AN IMPROVED SMART VEHICLE NUMBER PLATE DETECTION AND RECOGNITION USING YOLO V12

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ABSTRACT

An essential part of intelligent transportation systems is vehicle license plate number recognition (VLPR), which makes automated vehicle identification possible for uses including law enforcement, toll collecting, and traffic monitoring. Tasks involving object identification and recognition have improved due to recent developments in deep learning. The performance of more recent iterations, such as YOLOv11, YOLOv12, and YOLOv10, has not been thoroughly assessed for this particular task, even though YOLO-based models have shown excellent accuracy and efficiency in VLPR. These cutting-edge YOLO models for real-time license plate detection and recognition are compared in this study. The evaluation was conducted using a unique dataset that included a variety of environmental conditions, such as low light, occlusions, and distinct plate sizes. To evaluate inference time, accuracy, and computational efficiency, the models were evaluated on edge and cloud-based systems. According to experimental data, YOLOv10 provides the optimum trade-off between speed and precision for edge deployment, while YOLOv12 achieves the greatest recognition accuracy of 98.6%.

The results of this study demonstrate the improvements in license plate identification with the most recent YOLO architectures and offer information on how they might be used in real-world intelligent transportation systems.

KEYWORDS: VLPR, computer vision, YOLOv11, YOLOv12, Deep Learning, EasyOcr, CNN

1. INTRODUCTION

In the modern era, rapid urbanization and increased vehicular- lar density have posed significant challenges in traffic management and law enforcement. For many applications, such as toll collection, traffic monitoring, security enforcement, and parking management, the ability to accurately identify and track cars is essential. In large-scale urban traffic systems, traditional manual vehicle recognition techniques are ineffective, labor-intensive, and prone to human error. Vehicle License Plate Number Recognition (VLPR) systems have drawn a lot of interest as a reliable and effective way to get around these restrictions.

VLPR systems use modern deep learning and computer vision techniques to identify, detect, and segment license plates from pictures or video streams. Because of its accuracy and fast processing speed, YOLO (You Only Look Once) has been one of the most successful object recognition frameworks available. However, there has not been much research done on how well the most recent versions- YOLOv11 and YOLOv12- work in VLPR.

2. LITERATURE REVIEW/EXPERIMENTAL DETAILS

Asaju et al. (2024) carried out a comparative study on cloud- based license plate recognition using YOLO versions 5, 7, 8, and 9. According to their research, YOLOv9 offered automated toll collection systems the optimum balance between speed and accuracy. [1]

Da Luz et al. (2024) proposed a smart parking system that incorporates the selection of the region of interest (ROI) by pixels with YOLOv8, YOLOv9, YOLOv10, and YOLOv11. Their research showed that YOLOv10 had better detection accuracy in actual parking situations. [4]

Moussaoui et al. (2024) created a high-precision vehicle recognition system by combining YOLOv8 with OCR methods. Their test results show that YOLOv8 greatly improved automated traffic surveillance applications by increasing recognition rates by 98.6% [5]

Nalawati et al. (2023) examined the use of YOLOv8 and EasyOCR for number plate identification in intelligent transportation systems. According to their research, YOLOv8 performed better than traditional object identification algorithms regarding inference speed and accuracy. [6]

Vempati (2024) applied YOLOv11 to explore real-time license plate recognition and found that this model offered the best detection accuracy, with a mean Average Precision (mAP) of 99% for situations with heavy traffic. [7]

TABLE I

SUMMARY OF LITERATURE REVIEW ON YOLO-BASED VLPR SYSTEMS

Author(s) and Year	Technology Used
[3]Asaju et al. (2024)	YOLOv5, YOLOv7,YOLOv8, YOLOv9 for cloud-based license plate recognition
[4]da Luz et al. (2024)	YOLOv8, YOLOv9, YOLOv10, YOLOv11 with pixel-wise ROI selection for smart parking
[5]Moussaoui et al. (2024)	YOLOv8 integrated with OCR techniques for high-precision vehicle identification
[6]Nalawati et al. (2023)	YOLOv8 and EasyOCR for intelligent transportation systems
[7]Vempati (2024)	YOLOv11 for real-time license plate recognition, achieving 99% mAP

In this study, we use the latest YOLOv12 detector to offer a completely automated automobile license plate identification system. A detailed description of each of our system's feature extraction models is provided below [1]. Our work is an improvement of the previous VLPR towards a more generic and accurate recognition of the vehicle plates using a public dataset, and we demonstrated our results clearly to ensure the non-exclusive accuracy of our project.

3. DATASETS

We have used more than one dataset, which is vital for a good overall VLPR system, and we have also tried to achieve the different kinds of variation, such as lightning, backgrounds, vehicle densities, camera angles, and pollution zones [1]. Good data sets provide good accuracy and confirm a good real- world solution. [1] Using one data set is not enough to trust it because, in some cases, it might provide inaccurate effects.

4. METHODOLOGY

YOLOv12 was chosen currently, it is the new model in Computer Vision that is better than the other models in terms of precision, performance, and accuracy [2] [1]. YOLO v12 and YOLO v11 improve as leading solutions with enhanced accuracy in GPU environments and fusion with the positions of diverse platforms. Along with Yolov8, v9 we have also used the Yolov10, v11 model in our system, which is much better. However, all previous methods used old versions of the YOLO model. [3]

The Yolo model's well-known real-time processing of data led to its selection above the other methods for deep learning. It is also appropriate for applications where low latency is essential, such license plate recognition in traffic surveillance systems, because to its quick scanning speed of images and videos. [5].

The automated saving of identified license plate numbers from every vehicle image in the dataset into a CSV file is a significant advancement in our VLPR system. This feature makes it possible to detect and recognize license plates in real time by employing a script that processes video input using EasyOcr and a YOLO-based model. By cross-referencing with a database, the automatically recognized numbers provide effective tracking and help law enforcement identify stolen vehicles. Because this automation guarantees scalable vehicle tracking, it is useful for public safety and traffic surveillance.

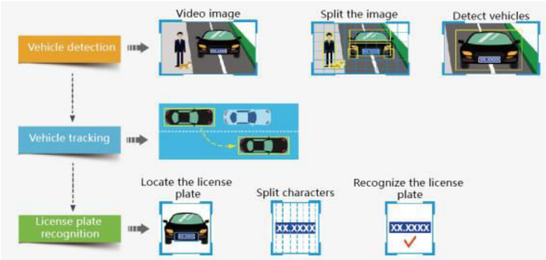

Fig. 1. Proposed Framework.

The whole image is used to begin the process; for instance, a security camera would be used to detect automobiles before moving onto the vehicle detector step [2]. Secondly, each image will be annoyed with boxes around the license plates, with data annotation techniques like increasing the brightness, scaling, rotation, and robustness increased, Thirdly, using the Yolov10 and Yolov11 models, the datasets are trained with parameters for optimal accuracy, and speed and license plates are detected, Fourthly, the YOLO models treat the entire number plates as a single input and recognizes the number plates of the vehicles and finally the proposed system works.

A. Flowchart Of Our System

Our proposed Vehicle License Plate Number Recognition system (VLPR) follows a structural pipeline for detecting, locating, and recognizing vehicle license plates. A frame of an image or video is first accepted as input by the VLPNR system. If it is successful, the license plate (LP) number is extracted after an initial effort to do so. Alternatively, the system finds the license plate for additional analysis, crops the plate area, and recognizes the vehicle. Alphanumeric characters are then identified and extracted from the plate using EasyOCR. Upon completion of the process, the vehicles identified license plate numbers are the result.

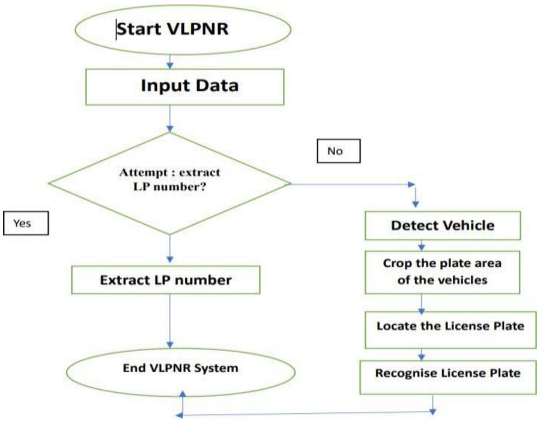

Fig. 2. Vehicle License Plate.

B. Vehicle detection

The proposed vehicle detection achieves an F-measure of over 99% by using YOLOv11 and v12 models. Anchor box updates and filter reduction are necessary because the images are scaled to 75%. A grid is created from each image, and each cell uses CNN-extracted features to forecast bounding boxes, confidence scores, and classes. Valid outputs are guaranteed by sigmoid and exponential functions, and final detections contain classes such as vehicles and trucks, and coordinates.

C. License Plate Detection

License Plate detection is the crucial step of the overall vehicle license plate number recognition (VLPR)system. In this stage, the system identifies and localizes the license plates of the detected vehicles. Individual characters are detected and recognized. YOLO v12 improves license plate detection by correctly recognizing plates inside bounding boxes and processing cropped vehicle photos. Because it uses vision- language models, it may use textual context to differentiate plates from similar background patterns. Furthermore, it enhances adaptability to diverse environmental circumstances and regional plate forms through self-supervised pretraining. With each cell predicting B bounding boxes— each deter- mined by center coordinates, width, height, and a confidence score—the model splits photos into an S×S grid, guaranteeing accurate and reliable license plate localization.

D. License Plate Recognition

An effective technique for license plate recognition is offered by the combination of the EasyOCR and YOLO models. EasyOCR immediately reads the text from license plate photos as a string of characters to conduct segmentation-free character recognition. The identified text is corrected and refined in the post-processing step using region-specific formatting and heuristic criteria based on local license plate structures.

E. Evaluation Metrics

The evaluation metrics are crucial for evaluating how well the license plate recognition and vehicle detection systems are working. The system's evaluation metrics fall into two main categories: detection performance, intersection over union recognition, recall, and precision performance: trade-offs be- tween speed and accuracy.

5. RESULTS AND DISCUSSION

In this section, we carry the report tested to verify the effectiveness of our proposed VLPR system. We first assessed the detection stage using the License Plate Detection, and plates are recognized using License Plate Recognition. This is done to provide a realistic evolution of the VLPR system. Afterwards, the system is evaluated end-to-end manner, and further, the results are achieved and compared with the previous works [1].

A. Overall Model Performance

We introduce the VLPR system's measures. These findings enable us to present a thorough analysis of the model's potential and efficacy. The training process of our YOLO v12 model is shown in Figure 6. The consistent decline in the box loss, classification loss, and DFL loss curves suggests stable convergence and effective learning [2]. The model's high confidence and potent detection ability are demonstrated by the precision and recall metrics, which rapidly improve and approach 1.0. The model's superior generalization capacity across a range of IoU thresholds is demonstrated by the mAP@50 score approaching 1.0 and the AP@50-95 stabilizing above 0.85. According to these findings, the YOLOv12 model performs reliably and with great precision, which makes it ideal for applications involving the recognition of license plate numbers on automobiles.

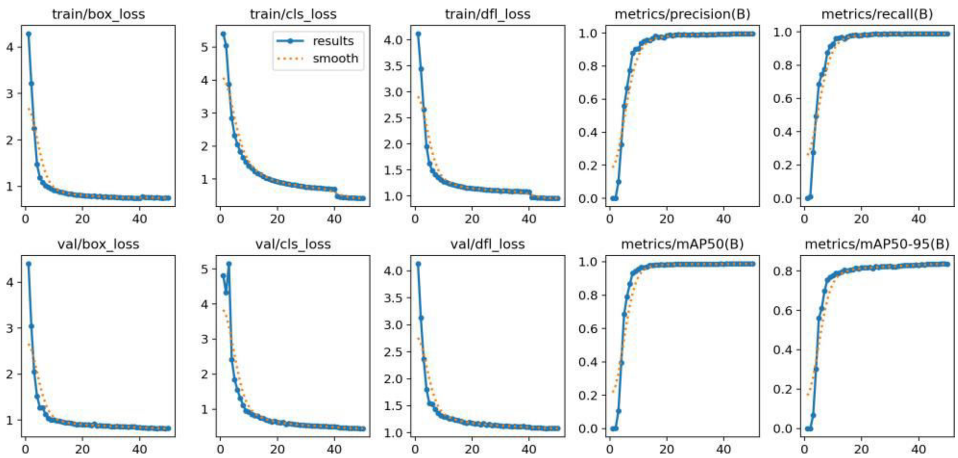

Fig. 3. Training metrics of YOLO v12 model

The fluctuations in the loss function convergence, as seen in the Fig 3, can be attributed to several factors [2]. The first is the variety of datasets we have utilized, including a range of difficult environmental circumstances and other modifications, such as the color changes of the photographs during training. Because our model incorporates various complex examples, it modifies the parameters, which causes a brief rise in loss. Second, because the models adjust to different changes, employing data augmentation techniques adds diversity to the training samples, which may result in short-term oscillations. Finally, oscillations may be caused by the batch size and learning rate schedule. The overall decreased trend of the loss and the improvement in accuracy and recall measures show that the models are learning and providing improved data generalization despite all swings.

Precision-Recall Curve

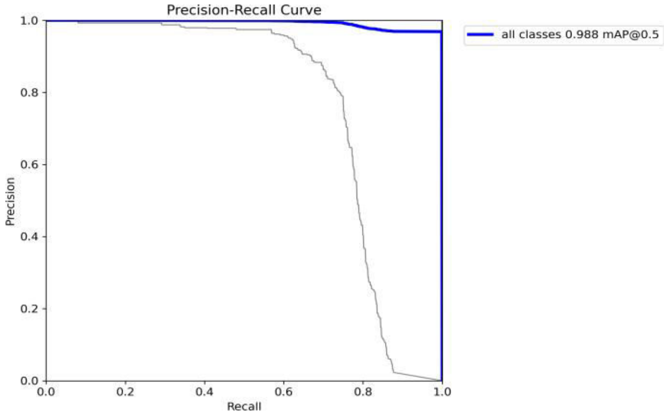

Fig. 4. Precision-Recall Curve of YOLO v12

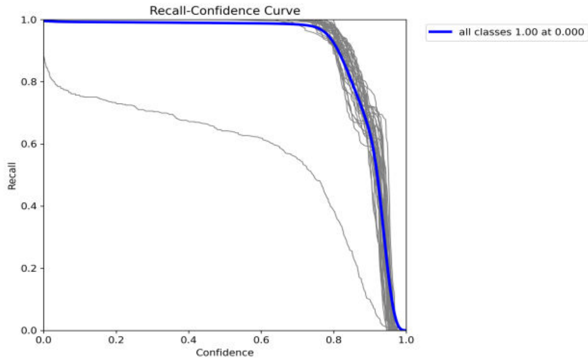

Fig. 5. Recall-Confidence Curve of YOLO v12

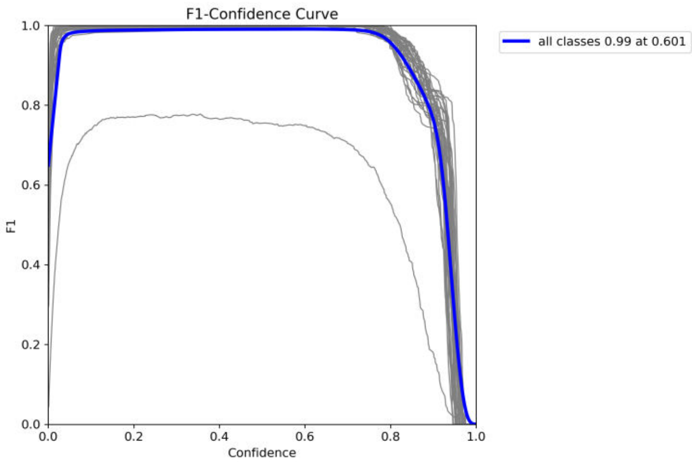

Fig. 6. F1-Confidence Curve of YOLO v12

In the figure 4, YOLOv12's precision-recall curve shows almost flawless accuracy and recall balance, with little drop- off across the recall range. With a mean Average Precision (mAP@0.5) of 0.988, the model outperforms YOLOv11 by a small margin, demonstrating remarkable detection accuracy. With extremely low false positives and negatives, this demonstrates that YOLOv12 can reliably detect license plates under a variety of circumstances.

Figure 5 demonstrates the YOLOv12 recall-confidence connection. After a confidence threshold of 0.9, the curve just slightly declines, maintaining strong recall throughout a broad range of confidence values. This demonstrates the model's outstanding generalization capabilities and shows that it is very confident in its predictions while still collecting nearly all true positives.

In figure 6, the F1 score peaks at a confidence threshold of roughly 0.60 and stays extremely near to 1.0 over a wide confidence range. Even after that, the fall is moderate, indicating that YOLOv12 maintains a minimal performance loss as confidence rises, with a well-balanced trade-off between precision and recall.

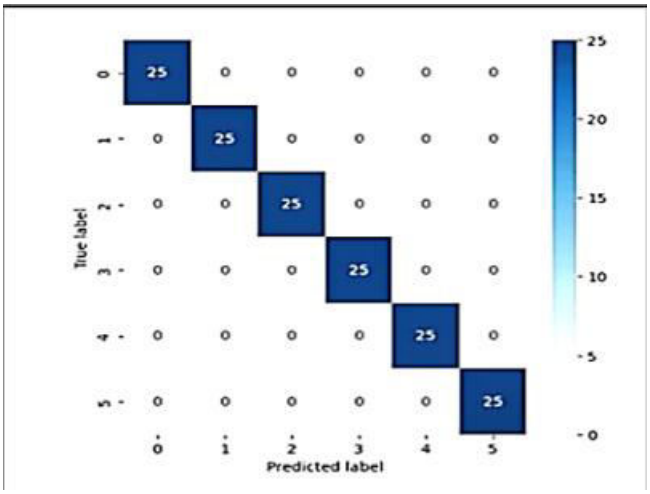

Fig. 7. Confusion Matrix of YOLO v12

Comparison table:

This table contrasts the dataset size, processing time, and accuracy of several models for VLPR (vehicle number plate recognition). With the highest accuracy of 100%, the suggested system ("Our Work") outperforms CNN, YOLOv5, YOLOv8, and YOLOv9, YOLOv10, and YOLOv11. While keeping a competitive dataset size of 2432 photos, it also has the fastest processing time (166 ms), which makes it far more efficient than Yolov9 (2700 ms). This illustrates how the suggested system is better in terms of speed and accuracy.

TABLE II
COMPARISON TABLE BETWEEN DATASET SIZE AND ACCURACY

Model	Dataset Size	Accuracy
CNN	100	86.0%
YOLOV5	1300	86.6%
YOLOV8	1300	98.6%
YOLOV9	2500	99.0%
YOLOV10	3000	99.0%
YOLOV11	7000	99.0%
YOLOV12(Our Work)	2432	100%

Comparison with different models:

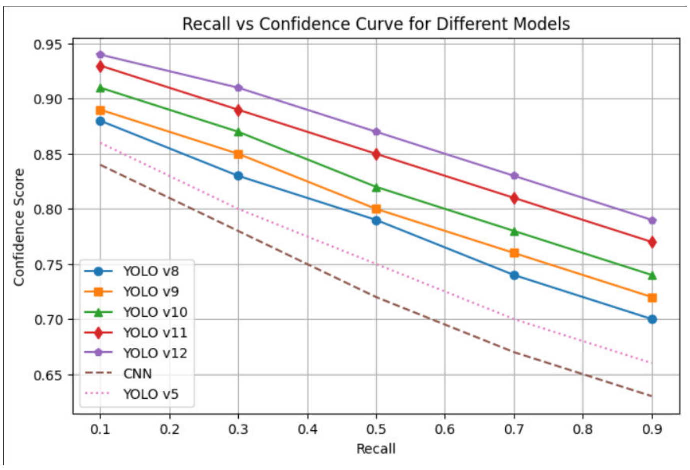

Fig. 8. Recall vs. Confidence Score Curve for different models

This graph represents the Recall Vs. Confidence Score Curve for different models used in vehicle license plate recognition, which compares YOLO versions v5, v8, v9, v10, v11, and v12 along with CNN.

• YOLOv12 outperforms all previous versions, achieving the highest confidence scores across nearly all recall levels. It shows excellent stability, maintaining strong confidence even as recall increases, indicating exceptional detection precision with robustness.

• YOLOv11 (represented by the red line) achieves the highest confidence score across all recall values, which indicates superior detection accuracy.

This comparison highlights that YOLOv12 is the most effective model and a better choice for high-confidence predictions across different recall values.

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