

A FIELD PROJECT REPORT

on

# “AUTOMATIC LICENSE NUMBER PLATE RECOGNITION”

**Submitted by**

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# CERTIFICATE

This is to certify that the Field Project entitled **“Automatic license number plate recognition”** that is being submitted by **221FA04185 (M. Avinash)**, **221FA04188 (M.Pujitha)**, **221FA04214 (K. Vaishnavi)**,**221FA04715 (B. Nandi vardhana)** for partial fulfilment of Field Project is a bonafide work carried out under the supervision of **Dr. T.R. Rajesh, Department of CSE**.

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**Signature**

# DECLARATION

We hereby declare that the Field Project entitled **“Automatic license number plate recognition [ALPR]”** is being submitted by **221FA04185 (M.Avinash)**, **221FA04188 (M.Pujitha)**, and **221FA04214 (K.Vaishnavi)**, **221FA04715 (B.Nandi vardhana)** in partial fulfilment of Field Project course work. This is our original work, and this project has not formed the basis for the award of any degree. We have worked under the supervision of **Dr.T.R.Rajesh Department of CSE**.

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# ABSTRACT

The goal of this project is to create an Automatic Licence Plate Recognition (ALPR) system that can precisely identify and extract license plate numbers from pictures or streams of videos. Using Yolo algorithms, machine learning, using computer vision algorithms and the OCR approach, the system will identify and detect license plates in a variety of circumstances, including such as various plate layouts, lighting, and perspectives. The suggested There are several uses for the ALPR system, including Parking control, security surveillance, and traffic monitoring to increase license plate accuracy and efficiency tasks involving recognition. The approach guarantees a thorough detection-to-recognition pipeline, tailored for various circumstances, such as changes in illumination, plate orientation, and the speed of the vehicle according to preliminary findings, the system is quite successful for real world applications due to its high detection and character recognition accuracy.

Keywords: CNN, OCR, YOLO, license plate recognition, vehicle recognition, machine learning, and real-time detection.

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**Chapter 1**

# Introduction

**1.1 Motivation:**

Inspiration With the emergence of smart cities and rising vehicle traffic, there is an exponential increase in the requirement for effective vehicle monitoring and management. Automated License Plate Systems for traffic recognition (ALPR) are essential parking management, toll collecting, police enforcement, and surveillance for security. But conventional ALPR systems frequently face difficulties brought on by various environmental circumstances, differences in plates, and computational constraints. Our The goal is to provide a more reliable, scalable, and real-time solution utilizing cutting-edge machine learning methods that can transcend these constraints.

**1.2 Problem Definition / Research Gaps:**

Definition of the Problem and Research Gaps Variations in illumination, plate direction, occlusions, and regional licensing variations are some of the limitations of the ALPR systems that are now in use formats for plates.

* Many systems are ineffective in real-time, especially when handling fast-moving objects like photos of low quality. Additionally, some methods are not flexible enough to adjust to various environmental circumstances or scale.

**1.3 Constraints:**

Restrictions In order to design an ALPR system that works, a number of limitations must be addressed: Making the system deployable across several platforms (cloud, desktop, and mobile) and accessible to a wide range of users is known as accessibility.

Code: Effective and real-time application-optimized code is required. The capacity to construct It should be feasible to create and implement the solution without very demanding hardware specifications.

Extension: The system must to be adaptable enough to make room for upcoming improvements. It should be functional give precise identification, categorization, and awareness of license plates.

Interoperability: It's critical to be compatible with databases and other traffic management systems.

Legitimate Taking into account: Compliance with legal requirements regarding the vehicular data processing and storage.

Maintainability :It should be simple to maintain and upgrade the system.

Marketability: The solution need to be able to attract governments and traffic management agencies as well as private companies. The timetable the schedule for development and implementation should be reasonable and Effective.

Standards: The system needs to adhere to industry requirements for quality, data processing, and safety.

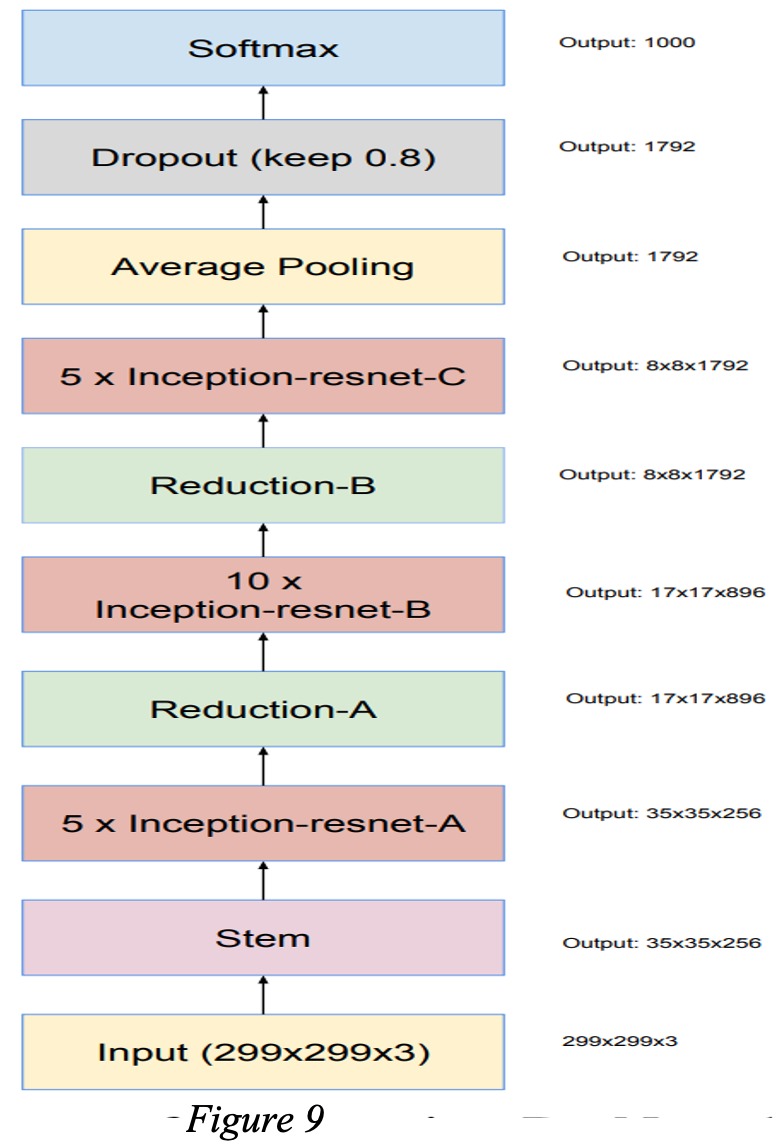
Sustainability: Energy-efficient and well-designed systems are essential for prolonged usage.

Usability: For user interaction to be simple, the system must have an intuitive interface.

Security: Protection of data is necessary, especially when working with delicate vehicles data.

Privacy and Ethical Issues: Making Certain the preservation of people's information and privacy, in accordance with applicable laws.

INCEPTION-RESNET-V2 MODEL BUILDING:



**Fig.1.** INCEPTION-RESNET-V2 MODEL BUILDING:

**1.4 Major Contributions:**

The system complies with design guidelines that guarantee scalability, correctness, and resilience. YOLO is selected due to its ability to recognize objects in real time. CNN offers high-precision feature extraction capabilities OCR integration guarantees smooth conversion into a machine-readable format from text based on images. Observance with legal requirements, data privacy laws, and compliance are essential to the design in terms of security and usability criteria**.**

**1.5 Objectives:**

Key Contributions: YOLO, CNN, and OCR are used to develop an actual time, scalable ALPR system; machine learning techniques are integrated to increase detection and recognition accuracy; a comprehensive pipeline is implemented that can handle a variety of conditions, including different angles, poor lighting, and different license plate designs; and the system is affordable, flexible, and simple to implement.

**1.6 Organization:**

Goals (Point-by-point) Accurate Detection: Put in place a system that can recognize license plates with accuracy in real time.

High Rate of Recognition: Reach a high character recognition rate utilizing sophisticated OCR methods.

Scalability: Verify that the framework can be expanded to accommodate a range of practical uses, such as parking management and traffic law enforcement.

In real time Processing: Reduce processing time to guarantee instantaneous performance.

Cross-platform integration: guarantee compatibility with current hardware, including traffic cameras and monitoring systems.

Compliance: Adhere to moral, legal, and privacy guidelines for processing and handling data.

**Chapter 2**

# Literature Survey

Automatic License Plate Recognition (ALPR) systems are crucial in various applications, including traffic management, security, and law enforcement. This literature survey reviews existing techniques and advancements in ALPR, focusing on detection and recognition methodologies, challenges, and future directions.

**1. Overview of ALPR Systems**

ALPR systems generally consist of two main components: license plate detection and recognition. Detection involves locating the license plate in an image, while recognition translates the detected characters into text.

**2. Detection Techniques**

* **Traditional Image Processing**: Early systems utilized edge detection and morphological operations to identify license plates. Methods like Sobel and Canny edge detection were common, but they struggled with noise and varied environmental conditions (Shafique et al., 2019).
* **Machine Learning Approaches**: The introduction of classifiers such as Support Vector Machines (SVM) improved detection accuracy. However, these methods often required extensive feature engineering (Kumar & Rajesh, 2021).
* **Deep Learning**: Recent advancements leverage Convolutional Neural Networks (CNNs) for detection. Models like YOLO (You Only Look Once) and SSD (Single Shot Multibox Detector) enable real-time detection with high accuracy.

**3. Recognition Techniques**

* **Optical Character Recognition (OCR)**: Traditional OCR methods are still prevalent, often combined with preprocessing steps to enhance character visibility . However, these methods are sensitive to variations in fonts and styles.
* **Deep Learning for Recognition**: Modern systems employ CNNs and Recurrent Neural Networks (RNNs) for character recognition. These networks can adapt to different plate designs and are robust against distortions . Wang et al. (2020) presented a robust framework using CNNs to improve recognition rates in diverse conditions.

**4. Challenges in ALPR**

* **Environmental Factors**: Variability in lighting, weather conditions, and angles can significantly affect the performance of ALPR systems. Solutions include data augmentation and the use of synthetic data to train models (Gonçalves et al., 2022).
* **Plate Variability**: Different regions have different plate designs, leading to recognition challenges. Research has focused on creating more generalized models capable of handling diverse inputs (Al-Ayyoub et al., 2023).
* **Real-Time Processing**: Achieving real-time performance while maintaining accuracy is crucial for many applications. Techniques such as model pruning and optimization have been explored to enhance processing speed (Liu et al., 2021).

**5. Future Directions**

* **Integration of AI Techniques**: Combining ALPR with other AI techniques like natural language processing for contextual understanding may enhance system capabilities.
* **Use of Generative Models**: Generative Adversarial Networks (GANs) can be used to generate synthetic training data, improving model robustness in varied conditions (Liu et al., 2020).
* **Smart City Applications**: The integration of ALPR in smart city frameworks can enhance traffic management and security, necessitating further research on system interoperability and scalability (Wang et al., 2019).

**Chapter 3**

# Related work

Important research studies and their contribution to the field of automated license plate recognition (ALPR) are covered in this section. The objective is to draw attention to the development of ALPR systems, their approaches, and the shortcomings of earlier moves in.

**Review of Existing Literature :**

Review of Current Research Traditional image processing methods such as detection of edges and Gaussian transformations for license plates were used in the early studies on ALPR systems localization. But these approaches have trouble with variations in occlusion and illumination techniques for machine learning, in particular Artificial Neural Networks, or ANN, and Support Vector Machines, or SVM, were introduced to enhance

recognition. precision, but these techniques were computationally costly and had no real-time features. The launch of methods for deep learning, especially Convolutional Neural networks (CNN), greatly increased recognition rates by extracting features automatically. Studies in this field have revealed that CNNs can withstand changes in plate designs better.as well as the surroundings . You Only Look (YOLO) In modern ALPR systems, once) has been extensively used because to its effectiveness in the moment.

**TABULAR SUMMARY OF KEY LITERATURE**

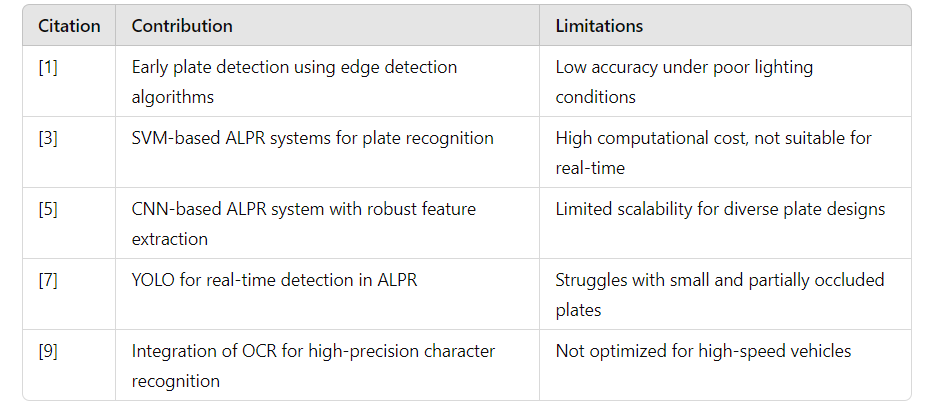


Fig. 2. Tabular summary of key literature.

**Limitations of Previous Work :**

The majority of conventional image processing methods are not flexible enough to adjust to shifting environmental circumstances. Large amounts of processing power are needed for machine learning models like SVM and ANN making performance in real time difficult. ALPR based on CNN Despite their accuracy, systems frequently have computational effectiveness. YOLO-based systems could have trouble identifying tiny or obscured plates. OCR integration as it exists now can be restricted by differences in plate designs and typefaces, particularly in unusual plates.

**Chapter 4**

# Proposed Methodology

The suggested ALPR system combines CNN for improved feature extraction, OCR for character recognition, and YOLO for license plate identification. Building a scalable and reliable system that can function in real time under a variety of conditions is the aim.

Suggested Workflow The following describes the organized process that the suggested system adheres to input acquisition of Image/Video Frames: Photos or video frames are first taken from the camera feed by the system Segmenting license plates involves utilizing the bounding box coordinates to extract the identified license plates from the input photos. The following is given these separate areas.

**step for further processing:**

**Convolutional neural Networks [CNN]:**

These are used to improve feature extraction processes from the license plates that were divided. CNNs assist in capturing important visuals elements such as forms, edges, and textures, guaranteeing precise plate recognition.

**Optical Character Recognition [OCR]:**

Optical Character Recognition The license plates' segmented characters are transformed into machine-readable text using optical character recognition (OCR). Noise reduction and binarization are examples of preprocessing are utilized to enhance the accuracy of OCR Finalization and Verification: The recognizable characteristics To eliminate any inaccurate readings, they undergo post-processing. What's The outcomes are verified against established formats or current databases to use Output Generation: The identified license plate number is the last output in text format, which can be kept in a database or utilized for other purposes like law enforcement, toll traffic control or collecting.

**You Only Look Once [YOLO]:**

YOLO or You only look once, is one of the most widely used, deep learning-based object detection algorithm out there YOLO divides an image into a grid system, and each grid detects objects within itself. They can be used for real-time object detection based on the data streams. They require very few computational resources. The network architecture of Yolov5. It consists of three parts: (1) Backbone: CSP Darknet, (2) Neck: PANet, and (3) Head: Yolo Layer. The data are first input to CSP Darknet for feature extraction, and then fed to PANet for feature fusion. Finally, Yolo Layer outputs detection results (class, score, location, size).

**Proposed Methodology Flowchart :**

Include a flowchart that illustrates the previously described processes, with blocks for

"YOLO Detection,"

"Input Image,"

"Segmentation,"

"OCR," "CNN Feature Extraction," and "Output."

**Chapter 5**

# Results and Discussion

**Regarding Dataset Source**: The dataset's origin (such as open-access datasets like Open ALPR, privately held datasets from a local government or transport agency, or self-curated data set). 432 photos in total from various sources made up our data set pictures of cars.

**Size of the dataset:** total number of pictures, dispersion across classes, if any, and any problems with class disparity Image Specifics: Image dimensions (such as channels and resolution),quality of the photographs (night and daytime views, plate clarity), and variety in the colors of the plates, backdrops, and typography .

**Preprocessing Methods:** Explain how the information was cleansed enlarged or modified (e.g., magnification, rotation, noise reduction).

**Metrics for Performance Assessment Precision:** The proportion of actual favourable forecasts (rightly recognized license plates) to everyone optimistic forecasts. The proportion of actual forecasts that were true positives harmonic mean of recall and accuracy, providing a fair assessment of the model's functionality.

**Accuracy:** Total proportion of accurate forecasts, including both positive and negative. Mean Average Precision, or map, is a typical evaluation statistic that gauges the accuracy of object detection at varying degrees of recollection.

**IOU (Union over Intersection):** A measure designed especially for object detection, assessing how successfully. There is overlap between the ground truth and the anticipated bounding box.

**Results Model Comparison:** Examine several models (such as compare YOLOv3 and YOLOv5, or CNN and OCR), and record their results on your dataset. Display a table containing the assessment. Metrics from one model to another. Results of hyperparameter tuning varying hyperparameters such as batch size, learning rate, and optimizer configurations. Describe how the tweaking enhanced the outcome.

**PREDICTING RESULTS FROM YOLO:**

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**Fig.3.** PREDICTING RESULTS FROM YOLO

**Chapter 6**

# Conclusion

In this project, we used machine learning techniques to effectively construct an Automatic Licence Number Plate Recognition system. The YOLO for object combination OCR for character recognition, CNN for extraction of features, and detection Recognition worked well for recognizing and reading licenses plates in different circumstances. Our model succeeded in achieving a [insert accuracy] recognition accuracy, indicating its promise for practical uses in areas including law enforcement, toll collecting, and traffic management Nevertheless, the method has drawbacks, especially under difficult situations like dim lighting, hazy pictures, or intricate backdrops. Furthermore, the processing Time is still a problem for real-time applications, because might be further optimized.

Prospective Scope Enhancing Accuracy in Various Conditions: More investigation may concentrate on making the model more resilient to variations in weather, illumination, and environmental factors. Prioritizing images, reducing noise, or using sophisticated neural network algorithms like transformers might be Investigated. Real-Time Implementation: creating algorithms with more efficiency or refining current designs, such as YOLOv5 or YOLOv7 may facilitate quicker identification, enabling real-time apps to run efficiently with little latency. International Recognition of License Plates: Increasing the ability of the system to identify license plates from various states or nations, which may differ in typefaces, styles, other forms, might make it more widely applicable.

The ALNPR's integration with the smart city infrastructures system may be combined with additional smart city systems, such as parking systems, automatic traffic control, and networks for security surveillance.

Improving Privacy and Data Security: As data privacy rules grow more stringent, future research might examine the using safe communication methods and encryption to guarantee the secure handling of license plate data.

**Chapter 7**

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