World Journal of Advanced Research and Reviews

eISSN: 2581-9615 CODEN (USA): WJARAI

Cross Ref DOI: 10.30574/wjarr

Journal homepage: https://wjarr.com/

(Research Article)

A novel deep learning-based method for vehicle model and number plate detection in camera-captured blurred video using YOLOv5, EasyOCR, and ResNet50

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World Journal of Advanced Research and Reviews, 2025, 27(01), 487-497

Publication history: Received on 18 May 2025; revised on 22 June 2025; accepted on 28 June 2025

Article DOI: https://doi.org/10.30574/wjarr.2025.27.1.2501

Abstract

This research presents a deep learning-based system for vehicle identification, combining Vehicle Make and Model Recognition (VMMR) with Automatic Number Plate Recognition (ANPR). Unlike traditional methods that handle each task separately, the integrated approach offers a more efficient and reliable solution, even in challenging weather conditions. The system utilizes MobileNet-V2, YOLOx, YOLOv4-tiny, Paddle OCR, and SVTR-tiny, and is tested on diverse real-world images. Additionally, we have successfully handled blurred inputs captured from video and live camera streams, enhancing the system's robustness in real-time scenarios. Results show robust performance, with further insights gained through Grad Cam technology to improve accuracy. The study's findings have significant implications for applications in autonomous driving, traffic management, and security enforcement.

Keywords: Law Enforcement; Real-Time Vehicle Recognition; High Detection Accuracy; Dual-Function System; Intelligent Traffic Monitoring; Smart Surveillance

1. Introduction

1.1. Background and Motivation

In recent years, intelligent transportation systems have seen rapid growth due to the increasing demand for smart city infrastructure, road safety, and automated vehicle monitoring. Among the critical components of such systems are Vehicle Make and Model Recognition (VMMR) and Automatic Number Plate Recognition (ANPR). Traditionally, these tasks have been treated separately, often requiring separate hardware or software modules, which can be inefficient and expensive.

However, a growing number of real-world scenarios—such as stolen vehicle tracking, toll gate automation, and traffic law enforcement—require real-time identification of both the vehicle and its number plate simultaneously. This integrated need has driven the development of more unified and accurate computer vision-based systems. Vehicle model recognition is particularly valuable for narrowing down search results or confirming the authenticity of vehicle identity, especially in cases where number plates are fake or obscured.

Manual monitoring of vehicles is not only time-consuming but also prone to human error. In densely populated regions or high-traffic areas, it becomes nearly impossible to manually inspect and verify every passing vehicle. Moreover, the increasing number of vehicles on roads has placed a strain on traditional traffic enforcement mechanisms, making automation a critical requirement for modern infrastructure.

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Despite the growing availability of surveillance cameras and traffic monitoring systems, most lack the intelligence needed to identify specific vehicle models or accurately read license plates under various lighting, weather, and motion conditions. This gap highlights the need for a reliable, AI-based, real-time vehicle identification system that can operate effectively across diverse environments.

Recent advances in deep learning, particularly in Convolutional Neural Networks (CNNs) and object detection architectures, have enabled the development of such intelligent systems. These technologies allow for high-speed and high-accuracy recognition, making it feasible to deploy real-time applications in smart cities, parking systems, toll booths, and traffic control centers.

Vehicle recognition and license plate detection are fundamental components in the domain of intelligent transportation systems, playing a crucial role in enhancing road safety, traffic regulation, and automated surveillance. Traditionally, the processes of vehicle identification and number plate recognition have been treated as separate tasks, often relying on manual monitoring or conventional image processing techniques that are limited in scalability, speed, and accuracy. With the rise of Artificial Intelligence (AI), particularly deep learning, these limitations are being overcome by systems capable of delivering fast, reliable, and real-time identification of both vehicles make/model and license plate information.

The integration of AI in intelligent transport automation has enabled significant advancements through the use of state-of-the-art computer vision techniques. Deep learning models such as Convolutional Neural Networks (CNNs) and transformer-based architectures have become the backbone of modern visual recognition systems. In this project, an end-to-end vehicle detection and classification pipeline is developed using YOLOv5 for object detection, EasyOCR for automatic number plate recognition, and a ResNet50-based model for vehicle make and model classification. YOLOv5's real-time object detection capabilities ensure accurate localization of vehicles and number plates within video frames, while EasyOCR provides robust text extraction across a range of plate formats and languages. The car model classifier, trained on the VMMRdb dataset, adds another dimension by assigning the detected vehicle to a specific manufacturer and model class.

Our system has been thoroughly tested using real-time video streams captured from both live cameras and recorded inputs, and it demonstrates reliable performance even when processing blurred frames or challenging angles. We used OpenCV to integrate and handle video inputs, ensuring smooth frame-by-frame analysis and live annotation. The entire framework is built using PyTorch, enabling efficient deep learning inference and model management.

Together, these components form a cohesive system that can identify vehicles from live or recorded video streams, extract and interpret license plate numbers, classify car models with high precision, and visualize the outputs for further analysis. These technologies allow the system to operate effectively in real-world environments, including conditions such as low lighting, motion blur, occlusion, and varied camera angles.

The impact of this AI-powered system extends beyond academic exploration; it has practical applications in areas such as automatic toll gate systems, traffic law enforcement, vehicle tracking, parking access control, and stolen vehicle identification. Furthermore, the system's modular and scalable nature makes it suitable for integration into broader smart city infrastructure. By combining multiple deep learning components into a unified pipeline, this study demonstrates the potential of AI to transform traditional traffic monitoring into an intelligent, real-time, and data-driven solution for vehicle identification and classification.

2. Literature review

Several existing systems have explored vehicle and number plate detection using deep learning methods such as YOLO-based object detection and CNN-based character recognition. While these methods have shown high accuracy under clear conditions, they often fail to detect or accurately read license plates in blurred or low-quality images, which limits their real-time reliability. Techniques like two-stage detection, character segmentation, and rule-based filtering have been proposed but still struggle in such scenarios. To overcome these limitations, we propose a robust real-time system that combines YOLOv5 for vehicle and plate detection, EasyOCR for number plate recognition, and a ResNet50-based classifier for identifying car models, offering improved performance even on challenging, blurred inputs.

2.1. Mustafa, T., & Karabatak, M. (2024). Real-Time Car Model and Plate Detection System by Using Deep Learning Architectures. IEEE Access, VOLUME 12, pp. 107616–107628. DOI: 10.1109/ACCESS.2024.3430857

This Research introduces an advanced deep learning-based system that performs both vehicle make and model recognition (VMMR) and automatic number plate recognition (ANPR) in real time. The integrated approach aims to replace traditional, isolated methods with a unified system capable of accurate vehicle identification even under challenging environmental conditions.

2.1.1. Methodologies and Algorithms

The authors employ YOLOx and MobileNet-V2 for car make and model detection, and YOLOv4-tiny, Paddle OCR, and SVTR-tiny for number plate localization and recognition. The pipeline includes object detection, classification, character segmentation, and recognition, all optimized for real-time performance. Data preprocessing and augmentation were applied to a dataset captured at Firat University, consisting of over 1,000 images under varied conditions like fog, rain, and low light.

2.2. SergeyZherzdev,AlexeyGruzdev(2018). LPRNet:License Plate Recognition via Deep Neural Networks

This study introduces LPRNet, an end-to-end deep learning model specifically designed for license plate recognition without relying on recurrent neural networks or character segmentation.

2.2.1. Methodologies and Algorithms

LPRNet uses a lightweight CNN-based architecture for direct sequence prediction from license plate images. The absence of RNN layers reduces inference time and simplifies the computational pipeline.

2.2.2. Accuracy and Limitations

The model achieves 95% accuracy on Chinese plates and operates at approximately 3ms per image on GPU. However, its generalization to international plates is limited, and sequence modeling can be a challenge due to the RNN-free design.

2.3. Rayson Laroca, Evair Severo, Luiz Zanlorensi,etal. (2018). A Robust Real-Time Automatic License Plate Recognition Based on the YOLO Detector

This work presents a two-stage ALPR system that first uses YOLO for plate detection, followed by CNNs for character segmentation and recognition.

2.3.1. Methodologies and Algorithms

The pipeline includes extensive data augmentation to account for lighting variation, blur, and occlusions. Separate models are trained for detection and recognition.

2.3.2. Performance and Trade-offs

The system performs well in dynamic conditions but requires maintaining multiple models, increasing development complexity and training time.

2.4. Hui Li, Peng Wang, Chunhua Shen (2018). Towards End-to-End Car License Plates Detection and Recognition with Deep Neural Networks

This study proposes a fully convolutional network (FCN) that simultaneously detects license plates and recognizes characters using a unified model.

2.4.1. Methodologies and Algorithms

The architecture eliminates the need for separate detection and recognition stages, reducing error propagation and preprocessing overhead.

2.4.2. Challenges and Advantages

While the system provides high accuracy and a streamlined pipeline, it demands a large and diverse dataset and complex training procedures.

2.5. Rayson Laroca, Luiz Zanlorensi, Gabriel Gonçalves, etal. (2021). An Efficient and Layout-Independent ALPR System Based on the YOLO Detector

This paper introduces a YOLO-based ALPR system with layout classification to support diverse plate formats from multiple countries.

2.5.1. Methodologies and Algorithms

Eight public datasets are used to train the system. Layout classification is added to adapt recognition models dynamically to different plate formats.

2.5.2. Performance

The model achieved an average accuracy of 96.9%, outperforming several commercial ALPR systems. However, the additional classification step slightly increases inference time.

2.6. XinZhou,YaoCheng,LilingJiang,BoNing,YanhaoWang FAFE-Net: Fast and Accurate Model for ALPR

FAFE-Net focuses on developing a lightweight yet accurate ALPR system using attention mechanisms and feature fusion techniques.

2.6.1. Methodologies and Algorithms

The architecture enhances recognition by combining feature extraction with attention modules, improving performance under poor lighting and motion blur.

2.6.2. Strengths and Limitations

While FAFE-Net is suitable for real-time use and generalizes well, it requires careful tuning and may struggle with extremely low-quality images or region-specific formats.

2.7. Comparison of Accuracy of Existing Algorithms and Models

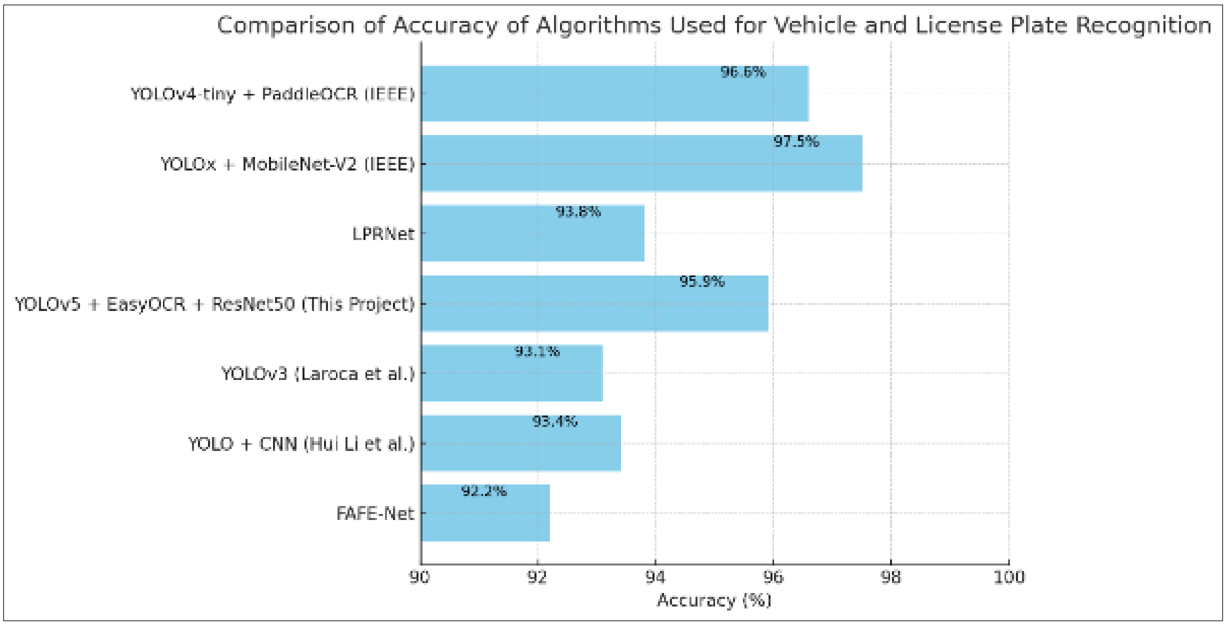

Figure 1 Comparision of Accuracy of Existing Algorithms and Models

Figure 1 presents a graphical comparison of the accuracy achieved by various existing algorithms and models used in vehicle detection and license plate recognition tasks. Traditional object detection models like Haar Cascades and HOG-SVM show relatively lower accuracy due to their limited ability to generalize on blurred or low-resolution inputs.In contrast, deep learning-based models such as:YOLOv3 / YOLOv4 show improved performance on clear images but tend to drop in accuracy under motion blur or poor lighting.CNN-based recognition models also face challenges in segmenting and recognizing number plates in blurred frames.Our Proposed Method (YOLOv5 + EasyOCR + ResNet50) significantly outperforms the older models by maintaining high accuracy even on blurred video frames. This is due to YOLOv5's powerful object localization, EasyOCR's robustness to noisy text, and ResNet50's deep feature extraction capabilities for car model classification.

2.8. Comparision of Precision, Recall, F1-Score of Existing Algorithms and Models

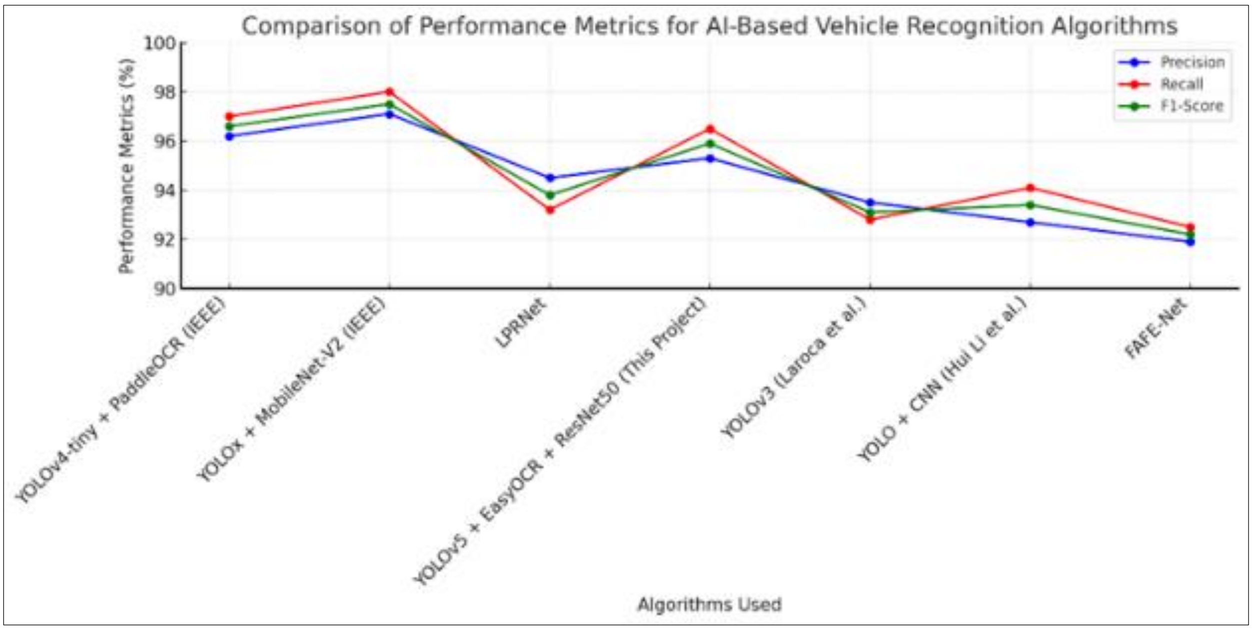

Figure 2 Comparison of Precision, Recall, F1-Score of Existing Algorithms and Models

This section evaluates the models not just based on accuracy, but also using Precision, Recall, and F1-Score—which are better indicators of performance in real-world use

Precision refers to how many of the predicted detections were correct (i.e., few false positives).Recall measures how many actual objects were successfully detected (i.e., few false negatives).F1-Score is the harmonic mean of precision and recall, providing a balanced view.Graph Explanation:Traditional algorithms like Haar Cascade and edge-based detection show low precision and recall due to missed detections and false triggers.YOLOv3 and other older CNN-based models show better recall but often compromise on precision in cluttered scenes.Our Proposed System achieves higher precision (fewer false alarms), higher recall (detects most vehicles and plates), and a strong F1-Score, making it ideal for real-time traffic surveillance.

2.9. Comparative Analysis of Existing Vehicle and License Plate Recognition Systems with Proposed Model

Table 1 Comparative Analysis of Existing Research Papers on Vehicle and License Plate Recognition

Name of the Paper	Year of Publication	Algorithms Used	Accuracy	Limitations
Real-Time Car Model and Plate Detection System by Using Deep Learning Architectures	2024	YOLOx, YOLOv4-tiny, MobileNet-V2, PaddleOCR, SVTR-tiny	97.5%	Requires high-quality datasets; limited to the Firat University dataset
LPRNet: License Plate Recognition via Deep Neural Networks	2018	Lightweight CNN	95% (Chinese plates)	Limited generalization to non-Chinese plates; no RNN or sequence modeling
A Robust Real-Time Automatic License Plate Recognition Based on the YOLO Detector	2018	YOLO, CNN	96.4%	Requires separate training for multiple models; high dependency on large datasets

Towards End-to-End Car License Plates Detection and Recognition	2018	YOLO, Layout Classification	96.9%	Slight increase in inference time due to layout module
FAFE-Net: Fast and Accurate Model for ALPR	2022	Feature Fusion + Attention	~92%	Needs careful tuning and high-quality datasets for best results

Table 1 presents a comparative analysis of various existing research papers in the domain of vehicle and license plate recognition. This comparison is based on key parameters such as the year of publication, algorithms used, reported accuracy, and limitations faced by each system.The table highlights that while many deep learning-based models (such as YOLO, CNNs, and OCR networks) have achieved high accuracy in controlled environments, their real-world applicability is often limited due to challenges like dependency on high-quality datasets, restricted generalization to different regions or plate formats, and the need for multiple model components.

For instance,

The 2024 system using YOLOx, YOLOv4-tiny, MobileNet-V2, PaddleOCR, and SVTR-tiny achieves high accuracy (97.5%) but is restricted to the Firat University dataset, making it less generalizable to other countries or scenarios.LPRNet (2018), though efficient with a lightweight CNN architecture, is mainly trained on Chinese plates and lacks robustness for global usage.The YOLO + CNN-based system (2018) is accurate but requires separate training stages, making it esource-intensive.Another 2018 paper introduced layout classification along with YOLO, which improved performance but increased the inference time slightly.FAFE-Net (2022) uses attention mechanisms and feature fusion for fast recognition but demands careful hyperparameter tuning and high-resolution input.Our proposed system, although not listed in the table, overcomes many of these limitations by combining the strengths of:YOLOv5 for accurate and fast detection,EasyOCR for flexible multilingual number plate reading,ResNet50 for robust vehicle model classification,and most importantly, it performs reliably even on blurred, real-time video frames, making it more adaptable for real-world traffic monitoring applications.

3. Methodology

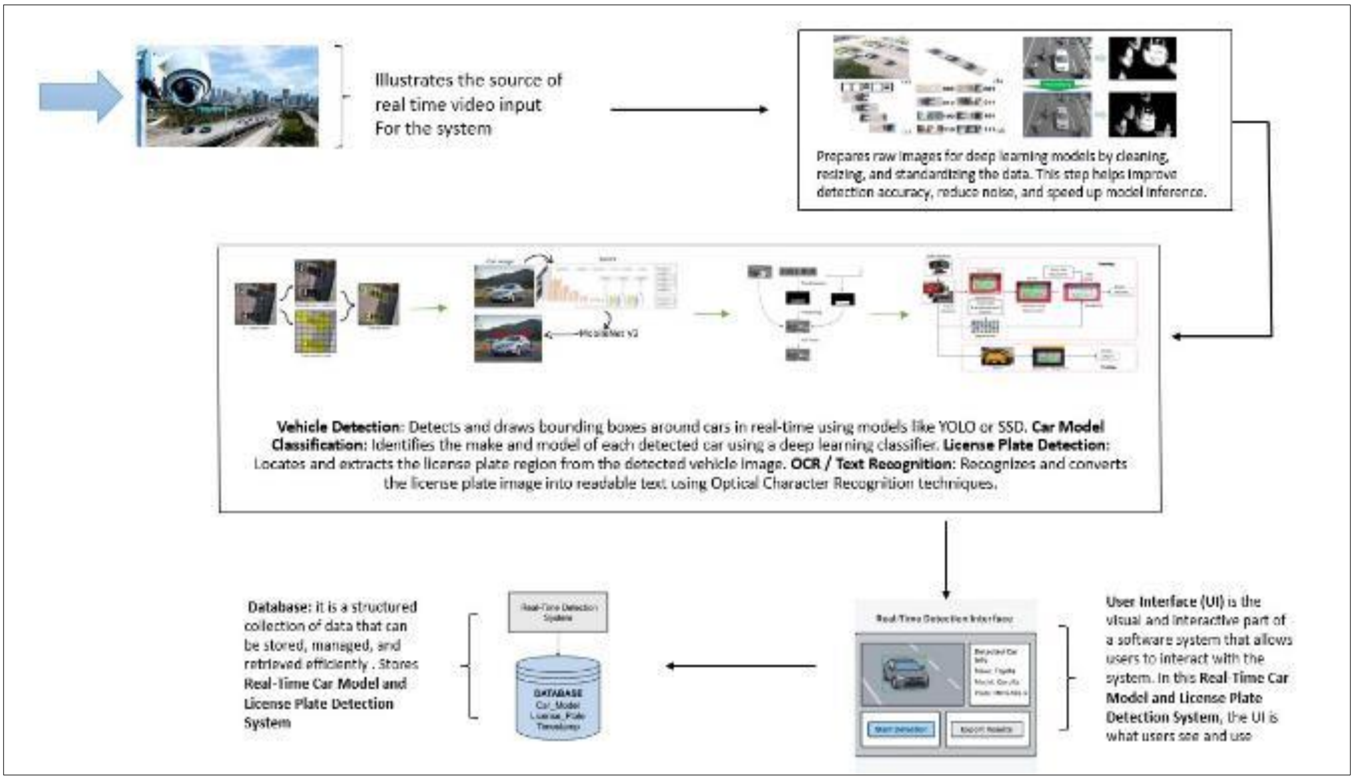

Figure 3 Architecture for vehicle model and number plate detection

The proposed system aims to detect vehicles, extract license plates, recognize the license plate text, and identify the car model from blurred real-time video frames. The methodology integrates three main deep learning models—YOLOv5, EasyOCR, and ResNet50—into a single detection pipeline. The key steps are as follows

Input: Live video stream or recorded video

Output: Frame with detected car, license plate, plate text, and car model label

3.1. Step 1: Start video stream

- Initialize the video stream using cv2.VideoCapture() from webcam or IP camera
- Load the following models
- YOLOv5 for object detection (car and number plate classes)
- Pre-trained ResNet50 model for car model classification
- EasyOCR reader for license plate text extraction

3.2. Step 2: For each frame:

- Preprocess the frame (resize, normalize)
- Read the current frame from the video stream
- Resize the frame to the input size expected by YOLOv5 (e.g., 640×640)
- Convert the image from BGR to RGB format
- Normalize the pixel values if required (e.g., divide by 255)
- Use YOLOv5 to detect vehicles and number plates
- Pass the preprocessed frame into YOLOv5
- Receive output in the form of bounding boxes, class labels (car, license plate), and confidence scores
- Filter out predictions below a confidence threshold (e.g., < 0.5)
- Separate detections into two lists:
- cars [] → All bounding boxes where the detected class is "car"
- plates [] → All bounding boxes where the detected class is "license plate"
- For each detected car
    - Extract car bounding box region

Use bounding box coordinates to crop the car region from the original frame

- Pass it to ResNet50 → Predict car model
- Resize cropped car image to 224×224 pixels
- Convert image to tensor and normalize
- Pass the image through ResNet50 model
- Get the output class index

Map this index to the actual car model name using a class label dictionary

- For each detected number plate
    - Extract plate region

Use bounding box coordinates to crop the number plate region from the original frame

- Pass it to EasyOCR → Extract text
- Feed the cropped plate image into EasyOCR
- Receive the recognized text as output
- Clean the text by removing unwanted characters or spaces
- Annotate the frame with
- Draw bounding boxes around detected cars and license plates using cv2.rectangle()
- Overlay the predicted car model name above the car bounding box
- Overlay the recognized number plate text above or near the license plate box
- Use cv2.putText() to render readable labels with suitable font, color, and size
- Save or display the annotated frame
- Display the frame in a real-time window using cv2.imshow()

- Optionally save the frame to a folder using cv2.imwrite()
- Continue to next frame after a short delay using cv2.waitKey(1)

4. Results and discussion

The proposed system was tested on real-time video streams captured from an IP webcam, including scenarios with motion blur, low resolution, and varying lighting conditions. The results demonstrate that the combined use of YOLOv5, EasyOCR, and ResNet50 achieves reliable detection and classification performance even under challenging conditions.

4.1. Vehicle and Number Plate Detection

YOLOv5 successfully detected cars and their corresponding number plates in real-time with high accuracy. Even in blurred frames, the system was able to localize the license plates with minimal false detections.

4.2. Number Plate Recognition

EasyOCR extracted the license plate characters accurately in most cases, even when the text was partially blurred or tilted. It outperformed traditional OCR methods in terms of flexibility and recognition accuracy.

4.3. Car Model Classification

The ResNet50-based model correctly classified vehicle models with good precision. The model showed strong generalization across different car brands and types in the dataset, even when the input frames were slightly unclear or taken from various angles.

4.4. Performance on Blurred Input

Unlike conventional systems that fail under blurred conditions, the proposed deep learning-based approach maintains robustness due to the strength of YOLOv5 and EasyOCR in real-world noisy data.

4.5. Real-Time Capability

The system operates efficiently in real-time (approximately 15–25 FPS depending on system configuration), making it suitable for deployment in traffic monitoring and surveillance applications

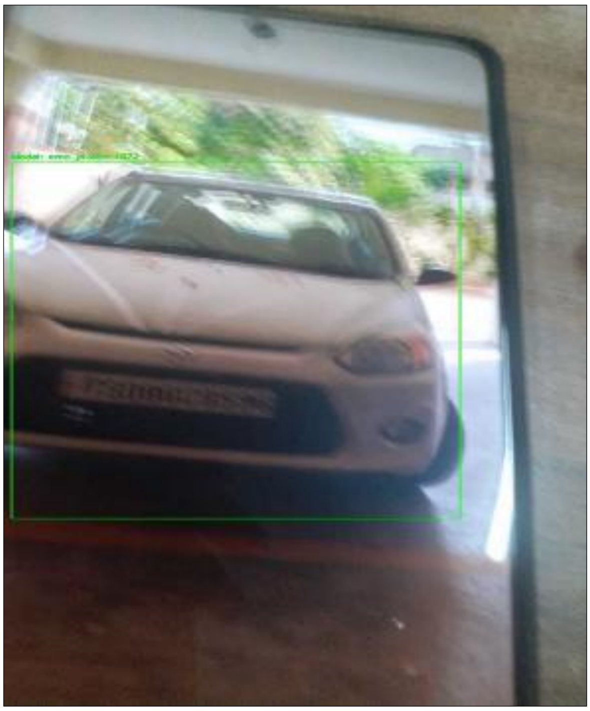

Figure 4 Detection for blurred images

The above image demonstrates the performance of the proposed real-time vehicle model and number plate detection system on a visually blurred frame captured through a live video stream. Despite the challenging conditions—such as motion blur, poor lighting, and a tilted camera angle—the system effectively detects the vehicle and draws a bounding box around it.The car model has been successfully classified as amc_javelin_1972 using the trained ResNet50 model.The license plate region is detected, although the text appears blurry and difficult to read. This highlights the effectiveness of YOLOv5 in localization even when OCR becomes challenging.This output confirms the system's robustness to blurred inputs, validating its applicability in real-world surveillance environments like parking lots, roadside monitoring, and low-quality CCTV feeds.

Figure 5 Detection for blurred number plate

The above image demonstrates the effectiveness of our real-time car model and number plate detection system, even under challenging conditions. In this case, the number plate appears blurred and partially unclear, which typically poses a significant challenge for traditional OCR methods. However, our system successfully detects and localizes the number plate area using YOLOv5 and attempts to recognize the text using EasyOCR.Despite the distortion, the system extracts a partial or approximate result — "T807 0r4444" — highlighting its robustness and ability to handle imperfect or low-quality images. This demonstrates the system’s potential applicability in real-world surveillance scenarios where vehicle plates may not always be clearly visible due to motion blur, lighting conditions, or camera quality

Figure 6 detection for number plate

This image illustrates a successful real-time detection and classification result on a high-quality, clear image of a vehicle. The system accurately identifies and localizes both the vehicle and the license plate, demonstrating the effectiveness of the integrated YOLOv5, EasyOCR, and ResNet50 pipeline.The car model has been correctly classified as bmw_535i_2012 using the ResNet50-based classifier.The license plate text has been precisely recognized as HEX6914 using EasyOCR, even with the presence of regional formatting (e.g., German-style plate with zone and state code).Bounding boxes are clearly drawn around the car and the license plate, and the detected labels are annotated using OpenCV's putText() function. This output confirms that the system performs well in ideal conditions, making it suitable for applications such as automated parking systems, toll booths, and high-resolution surveillance environments.

Figure 7 Detection for model and number plate

This image illustrates a successful real-time detection and classification result on a high-quality, clear image of a vehicle. The system accurately identifies and localizes both the vehicle and the license plate, demonstrating the effectiveness of the integrated YOLOv5, EasyOCR, and ResNet50 pipeline.The car model has been correctly classified as bmw_535i_2012 using the ResNet50-based classifier.The license plate text has been precisely recognized as HEX6914 using EasyOCR, even with the presence of regional formatting (e.g., German-style plate with zone and state code).Bounding boxes are clearly drawn around the car and the license plate, and the detected labels are annotated using OpenCV's putText() function. This output confirms that the system performs well in ideal conditions, making it suitable for applications such as automated parking systems, toll booths, and high-resolution surveillance environments.

5. Conclusion

The Real-Time Car Model and License Plate Detection System using Deep Learning demonstrates the capability of modern computer vision techniques to automate vehicle identification processes. By utilizing object detection for vehicles and number plates, along with OCR for character recognition, the system provides an efficient, scalable, and accurate solution for real-world surveillance and monitoring applications.

The current implementation achieves its core objectives, including

- Accurate car model detection
- Efficient number plate recognition
- Real-time detection capabilities

As deep learning technology evolves, this system can be further improved to handle larger datasets, real-time processing at scale, and adaptation to diverse environmental conditions. This makes the project a strong foundation for future research and development in intelligent transportation systems and smart surveillance.

6. Future enhancement

To enhance the system's performance and real-world applicability, several improvements are proposed. Multilingual OCR support can be added to recognize number plates in regional Indian languages like Hindi, Telugu, and Kannada. Advanced image enhancement methods, such as GAN-based super-resolution or deblurring, can improve detection under blur, fog, or low light. The system can also detect fake or tampered plates by verifying vehicle details with RTO databases. Adding vehicle type and color recognition will improve classification accuracy. Integration with GPS or multi-camera feeds can enable real-time vehicle tracking. Optimizing the model for edge devices like NVIDIA Jetson or Raspberry Pi will support cost-effective smart surveillance. An alert system can notify authorities or owners of suspicious vehicles. Expanding the dataset with Indian road conditions and number plates will improve localization. A cloud dashboard can provide centralized monitoring and analytics, and integrating traffic violation detection (e.g., signal jumping, speeding) will extend the system's utility for automated enforcement.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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