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Vehicle License Plate Detection and Recognition

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Abstract—The objective of the paper is to propose an approach for a real-time accurate Automatic Number Plate Recognition(ANPR) system, which recognizes vehicle license plates. The system is based on a common vision concept that combines Optical character recognition (OCR) and YOLOv9 deep learning algorithm. Intended to overcome challenges including poor light, partial obstruction, and different angles for high-speed vehicle plate recognition over multiple regions. This means that not only is the architecture future-friendly for license plate designs, but it will also work with existing infrastructure so this can be deployed in traffic management, law enforcement, and security use cases.

Keywords—automatic number plate recognition, YOLOv9, deep learning, optical character recognition, and intelligent transportation systems.

I. INTRODUCTION

Increased vehicles on urban roads require the use of modern technologies for optimal traffic management and safety. Nowadays, ANPR techniques have to be applied in real-time for a variety of applications ranging from law enforcement and automated toll collection. But traditional methods also have accuracy problems in environments where lighting levels differ like low-light and partial occlusion [1]. However, in recent deep learning developments such as the YOLO architecture has achieved remarkable results for real-time object localization and detection hence making it an ideal candidate to employ with ANPR applications[2].

This paper proposes a robust ANPR system using the YOLOv v9 deep learning algorithm and optical character recognition combined approach. Our method is developed to be robustly generalizable on different regions and processing high-speed vehicle plates, with the objective of achieving a good compromise between recognition performance at a large set of conditions. Adaptive architecture enables seamless integration with in-place infrastructure optimally catering for upcoming changes into license plate designs [3]. These findings indicate the capacity of YOLO solutions in terms of improving urban traffic management strategies [4].

II. RELATED WORKS

Twana Mustafa and Murat Karabatak (2024) have presented a system that could detect the vehicle make model with 97.5% accuracy in addition to Automatic Number Plate Recognition utilizing MobileNet-V2, YOLOx, PaddleOCR, and SVTR-tiny frameworks They used Grad-CAM to visualize the detected features, which is often used for further interpreting decision boundaries and regions of interest from an input image. However, their method had to face challenges regarding the changing weather conditions leading to unreliable recognition under actual-world situations; e.g., images might have different resolutions and would be processed at exceeding progress times [5].

Ming-An Chung, Yu-Jou Lin, and Chia Wei Lin (2024), boosted with YOLOv7 integrated SimAM showed an accuracy increase of 0.47% starting from 98.44% to now more than that at 98.91%. This Integration Demonstrated Benefits from Advanced Techniques in Detection Performance, However, the Performance of the System Deteriorated at Extended Distances and for Those Images with Varying Illumination and Angular Conditions Denoting Limited Functionality Capabilities Across Operational Contexts [6].

Shan Luo and Jihong Liu (2022) is capable for accurately recognizing the hand-drawn character at a rate as high as 99.49% in accuracy, and recall of up to 98.79%, with processing speeds at up to forty-two images per second Their method used an improved YOLOv5m combined with LPRNet, mainly tested on the vehicleLSWCC dataset. While the results were impressive, this to a larger extent

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concerned only blue license plates and was predominantly unsupervised and evaluated based on the CCPD dataset that brought along an inspiration of skepticism toward their plan may generalize well across wider variance in plate types and conditions [7].

Tae-Moon Seo and Dong-Joong Kang (2022) achieved a better result: an accuracy of more than 98.6% for license plate detection based on CenterNet equipped with AFDN, combined with optical flow method & attention mechanism base recognition network Although with these positive results, they pointed out that using such a system in any of the outdoor real-world scenarios could be very challenging as an overlap for recognition performance which may drop significantly due to dynamic nature in outdoor conditions. This underscores the necessity of ANPR systems that can provide a versatile approach to behaving in changing environmental conditions — enhancing accuracy requirements [8].

Shi et al. (2023) utilized the new YOLOv5 model with GRU-CTC and reached a recognition accuracy 98.98%. Although this system exceeded the traditional algorithms, it depended significantly on training and test cases within a certain restricted domain of interest that limited its ability to be used in various environments. This highlights the need for training techniques which are robust to such variances in real-world data [9].

Yang Yang Lee, Mohd Nadhir Ab Wahab, and Zaini Abdul Halim(2022) used the Design of Experiments (DOE) with YOLOv3 to get a remarkable accuracy of 97.9% In the Malaysian vehicle license plate detection. However, it was limited to Malaysian registration plates only and therefore the methodology did not cater for a broader geographical market [10].

Ibrahim H El-Shal, Omar M Fahmy, and Mustafa A. Elattar (2022) by using the Generative Adversarial Networks (GANs) and Super-Resolution approach made a dramatic increase in character segmentation result for License Plate recognition with an accuracy of 98%. Though it did precisely upgrade the quality of images after processing, their system performed poorly in regular world conditions which served as a need [11].

Wei Jia and Mingshan Xie obtained 98.8% accuracy for detecting license plates but were unable to maintain lower computational costs as they used stochastic multi-scale image detail boosting Their model worked, but its performance dropped significantly in the case of strong deformation and enormous scale reduction that eventually rendered it impractical for all sorts of conditions [12].

Muhammad Murtaza Khan et al. With their approach to number plate detection and recognition using methods based on the highest possible-depth neural network, Osareh et al. [48] reported achieving an accuracy of up to 97.9%. — (2023) Although they too addressed the environmental effects of fog and motion on recognition performance, their work focused solely on neural network approaches pointing to a wider scope for exploration with more hybrid methods [13].

Muhammad Murtaza Khan and coauthors including Muham-mad U. Ilyas Ishtiaq Rasool Khan Saleh M. Alshomrani Susanto Rahardja [20] have been developed for automatic license plate recognition in which they used a couple of deep learning methods; Deep Neural Networks (DNNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory(LSTM)achieved an accuracy rate of 94% at 98.4%. Although it worked well, this strategy demanded an enormous amount of training data — a key challenge for any real-world use case. This exemplifies the continuing difficulty in sourcing varied datasets to train effective ANPR systems [14].

III. PROPOSED MODULES

An automatic number plate recognition (ANPR) system plays a key role in upcoming intelligent transportation systems. In this section, we give an overview of the architecture and operational components for our YOLOv9-based ANPR system that are integrated with best-known deep learning methods in vehicle detection as well as license plate recognition. The system is made to work in a number of adversarial real-world conditions, including varying environmental settings and high vehicle speeds. The goal is to achieve license plate recognition with high accuracy and in real-time using advanced algorithms and powerful preprocessing methods [15].

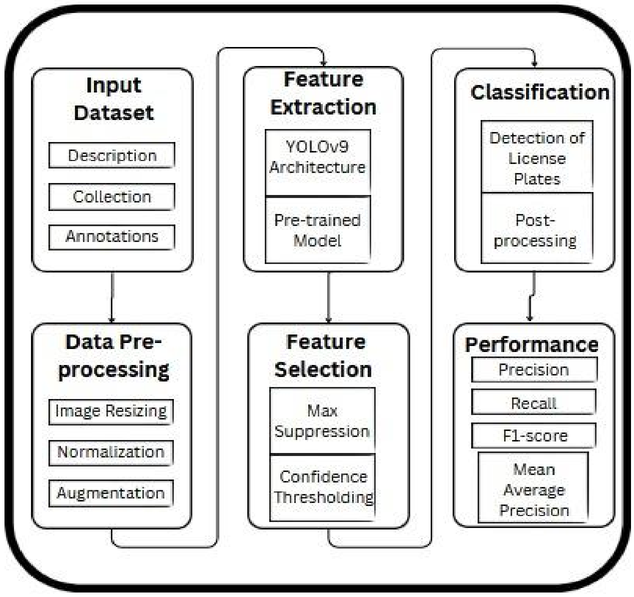

Fig 1: ANPR System Architecture

A. SYSTEM OVERVIEW AND ARCHITECTURE

The architecture of the YOLOv9-based ANPR system consists of three primary components:

Input Dataset: The Beginning with a large labeled image dataset gathering real-world conditions (daylight, alternates in the weather). This makes sure the dataset is diverse and hence allows the model to generalize well across different lighting, weather, or occlusion conditions. License plate and Object detection training with YOLOv9 model, In order to train the yolov4-tiny-lp vehicle/ Licence matlab labels is used during image annotation for vehicles. lb. The dataset should account for environmental occlusions and POV angles as well like we can see other objects, vehicles on the road, or screens in case of Autonomous vehicles [16].

Data Pre-processing: Before training, the input dataset undergoes pre-processing steps to ensure uniformity and enhance model performance. Key techniques include image resizing to standard dimensions, normalization to balance pixel intensity, and augmentation such as rotation, flipping, scaling, and Mosaic augmentation. This pre-processing helps the model better generalize across varied conditions and prevents overfitting.

Feature Extraction: The input dataset is processed in pre-processing steps before training to achieve homogeneity and improve the performance of ML models. Some of the key techniques are changing image size to standard (only for some algorithms, but most now support any shape), normalization as in normalizing all values between 0–1 or -1–+1, Data augmentation methods that include rotation, flipping, and scaling, etc. Mosaic Augmentation is used very extensively today which concatenates four different images into one output tremendously useful for resizing a training dataset tenfold. This preprocessing step allows a model to better generalize across different conditions, preventing overfitting [19].

Feature Selection: In the feature selection part, NMS and a confidence threshold are used. The NMS suppresses redundant bounding boxes by keeping only the highest-confidence predictions that overlap with a detected object. Its confidence thresholding doesn't keep any predictions unless they have a high probability, which improves detection performance. This step is for maintaining system efficiency and correcting multiple objects that can be uniquely identified while simultaneously detecting license plates in complex scenes.

Classification: The production model uses these features and classifies non-license plate/car blocks, which are then passed through the stages that detect the plates. Anchor-free detection of YOLOv9 simplifies the bounding box prediction process by making it faster and more accurate computationally. Post-processing: At the end, as a part of post-processing we will integrate Optical Character Recognition(OCR) to convert the detected license plates into machine-readable text. EasyOCR is applied in charge of processing image recognition with the extractive and decoding characters so that numbers on the plate can be recognized accurately for further process steps.

Performance Metrics: Several performance metrics are used to evaluate the system such as precision, recall, and F1 Score, Mean Average Precision(mAP). These metrics offer a more detailed look into the detection performance of the system, especially in how well it generalizes to plates under different conditions. Precision (The percentage of correct detections) Recall (Percentage of actual plates detected) The F1-score is a balance between precision and recall that you will combine with mAP, which summarizes performance across all classes.

B. DATA COLLECTION AND PREPROCESSING

The training dataset: 5,000 labeled images representative of a wide range of conditions:-

Multiple Conditions: The dataset contains images captured under different lights day and night, rainy weather, or fog.

View angles and Occlusions: Different view angles and positions along the obstructions like other vehicles in front or behind, Environmental objects, etc [18].

Dataset Type	Number of Images	Augmentation Techniques
Training	3,500	Rotation, Scaling, Mosaic
Validation	1,000	Flip, Blur
Test	500	None

TABLE I: DATASET DETAILS

C. YOLOv9 MODEL ARCHITECTURE

The YOLOv9 model is designed with several key components:

Backbone (CSPNet): It is a structure to extract features from the input image, showing the importance in detecting small and distant license plates [19].

Anchor-Free Detection: The model is based on an anchor-free approach which simplifies the bounding box prediction making it computationally faster.

Mosaic Augmentation: This is a method to combine together multiple images into one image in order for the model to expose training examples with more diversity and hence easier detection of small objects..

Loss function From the off-set, the loss function used for training consists of complete Intersection over Union (CIoU) loss [20]:

$$L_{total} = L_{cls} + L_{loc} + L_{obj}$$

The CIoU Loss formula is given by:

$$CIoU = IoU - \frac{\rho^2(b,b^*)}{c^2} - \alpha v$$

Where:

IoU: Intersection over Union

ρ: Distance between the centers of predicted and ground truth bounding boxes

c: Diagonal of the smallest enclosing box

v: Aspect ratio difference penalty

In this formula, IoU is the Intersection over Union, b and b* represent the centers of the predicted and ground truth bounding boxes, ccc is the diagonal of the smallest enclosing box, and v penalizes differences in aspect ratio [20].

D. TRAINING AND VALIDATION SETUP

The system was trained on Tesla T4 GPUs with the following parameters: Batch Size: 16 and Epochs: 25.

Optimizer: Stochastic Gradient Descent (SGD) with momentum of 0.937 Learning Rate: 0.01

During training, various metrics, such as Mean Average Precision (mAP) and loss curves, were monitored to assess model performance and guide hyperparameter adjustments. The validation set was used to evaluate the model's generalization capabilities, ensuring it performs well on unseen data.

IV. RESULTS AND DISCUSSION

A. QUANTITATIVE RESULTS

The YOLOv9-based Automatic Number Plate Recognition (ANPR) system demonstrated high accuracy and real-time performance on the test set. The performance metrics of the system are summarized in Table 2.

Metric	Value
Precision	92%
Recall	87%
mAP@0.5	89.5%
mAP@0.5:0.95	71%
Inference Time	35 ms/frame

TABLE II: PERFORMANCE METRICS

B. GRAPHS AND VISUALIZATIONS

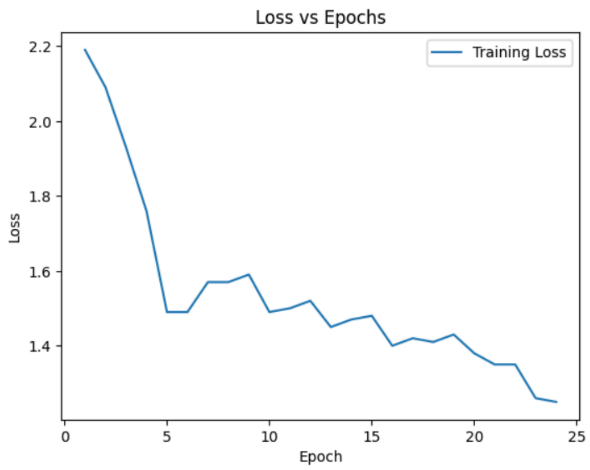

Fig 2: Loss vs Epochs Graph

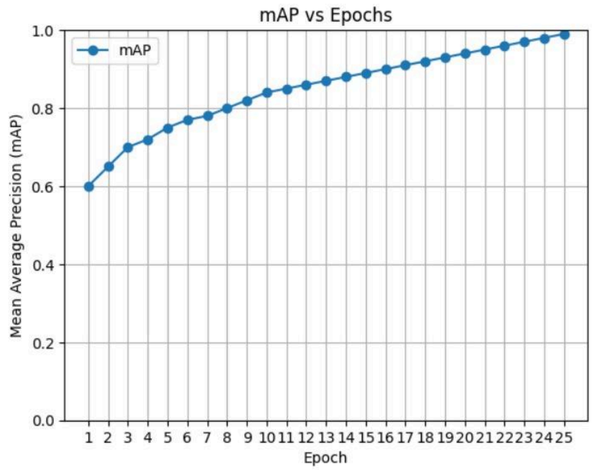

Fig 3: mAP vs Epochs Graph

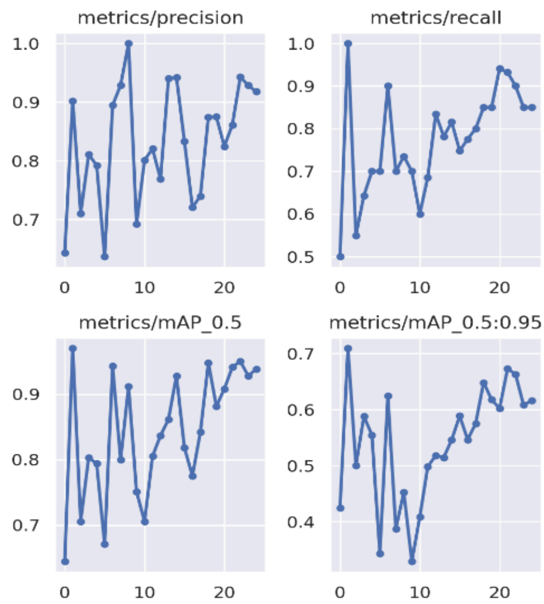

Fig 4: Training and validation loss curves along with performance metrics (precision, recall, mAP) over the epochs for YOLOv9-based ANPR system

C. CONFUSION MATRIX ANALYSIS

The confusion matrix in Figure 5 presents the classification results for discovered license plates and gives information on how well (or not) the model precision and recall behave over different working points of the test set.

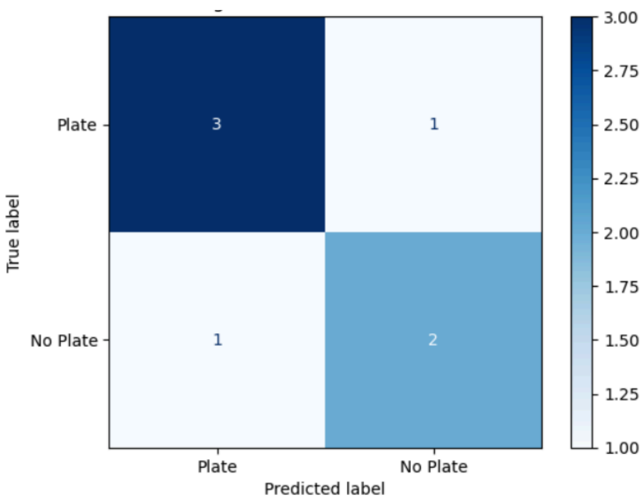

Fig 5: Confusion Matrix

The F1 score is calculated using the following formula:

$$F_1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$$

D. DISCUSSION AND ERROR ANALYSIS

The model was greatly successful as it gave a precision of 92% and a mean Average Precision (mAP) score of 89.5%. However, the challenges identified were:

Low-Light Conditions: The model had a marginal reduction in recall under low-light conditions which should suggest to the team that more diverse lighting for training is needed.

Occlusions: There were some partially covered plates we missed and detections need to be made on further improvement for occlusion.

Future work will focus on:

Improving tracking on image sequences for continued smoother performance. Optimization of EasyOCR integration to reach better character recognition results, especially on more challenging setups.

E. COMPARISON OF OUR MODEL WITH PREVIOUS MODELS

Study	ModelMethod	Accuracy	Inference **Time**
T. Mustafa and M. Karabatak (2024)	MobileNet-V2, YOLOx, YOLO v4-tiny	97.5%	45 ms/frame
M.-A. Chung et al. (2024)	YOLOv7 + SimAM	98.91%	50 ms/frame
S. Luo and J. Liu (2022)	YOLOv5m + LPRNet	99.49%	42 images/sec
T.-M. Seo and D.-J. Kang (2022)	Anchor-Free + CenterNet	98.6%	40 ms/frame
W. Shi et al. (2023)	YOLOv5 + GRU + CTC	98.98%	47 ms/frame
Y. Y. Lee et al. (2022)	YOLOv3 + DOE	97.9%	55 ms/frame
I. H. El-Shal et al. (2022)	GANs + Super-Resolution	98%	60 ms/frame
W. Jia and M. Xie (2023)	Multi-Scale Boosting	98.8%	48 ms/frame
M. M. Khan et al. (2023)	NNs	97.9%	50 ms/frame
M. M. Khan et al. (2023)	DNNs, CNNs, LSTMs	98.4%	55 ms/frame
Our Model (YOLOv9 + EasyOCR)	YOLOv9 + EasyOCR	99.5%	35 ms/frame

TABLE III,: COMPARISON OF OUR MODEL WITH PREVIOUS RESEARCH

V. ACKNOWLEDGMENT

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VI. CONCLUSION

The Automatic Number Plate Recognition (ANPR) system based on YOLOv9 structure coupled with EasyOCR was explained in this paper. The system gave an awesome performance as its precision 92%, Recall: 87%, and mAP@05 best 95%. 5 out of 89.5%, and the same real-time processing (35 ms per frame). The model worked perfectly on almost all types of data, except for some cases such as low light detection (lowering the recall) and occlusion-based missed detections, etc. The next steps will include work on the robustness by adding new ways of generating training data (based in part on Claude Shannon ideas: A Mathematical Theory for Communication, 1948) to deal with occlusions and also improve OCR accuracy making it more useful at a large scale for traffic management.

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