scalability improvements.

Shrivastava et al. (2020)[6] propose a CNN-based automated vehicle registration number plate recognition system that preprocesses images by converting RGB to grayscale, applying Sobel edge detection, and performing noise reduction. The system utilizes Hough Transform and morphological operations for plate localization and segmentation. It achieves a high accuracy of around 99%, even with images captured from different angles and under varying conditions. However, system performance may be impacted by poor image quality and diverse environmental factors, highlighting the need for further optimization.

Reddy SP et al. (2021)[7] developed an ANPR system to manage entry and exit, where the image of a vehicle is captured by using a high-resolution camera. Now, the image is again enhanced through the application of Gaussian filters and adaptive thresholding for better image quality. This system recognizes the position of the number plate, applies edge detection, and contour extraction algorithms, further breaking them down into characters, then for segmented recognition. The above system also reduces manual record keeping, thus enhancing accuracy and efficiency. But the performance is capped in terms of poor visibility or distance between the vehicle and the camera and; therefore, it will have to get better in the future for better mass surveillance capabilities in these regards.

Kakani et al. (2017)[8] propose an improved OCR-based automatic vehicle number plate recognition system using a feature-trained neural network. The system combines edge detection, vertical/horizontal band clipping, and skew correction for precise number plate localization, followed by binary image transformation and dilation for character segmentation. It achieves a high recognition accuracy of 94.45% with an efficient processing time of less than 1 second. However, its accuracy is sensitive to environmental conditions, and MATLAB's processing time limits its applicability for real-time systems, despite its adaptability to untrained inputs.

Wang et al. (2024)[9] present a novel license plate recognition framework combining improved YOLOv8 for license plate detection and LPRNet for recognition. By incorporating the Biformer attention mechanism and Depthwise Separable Convolution, the model achieves enhanced efficiency and accuracy. Tested on the CCPD2019 dataset, it demonstrated high performance with a mAP50 of 0.994 and an overall recognition accuracy of 98.05%. The lightweight architecture ensures adaptability for embedded devices, making it suitable for real-world applications in traffic management under diverse environmental conditions.

Uma Maheswari et al. (2022)[10] present an Integrated Number Plate Recognition System that employs threshold-based methods and K-Nearest Neighbors (KNN) for automatic number plate detection and tracking. Their approach utilizes techniques such as morphological operations, contour detection, and various thresholding methods to enhance image processing. The KNN classifier is subsequently applied to improve accuracy in recognizing license plates.

He et al. (2024)[11] propose a vehicle matching algorithm designed to maximize travel time probability using Automatic License Plate Recognition (ALPR) data. The methodology addresses challenges such as recognition errors and unmatched vehicles by integrating modules for travel time distribution estimation, probability computation, and confidence interval analysis.

The algorithm utilizes restricted fuzzy matching and an optimization model to enhance vehicle matching accuracy. Tested under varying lighting and weather conditions, the approach demonstrated superior performance compared to benchmark methods, achieving over 90% accuracy even in adverse scenarios. This work highlights the potential of ALPR data for robust traffic monitoring and vehicle re-identification.

3. METHODOLOGY

In this study, we combine Large Language Models (LLMs) with Optical Character Recognition (OCR) approaches to propose an improved Vehicle Number Plate Recognition (VNPR) system. Using YOLO (You Only Look Once) for object detection, the system can precisely identify license plates and extract pertinent information from photos. The LLM also offers thorough vehicle descriptions. By merging cutting-edge object detection and language models, the goal is to increase the overall accuracy of VNPR systems while guaranteeing reliable performance in security and surveillance applications.

3.1 Pre-Processing

The camera captures real-time images, which undergo several preprocessing steps to enhance their quality and ensure they are suitable for further processing and detection. These steps include:

1.Normalization: Pixel values are scaled to a standard range (e.g., 0-1 or -1 to 1) to ensure uniformity and facilitate better model convergence during training.

2.Contrast Adjustment: Techniques such as histogram equalization or adaptive histogram equalization are applied to improve the visibility of features in low-contrast regions, particularly useful in varying lighting conditions.

3.Noise Reduction: Filters like Gaussian or median filters are used to reduce noise caused by environmental factors, such as rain, dust, or camera sensor imperfections, while preserving important details.

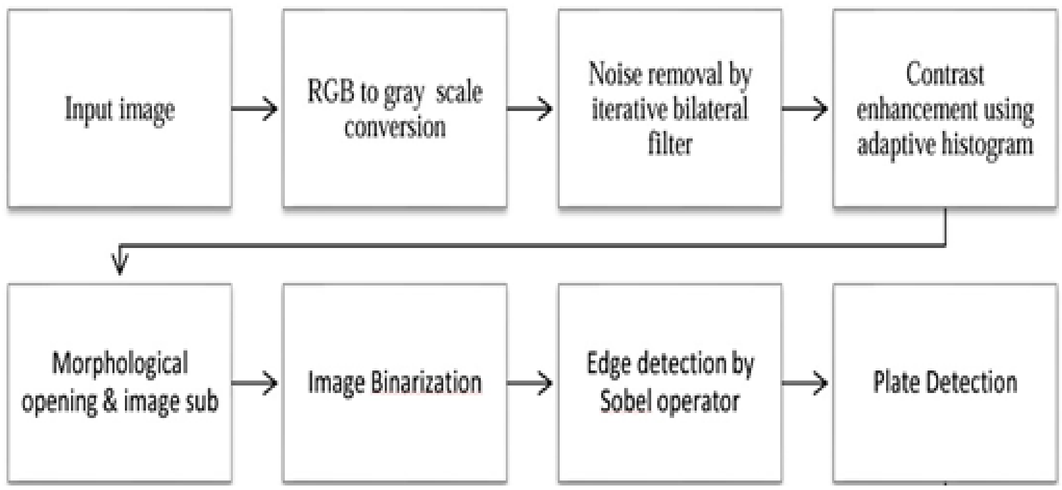

Fig. 1. Dataset Preprocessing Steps

4.Resizing: All images are resized to a fixed resolution to ensure compatibility with the model input layer, often matching the model's expected input dimensions (e.g., 416x416 for YOLO models).
5.Cropping: Irrelevant portions of the image are removed based on ROI (Region of Interest) detection, leaving only the areas likely to contain license plates.

3.2 Plate Detection Using YOLO

The YOLO algorithm separates the plat from its background by identifying it in the captured frame. These models are quick and precise for real-time object detection.

Fig. 2. Detected License Plate

3.3 Number Plate Extraction

After the car has been identified, YOLO is used once more to find and retrieve the license plate. After the number plate has been extracted, it is segmented to separate the individual characters.

The number plate's characters are divided using contour-based techniques. Following segmentation, these characters are recognized using an LLM-based OCR classifier, which guarantees excellent accuracy and lessens confusion between characters that seem alike.

3.5 Database Integration and Real-Time Image Cross-Checking

To save previously taken pictures of license plates and the related owner data, a database is put in place. This database serves as a vehicle identification reference. As previously mentioned, pre-processing and number plate extraction are applied to newly recorded images in real-time. To confirm whether the car is registered, the retrieved license plate is subsequently compared to the database using matching algorithms.

3.6 Alert System for Entry and Exit Times

The system records the vehicle's entry or exit time after the number plate has been successfully verified. The owner of the vehicle then receives real-time warnings about the condition of their vehicle, including access and exit times. By enabling real-time tracking of vehicle movements, this improves security.

3.7 LLM for Vehicle Descriptions

The LLM is used to provide comprehensive details about the identified vehicle, including make, model, and color, in addition to number plate recognition.

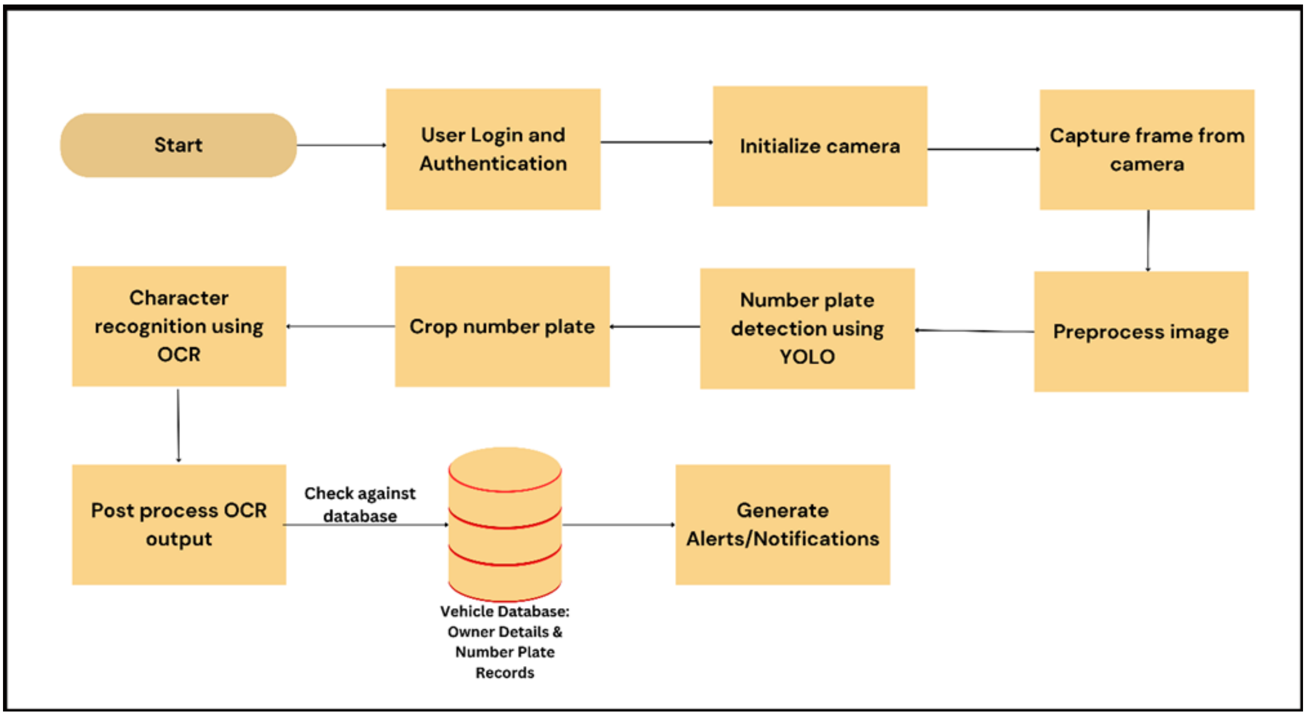

Fig. 3. Proposed System

3.4 Character Segmentation and Recognition

4. MATHEMATICAL MODEL

1.RGB to Grayscale Conversion (Averaging Method):

Gray(x,y)=(R(x,y)+G(x,y)+B(x,y))/3

where R, G, B and are the red, green, and blue pixel values, and Gray is the grayscale output at pixel location (x,y).

2.Edge Detection using Sobel Operator:
The horizontal Sobel operator, T_X, and the vertical Sobel operator, T_Y, are applied to the image B as:

$$T_X=\begin{pmatrix}1 & 0 & -1\\ 2 & 0 & -2\\ 1 & 0 & -1\end{pmatrix}*B \quad T_Y=\begin{pmatrix}-1 & -2 & -1\\ 0 & 0 & 0\\ 1 & 2 & 1\end{pmatrix}*B$$

The edge pixel EG(m,n) is calculated as:

Edge pixel $E_G(m,n)=|C(m,n)* T_x| + |C(m,n)* T_y|$

where C(m,n) represents pixel values of input image.

3.The mathematical function for a 2D convolution operation in image enhancement can be represented as:

$$(I \times K)(x,y) = \sum_{i=-a}^{a} \sum_{j=-b}^{b} I(x-i, y-j) \cdot K(i,j)$$

In this equation, $(I \times K)(x, y)$ denotes the result of the convolution operation at a specific pixel location (x, y) in the output image. I represents the input image, and K is the convolution kernel. The summation is carried out over i and j, where a and b are the half-widths of the kernel in the horizontal and vertical directions, respectively.

5. RESULTS AND DISCUSSION

In this part, we compare the accuracy attained by methods for vehicle number plate identification that have already been put into practice. This comparison makes it easy to see how accuracy has improved over time and demonstrates how well different methods—like deep learning and conventional OCR—work. The accuracy and main algorithms used in each of the techniques examined from the body of current research are compiled in Table 1.

Table. 1 Results of Different Combination of Algorithms

Algorithm	Accuracy (%)
YOLOv5 + OCR	95.2
Faster R-CNN + OCR	91.5
SSD + EAST + OCR	93.7
YOLOv4 + CRNN	94.8
RetinaNet + OCR	92.3
Mask R-CNN + OCR	94.6
EfficientDet + OCR	93.9
Cascade R-CNN + OCR	90.7
YOLOv5 + CRNN	94.8

Table. 2 Average accuracy scores reported in existing work for different datasets.

Papers	Accuracy				
	Caltech Dataset	AOLP Dataset	PKU Dataset	OpenALPR Dataset	SSIG Dataset
CNN Based Methods	85.4	95.3	NA	84.05	8.88
RNN Based Methods	95	94.6	95	NA	NA
YOLO Based Methods	96.9	93.4	NA	94.6	92.75

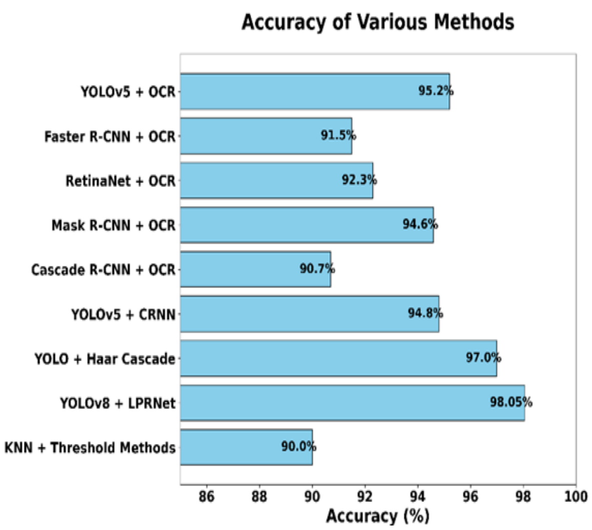

Fig. 3 Accuracy Comparison of Various License Plate Recognition Methods

6. LIMITATIONS AND FUTURE WORK

The VNPR system, while effective, faces limitations such as reduced performance under challenging conditions like low light, glare, or adverse weather, and difficulty handling motion blur from fast-moving vehicles. Its training dataset lacks diversity, limiting accuracy with non-standard or damaged license plates. High computational requirements restrict deployment in resource-constrained settings, and the reliance on pre-trained models limits adaptability to regional formats. Privacy concerns arise from potential data misuse, and adversarial attacks can compromise reliability. Future work should focus on advanced imaging for challenging conditions, improved preprocessing, diverse datasets, lightweight models for scalability, multi-modal data integration, active learning for adaptability, and robust privacy and security measures to enhance system effectiveness and societal impact.

7. CONCLUSION

The suggested VNPR method achieved a number of important and pertinent results. First of all, regardless of the kind of real-world conditions that occurred, it successfully integrated YOLO toward object detection and, in the situation tested, essentially and accurately localized and retrieved number plates. By reducing the errors that are typically present in traditional OCR systems—which are frequently prone to them in cases of similar or unclear characters—LLM-aided OCR dramatically improved character recognition.

Additionally, it provided real-time entry and exit alert timings for the vehicles to the owners and verified proper vehicle identification by cross-checking real-time photos of license plates against an existing database.

Additionally, by accurately describing the car, the LLM enhanced the system's functioning and offered another layer of contextual information that was helpful for security and monitoring.

When compared to traditional methods, the system's whole holistic approach to car detection performed better in terms of accuracy, processing speed, and contextual comprehension.

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