International Research Journal on Advanced Engineering and Management
https://goldncloudpublications.com
https://doi.org/10.47392/IRJAEM.2025.0221
e ISSN: 2584-2854
Volume: 03
Issue: 04 April 2025
Page No: 1359 - 1363

Traffic Violation Detection Using Deep Learning

Mr. S. Suresh[1], J Gopalakrishnan[2], K Guruseelan[3], S Giridharan[4], K Gururajan[5]
[1] Asst Professor, poonamallee Chennai,602001, India.
[2,3,4,5]UG Student, Pudukkottai,614616, India.
Emails ID: *ssuresh.pec@gmail.com[1], gopalakrishnan122005@gmail.com [2], guruseelankabio@gmail.com[3], giridharanselvam08@gmail.com[4], gurukolanjirajan1603k@gmail.com[5]*

Abstract
Traffic violation detection is a crucial aspect of intelligent transportation systems, enabling automated identification of vehicles for security, law enforcement, and toll collection. This process involves image acquisition, pre-processing, segmentation, feature extraction, and character recognition. Various techniques, including edge detection, morphological operations, and deep learning-based object detection models, enhance accuracy and robustness. Convolutional Neural Networks (CNNs) and You Only Look Once (YOLO) models have significantly improved real-time detection performance. Challenges such as varying lighting conditions, occlusions, and diverse plate formats necessitate adaptive algorithms. Optical Character Recognition (OCR) is employed to extract alphanumeric details. Machine learning and deep learning techniques refine detection precision. Integration with cloud computing and IoT enhances scalability and deployment. Future advancements focus on improving accuracy, speed, and adaptability to complex environments.

Keywords: *Parking & Toll Collection*, K-Nearest Neighbors, Traffic Violation Detection Using Deep Learning.

1. Introduction

Vehicle Number Plate Recognition (VNPR) is widely used in traffic monitoring, law enforcement, and automated systems. Traditional methods struggle with variations in lighting, angles, and plate designs. Deep learning offers a more accurate and robust solution by automating plate detection and character recognition. This paper explores a CNN-based approach to improve recognition accuracy, making it suitable for real-time applications in security, toll collection, and parking management [1-5]. Vehicle Number Plate Recognition (VNPR) has become an essential component of modern intelligent transportation systems, significantly enhancing traffic management, law enforcement, toll collection, and parking control. With the rapid increase in vehicular traffic and the inherent variability in license plate designs, traditional methods that depend on handcrafted features and rule-based algorithms often struggle to cope with challenges such as varying illumination, occlusions, motion blur, and diverse plate formats. In contrast, deep learning approaches, particularly those leveraging convolutional neural networks (CNNs), have revolutionized the field by automatically learning robust and discriminative features from large datasets. This advancement allows for more accurate and efficient detection of license plates, even in complex real-world scenarios, and facilitates the subsequent extraction of alphanumeric characters using advanced optical character recognition (OCR) techniques.

2. Literature Survey

2.1 Objective

The objective of this project is to develop an efficient and automated vehicle number plate detection system using image processing and deep learning techniques. By leveraging advanced object detection models such as Convolutional Neural Networks (CNNs) and You Only Look Once (YOLO), the system aims to enhance accuracy and robustness in diverse conditions. It seeks to address challenges like varying

e ISSN: 2584-2854
Volume: 03
Issue: 04 April 2025
Page No: 1359 - 1363

lighting conditions, occlusions, and different plate formats while ensuring real-time processing for applications in law enforcement, toll collection, and traffic monitoring. Optical Character Recognition (OCR) will be integrated to extract alphanumeric details from detected plates. Additionally, the system's performance will be evaluated using metrics such as accuracy, precision, and processing speed. To improve scalability and remote accessibility, integration with cloud computing and IoT will be explored. Ultimately, this project aims to contribute to advancements in intelligent transportation and automated surveillance systems.

2.2 Scope

2.2.1 Traffic Management & Law Enforcement

- Automates vehicle identification for monitoring traffic violations and enforcing laws.
- Assists in detecting stolen or suspicious vehicles by cross-referencing databases.

2.2.2 Parking & Toll Collection

- Enables automated entry and exit for smart parking systems.
- Facilitates electronic toll collection without manual intervention.

2.2.3 Security & Surveillance

- Enhances security at sensitive locations by tracking vehicle movements.
- Supports access control systems for restricted areas like military zones, corporate offices, and gated communities.

2.2.4 AI-Driven Plate Recognition

- Utilizes machine learning (ML) and deep learning models for accurate number plate detection.
- Adapts to different lighting conditions, plate formats, and environmental variations.

2.2.5 Real-Time Alerts & Reporting

- Sends notifications for unauthorized or blacklisted vehicles in real-time.
- Generates reports for traffic analysis, law enforcement, and urban planning.
-

2.2.6 Scalability & Integration

- Deployable in various sectors, including transportation, logistics, and government agencies.
- Easily integrates with existing surveillance cameras, databases, and smart city infrastructure.

3. Proposed Methods

3.1 Proposed Work

The proposed vehicle number plate recognition system utilizes deep learning techniques to achieve accurate and efficient plate detection and character recognition. The system is divided into two main stages: plate detection and character recognition. In the first stage, a Convolutional Neural Network (CNN)-based object detection model, such as YOLO (You Only Look Once) or Faster R-CNN, is employed to localize vehicle number plates in real-time from images or video frames. This model is trained on a diverse dataset to ensure robustness against variations in lighting, angles, and plate designs [6-10]. Once the plate is detected, it undergoes preprocessing techniques such as noise reduction, contrast enhancement, and geometric transformations to improve recognition accuracy.

3.2 Existing System

Traditional Vehicle Number Plate Recognition (VNPR) systems rely on image processing and machine learning techniques for plate detection and character recognition. These methods typically involve edge detection, morphological operations, and contour analysis to localize the number plate in an image. Once detected, Optical Character Recognition (OCR) techniques, such as template matching or handcrafted feature extraction, are applied to recognize the alphanumeric characters. While these approaches have been used for years, they suffer from several limitations, including sensitivity to variations in lighting, angles, occlusions, and different plate formats. Machine learning-based approaches, such as Support Vector Machines (SVMs) and K-Nearest Neighbors (KNN), have been introduced to improve accuracy, but they still require extensive feature engineering and manual tuning. Additionally, traditional OCR methods struggle with distorted or low-quality images, leading to errors in character recognition. Figure 1 shows Traffic Violation Detection Using Deep Learning.

e ISSN: 2584-2854
Volume: 03
Issue: 04 April 2025
Page No: 1359 - 1363

Architecture Diagram:

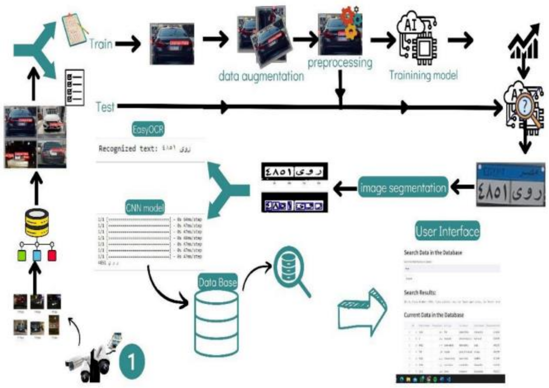

Figure 1 Traffic Violation Detection Using Deep Learning

3.3 Modules

3.3.1 Image Acquisition

- Captures images or video frames from cameras in real-time.
- Handles variations in resolution, lighting conditions, and motion blur.

3.3.2 Preprocessing

- Enhances image quality by applying noise reduction, contrast adjustment, and edge detection.
- Converts the image to grayscale and applies thresholding for better feature extraction.

3.3.3 Number Plate Detection

- Uses a deep learning-based object detection model (e.g., YOLO or Faster R-CNN) to accurately locate the number plate.
- Ensures robust detection under different conditions such as occlusions, distortions, and angle variations.

3.3.4 Character Segmentation

- Extracts the region containing the number plate and segments individual characters.
- Uses contour analysis and bounding box techniques to isolate characters for recognition.

3.3.5 Character Recognition

- Implements an Optical Character Recognition (OCR) model, such as CNN-based OCR or Transformer-based architectures, to identify alphanumeric characters.
- Handles different fonts, sizes, and distortions for accurate recognition.

3.3.6 Post-Processing and Validation

- Applies lexicon-based corrections and confidence-based filtering to refine the recognized text.
- Cross-checks with databases for verification in law enforcement, toll collection, or parking management systems.

3.3.7 Result Display and Storage

- Displays the recognized license plate on a user interface.
- Stores the extracted data in a database for further processing and analysis.

4. Performance Analysis

Deep learning-based vehicle number plate detection for traffic violations requires evaluating its effectiveness using key performance metrics. The performance analysis involves assessing detection accuracy, processing speed, robustness to variations, and real-world applicability [11-13].

4.1 Detection Accuracy

- **Precision:** Measures the percentage of correctly detected number plates among all detected plates.Precision=TPTP+FPPrecision = \frac{TP}{TP + FP}Precision=TP+FPTP
- **Recall:** Measures the percentage of actual number plates correctly detected. Recall=TPTP+FNRecall = \frac{TP}{TP + FN}Recall=TP+FNTP
- **F1-Score:** Harmonic mean of precision and recall. F1=2×Precision×RecallPrecision+RecallF1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}F1=2×Precision+RecallPrecision×Recall
- **mAP (Mean Average Precision):** Measures detection accuracy across different confidence thresholds.

4.2 Processing Speed (Inference Time)

- **Frames Per Second (FPS):** Measures the speed at which the model processes video frames.
- **Latency (ms/frame):** Time taken by the model to detect a number plate in a single frame.
- **Real-Time Capability:** If the model achieves at least 30 FPS, it can be used for live traffic monitoring.

e ISSN: 2584-2854
Volume: 03
Issue: 04 April 2025
Page No: 1359 - 1363

4.3 Robustness Analysis

- **Lighting Conditions:** Performance under bright sunlight, shadows, and night-time.
- **Weather Conditions:** Effectiveness in rain, fog, and dusty environments.
- **Angle and Occlusion:** Handling skewed, tilted, or partially blocked number plates.
- **Different License Plate Formats:** Adaptability to different fonts, colors, and regions.

5. Experimental Results

5.1 Dataset Used

- Public datasets like AOLP, UFPR-ALPR, or custom traffic footage.
- Number of images/videos used for training and testing.

5.2 Model Performance

- YOLOv8 / Faster R-CNN / SSD results comparison.
- Training time vs. accuracy trade-off.
- Confusion Matrix Analysis: To check false positives and false negatives.

Table 1 Comparison

METRICS	Deep Learning-Based	Traditional OCR-Based
Accuracy	High (>90%)	Moderate (~70-80%)
Speed	Fast (real-time possible)	Slow (depends on feature extraction)
Robustness	Works in various conditions	Struggles with low resolution, lighting issues
Scalability	Easily scalable with better models	Limited to predefined rules
Adaptability	Learns from data, handles variations	Fixed rules, difficult to improve

Conclusion

Deep learning-based vehicle number plate detection has proven to be highly accurate, efficient in real-time scenarios, and robust in various conditions, making it a powerful tool for traffic violation monitoring and enforcement. Its ability to handle diverse lighting, weather, and occlusion challenges enhances its reliability in real-world applications. Looking ahead, significant improvements can be achieved by focusing on advanced techniques for detecting plates in low-quality images, optimizing computational efficiency for seamless real-time processing on embedded systems, and integrating with intelligent traffic management frameworks. These enhancements will further strengthen its scalability, accuracy, and overall impact in modern smart transportation systems. Table 1 shows Comparision.

References

[1]. S. Vijayalakshmi, S. Goutham, K. R. Kavitha, K. Jawahar and R. Gowtham Kumar, "Number Plate Tracking System Using OCR", Annals of RSCB, pp. 1986-1990, May 2021.

[2]. Shubhra Tonge, Bhavisha Hemwani, Gulshan Thawani, Sonnal Katara and Nikhil Dhanwani, "AUTOMATIC NUMBER PLATE RECOGNITION", published by International Research Journal of Modernization in Engineering Technology and Science, vol. 4, 2022.

[3]. Arun Vaishnav and Manju Mandot, "Information and Communication Technology for Sustainable Development", vol. 933-ocr, 2020.

[4]. T. Damak, O. Kriaa, A. Baccar, M. A. Ben Ayed and N. Masmoudi, "Automatic Number Plate Recognition System Based on Deep Learning", World Academy of Science Engineering and Technology International Journal of Computer and Information Engineering, vol. 14, no. 3, 2020.

[5]. Shrutika Saunshi, Vishal Sahani, Juhi Patil, Abhishek Yadav and Sheetal Rathi, "License Plate Recognition Using Convolutional Neural Network IOSR Journal of Computer Engineering".

[6]. N.Eswar, Dr. D. Gowri Shankar Reddy, “Morphological Operation based Vehicle Number Plate Detection,”International Journal of Engineering Research And, V9

(02), 2020.

[7]. N.O. Yaseen, S.G.S. Al-Ali, A. Sengur, “An Efficient Model for Automatic Number Plate Detection using HOG Feature from New North Iraq Vehicle Images Dataset,” 1st International Informatics and Software Engineering Conference: Innovative Technologies for Digital Transformation, IISEC 2019 - Proceedings, 2019.

[8]. K.D. Ban, Y. Yoon, H.S. Yoon, J. Kim, “Number detection in natural image with boosting classifier,” 2012 9th International Conference on Ubiquitous Robots and Ambient Intelligence, URAI 2012.

[9]. M. Molina-Moreno, I. Gonzalez-Diaz, F. Diaz-De-Maria, “Efficient Scale-Adaptive License Plate Detection System,” IEEE Transactions on Intelligent Transportation Systems, 20(6), 2109–2121, 2019.

[10]. Shraddha S Ghadage and Sagar R Khedkar, "A Review Paper on Automatic Number Plate Recognition System using Machine Learning Algorithms", International Journal of Engineering Research & Technology (IJERT), vol. 8, no. 12, 2019.

[11]. Junqing Tang et al., "Automatic number plate recognition (ANPR) in smart cities: A systematic review on technological advancements and application cases", Cities, vol. 129, pp. 103833, 2022.

[12]. S.Babbar, S.Kesarwani, N.Dewan, K.Shangle, S.Patel, “A New Approach For Vehicle Number Plate Detection,”2018 11th International Conference On Contemporary Computing, IC3 2018, 1–6, 2018.

[13]. Maham Saeed Salma, Rauf Ur Rahim, Muhammad Gufran Khan, Adil Zulfiqar And Muhammad Tahir Bhatti, "Development Of ANPR Framework For Pakistani Vehicle Number Plates Using Object Detection And OCR", Complexity, Vol. 2021.