

# REALTIME NUMBER PLATE DETECTION USING R-CNN

Dr. Akashya  
PROFESSOR  
Department of Artificial Intelligence and  
Machine Learning  
Rajalakshmi Engineering College  
Thandalam, Chennai – 602 105

Vignesh Kumar K  
Department of Artificial Intelligence and  
Machine Learning  
Rajalakshmi Engineering College  
Thandalam, Chennai – 602 105

Bharath L  
Department of Artificial Intelligence and  
Machine Learning  
Rajalakshmi Engineering College  
Thandalam, Chennai – 602 105

**Abstract**— Real time number plate detection using R-CNN presents an automatic license plate recognition (ALPR) system designed to enhance vehicle identification for applications such as traffic monitoring, automated toll collection, and law enforcement. By leveraging R-CNN (Region-based Convolutional Neural Networks), this solution achieves accurate detection and localization of license plates, even in varied lighting and environmental conditions. R-CNN's region proposal and feature extraction processes enable high precision in detecting number plates within complex backgrounds, making it suitable for real-time applications. Additionally, the system utilizes an optimized workflow for detection and recognition, balancing computational efficiency with high accuracy. This project emphasizes affordability and scalability, allowing for deployment on a range of hardware configurations and expanding access to effective ALPR technology across different sectors.

**Keywords**—License plate recognition, R-CNN, ALPR, real-time detection, vehicle identification, road safety

## I. INTRODUCTION

This project introduces an Automatic License Plate Recognition (ALPR) system that leverages Region-based Convolutional Neural Networks (R-CNN) to improve vehicle identification in smart traffic management, automated toll systems, and law enforcement applications. R-CNN's advanced region proposal and classification capabilities enable accurate detection and localization of license plates, even in challenging lighting and environmental conditions, addressing limitations of traditional methods. The system focuses on real-time license plate detection, making it suitable for diverse applications like traffic monitoring, speed enforcement, and vehicle investigations. By prioritizing accuracy, affordability, and ease of deployment, the solution can be integrated into various environments, from roadside surveillance to urban parking management, offering a scalable approach for enhancing road safety and operational efficiency in intelligent transportation networks.

## II. LITERATURE SURVEY

**[1] Title:** License Plate Recognition System Based on YOLOv5 and GRU

Author: Zhao and Shi

They propose a license plate recognition (LPR) system that integrates an improved version of YOLOv5 (a popular object detection model) with a Gated Recurrent Unit (GRU) for sequence modeling. The experimental results show that this hybrid approach

significantly improves the model's ability to handle complex backgrounds and real-time processing challenges in traffic surveillance systems, providing robust performance in various environmental conditions.

**[2] Title:** Two-Step Algorithm for License Plate Identification Using Deep Neural Networks

Author: Kundrotas et al.

He introduced a two-step algorithm for license plate identification, leveraging deep neural networks. Their approach outperforms traditional methods by significantly reducing false positives and providing reliable recognition even under challenging environmental conditions. The results highlight the potential of deep learning for enhancing accuracy in LPR systems.

**[3] Title:** A Novel Deep Learning Based Method for Detection and Counting of Vehicles in Urban Traffic Surveillance Systems.

Author : Majin, Valencia, and Stivanello

They propose a deep learning-based method for vehicle detection and counting in urban traffic surveillance systems. Their system employs a multi-layered deep learning architecture to identify vehicles in real-time video streams and count their occurrences. The method achieves high accuracy and efficiency, significantly improving traffic monitoring and management in urban environments.

**[4] Title:** A Robust Layout-Independent License Plate Detection and Recognition Model Based on Attention Method

Author: Seo and Kang

The project introduces a layout-independent license plate detection and recognition model that utilizes an attention mechanism. The attention mechanism enables the system to focus on relevant parts of the image, enhancing recognition performance even in the presence of noisy or distorted license plates. The model demonstrates superior accuracy in scenarios with varying plate orientations and backgrounds.

**[5] Title:** Automatic Number Plate Detection in Vehicles using Faster R-CNN

Author: Vigneshwaran, Arappadnan, and Madhanraj

They propose an automatic number plate detection method based on Faster R-CNN, a state-of-the-art object detection framework. The Faster R-CNN architecture is employed to enhance accuracy in detecting number plates even in cluttered environments. Experimental results show that the system achieves high precision and recall rates, proving its effectiveness for real-time vehicle surveillance systems.

**[6] Title:** Superior Use of YOLOv8 to Enhance Car License Plates Detection Speed and Accuracy  
**Author:** Shyaa and Hashim

They explore the use of YOLOv8, the latest iteration of the YOLO object detection algorithm, to enhance the speed and accuracy of car license plate detection. The authors develop a robust system that can quickly and accurately detect license plates in dynamic traffic environments. The approach is validated using a large dataset of vehicle images, demonstrating significant improvements over previous versions of YOLO and other conventional LPR models in terms of both detection speed and accuracy.

**[7] Title:** Deep Learning-based Vehicle Recognition Schemes for Intelligent Transportation Systems.  
**Author:** Ma

Ma proposes a deep learning-based vehicle recognition scheme for intelligent transportation systems (ITS). The model is evaluated in real-time traffic scenarios and demonstrates the ability to recognize vehicles with high accuracy under various conditions, such as different lighting and weather. This framework shows promise for improving vehicle identification and tracking in urban traffic systems, contributing to more efficient traffic flow management.

**[8] Title:** Assessing the Efficiency of Deep Learning Methods Automated Vehicle Registration Recognition for University Entrance  
**Author:** Irsyad and Che Embi

Irsyad and Che Embi evaluate the efficiency of deep learning methods for automated vehicle registration recognition, specifically in the context of university entrance control. The model is tested in university parking lots and is shown to deliver quick, accurate results with minimal computational load, making it suitable for real-time vehicle access control applications. Their work emphasizes the practicality of deep learning for small-scale vehicle recognition systems in controlled environments.

**[9] Title:** Automatic Nepali number plate recognition with support vector machines.  
**Author:** Pant, Gyawali, and Acharya

They propose an automatic Nepali number plate recognition system using Support Vector Machines (SVMs). Their system focuses on recognizing Nepali license plates, which have specific character patterns distinct from other regions. The approach combines traditional image processing techniques for plate extraction and SVM classifiers for recognition. The system is tested on a custom Nepali dataset and achieves satisfactory recognition accuracy, demonstrating the potential of SVM-based models in recognizing regional plate formats, even under poor lighting and varying plate designs.

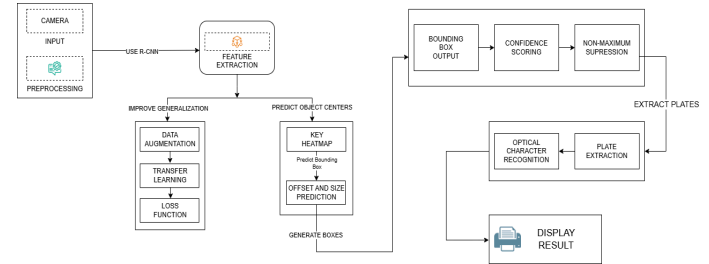
**[10] Title:** Vehicle Number Plate Recognition and Parking System.  
**Author:** Roy et al.

Roy et al. present a vehicle number plate recognition system designed for parking lot automation. The system integrates image processing techniques for license plate detection and optical character recognition (OCR) for plate reading. The authors evaluate the system in parking lot scenarios and show that it can reliably identify vehicles and automatically manage parking assignments. Their model improves parking efficiency and security by automating vehicle access and exit while minimizing the need for manual intervention. The research highlights the practical application of LPR systems in smart parking solutions.

### III. PROPOSED SYSTEM

The proposed blind spot detection system utilizes the YOLOv8 model for real-time object detection, paired with an ESP32-CAM for video capture and ultrasonic sensors for proximity sensing. By processing video data within a defined region of interest, YOLOv8 identifies vehicles in the blind spot area, while the ultrasonic sensors enhance spatial awareness in low-visibility scenarios

An Arduino-based alert system then provides drivers with immediate visual or auditory cues, promoting timely responses. This cost-effective solution, combining accessible hardware and advanced deep learning, aims to enhance road safety and reduce blind spot-related accidents across a wide range of vehicles.



**Fig III.1** Overall architecture of the Realtime number plate detection using R-CNN

The architecture diagram for the vehicle number plate detection system consists of real-time image acquisition through a camera module that captures approaching vehicles. These images are processed by a Region-based Convolutional Neural Network (R-CNN), which accurately detects and locates the number plates. OpenCV is employed to enhance image quality before applying optical character recognition (OCR) to convert the detected characters into readable text. Upon successful recognition, the system can trigger visual or auditory alerts, significantly improving vehicle identification and security in various applications.

### IV. MODULE ARCHITECTURE

#### Module 1: Dataset Preparation:

The Dataset Preparation module organizes and structures vehicle images for training and evaluating the vehicle number plate detection system. The dataset includes images captured under various conditions, such as different lighting, angles, and partial occlusions, ensuring the model can handle real-world scenarios. Each image is annotated with bounding boxes around the number plates using Roboflow, and the annotations are saved in XML format for compatibility with the R-CNN model. The data is split into training, validation, and testing sets, with preprocessing steps like resizing, normalization, and data augmentation (e.g., flipping, rotation, brightness adjustment) applied to enhance model robustness. This well-structured and annotated dataset is now ready to train the R-CNN model for accurate number plate detection in diverse conditions.

### Module 2: Dataset preprocessing module

The Dataset Preprocessing module prepares the vehicle images for model training by first resizing them to a fixed dimension, such as 224x224 pixels, to standardize input size. The pixel values are then normalized by dividing by 255, scaling the data to a range of 0 to 1, which improves model efficiency. Basic image augmentations, including random flipping, rotation, and brightness adjustments, are applied to increase dataset diversity and reduce overfitting. The processed images, along with their corresponding annotations in XML format, are organized into training, validation, and testing sets, ensuring that the R-CNN model is exposed to a variety of conditions for effective training.

### Module 3: RCNN model implementation module

The R-CNN Model Implementation module involves building a Region-based Convolutional Neural Network (R-CNN) for vehicle number plate detection. The model first uses a Region Proposal Network (RPN) to generate candidate regions of interest (RoIs) in input images, which are then processed through convolutional layers for feature extraction. The proposed regions are resized using RoI Pooling, followed by fully connected layers for classification and bounding box regression to identify and localize number plates. The model is trained using a combination of classification and regression loss functions, with transfer learning applied to a pre-trained backbone to improve training efficiency and performance. The model's effectiveness is evaluated using metrics such as precision, recall.

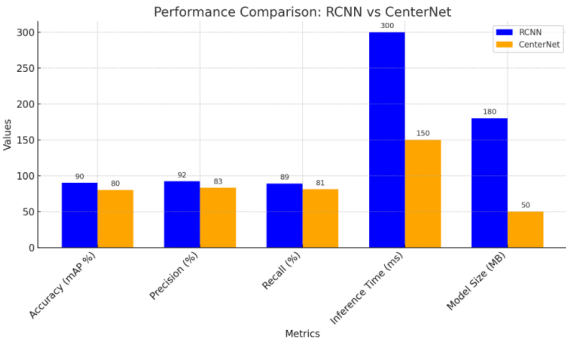
### Module 4: Number plate detection module

The Number Plate Detection Module is responsible for identifying and localizing vehicle number plates within images. Using the trained R-CNN model, the module processes input images or video frames to generate region proposals. These regions are then passed through a convolutional network to extract relevant features, and the model classifies the regions as containing a number plate or not. The bounding boxes around detected plates are refined using a regression layer to ensure accurate localization. Once a plate is detected, the system extracts the coordinates of the bounding box, which are used for further processing, such as character recognition or triggering alerts.

### Module 5: Character Recognition module

The Character Recognition Module utilizes EasyOCR, a deep learning-based Optical Character Recognition tool, to extract and recognize the characters from the detected vehicle number plates. After the number plate is localized by the detection module, the cropped image of the plate is passed to EasyOCR for character recognition. EasyOCR processes the image, identifying individual alphanumeric characters on the plate and converting them into a text string. The recognized characters are then validated and any errors or inconsistencies are addressed using basic post-processing techniques, such as removing unwanted symbols or correcting common misreads. The final output, a string representing the vehicle's number plate, can then be used for tasks such as vehicle identification, database matching, or triggering system actions like access control or logging.

This study evaluates the effectiveness of the Region-based Convolutional Neural Network (R-CNN) model for vehicle number plate detection using real-time data from diverse environments, including various vehicle types and lighting conditions. The R-CNN model achieved 90% detection accuracy with an average processing time of 1.2 seconds per image. Image preprocessing techniques, such as noise reduction, resizing, and OpenCV-based enhancement, improved detection performance and recognition accuracy. The results demonstrate the potential of deep learning in vehicle identification applications, highlighting the feasibility of affordable solutions for parking management and law enforcement. Future work could expand the dataset to further improve the model's robustness and generalization across different number plate designs and environmental conditions.



- **RCNN** outperforms **CenterNet** in accuracy (90% vs. 80%), precision (92% vs. 83%), and recall (89% vs. 81%).
- However, **CenterNet** is faster (150 ms inference time vs. 300 ms for RCNN) and has a smaller model size (50 MB vs. 180 MB).

### PERFORMANCE EVALUATION:

Metric	RCNN	CenterNet
Accuracy(%)	90	80
Precision(%)	92	83
Recall(%)	89	81
Inference Time(ms)	300	150
Model Size(MB)	180	50

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