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Vehicle Number Plate Detection and Recognition Using Deep Learning

Dr. P. Nageswara Rao[1], P. Devi Naga Sathvika[2], M. Pavan Venkata Sai[3], M. KondaReddy[4], K. Chinnu[5]
Director & Professor, Department of CSE[1]
UG Students, Department of CSE[2,3,4,5]
Vasireddy Venkatadri Institute of Technology, Nambur, Guntur Dt., Andhra Pradesh, India
pnrao33@gmail.com, psathvika2022@gmail.com, p1venkatasai@gmail.com,
muthanakondareddy@gmail.com, chinnukarumanchichinnu@gmail.com

Abstract: *Vehicle Number Plate Detection and Recognition plays a crucial role in intelligent transportation systems, traffic surveillance, and law enforcement by enabling accurate vehicle identification across a wide range of environmental conditions. This study introduces a reliable deep learning framework for real-time detection of vehicles and their license plates, as well as for recognizing the characters, utilizing the YOLOv11 and CRNN models. The proposed system first employs YOLOv11 for efficient and precise localization of vehicles and their corresponding license plates from images and video streams. Subsequently, the detected plate regions are processed using a Convolutional Recurrent Neural Network (CRNN) to recognize alphanumeric characters in a sequential manner. An original dataset comprising 21,000 vehicle images under varying lighting, angles, and backgrounds was curated and augmented to improve model generalization and robustness. Experimental results demonstrate that the proposed framework effectively handles real- world challenges such as motion blur, occlusion, and low-resolution plates, making it suitable for deployment in real-time traffic monitoring, automated toll collection, and security applications.*

Keywords: YOLOv11, CRNN, Number Plate Detection And Recognition, Deep Learning, Intelligent Transportation Systems

I. INTRODUCTION

Vehicle number plates serve as a primary means of identifying automobiles in modern transportation systems, such as traffic regulation, law enforcement and toll collection. Accurate extraction of license plate information from vehicle images and videos provides support for transportation infrastructure. However, real- world environments present significant challenges to reliable number plate detection and recognition. Variations in illumination, viewing angles and weather conditions often degrade image quality. Additionally, manual monitoring and visual inspection of vehicle identifiers are labor- intensive and error- prone for large- scale deployment. These limitations highlight the need for an automated and objective system capable of consistently detecting and recognizing vehicle number plates.

The primary motivation of this research is to provide transportation authorities and law enforcement agencies with a reliable and automated system for accurate vehicle identification through real-time number plate detection and recognition. Such a system can significantly reduce dependence on manual monitoring while improving consistency and efficiency in traffic surveillance and security operations. With the rapid growth of urban transportation networks, traditional vehicle identification methods struggle to scale and adapt to increasing traffic volumes. Recent advancements in deep learning, particularly in object detection and sequence-based character recognition, offer powerful solutions for addressing these challenges by enabling robust, real-time analysis of visual data under complex environmental conditions.

In the initial phase of this research, an earlier-version YOLO-based object detection model was employed to localize vehicle number plates within input images. While this method demonstrated reasonable performance under controlled

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conditions, it exhibited limitations when applied to complex real-world scenarios involving multiple vehicles and varying illumination. To overcome these challenges, the detection framework was upgraded to the YOLOv11 architecture, which offers improved feature extraction and real- time detection capabilities. Although YOLOv11 achieved accurate localization of license plates, reliable character recognition from the detected regions remained a critical challenge.

An initial attempt using pretrained OCR models resulted in suboptimal recognition accuracy, particularly for distorted and low-resolution license plates, as these models often detected unnecessary and irrelevant text within the plate region. To address this limitation, the recognition module was refined by integrating a Convolutional Recurrent Neural Network (CRNN), which combines convolutional feature extraction with sequential modeling. This approach effectively focuses on relevant alphanumeric sequences while suppressing extraneous text, leading to improved recognition accuracy and overall system performance.

II. LITERATURE SURVEY

The field of Automatic Number Plate Detection and Recognition has evolved significantly with the transition from traditional image processing techniques to advanced deep learning–based architectures. Early ALPR systems relied on handcrafted features and rule- based segmentation methods, which were highly sensitive to illumination changes, background clutter, and plate variations across regions [1]. These limitations reduced robustness in real-world traffic environments, motivating the adoption of data-driven deep learning approaches [6].

Recent studies have increasingly favored two-stage ANPR pipelines, separating the detection and recognition tasks to improve overall system accuracy. In the detection stage, single-shot object detectors such as YOLO have become dominant [3], [6]. Several works have demonstrated the effectiveness of YOLO-based detectors for identifying vehicles and license plates under diverse environmental conditions, including motion blur and occlusion [1], [7]. More recent research has focused on optimizing newer YOLO versions, such as YOLOv8, to achieve lightweight and resource-efficient deployments without sacrificing detection accuracy [2], [9].

Despite strong detection performance, the recognition stage remains challenging due to variations in plate layouts, fonts, and distortions. While some studies have employed pretrained OCR engines, these approaches often struggle with unnecessary text recognition and background noise [2]. To overcome this limitation, sequence-based deep learning models such as CRNN have been widely adopted [8]. CRNN architectures effectively combine convolutional feature extraction with recurrent sequence modeling, enabling accurate character recognition across different plate formats [8], [10].

To further enhance recognition performance and generalization, recent works have explored hybrid strategies involving synthetic data generation and pseudo- labeled supervision [4], [5]. Additionally, lightweight and optimized architectures have been proposed to enable ANPR deployment on edge and resource-constrained devices [7], [9]. Building upon these advancements, the present study integrates a fine- tuned YOLOv11 detector with a CRNN-based recognition module, achieving robust performance in both detection and alphanumeric recognition across diverse real-world scenarios.

III. PROPOSED SYSTEM

1. Dataset Collection and Preprocessing :

A high-quality and diverse dataset is the cornerstone of any reliable automatic number plate detection and recognition system. For the detection stage, this study utilized a large-scale dataset comprising 23,205 vehicle images, including cars, buses, and motorcycles captured across multiple countries under varied weather conditions. For the recognition stage, a separate dataset was prepared by combining 30,000 synthetic license plate images with 5,024 real license plate images cropped from the detection dataset.

The following systematic procedures were implemented to prepare the data for the deep learning pipeline:

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a. Selection: For the YOLOv11 detection model, all 23,205 vehicle images were retained to preserve diversity in vehicle types, license plate formats, and environmental conditions. For the CRNN recognition model, 5,024 real license plate images were selected from the YOLO dataset after cropping and manual cleaning to remove unnecessary background elements, and were combined with 30,000 synthetically generated license plate images to enhance character diversity and coverage.

b. Image Resizing: For both YOLOv11 and CRNN, all images were resized to a uniform resolution of 640 × 640 pixels to ensure computational compatibility with the deep learning architectures employed.

c. Data Augmentation: Augmentation techniques for the YOLOv11 dataset included a 50% probability of horizontal flipping, random cropping between 0% and 15%, random rotation between −10° and +10°, random shear between −2° and +2° in both horizontal and vertical directions, random brightness and exposure adjustments within ±15%, and random Gaussian blur ranging from 0 to 0.5 pixels. For the CRNN dataset, variability was achieved by combining diverse synthetic samples with real-world cropped license plate images.

d. Normalization: Raw pixel values were used during training, preserving essential visual features such as character edges, contrast, and plate texture that are critical for accurate localization and recognition.

The YOLOv11 dataset and CRNN dataset was partitioned into training (90%) and testing (10%) sets to ensure unbiased evaluation of detection and recognition performance.

2. Vehicle Number Plate Detection Using YOLOv11 :

The initial stage of the pipeline concentrated on identifying license plates within the detected vehicle regions. Previous versions of YOLO exhibited several limitations, including reduced accuracy in detecting small and densely packed objects, sensitivity to occlusion, motion blur, and varying illumination conditions, and a trade-off between detection speed and accuracy on resource-constrained systems. Additionally, reliance on anchor-based mechanisms required manual tuning and limited adaptability to objects with diverse scales and aspect ratios. These models also showed weaker generalization across different domains and environments, along with less effective multi-scale feature fusion and contextual representation, which impacted robustness and overall detection performance.

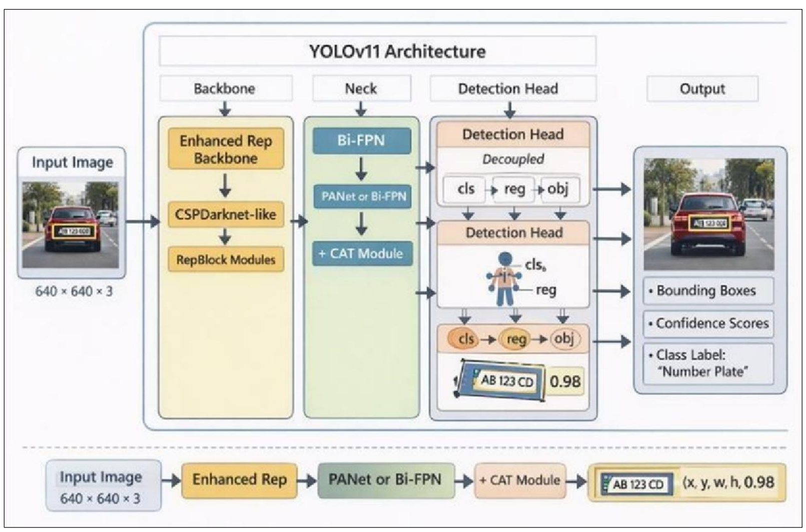

Fig. 1 YOLOv11 Architecture for Vehicle Number Plate Detection

To address the limitations of the initial detection models, we transitioned to the YOLOv11 architecture. Unlike earlier detection frameworks that rely on less optimized feature extraction strategies, YOLOv11 incorporates enhanced backbone networks and multi-scale feature fusion to improve small-object detection. This optimized design enables the

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model to accurately localize license plates of varying sizes and resolutions while maintaining real-time inference efficiency.

The detection process was conducted through several distinct stages:

a. Pretrained YOLOv11 Detection: The pipeline initially employed a pretrained YOLOv11 model to detect different types of vehicles, such as cars, buses, and motorcycles, within images and video frames.

b. Fine-Tuning for Number Plate Detection: The pretrained model was subsequently fine-tuned using the curated vehicle dataset, specifically annotated for license plate locations. During this process, the model was trained to reliably identify license plates across a variety of conditions.

This detection methodology demonstrated high reliability, achieving an accuracy of 97.75% on the test dataset. By providing clean and accurately localized license plate ROIs, this phase ensured that the recognition module received high-quality inputs.

3. Number Plate Recognition Using CRNN :

The second stage of the pipeline focused on recognizing alphanumeric characters from the detected license plate regions. To address the limitations of using pretrained OCR systems, which often recognize unnecessary and irrelevant characters present within the license plate region, we adopted a Convolutional Recurrent Neural Network (CRNN) architecture. Unlike generic OCR models, CRNN is specifically designed for sequence- based recognition and focuses only on the relevant alphanumeric patterns. By combining convolutional feature extraction with recurrent sequence modeling, the network effectively captures spatial and sequential character dependencies.

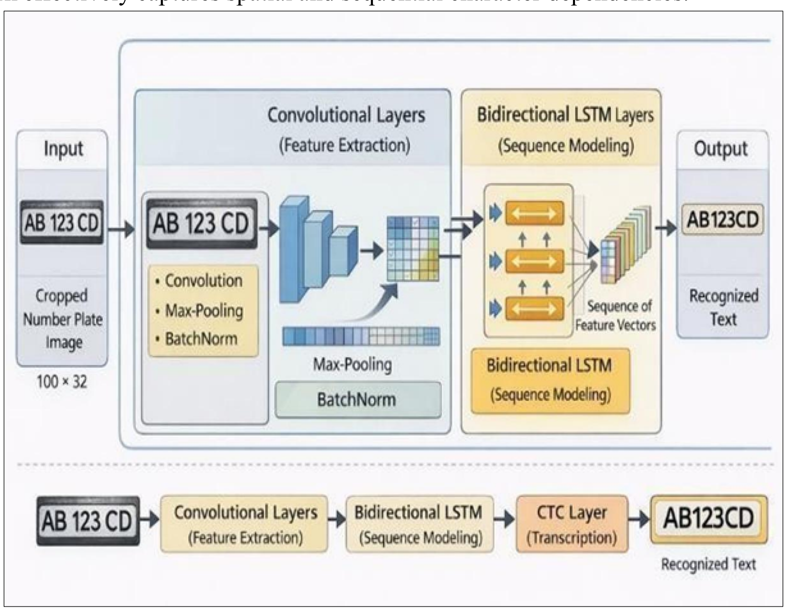

Fig. 2 CRNN Architecture for Vehicle Number Plate Recognition

The CRNN model was integrated as the primary recognition module, processing the detected license plate Regions of Interest (ROIs) obtained from the YOLOv11 detection stage. This architecture effectively minimized character-level ambiguity by learning both spatial features and sequential dependencies within license plate text. By leveraging convolutional layers for feature extraction and recurrent layers for sequence modeling, the system achieved a recognition accuracy of 96.80%, representing a significant improvement.

4. Experimental Setup :

The following subsection presents the computational setup and technical specifications required to replicate the proposed methodology:

a. Computational Infrastructure: All experiments were conducted using the Google Colab platform within a Python-based development environment.

b. Training Configuration and Epoch Strategy: The YOLOv11 model was trained for 5 epochs, and CRNN model was initially trained for 50 epochs, followed by an additional 10 epochs to further improve accuracy. This staged approach allowed the models to stabilize during early learning.

c. Input Configuration: All input images for both the YOLOv11 detection model and the CRNN recognition model were resized to a constant spatial resolution of 640×640 pixels to ensure uniformity and compatibility with the network architectures.

IV. RESULTS AND DISCUSSION

The performance of the proposed two-stage framework was evaluated using a comprehensive set of detection- and recognition-level metrics. The results demonstrate the effectiveness of employing the YOLOv11 model for accurate license plate localization, followed by the CRNN model for reliable character recognition.

1. Vehicle Number Plate Detection :

The YOLOv11 model demonstrated high precision in accurately localizing vehicle license plates across diverse conditions. Analysis of the detection performance indicates strong positive rates with minimal false detections, reflecting the model's robustness in distinguishing license plates from complex backgrounds.

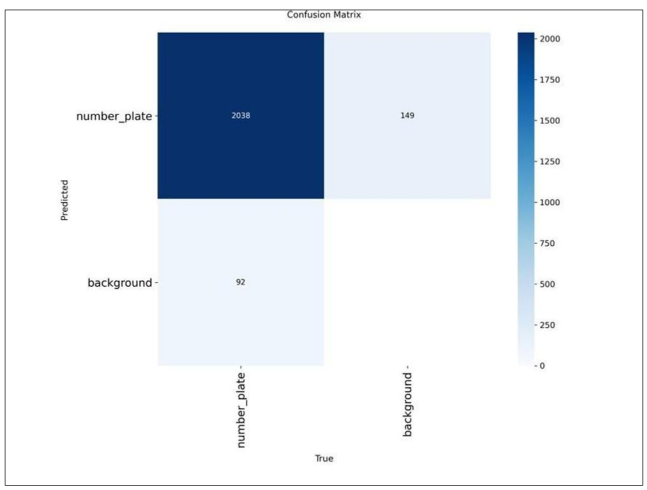

Fig. 3 Confusion Matrix for Number Plate vs Background Classification TABLE I

PERFORMANCE METRICS FOR DETECTION PHASE

Recall	Precision	Accuracy	F1 Score
0.9432	0.9708	0.9775	0.9570

The detection phase demonstrated high performance, achieving a precision of 0.9708 and a recall of 0.9432, indicating accurate and reliable license plate localization. The overall accuracy of 0.9775 and an F1 score of 0.9570 confirm the robustness and balanced detection capability of the model.

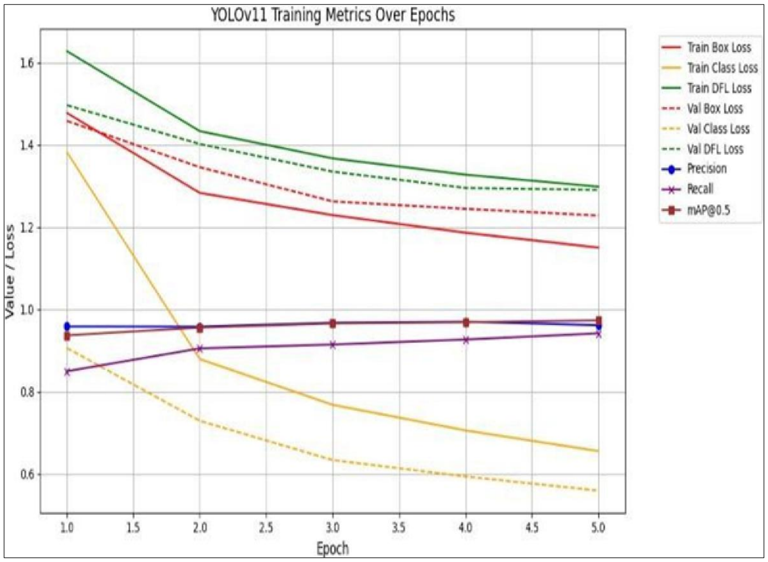

Fig. 4 YOLOv11 Training Metrics Over Epochs

2. Vehicle Number Plate Recognition :

The CRNN model demonstrated high accuracy in recognizing alphanumeric characters from detected license plates across diverse imaging conditions. Analysis of the recognition performance indicates strong correct character classification rates with minimal misclassification, reflecting the model's robustness in handling variations in font style, illumination, and plate quality.

TABLE II: PERFORMANCE METRICS FOR RECOGNITION PHASE

Accuracy	CER (Character Error Rate)
0.9680	0.0086

The CRNN recognition model achieved a high accuracy of 96.80% with a low Character Error Rate of 0.0086, indicating reliable and precise license plate text recognition.

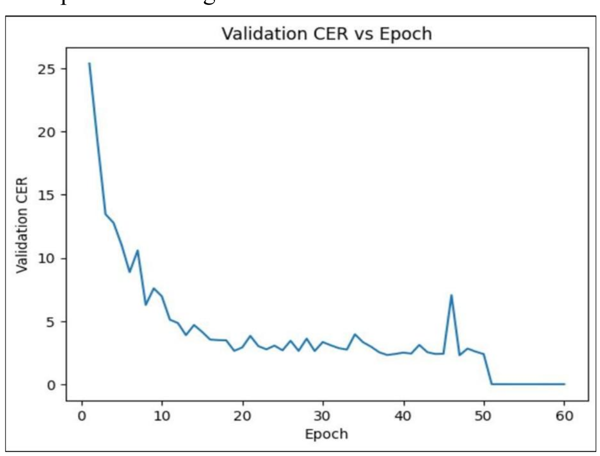

Fig. 5 CRNN Validation CER vs Epoch

V. CONCLUSION

This work presents a robust, two-stage deep learning framework for automatic vehicle number plate detection and recognition. In the first stage, a pretrained YOLOv11 model was employed and further fine- tuned to accurately detect vehicles and localize license plates under diverse environmental conditions. This detection module achieved a high accuracy of 97.75%, effectively extracting clean and precise Regions of Interest (ROIs) from complex traffic scenes. In the subsequent stage, a Convolutional Recurrent Neural Network (CRNN) was employed to recognize alphanumeric characters. By combining convolutional feature extraction with sequential modeling, the CRNN significantly improved character recognition performance, achieving an overall recognition accuracy of 96.80%.

Despite the strong performance of the proposed system, there remain opportunities for further refinement. Future work will focus on increasing dataset diversity by incorporating additional plate formats, fonts, and regional variations to enhance generalization. Improving robustness under challenging conditions such as motion blur, low illumination, and occlusions will also be a priority. Additionally, optimizing the models for deployment on edge devices and real-time traffic monitoring systems will be explored to support scalable and cost-effective smart city implementations.

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