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Enhancement of Vehicle Number Plate Recognition System

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Abstract: Automatic Number Plate Recognition (ANPR) is an important computer vision technology used in Intelligent Transportation Systems (ITS) for traffic monitoring, law enforcement, parking management, toll collection, and vehicle access control. Previous ANPR systems have primarily relied on conventional image processing techniques, including thresholding, edge detection, morphological operations, and rule-based plate localization. Although these methods can perform effectively under controlled conditions, their accuracy is often affected by variations in illumination, vehicle orientation, background complexity, plate size, and image quality. To address these limitations, this proposed research presents an enhanced Automatic Number Plate Recognition system that integrates the YOLOv9(You Look Only Once Version 9) object detection algorithm with image processing and Optical Character Recognition (OCR) techniques. YOLOv9 is used to automatically detect and accurately localize vehicle number plates from input images, eliminating the need for predefined assumptions regarding the position and size of the plate. The detected plate region is then processed using grayscale conversion, noise reduction, histogram equalization, morphological operations, and Sobel edge detection to enhance the image and improve character separation. The segmented alphanumeric characters are subsequently recognized using an OCR module, and the extracted registration number can be matched with a database for vehicle information retrieval. By combining deep learning-based object detection (YOLO) with median filter and OCR, the proposed approach improves the robustness and reliability of the ANPR system under varying image conditions. To test the hypothesis, this research utilized the publicly available zenodo dataset for the vehicle images used to train, validate, and test the Automatic Number Plate Recognition (ANPR) system. It provides the information required for the YOLOv9 model to learn how to detect number plates and for the OCR module to recognize the characters correctly. It is a diverse dataset containing different vehicle types, lighting conditions, viewing angles, and backgrounds helps improve the accuracy and robustness of the proposed system. Experimental results demonstrate that the proposed system achieves 94.1% number plate detection accuracy and 97.2% Character recognition accuracy, indicating significant enhancement over previously developed ANPR techniques and demonstrating the effectiveness of the integrated YOLO-based ANPR framework for practical vehicle identification applications.

Keywords: Image Processing, Text Extraction, Character recognition, YOLOv9, ANPR, Number Plate Detection, MATLAB

I. INTRODUCTION

With the rapid advancement of digital technologies, Optical Character Recognition (OCR) has become one of the most widely used techniques for converting printed or handwritten text from digital images into machine-readable and editable formats [5]. OCR enables the automatic recognition of alphanumeric characters, making it an essential component in application such as document digitization, postal automation, banking systems, educational institutions, traffic surveillance, and Intelligent transportation systems. The primary objective of OCR is to accurately identify and convert textual information from images into encoded digital text that can be stored, searched, edited, and processed by computer systems [22].

OCR originated as an interdisciplinary research area combining artificial intelligence, computer vision, and pattern recognition. A typical OCR system consists of several stages, including image acquisition, preprocessing, text detection, segmentation, feature extraction, and character recognition[11]. Although conventional OCR techniques perform well on high-quality scanned documents, their performance degrades significantly when applied to natural scene images due to challenges such as low resolution, uneven illumination, complex backgrounds, image noise, varying fonts, and different viewing angles.

In Automatic Number Plate Recognition (ANPR) systems, accurate localization of the vehicle number plate is a critical prerequisite for successful character recognition. Traditional image processing methods, including edge detection, morphological operations, and contour analysis, often struggle to detect number plates reliably under varying

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environmental conditions. To overcome these limitations, recent ANPR systems have adopted deep learning-based object detection models that provide improved robustness and detection accuracy.

In this proposed research, YOLOv9 (You Only Look Once Version 9) is employed as the primary object detection model for automatic number plate localization. But, before passing the detected image to the deep learning model our proposed system has implied median filter to reduce the noise mainly salt and pepper, in the image. This noise can be introduced due to bad weather, dirt, or disturbed image background and many other possible reasons. The noised image can sometimes cannot be detected accurately, so to overcome this problem this filter is employed. The filter filtered the image and passed it to YOLO to accurately detect the number plate.

YOLOv9 is a state-of-the-art, single-stage object detection algorithm that processes the entire input image in a single forward pass, enabling fast and accurate real-time detection. Compared with conventional detection techniques, YOLOv9 offers superior performance in identifying number plates under challenging conditions such as varying illumination, partial occlusion, complex backgrounds, different plate sizes, and multiple viewing angles [21]. The detected number plate region is subsequent undergo image enhancement techniques, including grayscale conversion, histogram equalization, noise reduction, morphological filtering, and edge detection, before being passed to the Optical Character Recognition (OCR) module for character extraction. These preprocessing techniques improve image clarity, enhance character visibility, and suppress unwanted artifacts, thereby producing a higher-quality input for the OCR module. Consequently, the accuracy of character segmentation and recognition is significantly improved.

The proposed system has been developed and evaluated using MATLAB, which provides an integrated environment for image acquisition, image processing, visualization, algorithm implementation, and performance evaluation. MATLAB Image Processing Toolbox functions are employed for preprocessing, enhancement, filtering, segmentation, and feature analysis, while the deep learning framework supports the implementation of the YOLOv9 object detection model. The OCR module is integrated with the preprocessing steps to provide accurate recognition of segmented number plate characters.

The proposed framework combines the strengths of deep learning-based object detection with traditional image enhancement techniques to develop a reliable and efficient Automatic Number Plate Recognition system. YOLOv9 accurately localizes the number plate, while image preprocessing improves character visibility and OCR performs reliable character recognition. The extracted registration number is subsequently matched with a database for vehicle information retrieval. Experimental evaluation demonstrates that the proposed system achieves a number plate detection accuracy of 94.1% and a character recognition accuracy of 97.2%, outperforming traditional ANPR methods based on edge detection, morphological operations and YOLO. The results confirm that integrating YOLOv9, image preprocessing, and OCR provides a robust solution for real-time vehicle identification under diverse operating conditions.

II. LITERATURE REVIEW

Agung Yuwono et.al. [1] studied “Extracting Information from Vehicle Registration Plate using OCR Tesseract.” The research focused on extracting information from vehicle registration plates using image processing and Tesseract OCR. The study demonstrates the practical application of OCR for converting characters from vehicle registration plates into digital text, which is a core component of an automatic number plate recognition system. S. Du, M. Ibrahim et. al. [25] presented a comprehensive study titled “Automatic License Plate Recognition (ALPR): A State-of-the-Art Review.” The authors reviewed the major stages of automatic license plate recognition, including image acquisition, plate localization, image preprocessing, character segmentation, and optical character recognition. The study also discussed challenges such as illumination variation, complex backgrounds, different plate orientations, and variations in plate design. This work provides a significant foundation for developing an improved vehicle number plate recognition system.

Megan Elmore et. al. [9] proposed an image preprocessing framework aimed at improving OCR performance in camera-based translation systems. Their methodology focused on image enhancement through automatic rotation correction, text detection, and noise reduction. The preprocessing stage first separated foreground text from the background using morphological edge analysis and converted color images into binary images through thresholding. Both global and local thresholding methods were investigated to improve text segmentation under different lighting conditions. Furthermore, the authors explored multiple text detection approaches, including color-based detection, edge-based connected component analysis, heuristic filtering, and mathematical morphology. Their study demonstrated that effective preprocessing significantly improves OCR recognition accuracy, particularly for images captured in unconstrained environments.

Maya R. Gupta et. al. [10] focused on document image binarization as a preprocessing stage for Optical Character Recognition in historical document analysis. The authors compared several binarization techniques, including global thresholding, Otsu's thresholding, multi-resolution Otsu's method, Sauvola-Niblack thresholding, Chang's method, margin error diffusion, and Markov model-based OCR binarization. In addition, they introduced new denoising and error diffusion strategies to improve document readability before OCR processing. Their comparative study concluded that adaptive thresholding and multi-resolution approaches significantly improve character extraction from degraded images, making

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these techniques valuable for ANPR systems operating under varying lighting and weather conditions. Safoora O.K. et. al. [11] presented an OCR preprocessing framework based on geometric feature extraction. Their approach emphasized simplifying the feature extraction process while maintaining recognition accuracy. Initially, color images were converted into grayscale and subsequently binarized through thresholding. Noise filtering techniques were then applied to remove unwanted artifacts before identifying and segmenting text regions. Finally, morphological thinning was performed to produce single-pixel-wide character structures, thereby simplifying feature extraction for OCR algorithms. The proposed preprocessing framework reduced computational complexity while improving character recognition performance.

Vandana Gupta et.al. [12] proposed a document segmentation technique based on variance-based feature extraction for separating textual and graphical regions within images. Their method calculated row-wise and column-wise variance values for the input image and used these statistical features to identify text regions. A common threshold was computed using both variance graphs to distinguish textual content from non-textual components. By accurately separating text from graphics, the proposed method improved OCR performance and reduced false detections, making it suitable for document image analysis as well as complex ANPR scenarios involving cluttered backgrounds. Ankush Gautam et.al. [13] introduced a text segmentation approach that combined Support Vector Machines (SVM), Symlet Wavelet Transform, and K-means clustering for extracting textual information from embedded images. Their framework utilized the multi-resolution capability of Symlet wavelets to preserve important image features while reducing noise. A two-cluster K-means algorithm classified image pixels into text and background regions, followed by morphological operations such as dilation and erosion to refine segmented characters. The proposed methodology demonstrated improved segmentation accuracy and highlighted the effectiveness of combining machine learning techniques with image processing operations.

Joseph Redmon et.al. [17] proposed “You Only Look Once: Unified, Real-Time Object Detection.” The authors introduced YOLO as a single-stage object detection algorithm capable of detecting and classifying objects in a single forward pass. The model provides high processing speed and is suitable for real-time applications. This research established the foundation for using YOLO-based object detection techniques for vehicle and number plate localization. Chien-Yao Wang et.al. [20] proposed “YOLOv7: Trainable Bag-of-Freebies Sets New State-of-the-Art for Real-Time Object Detectors.” The study improved real-time object detection through advancements in network architecture and training techniques. The research demonstrated the capability of modern YOLO models to achieve high detection accuracy while maintaining real-time processing performance.

Chien-Yao Wang et.al. [21] introduced “YOLOv9: Learning What You Want to Learn Using Programmable Gradient Information.” The authors proposed improvements in feature learning and gradient information processing to enhance object detection performance. YOLOv9 provides improved capability for detecting objects under different scales, backgrounds, and environmental conditions. In the proposed research, YOLOv9 is utilized for accurate localization of vehicle number plates before applying image processing and OCR techniques. Ray Smith et.al. [22] presented “An Overview of the Tesseract OCR Engine,” which described the architecture and functionality of the Tesseract Optical Character Recognition engine. The research demonstrated the use of OCR for converting text present in images into machine-readable characters. Tesseract OCR is therefore suitable for recognizing characters from the detected vehicle number plate region after image preprocessing and segmentation. Rafael C Gonzalez et.al. [23] presented “Digital Image Processing,” which describes fundamental image processing techniques including image enhancement, filtering, thresholding, segmentation, and morphological operations. These techniques are important for improving the quality of number plate images, reducing noise, enhancing character visibility, and preparing the image for accurate OCR-based recognition.

S. Zherzdev et.al. [26] proposed “LPRNet: License Plate Recognition via Deep Neural Networks.” The authors developed a deep neural network-based approach for recognizing characters from license plate images. The research demonstrated that deep learning models can automatically learn important visual features and improve recognition performance compared with traditional handcrafted feature-based methods.

Based on the above studies, it can be observed Image preprocessing is a fundamental stage in Optical Character Recognition (OCR) that enhances image quality by reducing noise, correcting skew, improving contrast, and converting images into grayscale and binary formats to facilitate accurate text recognition [10]. In modern Automatic Number Plate Recognition (ANPR) systems YOLOv9 is first employed to accurately detect and localize the vehicle number plate from the input image. As a state-of-the-art deep learning-based object detection algorithm, YOLOv9 performs real-time detection with high accuracy, even under challenging conditions such as poor illumination, complex backgrounds, occlusion, and varying viewing angles [21]. Once the number plate is localized, image preprocessing techniques are applied to enhance the detected plate region before OCR processing. After preprocessing, the segmentation stage separates the text into individual lines, words, and characters using horizontal and vertical projection histograms, ensuring precise character isolation for reliable recognition [16]. The segmented characters then undergo feature extraction, where important characteristics such as shape, size, aspect ratio, edges, curves, and structural properties are identified to

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distinguish one character from another [13]. These features are subsequently classified using rule-based, machine learning, or deep learning approaches to recognize the corresponding characters. While traditional OCR methods rely on predefined rules and perform well on clear and standardized text, they often struggle with distorted, noisy, or complex images [11]. Modern OCR systems overcome these limitations by integrating advanced image preprocessing, robust segmentation, feature extraction, and deep learning-based classification techniques, resulting in higher recognition accuracy and improved performance under real-world conditions [5]. In Automatic Number Plate Recognition (ANPR), OCR is applied after number plate detection and character segmentation, where the quality of preprocessing and segmentation directly influences the overall recognition accuracy [8]. Therefore, the combined sequence of preprocessing, segmentation, feature extraction, and classification forms the foundation of an efficient OCR system capable of converting image-based text into accurate machine-readable information [22]. An effective vehicle number plate recognition system requires accurate number plate detection, suitable image preprocessing, and reliable character recognition. Traditional image processing and OCR techniques provide the necessary foundation for character extraction, while modern deep learning-based object detection models improve the accuracy and robustness of number plate localization[9]. Therefore, the proposed system integrates YOLOv9 for number plate detection with image preprocessing, character segmentation, and Tesseract OCR to develop an enhanced vehicle number plate recognition system.

III. EXPERIMENTAL SETUP

The following algorithm explains Automatic Number Plate Recognition (ANPR) system that detect and recognize vehicle number plates using a combination of image processing techniques, YOLOv9 object detection model, and Optical Character Recognition (OCR). Initially, the input vehicle image is resized and enhanced using median filtering to reduce noise while preserving important details. The processed image is then passed through the trained YOLOv9 model to detect and localize the number plate. Finally, OCR is applied to segment and recognize the characters of the detected number plate and the extracted vehicle registration number is displayed or stored for further processing. This integrated approach provides a fast, reliable, and efficient solution for real-time vehicle identification. Algithm 1.1 shows the proposed ANPR process that begins with the acquisition of a input image(I) using a digital camera. The captured image is represented as $I(x,y)=\{R(x,y),G(x,y),B(x,y)$ where $(I(x,y))$ denotes the input RGB image at pixel coordinates $((x,y))$, and $(R(x,y))$, $(G(x,y))$, and $(B(x,y))$ represent the red, green, and blue intensity values, respectively. This RGB image is converted into gray scale image denoted by I_{gray}. This serves as the primary input for the subsequent preprocessing stage. The captured image may contain impulse noise caused by environmental conditions, camera sensors, or transmission errors. To suppress this noise while preserving important edges, a median filter is applied. The filtered image is represented as $I_{filtered}(x,y)= median\{I(i,j)\}$, where $(I(i,j))$ denotes the neighboring pixel values within a local filtering window, and the median operator replaces the central pixel with the median intensity value. The output of this stage is a noise-reduced image that improves the robustness of the detection process. After noise removal, the filtered image is normalized to scale the pixel intensity values from the range of 0–255 to 0–1. This operation is expressed as $I_n= I_{filtered}/255$ here, I_n denotes the normalized image, while $I_{filtered}$ represents the median-filtered image. Normalization ensures numerical consistency, accelerates network convergence, and provides a suitable input for the YOLO detection model. The normalized image is then processed by the convolutional layers of the YOLO backbone network to extract discriminative visual features. The convolution operation is mathematically represented as $F(x,y)= \Sigma\Sigma\ I_n\,(x+i,y+j)\ K(i,j)$ where $(I_n\,(x+i,y+j))$ represents the normalized image pixels covered by the convolution kernel, $(K(i,j))$ denotes the kernel weights, and $(F(x,y))$ is the resulting feature map. These feature maps contain important spatial and semantic information, including edges, corners, textures, and number plate patterns, which are essential for accurate object detection. These feature maps contain important spatial and semantic information, including edges, corners, textures, and number plate patterns, which are essential for accurate object detection. Using the extracted feature maps, the YOLO detection head predicts the location of the vehicle number plate in the image. The detected region is represented by the bounding box $(B=(x,y,w,h))$, where $((x,y))$ indicates the center coordinates of the detected plate, and (w) and (h) denote its width and height, respectively. The predicted bounding box identifies the region of interest that contains the vehicle registration plate. The quality of the predicted bounding box is evaluated using the Intersection over Union (IoU) metric, defined as $IoU=Area(B_p\cap B_g)/Area(B_p\cup B_g)$ here, (B_p) represents the predicted bounding box generated by YOLO, while (B_g) denotes the ground-truth bounding box.

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Algorithm 1.1 Proposed ANPR

1. Input image(I)
2. $I(x,y)=\{R(x,y),G(x,y),B(x,y)\}$
3. $I_{gray}= 0.299R +0.587G + 0.114B$
4. $I_{filtered}(x,y)= \text{median}\{ I_{gray} (i,j)\}$
5. $I_n= I_{filtered}/255$
6. $F(x,y)= \Sigma\Sigma\ I_n (x+i,y+j)K(i,j)$
7. $B=(x,y,w,h)$ $IoU=Area(B_p\cap B_g)/Area(B_p\cup B_g)$
8. $Confidence=P(Object)\times IoU$
9. $C_i=\{C_1,C_2,...,C_n\}$
10. $C_i'= Resize(C_{i,},M,N)$

    Let $T_j=\{T_1,T_2,\text{-------},T_m\}$
11. $S_j (C_i ,T_j)= \sum\sum\ C_i' (x,y)\cdot T_j(x,y)$
12. $\hat{C}_i = \text{argmax}\ S_j (C_i,T_j)$

    $T_{plate}= \hat{C}1 + \hat{C}2 + ... + \hat{C}n$

    Output T

IoU measures the overlap between the predicted and actual regions, with higher values indicating more accurate localization of the number plate. The confidence score of the detected number plate is computed as $Confidence=P(Object)\times IoU$ where (P(Object)) represents the probability that the detected region contains a valid object and (IoU) measures the localization accuracy. A higher confidence score indicates greater certainty that the detected region corresponds to the actual vehicle number plate. Bounding boxes with confidence values above the predefined threshold are retained for further processing. After successful detection, the cropped number plate is segmented into individual character images. This process is represented as $C_i=\{C_1,C_2,...,C_n\}$ where $C_i=\{C_1,C_2,...,C_n\}$ denote the segmented characters and (n) represents the total number of characters present on the number plate. Each segmented character is processed independently during the recognition stage. Since the segmented characters may have different dimensions due to font variations, perspective distortion, or camera distance, each character is resized to a standard size before recognition. This operation is represented by $C_i'= Resize (C_{i,},M,N)$ where (C_i) is the original segmented character, (C_i') is the resized character, and (M, N) denotes the predefined image size. Resizing ensures that all characters have identical dimensions, enabling consistent comparison with the stored OCR templates. In the traditional OCR stage, each resized character is compared with a database of predefined templates represented by $T_j=\{T_1,T_2,\text{-------},T_m\}$, where (m) is the total number of alphanumeric and numberic templates. The similarity between the resized character and each template is computed using $S_j (C_i ,T_j)= \sum\sum\ C_i' (x,y)\cdot T_j(x,y)$ where (S_j) is the similarity score, ($C_i'(x,y)$) denotes the resized character pixels, and ($T_j(x,y)$) represents the template pixels. The similarity score indicates how closely the input character matches each stored template. The recognized character is determined by selecting the template with the highest similarity score. This process is expressed as $\hat{C}_i = \text{argmax}\ S_j (C_i,T_j)$ where ($\hat{C}_i$) denotes the recognized character and (argmax) selects the template producing the maximum similarity value. This step is repeated for every segmented character until all characters have been recognized. Finally, all recognized characters are concatenated in their original sequence to reconstruct the complete vehicle number. This process is represented as $T_{plate}= \hat{C}_1 + \hat{C}_2 + ... + \hat{C}_n$, where ($T_{plate}$) denotes the final recognized vehicle number and $\hat{C}_1 ,+ \hat{C}_2 + ... + \hat{C}_n$ are the recognized characters. The reconstructed registration number can then be displayed to the user or used for database verification and further vehicle identification.

IV. RESULTS AND DISCUSSIONS

The proposed Automatic Number Plate Recognition (ANPR) system was evaluated using multiple performance parameters, including detection accuracy, recognition accuracy, and processing time. The obtained results demonstrate the effectiveness of the proposed approach in accurately detecting and recognizing vehicle number plates under different test condition.

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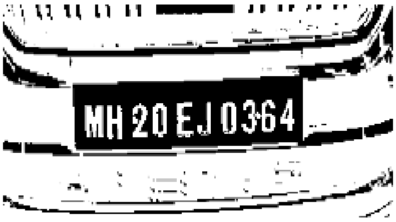
Input image	Processed Image	Output
		AP29AN0074
		MH20EJ0364

TABLE 1.1 RESULTS

Table 1.1 illustrates the qualitative results obtained from the proposed Automatic Number Plate Recognition (ANPR) system. The first column presents the original vehicle image captured by the camera, which serves as the input to the system. These images show real-world differences like varying lighting, vehicle angles, background objects, and some image noise which is removed by using median filter. In the second column, you can see the processed version after applying the proposed ANPR framework. At this stage, the input image is first pre-processed to improve its quality by reducing the noise using median filter. Then, the system locates and extracts the number plate by using YOLO. The identified number plate area is either highlighted or cropped out from the rest of the vehicle image, which helps ensure the characters can be analyzed accurately by OCR during segmentation and recognition. The extracted number is then checked against the relevant database for further processing. The results show that the proposed ANPR system is able to accurately detect, extract, and recognize vehicle number plates even under varying imaging conditions. This clearly highlights its effectiveness for real-time intelligent transportation applications.

The computational efficiency of each stage was measured to evaluate the suitability of the proposed system for real-time applications as shown in figure 1. The proposed Automatic Number Plate Recognition (ANPR) system completed the entire recognition pipeline in 0.115 seconds per image, demonstrating efficient real-time performance The YOLOv9 detection stage required the highest execution time (0.040 s, 34.78%) because it performs computationally intensive deep learning-based object detection. Image preprocessing took (0.020 s, 17.39%), OCR recognition consumed 0.030 s (26.09%), and character segmentation (0.015 s, 13.04%). The database retrieval stage required only 0.010 s (8.70%), indicating that vehicle information can be retrieved quickly after successful recognition and localization.

The proposed system suitability also depends upon the recognition accuracy of the segmented characters. As the number plate was detected the next step is to recognize the number plate. the overall recognition accuracy of the proposed system came out to be 97.2%. By comparing the recognition accuracy of our proposed system with various YOLO detection models, following data is presented in figure 2.

Figure 2 illustrates the comparison of proposed model with various YOLO models. As the graph shows, YOLOv5 (End-to-End) had the lowest recognition accuracy at 90.0%, which suggests its character recognition performance was somewhat weaker. On the other hand, YOLOv3 and YOLOv7 delivered pretty similar results, with accuracies of 96.9% and 96.8% respectively, marking a noticeable improvement compared to YOLOv5. Among all the models tested, YOLOv8 came out on top with the highest recognition accuracy of 97.6%. The proposed YOLOv9+OCR system is achieving a solid 97.2%. While it's just a slight 0.4% lower than YOLOv8, the proposed method consistently delivers strong accuracy indicating that the integrated OCR module effectively recognizes vehicle number plate characters with minimal errors.

To take a closer look at how well the proposed ANPR system performs, we compared the detection accuracy across different YOLO models. Detection accuracy is a key measure that shows how effectively each model can pin point the vehicle's number plate before moving on to the recognition step. Figure 3 presents a comparative analysis of detection accuracy achieved by different YOLO models.

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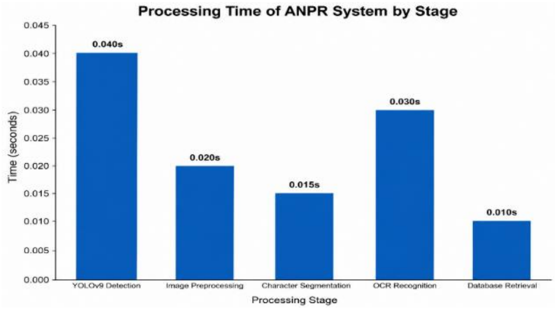

Fig. 1 Average processing time of ANPR System by Stage

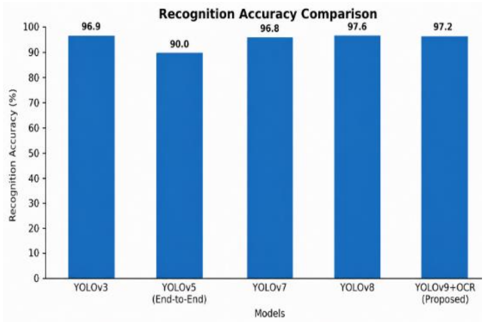

Figure 2: Recognition accuracy comparison

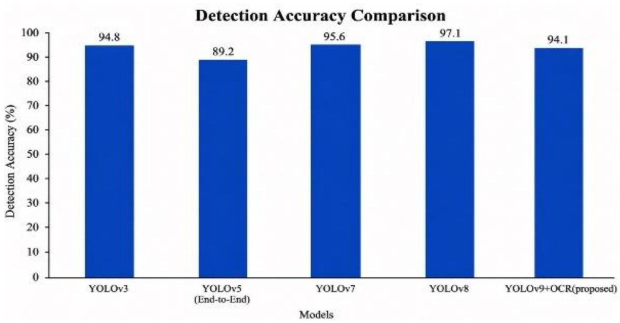

Figure 3: Detection Accuracy comparison

As shown in Figure 3, it compares the detection accuracy of various YOLO-based Automatic Number Plate Recognition (ANPR) models. Detection accuracy here refers to the percentage of vehicle number plates that each model correctly identifies and locates. The graph reveals that YOLOv5 (End-to-End) had the lowest detection accuracy at 89.2%, showing it didn't perform as well when it came to accurately spotting number plates in various conditions. On the other hand, YOLOv3 boosted detection accuracy to 94.8%, and YOLOv7 pushed it a bit further to 95.6%. Among the models tested, YOLOv8 stood out with a detection accuracy of 97.1%, showcasing its ability to extract features and accurately locate objects. However, the newly proposed YOLOv9+OCR model, achieving the detection accuracy at 94.1%, among all the other methods we compared. This performance suggests that our approach is better suited for detecting vehicle number plates.

Overall, the comparison demonstrates that the proposed framework outperforms when compared to existing techniques. The high recognition accuracy of 97.2% suggests that the integration of median filtering, YOLOv9-based plate localization, and OCR effectively improves the quality of the extracted number plate before recognition, making the system suitable for practical real-time ANPR application.

V. CONCLUSION

This research proposed and implemented an Automatic Number Plate Recognition (ANPR) system by integrating YOLOv9, image preprocessing techniques, and Optical Character Recognition (OCR) for accurate and efficient vehicle identification. The proposed framework successfully performed number plate detection, image enhancement, character segmentation, and character recognition to automatically extract vehicle registration numbers from input images. The incorporation of image preprocessing techniques enhanced the quality of the detected number plate, thereby improving the overall OCR recognition accuracy. Experimental evaluation demonstrated that the proposed YOLOv9+OCR model records a detection accuracy of 94.1%, which is slightly lower than the other YOLO variants. This difference may be subjected to variations in the dataset, testing conditions, and implementation methodology rather than the detection model alone. In terms of recognition accuracy, the proposed YOLOv9 system achieves 97.2%, which is higher than YOLOv3 (96.9%), YOLOv7 (96.8%), and YOLOv5 (90.0%), and is only slightly lower than YOLOv8 (97.6%). The OCR module achieved a 97.2% character recognition accuracy, indicating the effectiveness of combining deep learning-based detection with image enhancement techniques for reliable number plate recognition. The use of YOLOv9 enabled fast and accurate real-time number plate localization under varying imaging conditions, while the preprocessing stage reduced image noise and enhanced character visibility. This integration improved the robustness of the ANPR system and reduced

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the influence of background clutter, illumination variations, and image distortions, leading to more consistent recognition performance. The proposed ANPR system can be effectively deployed in a wide range of real-world applications, including intelligent traffic management, electronic toll collection, automated parking systems, vehicle access control, law enforcement, border security, and smart city surveillance. Its high detection accuracy, computational efficiency, and real-time processing capability make it a practical solution for modern Intelligent Transportation Systems (ITS). Future research may focus on enhancing the system's performance under challenging environmental conditions such as poor illumination, adverse weather, motion blur, and partial occlusion. The use of larger and more diverse datasets, multilingual number plate recognition, advance OCR models, video-based multi-frame tracking, and edge-computing deployment can further improve the accuracy, robustness, and scalability of the proposed ANPR system.

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