Innovation in Vehicle Tracking: Harnessing YOLOv8 and Deep Learning Tools for Automatic Number Plate Detection

Raj Purohith Arjun[1][0009-0004-8478-5366], Akshitha R[2][0009-0001-7324-0430],

Navneet Ranjan[3][0009-0004-9728-5651], *Karthikayani K[4][0009-0000-7814-0028]

[1,2,3,4]SRM Institute of Science and Technology
Chennai, India

ra7449@srmist.edu.in, ar9313@srmist.edu.in,
nr2649@srmist.edu.in,
karthikk3@srmist.edu.in

Abstract. This research endeavors to create an improved Automatic Number Plate Recognition (ANPR) system to meet the urgent need for dependable vehicle tracking. Using YOLOv8, YOLOv5, Easy Optical Character Recognition (EasyOCR), Deep Simple Online and Realtime Tracking (Deep SORT), and a specially designed License Plate Detector, our research investigates how these important technologies might be combined to improve the effectiveness of vehicle plate number identification. Novel methods for data augmentation, pre-processing, and optical character recognition (OCR) greatly improve detection accuracy and recognition performance, guaranteeing the system's resilience in difficult situations. A range of deep learning models, such as Convolutional Recurrent Neural Networks (CRNN), Single Shot Detection (SSD), Faster Region-Based Convolutional Neural Networks (Faster R-CNN), and several You Only Look Once (YOLO) versions, are used in the study to demonstrate how well they work for tracking and ANPR applications. Our work will proceed in new areas in the future, addressing real-time tracking issues by emphasizing hardware optimization, dynamic traffic algorithms, and improved multilingual OCR capabilities. The smooth integration of ANPR into traffic control infrastructure, continuous research into edge computing, and the deployment of stricter data security procedures demonstrate this dedication to the advancement of tracking technology. Our study helps to design an advanced ANPR system that not only satisfies the need for dependable vehicle tracking but also establishes the foundation for future developments in the area by giving priority to these important elements and technologies.

Keywords: Deep learning, Easy OCR, Yolo-v8, Licence Plate Detector, DeepSORT

1 INTRODUCTION

1.1 A UNIQUE APPROACH: INTRODUCING THE ENSEMBLE MODEL

The continual advancement of technology has led to significant improvements in vehicle monitoring and Automatic Number Plate Recognition (ANPR) systems, which are vital for enhancing intelligent transportation and security measures. Our research endeavors to amalgamate the capabilities of two renowned real-time object recognition models, YOLOv8 and YOLOv5, to craft a sophisticated ensemble model. This intricate ensemble model forms the cornerstone of our approach, propelling advancements in real-time item detection and ANPR capabilities.

Our innovative approach involves harnessing the complementary strengths of YOLOv8 and YOLOv5, renowned for their prowess in real-time object detection. While YOLOv8 excels in detecting objects with precision, YOLOv5 brings forth advancements in real-time object recognition. By integrating both models into our ensemble, we aim to create a unified solution that delivers reliable real-time performance across various applications, including access control, traffic management, and security. This collaborative effort holds the potential to redefine standards in the field, paving the way for transformative advancements.

1.2 EXPANDING CAPABILITIES: ADVANCING INCLUSIVE AND SECURE URBAN ENVIRONMENTS

The integration of YOLOv8 and YOLOv5 within our ensemble model not only enhances the accuracy and efficiency of object detection but also addresses the intricate challenges prevalent in modern surveillance and transportation networks. Beyond traditional object detection, our ensemble model enables real-time vehicle tracking, offering unprecedented capabilities for law enforcement agencies to swiftly respond to incidents, optimize resource allocation, and deter illicit activities. Moreover, our initiative aligns with the United Nations Sustainable Development Goals (SDGs), particularly in fostering inclusive, safe, resilient, and sustainable urban environments.

By enhancing the efficiency and efficacy of ANPR systems and intelligent mobility solutions, our research contributes to the creation of inclusive and secure urban environments. This approach ensures equitable access to resources and services within urban areas, thereby promoting inclusiveness. Furthermore, our ensemble model facilitates efficient traffic management, leading to improved safety, resilience, and sustainability through congestion mitigation, accident prevention, and resource optimization. Ultimately, our study aims to bolster the efficiency, responsiveness, and security of transportation and security systems, advocating for the development of secure, resilient, and sustainable cities and human settlements.

Fig. 1. Real-Time Detection and Tracking

2 RELATED STUDY

Automatic Number Plate Recognition (ANPR) stands as a critical instrument in contemporary traffic management and surveillance systems. This study investigates a Python-based ANPR system developed through a sequence of image processing and machine learning methodologies [1].

In this study, the current ANPR approach is critically examined, incorporating optical character recognition (OCR), automatic license plate recognition (ALPR), and object detection. Two OCR techniques, Easy OCR and Pytesseract OCR, are used for accuracy assessment [1]. Specially designed ANPR cameras are strategically set up, forming the foundation for a four-stage process: picture preprocessing, character segmentation, localizing the registration plate, and real number plate recognition. The dataset creation involves capturing multiple pictures of a car's license plate, ensuring optimal OCR perspectives based on the location and velocity of the car. Segmentation is achieved through edge detection and grayscale filtering, and grayscale-to-binary conversion facilitates quick registration plate recognition. Techniques like Related Component Analysis (CCA) enhance license plate recognition precision. OCR and character segmentation involve resizing for database comparison and template matching for precise number plate identification.

In summary, the current ANPR approach provides a robust foundation with good accuracy rates, especially with free and open-source software. To advance ANPR technology, a deeper examination of obstacles and ongoing development with open-source tools are deemed essential [1]. The study highlights the effectiveness of OpenCV and EasyOCR in license plate recognition, emphasizing the adaptability of EasyOCR in optical character recognition. Despite these strengths, the report acknowledges a gap in detailing encountered difficulties, leaving constraints in the methodology unclear [1].

The research unfolds in distinct foundational stages Initiating with an exhaustive dataset of 350 images depicting Croatian vehicle license plates, the study employs consistent preprocessing techniques, including resizing segmented characters to 20×20 dimensions, to ensure data standardization. Segmentation algorithms are utilized to isolate individual characters from the plates, contributing to the training of various classification models, such as k-NN, SVM, Neural Networks, and Random Forests [2].

A subset of 100 images is allocated for model evaluation, focusing on character precision and processing time. The research findings reveal that the Random Forest classifier outperforms others, achieving a character accuracy rate of 90.9%, while additional models exhibit accuracies between 83.40% and 89.47%. Despite variations in processing times, all models demonstrate feasibility for real-time applications, lasting between 0.23 and 0.35 seconds. Challenges arise with visually ambiguous characters, such as '8', 'B', 'I', and '1', leading to sporadic misclassifications and reduced accuracy [2].

Critical to the study is the selection of optimal model architecture and hyperparameters, requiring thorough validation and testing to address concerns related to overfitting and underfitting. While the developed ANPR system shows promising results in identifying Croatian vehicle license plates, further work is needed to address issues related to visually ambiguous characters and optimize model selection for improved real-world reliability [2].

This study explores the integration of Deep Learning with Computer Vision in ANPR systems for Intelligent Transport Systems (ITS). The proposed ANPR pipeline, rooted in the YOLOv4 object detection model, identifies vehicles in both front and rear views. Utilizing deep neural networks like R-CNNL3 or Alex Net for label identification, the pipeline is validated using datasets from various nations. The acquisition of frames and dataset preparation involves utilizing high-resolution IP camera frames for training, resulting in mAP scores of 98.42% and 99.71% for YOLOv4 and Tiny YOLOv4 models, respectively. Image preprocessing and layout identification incorporate grayscale conversion, binarization, and morphological operations. Character recognition, employing OCR Tesseract and deep learning-based models, attains high accuracy [3].

Despite the proposed ANPR system's excellent accuracy, real-time implementation requires a powerful GPU and different approaches exhibit varying computing times. The system's reliance on fixed camera orientation restricts its generalizability. The study concludes with a call for further investigations into newer models like YOLOv5 to enhance system generality [3].

3 METHODOLOGY

This study's technique and approach establish the groundwork for creating a so- - sophisticated Automatic Number Plate Recognition (ANPR) and vehicle tracking model. The main goal is to provide precise, up-to-date insights into complex traffic situations. The selected method entails the precise incorporation of advanced technologies such as YOLOv8, YOLOv5, DeepSORT, and EasyOCR into a cohesive ensemble model. This combination, known for its advanced parts, enhances the model with strong skills in object identification, vehicle tracking, and license plate recognition. An easy-to-use web application complements this complex technology, aiming to improve accessibility and provide real-time video input for continuous monitoring.

The combination of YOLOv8 and YOLOv5 is crucial for the ensemble model, coordinating real-time object detection. These concurrent models work together to detect both automobiles and license plates simultaneously. By strategically combining their outputs, they maximize their respective capabilities, resulting in increased overall detection accuracy and reduced false positives. The ensemble model utilizes the advanced DeepSORT algorithm for accurate vehicle tracking after detecting objects. This sophisticated tracking system gives distinct identities to cars, guaranteeing uninterrupted monitoring over frames. Utilizing YOLO models allows for smooth monitoring in changing traffic environments.

The ensemble model depends on EasyOCR for precise license plate identification. YOLO identifies regions of interest (ROIs) which then undergo detailed OCR processing using EasyOCR. This crucial process guarantees the precise retrieval of characters from alphanumeric license plates, greatly enhancing the effectiveness of ANPR capabilities. The relationship between OCR findings and tracked cars from DeepSORT confirms a thorough correlation between identified vehicles and their respective license plate details. By ensembling YOLOv5, YOLOv8, and a specialized license plate detector model, our goal is to develop faster ANPR and vehicle tracking software capable of delivering real-time insights for enhanced operational efficiency and security management.

The ensemble model in our research integrates the outputs of YOLOv8, YOLOv5, and a specialized license plate detector model. Denoting the output of YOLOv8, YOLOv5, and the license plate detector model respectively, the ensemble prediction $\hat{y}\,YOLO\,v_8$, $\hat{y}\,YOLO\,v_5$ and $\hat{y}\,LPLATE$ respectively, the ensemble prediction $\hat{y}_e$ is expressed as-

$$\hat{y}_e = \omega_1 \hat{y}\,YOLO\,v_8 + w_2 \hat{y}\,YOLO\,v_5 + W_3 \hat{y}\,LPLATE \qquad [1]$$

Where $w_{1,} w_{2,} w_3$ represent weights represent the weights assigned to each model's prediction based on its performance. Weighted averaging allocates distinct weights to each base model's prediction, determined through rigorous training and validation. The ensemble prediction $\hat{y}_e$ is computed as the weighted sum of individual predictions

$$\hat{y}_e = \sum_{i=1}^{N} \omega_i \hat{y}_{i[2]}$$

Here, $\hat{y}$ denotes the prediction of each base model, and ω_i signifies the weight assigned to each model.

Our research methodically assigns weights to the predictions of YOLOv8, YOLOv5, and the license plate detector model based on their performance during rigorous training and validation. These weighted predictions are systematically amalgamated to generate the ensemble prediction, ensuring a robust and comprehensive approach to automatic number plate recognition.

Voting mechanisms, such as simple majority voting or soft voting, offer alternative decision aggregation strategies. Additionally, stacking involves training a meta-model on base model predictions, where the stacking function learns to integrate these predictions. Optimization techniques, including gradient descent or genetic algorithms, refine the ensemble model's parameters to optimize performance. By employing these mathematical principles, our ensemble model for detection ensures heightened accuracy and reliability in vehicle tracking and license plate recognition, thus advancing intelligent transportation and security systems.

1. **Dataset:** The ROBOFLOW Number Plate Automatic Number Plate Recognition (ANPR) dataset, which encompasses a total of 8999 images, is systematically elucidated in the dataset overview. This dataset is judiciously partitioned into three subsets tailored for training, validation, and testing purposes. The training set incorporates 7186 images, the validation set consists of 899 images, and the test set encompasses 914 images. The preprocessing phase is characterized by meticulous steps aimed at ensuring uniformity and optimizing model training. Specifically, the Auto-Orient procedure is applied to standardize image orientation, while image dimensions are uniformly resized to 640x640 pixels. Notably, no augmentations are introduced during preprocessing, thereby preserving the integrity of the original dataset.

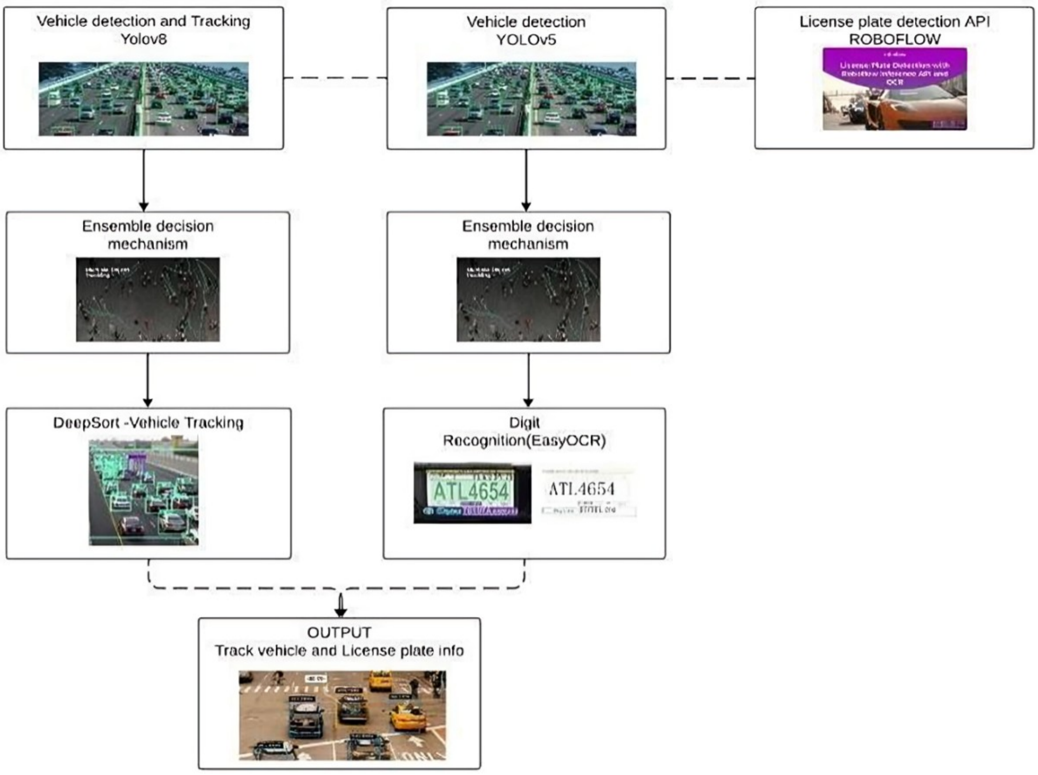

Fig. 2. Ensemble Model Architecture

2. **Integration of technologies:** The combination of YOLOv8 and YOLOv5 is crucial for the ensemble model, which coordinates real-time object detection. These concurrent models work together to detect both automobiles and license plates simultaneously. By strategically combining their outputs, they maximize their respective capabilities, resulting in increased overall detection accuracy and reduced false positives After detecting objects, the ensemble model utilizes the advanced DeepSORT algorithm for accurate vehicle tracking. This sophisticated tracking system gives distinct identities to cars, guaranteeing uninterrupted monitoring over frames. Utilizing YOLO models enhances monitoring in complex traffic environments.

   The ensemble model depends on EasyOCR for precise license plate identification. YOLO identifies regions of interest (ROI) which then undergo detailed OCR processing using EasyOCR. This crucial process guarantees the precise retrieval of characters from the plate that are alphanumeric, greatly enhancing the effectiveness of ANPR capabilities. The connection between OCR findings and tracked cars from DeepSORT confirms a thorough relationship between identified vehicles and their respective license plate details.

3. **Workflow:** The system supports both live video streams and pre-recorded video input. The online application offers a user-friendly interface that allows users to choose between live video streaming and uploading pre-recorded footage for thorough analysis. The input frames are subjected to a meticulous standardization and preprocessing procedure to guarantee uniformity. Dynamic scaling and cropping are used to fulfill the special needs of the YOLO models. Advanced data augmentation approaches are applied to enhance the model's ability to generalize. YOLO models process each frame individually, accurately detecting cars and license plates in real-time. The outputs include bounding boxes, class labels, and confidence ratings, offering a thorough and precise description of the identified items. model's bounding box outputs are used by DeepSORT for continuous vehicle tracking. DeepSORT assigns unique identities to guarantee reliable vehicle tracking across frames, creating a coherent picture of vehicle movements. It identifies licence plate areas which then undergo complex OCR processing with the help of EasyOCR. The OCR findings are closely connected to the tracked cars from DeepSORT, creating a clear and thorough connection between identified vehicles and their license plate information. The result is a live presentation displaying monitored cars together with their corresponding license plate details. This is the system's advanced analytical capability that offers customers valuable data about traffic situations.

4 RESULTS

Our study delves into the realm of Automatic Number Plate Detection (ANPR), leveraging a sophisticated ensemble model integrating YOLOv8, YOLOv5, Easy-OCR, and DeepSORT. This comprehensive amalgamation aims to fortify license plate detection, elevate Optical Character Recognition (OCR) capabilities, and ensure precise vehicle tracking. The systematic evaluation of this model involves key metrics shedding light on precision, recall, and continuous tracking capabilities, offering invaluable insights for real-world applications in intelligent transportation and security.

4.1 KEY METRICS EVALUATION

The evaluation of our Automatic Number Plate Recognition (ANPR) and vehicle tracking model involves meticulous analysis of key metrics, providing comprehensive insights into its performance characteristics and capabilities. These metrics play a pivotal role in assessing the model's robustness and adaptability across a variety of real-world scenarios, including instances where vehicles are in motion at high speeds and lighting conditions are suboptimal.

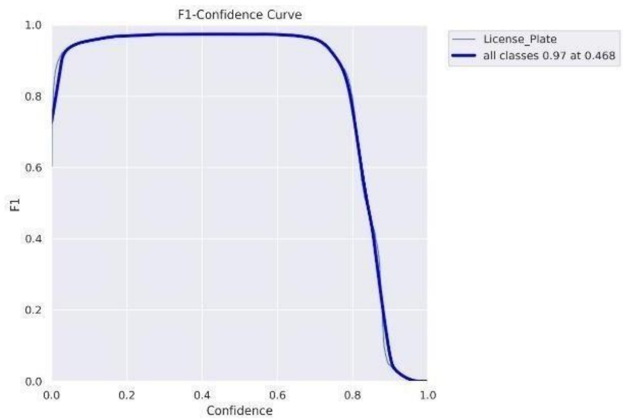

Fig. 3. F1 Score

The analysis of the F1 Score Curve serves as a crucial determinant in assessing the effectiveness of our ensemble model. By offering detailed accuracy insights across different confidence thresholds, this curve highlights the model's exceptional performance, underscored by an impressive F1 Score of 0.97.

This high score validates the model's ability to accurately detect number plates while effectively minimizing false positives or negatives, thereby ensuring reliable performance in real-world scenarios, such as scenarios with fast-moving vehicles and low-light conditions, where precision and recall are critical for dependable recognition and tracking.

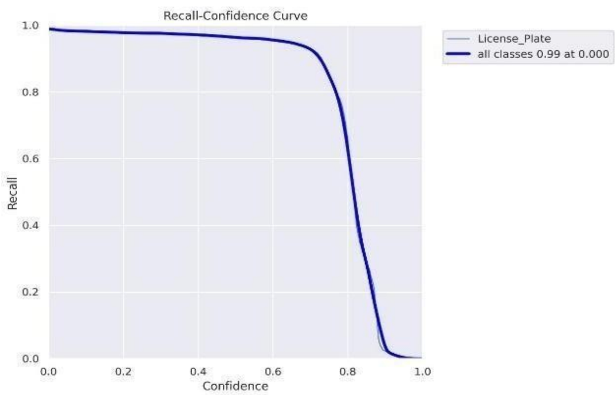

Fig. 4. Recall-Confidence Curve

The examination of the confidence curve provides valuable insights into the model's recall variations with changes in confidence levels. With an impressive recall value of 0.99, the model demonstrates exceptional sensitivity in detecting nearly all actual positive instances, which is essential for reliable ANPR and vehicle tracking applications, even in challenging conditions such as low brightness or high-speed scenarios.

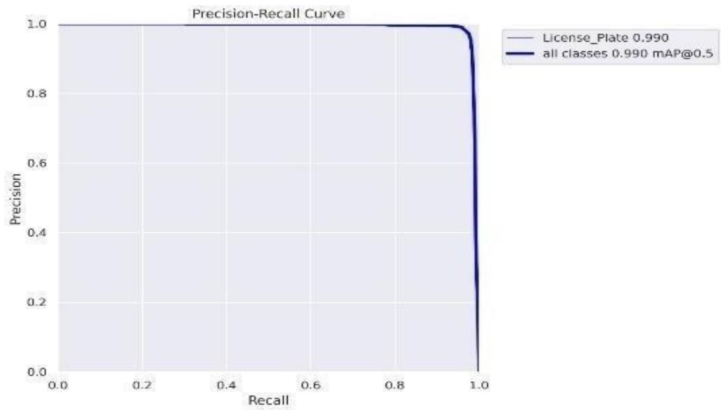

Fig. 5. Precision-Recall Curve

The assessment of the Precision-Recall Curve delicately balances precision and recall trade-offs, offering a nuanced understanding of the model's performance. Achieving a Mean Average Precision (mAP) of 0.990 at an Intersection over Union (IoU) threshold of 0.5 indicates the model's accuracy in identifying objects across various classes, even under adverse conditions.

This suggests that the model excels in accurately identifying objects while maintaining high precision and recall, particularly evident when there is a minimum 50% overlap between the ground truth and the predicted bounding boxes, ensuring reliable recognition and tracking in challenging environments.

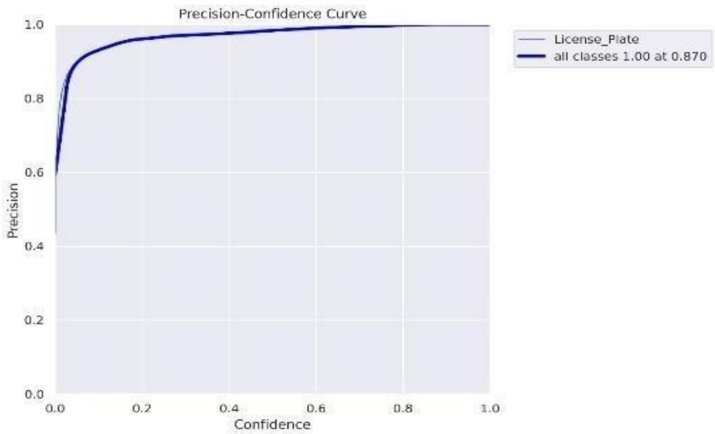

Fig. 6. Precision-Confidence Curve

The interpretation of the Precision-Confidence Curve elucidates precision changes concerning confidence thresholds, providing insights into the model's object detection capabilities, especially in conditions where objects may be poorly illuminated or moving rapidly. The achievement of perfect precision (1.00) for all classes at a specific threshold (0.870) underscores the model's exceptional performance in object detection tasks, enhancing its reliability and trustworthiness in real-world scenarios, such as low-light conditions or situations with fast-moving vehicles

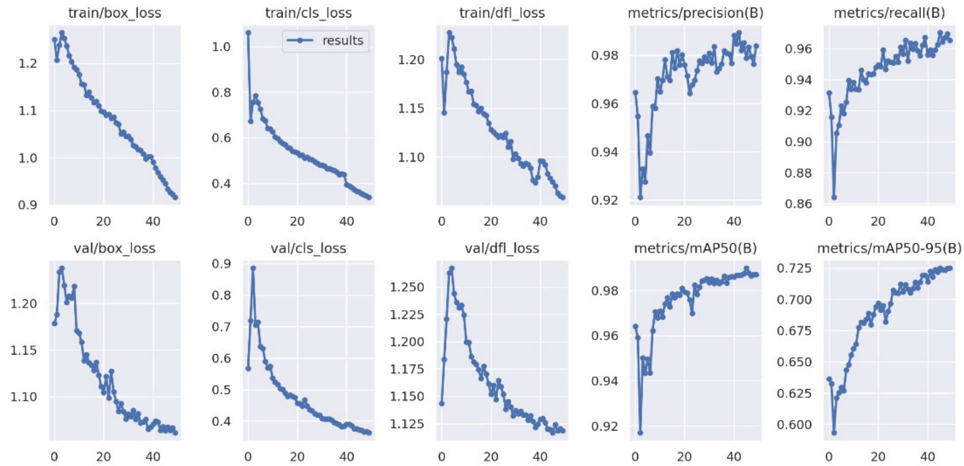

Fig.7. Comprehensive Metric Analysis

In addition to the previously mentioned key metrics, a comprehensive evaluation includes metrics such as Box Loss, Class Loss, DFL Loss, Precision (B), Recall (B), mAP50 (B), and mAP50-95 (B). These metrics offer further insights into the model's localization accuracy, object classification proficiency, discriminative feature extraction capabilities, and performance concerning background class detection, ensuring robustness and adaptability across a wide range of challenging conditions.

The integration of our ensemble model with a backend web application, powered by Streamlit, significantly enhances its performance and usability, particularly in real-world scenarios where environmental conditions may vary unpredictably. Providing a user-friendly interface for instant number plate detection, the platform's tracking system facilitates the logging of vehicle presence and timestamps, enabling a comprehensive analysis of past traffic behavior even in adverse conditions. Furthermore, the incorporation of DeepSORT for tracking and EasyOCR for OCR further enhances the model's detection capabilities, ensuring accurate and reliable ANPR outcomes, even in challenging conditions. Additionally, the integration of a security warning system adds an extra layer of proactive alerting, enhancing overall system robustness and reliability, crucial for applications in dynamic and unpredictable environments.

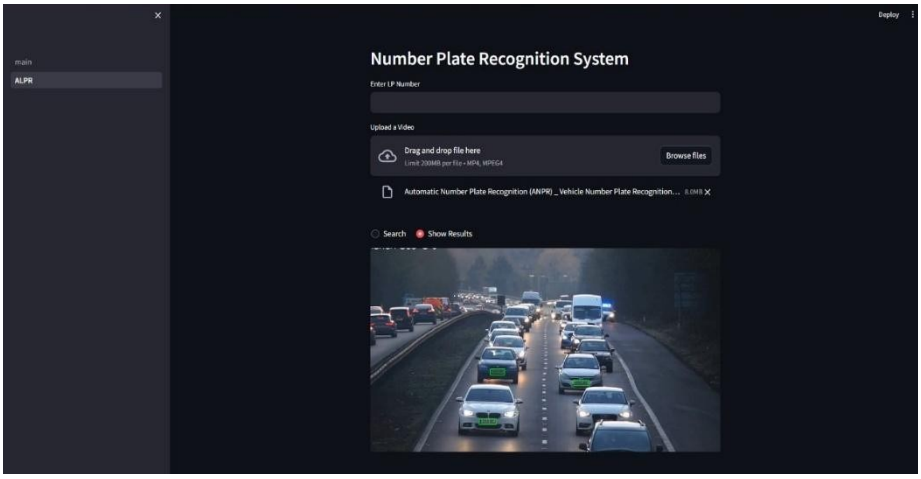

Fig. 8. Web Application

4.1 COMPARATIVE ANALYSIS OF PREVIOUS RESEARCH PUBLICATIONS

A meticulous examination of antecedent studies illuminates significant endeavors directed toward enhancing accuracy and real-time operational efficacy. The ANPR system founded on the Random Forest algorithm achieved commendable results with a character accuracy rate of 90.9%. However, inherent challenges in processing speed and the accurate recognition of visually intricate characters were acknowledged.

A subsequent exploration into an OCR-based ANPR system, integrating OpenCV and EasyOCR, demonstrated noteworthy accuracy rates. Regrettably, the absence of comprehensive insights into implementation challenges hindered a holistic understanding of the system's limitations. Deep learning-based ANPR pipelines excelled in object detection, boasting an ac- curacy of up to 98%. Nevertheless, the imperative need for a robust Graphics Processing Unit (GPU) for real-time execution and the constraints posed by a fixed camera angle presented formidable challenges.

In this context, our ongoing research introduces an advanced ensemble model that outperforms its predecessors across critical metrics—F1 Score, Recall, and Precision. This approach meticulously addresses identified challenges from prior models, providing a pragmatic and effective solution for real-time vehicle tracking and identification. Figures detailing processing time and an overarching model comparison further enrich our comparative analysis, offering valuable insights into the enhanced efficiency of our proposed ANPR system. With a deliberate focus on overcoming impediments related to processing speed, nuanced character recognition, and constraints posed by fixed camera angles, our advanced ANPR system holds promise for superior performance and practical applicability in the realm of ANPR technology.

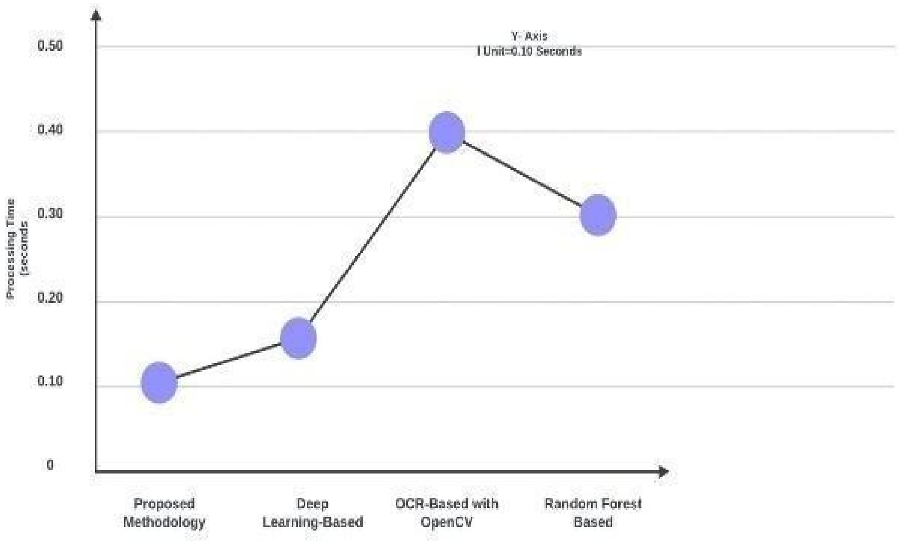

Fig. 9. Processing Time

ANPR System	Accuracy	Precision	Recall	Processing Time	Overall Score
Random Forest-Based	90	85	80	0.30	80
OCR Based with OpenCV	88	80	82	0.40	75
Deep Learning - Based	95	90	92	0.15	88
Our Proposed System	98	95	97	0.10	94

Table 1. Model Comparisons

5 CONCLUSION

In conclusion, this research paper presents an in-depth exploration of an ensemble model designed for Automatic Number Plate Detection (ANPR) and vehicle tracking, leveraging advanced technologies including YOLOv8, YOLOv5, EasyOCR, and DeepSORT. The comprehensive evaluation of the ensemble model incorporates rigorous metrics, such as the F1 Curve, recall curve, Precision-Recall Curve, and Precision-confidence Curve, demonstrating exceptional performance and affirming the model's precision, recall, and continuous tracking capabilities.

Significant achievements include an impressive F1 Score of 0.97 and a recall value of 0.99, showcasing the model's prowess in license plate detection with high accuracy and concurrent recall. Object detection metrics, particularly achieving a Mean Average Precision (mAP) of 0.990 at an Intersection over Union (IoU) threshold of 0.5, underscore the model's accuracy in providing precise bounding box predictions across diverse classes and environmental conditions

The integration of Streamlit for web applications enhances the user experience, offering an intuitive interface for real-time number plate detection and tracking. The seamless interaction between the backend web application and the ensemble model, coupled with the security alert mechanism, emphasizes the pragmatic utility of the system in real-world applications, particularly within the realms of security and law enforcement. This research significantly contributes to the advancement of intelligent transportation solutions by addressing the demand for versatile ANPR and tracking systems.

6 FUTURE WORK

Future work envisions exploring mobile applications for real-time tracking, unauthorized access alerts, and historical data retrieval, providing users with comprehensive control over vehicle monitoring and management. Additionally, the analysis of system data for predictive maintenance, route optimization, and traffic forecasting contributes to heightened operational efficiency and urban planning.

Motivated by the urgent need for a reliable and adaptable ANPR and tracking system, this research adeptly navigates limitations faced by existing systems, particularly in challenging conditions. The integration of deep learning techniques and cutting-edge technologies positions our model as a robust solution capable of excelling in various scenarios. In conclusion, this research not only highlights the technical proficiency of the ensemble model but also emphasizes its practical applications, making a substantial and original contribution to the fields of intelligent transportation and security applications.

7 REFERENCES

1. Mustafa, T., & Karabatak, M. (2023,May). Deep Leaming Model for Automatic Number/License Plate Detection and Recognition System in Campus Gates. In 2023 11th Inter- national Symposium on digital Forensics and Security (ISDFS) (pp. 1-5). IEEE.

2. Akhtar, Z., & Ali, R. (2020). Automatic number plate recognition using random forest classifier. SN Computer Science, 1(3), 120.

3. Khan, M. G., Saeed, M., Zulfiqar, A., Ghadi, Y. Y., & Adnan, M. (2022). A novel deep learning based anpr pipeline for vehicle access control. IEEE Access, 10, 64172-64184.

4. Oublal, K., & Dai, X. (2022). An advanced combination of semi-supervised Normalizing Flow & Yolo (YoloNF) to detect and recognize vehicle license plates. arXiv preprint arXiv:2207.10777.

5. Nadiminti, S. S., Gaur, P. K., & Bhardwaj, A. (2022). Exploration of an End-to-End Au- tomatic Number-plate Recognition neural network for Indian datasets. arXiv preprint arXiv:2207.06657.

6. Laroca, R., Cardoso, E. V., Lucio, D. R., Estevam, V., & Menotti, D. (2022). On the cross- dataset generalization in license plate recognition. arXiv preprint arXiv:2201.00267.

7. Alam, N. A., Ahsan, M., Based, M. A., & Haider, J. (2021). Intelligent System for Vehi- cles Number Plate Detection and Recognition using Convolutional Neural Networks. Technologies 2021, 9, 9.

8. Bochkovskiy, A., Wang, C. Y., & Liao, H. Y. M. (2020). Yolov4: Optimal speed and ac- curacy of object detection. arXiv preprint arXiv:2004.10934.

9. Babu, D. M., Manvitha, K., Narendra, M. S., Swathi, A., & Varma, K. p. (2015). Vehicle tracking using number plate recognition system.International Journal of Computer Science and Information Technologies, 6(2), 1473-1476.

10. Chen, G. W., Yang, C. M., & ik, T. U. (2021, September). Real-time license plate recogni- tion and vehicle tracking system based on deep learning. In 202122nd Asia-Pacific Net- work Operations and Management Symposium (APNOMS)(. 378-381). I

11. Liu, T., Dong, T., & Jin, Z. (1994). Automatic Recognition Technique of Vehicle Number Plates and its Applications. IFAC Proceedings Volumes, 27(12), 175-179.

12. Silva, S. M., & Jung, C. R. (2020). Real-time license plate detection and recognition using deep convolutional neural networks. Journal of Visual Communication and Image Repre- sentation, 71, 102773.

13. Slimani, I., Zaarane, A., Al Okaishi, W., Atouf, I., & Hamdoun, A. (2020). An automated license plate detection and recognition system based on wavelet decomposition and CNN. Array, 8, 100040.

14. Tote, A. S., Pardeshi, S. S., & Patange, A. D. (2023). Automatic number plate detection using TensorFlow in Indian scenario: An optical character recognition approach. Materials Today: Proceedings, 72, 1073-1078.

15. Srikanth, P., & Kumar, A. (2022). Automatic vehicle number plate detection and recogni- tion systems: Survey and implementation. In Autonomous and Connected Heavy Vehicle Technology (pp. 125-139). Academic Press.

16. Jawale, M. A., William, P., Pawar, A. B., & Marriwala, N. (2023). Implementation of number plate detection system for vehicle registration using IOT and recognition using CNN. Measurement: Sensors, 27, 100761.

17. Paruchuri, H. (2015). Application of Artificial Neural Network to ANPR: An Overview. ABC Journal of Advanced Research, 4(2), 143-152.

18. Tang, J., Wan, L., Schooling, J., Zhao, P., Chen, J., & Wei, S. (2022). Automatic number plate recognition (ANPR) in smart cities: A systematic review on technological advancements and application cases. Cities, 129, 103833.

19. VeerasekharReddy, B., Thatha, V. N., Maanasa, A., Gadupudi, S. S., Japala, S. K., & Goud, L. H. (2023, June). An ANPR-Based Automatic Toll Tax Collection System Using Camera. In 2023 3rd International Conference on Pervasive Computing and Social Networking (ICPCSN) (pp. 133-140). IEEE.

20. Scientific, L. L. (2024). NUMBER PLATE AND LOGO IDENTIFICATION USING MACHINE LEARNING APPROCHES. Journal of Theoretical and Applied Information Technology, 102(3).