ENHANCING LICENSE PLATE RECOGNITION SYSTEMS WITH YOLOv8 AND EASYOCR MODELS

Thesis Submitted
In Partial Fulfilment of the Requirements for the Degree of

MASTER OF TECHNOLOGY

in

Software Engineering

Submitted by

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May, 2025

ACKNOWLEDGEMENTS

I would like to express my deep appreciation to **Dr. Abhilasha Sharma**, Associate Professor at the Department of Software Engineering, Delhi Technological University, for her invaluable guidance and unwavering encouragement throughout this research. Her vast knowledge, motivation, expertise, and insightful feedback have been instrumental in every aspect of preparing this research plan.

I am also grateful to **Prof. Ruchika Malhotra**, Head of the Department, for her valuable insights, suggestions, and meticulous evaluation of my research work. Her expertise and scholarly guidance have significantly enhanced the quality of this thesis.

My heartfelt thanks go out to the esteemed faculty members of the Department of Software Engineering at Delhi Technological University. I extend my gratitude to my colleagues and friends for their unwavering support and encouragement during this challenging journey. Their intellectual exchanges, constructive critiques, and camaraderie have enriched my research experience and made it truly fulfilling.

While it is impossible to name everyone individually, I want to acknowledge the collective efforts and contributions of all those who have been part of this journey. Their constant love, encouragement, and support have been indispensable in completing this M.Tech thesis.

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CANDIDATE DECLARATION

I SWAPNIL SHUKLA hereby certify that the work which is being presented in the thesis entitled **“Enhancing License Plate Recognition Systems with YOLOv8 and EasyOCR Models”** in partial fulfillment of the requirements for the award of the Degree of Master of Technology submitted in the Department of Software Engineering, Delhi Technological University in an authentic record of my work carried out during the period from August 2023 to May 2025 under the supervision of Dr. Abhilasha Sharma.

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

Swapnil Shukla

This is to certify that the student has incorporated all the corrections suggested by the examiner in the thesis and the statement made by the candidate is correct to the best of our knowledge.

Signature of Supervisor(s) **Signature of External Examiner**

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CERTIFICATE BY THE SUPERVISOR

I hereby certify that **Swapnil Shukla (23/SWE/02)** has carried out their research work presented in this thesis entitled **“Enhancing License Plate Recognition Systems with YOLOv8 and EasyOCR Models”** for the award of **Master of Technology** from the Department of Software Engineering, Delhi Technological University, Delhi under my supervision. The thesis embodies results of original work, and studies are carried out by the student herself and the contents of the thesis do not form the basis for the award of any other degree to the candidate or to anybody else from this or any other University/Institution. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

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Enhancing License Plate Recognition Systems with YOLOv8 and EasyOCR Models

Swapnil Shukla

ABSTRACT

LPR systems have become an integral part of modern ITS as they enhance public safety, traffic flow and effectiveness of law enforcement operations. The structure of the thesis can be broken down into two key parts. The first section examines the current status of LPR technologies and the second part offers a possible approach based on Deep Learning. This section evaluates various machine learning and deep learning based techniques including KNN, CNN, LSTM, Faster R-CNN and YOLO algorithms. Assessing the performance of models under different kinds of data and evaluating their ability to solve actual problems encountered in diverse geographical settings is the main objective.

The final part presents a flexible, two-stage LPR pipeline that combines object detection by YOLOv8 and character recognition using EasyOCR. The dataset for both training and testing was composed of 27,900 car images retrieved from the Google Open Images collection. The system managed to identify the license plates with 73.82% accuracy overall. The model correctly detected license plates in 88.42% of the cases. It also achieved 100.00% accuracy in identifying the characters on each plate. The design of the system makes updating sub-models possible, ensuring flexibility and rapid responses under challenging conditions.

The report bridges the gap between theory and practice by providing insights into the implementation of License Plate Recognition (LPR) systems. It proposes practical methods to overcome challenges such as image distortion, character confusion and the ability to generalize on various license plate types. These areas, namely, multilingual support, generating synthetic data, rapid edge deployment and examining the utility of universal transformers in end-to-end LPR models, hold great potential for further exploration.

Keywords: License Plate Recognition (LPR), YOLOv8, EasyOCR, Deep Learning, Convolutional Neural Networks (CNN), Intelligent Transportation Systems, Character Recognition, Modular Pipeline, Object Detection.

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ALPR	Automatic License Plate Recognition
RNN	Recurrent Neural Network
CNN	Convolutional Neural Network
ANN	Artificial Neural Network
SVM	Support Vector Machine
AI	Artificial Intelligence
ML	Machine Learning
DNN	Deep Neural Network
RMS	Root Mean Square
mAP	Mean Average Precision
DL	Deep Learning
GPU	Graphics Processing Unit
Re-LU	Rectified Linear Unit
LPR	License Plate Recognition
LSTM	Long Short-Term Memory
YOLOv8	You Only Look Once (version 8)

CHAPTER 1

INTRODUCTION

This research study explores the application of various deep learning models to license plate recognition, specifically to the detection and character recognition stages. Our experimental results summarize the performance of a multiple-stage modular model, and demonstrate that the combination of a sequence of deep learning modules; e.g., object detection and OCR models, can meaningfully enhance performance in real-world computer vision applications in intelligent transportation systems.

1.1 Background

License Plate Readers (LPR) systems have experienced a massive growth in the recent decades because of increasing needs for automation in automotive surveillance, police enforcement, toll collection, and smart transportation infrastructures. Older LPR systems used manual or semi-automatic techniques, which were typically error-prone and time-consuming. Advances in computer vision and machine learning technologies, especially deep learning, have led to LPR systems that are much faster, accurate, and capable of processing in real-time in their use.

All the earlier techniques of LPR had used mainly conventional image processing techniques based on edge detection, morphological filtering, contour analysis, and character segmentation [4], [5]. The previous techniques were not able to deal with variable illumination, tilted images, and even different plate types. Additionally, they were not able to deal with occlusions and poor-quality images as well.

Due to the problems with other techniques, SVM, KNN, and Decision Trees became the top choices [3]. While the models improved their performance by learning from past data, they used lots of handpicked features and steps for preprocessing.

CNNs marked a significant change when it came to LPR research. LPR systems benefited significantly from CNNs that performed feature extraction from unprocessed images, leading to higher detection and recognition [1], [20]. Thanks to deep learning libraries such as YOLO [7], [8], [9], Faster R-CNN [28], and EfficientDet [27], developing LPR systems with fast processing and good accuracy became more simple.

YOLOv3 and YOLOv4 became faster and more accurate, thus making them suitable for use in LPR tasks where environments frequently change [7], [8]. With these new backbones and simpler structures, YOLOv5 and YOLOv8 increased their ability to run on edges [9], [18].

OCR has improved by changing from old rule-based methods like Tesseract [19] to current neural network technologies such as CRNN [11] and LPRNet [23]. RNNs or LSTM are included in these structures to address the sequential data in the input effectively [12], [14]. The popularity of EasyOCR comes from its support for various languages and its high performance under difficult conditions [12].

Several studies have offered ways to complete LPR pipelines. For instance, Subhahan et al. [12] chose YOLOv8 for object detection and LPRNet for the recognition stage, and their results clearly pointed to fast performance. Siona and coauthors [15] evaluated fine-tuned YOLO and DETR models for detecting Egyptian license plates. Moreover, Chandok et al. [16] suggested a YOLOv8n and EasyOCR system for Indian license plate recognition, displaying good accuracy and being real-time.

General-purpose LPR models cannot be developed without the help of datasets. The models improve in accuracy by using the CCPD, OpenALPR, and manually-labeled datasets. Experts say that by rotating, scaling, shifting the brightness, and applying affine transformation, images can be made to appear like photos in real life [10].

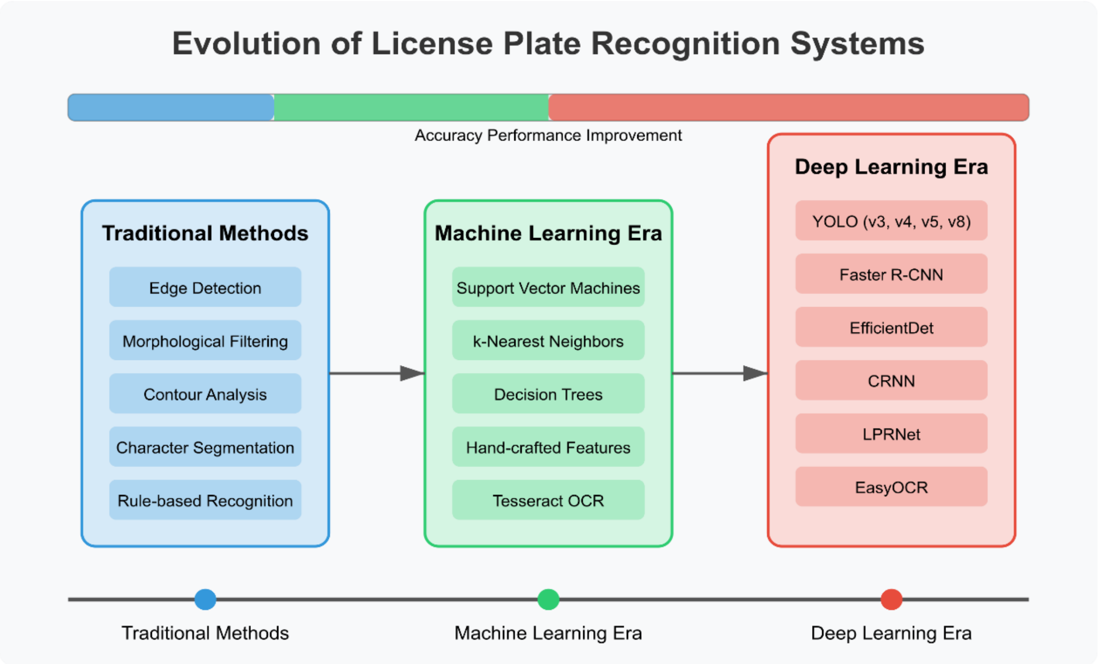

Fig 1.1. Technological Evolution of License Plate Recognition (LPR) Systems-from traditional image processing methods to machine learning and deep learning architectures.

Currently, LPR relies on a flexible piping approach using deep learning instead of old rule-based systems. Today, LPR benefits from using YOLOv8 for object detection and EasyOCR for OCR. It is preferred to take a two-step approach that is developed to quickly detect license plates in Indian scenarios.

It aims to provide two main benefits to the field of License Plate Recognition. At the beginning, it covers the pros and cons of modern and classical LPR methods as well as the sectors in which they are implemented. It presents an ongoing process that first detects license plates with YOLOv8 and reads the characters on the plates using EasyOCR. It was confirmed that the model produced satisfactory results on 27,900 tested images. The findings demonstrate that having modular designs is flexible and allows for modules to be easily updated. The system performs well in real life, and this makes it aid in better traffic management.

Converting LPR from using only the edges to using deep learning is a significant progress in computer vision and ITS. Even though artificial intelligence is more accurate and stronger, a successful deployment in the real world needs to consider many other factors. The method in this thesis aims to merge present-day detection and OCR approaches to tackle LPR with efficiency and scalability.

1.2 Objective

The main goal of this research is to develop, implement, and test a strong and modifiable License Plate Recognition (LPR) system using the latest deep learning methods with the ability to provide good accuracy and real-time execution under various real-world scenarios. This research will initially explore and critically examine current LPR methods from classical image processing methods to recent sophisticated deep learning models. The review covers object detection algorithms like Faster R-CNN, SSD, and different variations of YOLO, as well as character recognition methods like CNN-based OCR engines, LSTMs, and CRNNs. Through this review, the study states the existing gaps, challenges, and prospects in the area, primarily with regard to accuracy, speed, adaptability, and deployability. Capitalizing on these findings, the study further aims to create a two-stage LPR pipeline that combines YOLOv8, one of the latest and most effective object detection models, for robust and rapid license plate localization, and EasyOCR, a deep learning and multilingual OCR engine, for recognition of characters. The goal also involves sourcing and preparing a diverse set of more than 27,000 car images, capturing the diversity in plate styles, lighting, backgrounds, image resolutions, and environmental conditions. This dataset is used to train and test the pipeline to achieve generalization and resilience. Extensive performance measurement is conducted based on standard criteria like precision, recall, mAP, and end-to-end system accuracy. An additional important aim is to illustrate the feasability of modular design where detection and recognition modules are separately trainable or substitutable, allowing easy system update and customization for deployment in diverse scenarios. Also, the study aims to consider the viability of real-time deployment in smart transport applications including traffic law enforcement, automated toll collection, parking access control, and vehicle monitoring systems. In responding to critical shortcomings of current systems and offering a scalable and efficient solution, this study hopes to provide valuable contributions to LPR technologies in both academia and industry.

1.3 Problem Statement

As city infrastructure grows and vehicle counts multiply exponentially, efficient, automated vehicle monitoring systems have become more essential than ever before. License Plate Recognition (LPR) systems are the technological foundation for such automation, enabling numerous applications including traffic monitoring, toll fees, parking enforcement, and access control. Nevertheless, even with the advancements in computer vision and deep learning, developing a universally dependable, real-time LPR system that works reliably under various real-world conditions is a tough challenge.

Conventional LPR systems based on handcrafted features and traditional image processing methods are weak in terms of adaptability and robustness. Under different environmental conditions like lighting changes, motion blur, occlusion of plates, and distortion of camera angles, such systems usually fail. In addition, they are sensitive to license plate design and structure, which differ considerably across regions and countries in font, layout, size, language, and color.

Even with the introduction of deep learning, most current LPR solutions encounter some practical and technical issues:

- **Inconsistent Performance Across Conditions**: Deep learning algorithms can make excellent predictions on sanitized datasets but tend to struggle with real-world images containing noise, grime, inhomogeneous illumination, oblique viewing angles, and low resolutions.
- **Lack of Modularity**: Most systems are end-to-end solutions that cannot be separately tuned or replaced by the detection and recognition modules, hence not flexible or scalable.
- **Multilingual and Multiformat Complexity**: Some license plates contain non-Latin scripts, mixed languages, or special characters that are not well supported by general-purpose OCR systems.
- **Resource and Speed Constraints**: It is hard to achieve high accuracy and low inference time simultaneously, particularly for deployment in edge or embedded systems where computational resources are scarce.
- **Plate Detection Challenges**: Localization of license plates in cluttered scenes is still challenging, particularly when plates are partially occluded, damaged, or captured from wide angles.
- **Character Segmentation and Recognition**: Overlapping or close-set characters,

unusual fonts, or variations in position of characters make recognition even more challenging when segmentation is explicitly needed.

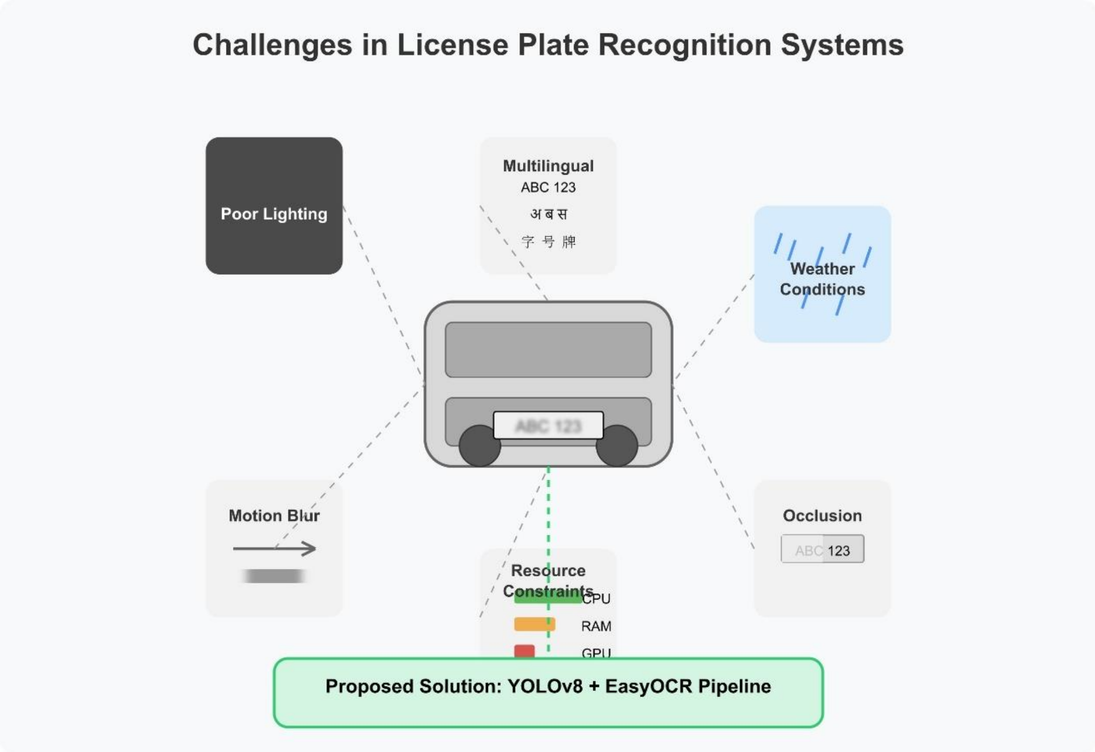

Fig 1.2. Key Challenges in License Plate Recognition Systems and the Proposed YOLOv8 + EasyOCR Pipeline Solution.

Against these ongoing issues, there is an urgent need for a high-performance, scalable, and modular LPR system that can work well in real-world conditions without sacrificing accuracy, flexibility, and speed. This thesis solves these challenges by advancing a two-stage LPR pipeline that combines YOLOv8 for license plate detection in efficient and accurate ways and EasyOCR for recognizing multilingual characters. The system is learned and tested in a big, diverse dataset in order to generalize over possible scenarios. The work aims to bridge the gap between existing academic solutions and practical needs by contributing a ready-to-use architecture in intelligent transportation systems and automated vehicle monitoring applications.

1.4 Motivation

High urbanization in metropolitans and rise in number of vehicles, make urgent need such type of intelligent automated systems for well management of transport infrastructure. Manual vehicle observance is not only labor time-consuming, error-prone, but also not applicable to the huge and many vehicles in burst traffic. The application has also brought License Plate Recognition (LPR) forward as a critical technology in ITS, allowing automation in traffic monitoring, tolling, parking control, and law enforcement. Their expanding usage in the international LPR market proves their essential place in the management of urban traffic and in public security. But, for all of their potential, existing LPR systems do suffer from some drawbacks when deployed in real, dynamic environments.

The motivation for this research stems from the need to overcome these limitations and contribute to the development of a robust, accurate, and adaptable LPR system. Many traditional and some modern LPR systems fail to deliver consistent results when faced with challenges such as varying lighting conditions, motion blur, camera angle distortions, and multilingual license plate formats. Moreover, systems that are not modular are difficult to maintain, upgrade, or scale, especially in real-time applications. These limitations highlight a clear gap between academic LPR models tested under ideal conditions and the practical needs of real-world deployments in diverse and often unpredictable environments.

Specifically, developments in deep learning; object detection and optical character recognition, in particular; offer an ideal opportunity to reinvent the LPR problem with a new, more efficient approach. YOLOv8, as a very fast and accurate object detector, and EasyOCR, as a strong multilingual OCR engine, provide the technical support required to construct a system that is not only high-performance but also modular and scalable. A pipeline that integrates these two components can provide real-time detection and recognition with enhanced precision and flexibility, even in suboptimal situations.

This research is further motivated by the potential societal impact of a reliable LPR system. From supporting law enforcement in identifying stolen vehicles to enabling smoother automated tolling and parking access, a dependable LPR solution can significantly enhance urban mobility and security. Additionally, by making the system modular and extensible, it opens avenues for integration with broader smart city platforms, vehicle analytics, and real-time traffic decision systems.

The ultimate motivation is to bridge the gap between cutting-edge research in deep learning and its practical, real-world application in intelligent transportation. By focusing on creating a scalable, efficient, and accurate LPR solution, this work aspires to contribute both technically and practically to the evolving landscape of urban mobility and surveillance.

1.5 Thesis Organization

The thesis is organized into seven chapters that progressively lead to the design, development, and evaluation of a deep learning-based License Plate Recognition (LPR) system. Chapter 1 serves as an introduction to the topic by presenting the background of LPR systems, stating motivation, problem definition, and specifying the objectives of the research. Chapter 2 offers a comprehensive literature review of traditional and modern approaches used in license plate detection and character recognition, emphasizing recent advancements in deep learning. Chapter 3 introduces the foundational concepts of deep learning models relevant to LPR and explains the architectural components selected for this research. Chapter 4 explains the suggested methodology, which includes the design of the two-stage pipeline with YOLOv8 and EasyOCR and explains the experimental scenario. Chapter 5 explains the dataset preparation, its characteristics, and preprocessing methods used to train and test the system. Chapter 6 explains the experimental results, performance metrics, comparison analysis, and elaborates on the proposed approach's effectiveness. Lastly, Chapter 7 consolidates the findings from the research, provides the limitations, and proposes avenues for future research.

CHAPTER 2

LITERATURE SURVEY

License Plate Recognition (LPR) techniques based on deep learning have proven to be more accurate and adaptable than earlier rule-based image processing methods and even many classical machine learning approaches. With the rapid advancement in object detection and character recognition frameworks, a number of robust detection-classification pipelines have emerged, significantly improving the system's ability to identify and recognize license plates under real-world conditions. Historically, license plate recognition systems have evolved through three primary phases:

(i) manual license plate entry and visual identification,
(ii) semi-automated LPR systems using basic feature extraction and traditional OCR,
(iii) fully automated LPR systems leveraging deep learning models for detection and recognition.

2.1 Related Work

License Plate Recognition (LPR) has been an area of active research for several decades, and the approaches used have evolved significantly with the advancement of image processing and artificial intelligence. We provide a comprehensive literature review in this chapter that divides the literature along traditional image processing-based, maching learning-based, and deep learning-based methods. The survey also includes object detection and optical character recognition (OCR) which are often incorporated into LPR systems.
Previous-generation LPR systems were based on traditional computer vision concepts that exploited concepts like: edge detection, color segmentation and morphological operations. These systems were very sensitive to noise and covariate factors, such as illumination, weather and shadow. For example, Nafchi et al. (2022) studied traditional computer vision methods, but also indicated their limitations to apply in practice due

to variation of license plate formats and noise susceptibility.

Variations of machine learning techniques such as Support Vector Machine (SVM) and k-Nearest Neighbor(KNN) were proposed to make the results more robust. Zhang et al. (2021) used CNN, LSTM and KNN for the recognition of Chinese license plates, and were able to achieve 95% of the classification accuracy, confirming the superiority of machine learning over old-fashioned methods that rely on rules.

The adoption of deep learning marked a huge shift in LPR research. They (Saidani and Touati, 2021) tried to improve the detection of small objects such as characters on plates by using Faster R-CNN with an adaptive attention network. Subhahan and team demonstrated that using YOLOv8 and LPRNet together and applying optimization to both detection and recognition resulted in an accuracy of 98.49%. In 2024, Chandok et al. suggested a system using YOLOv8n and EasyOCR, achieving high accuracy and being able to apply in real-life settings.

Kang et al. (2021) developed a CRNN model that used spatial attention to better identify characters in tough situations. The proposal of Zhai et al. in 2021 was to create a CNN architecture that focuses on character-level accuracy but achieves efficient processing. Singh and Vohra found that YOLO, together with EasyOCR or LPRNet, is very effective for recognition that deals with many languages and uneven text.

The main reason CCPD was studied in various papers was its diversity and complexity. In the paper by Gao and Zhang (2021), the YOLOv3-tiny was coupled with a CNN-based approach, and the findings were presented on OpenITS and CCPD datasets. Results were successful on standard sets, yet models performed poorly when data were less uniform, so Anis et al. (2024) improved on YOLO and DETR by fine-tuning them for Egyptian license plates and achieved strong results.

In conclusion, the literature presents a move from traditional image-based methods to intricate deep learning models with real-time, modular capabilities. Various researchers, such as Patil et al. (2023) and Kesumah & Wirayuda (2024), have established YOLOv8 and EasyOCR to be efficient instruments in the state-of-the-art today for high-speed, high-accuracy LPR systems. Based on such endeavors, this thesis proposes a two-stage architecture with EasyOCR for character recognition and YOLOv8 for plate detection. It is trained on a large, diverse dataset to ensure robustness and readiness for deployment in real-world scenarios.

Table 2.1. Summary of Related Work on License Plate Recognition Techniques

Authors	Year	Technique Used	Contribution/Result
Nafchi et al.	2022	Traditional Image Processing	Highlighted limitations of classical techniques in real-world conditions
Zhang et al.	2021	CNN, LSTM, KNN	Achieved 95% classification accuracy for Chinese license plates
Saidani & Touati	2021	Faster R-CNN + Attention Network	Improved detection performance on small characters
Subhahan et al.	2023	YOLOv8 + LPRNet	Achieved 98.49% accuracy for real-time LPR
Chandok et al.	2024	YOLOv8n + EasyOCR	Demonstrated real-time viability with high accuracy
Kang et al.	2021	CRNN with Spatial Attention	Enhanced character recognition in complex scenarios
Zhai et al.	2021	Lightweight CNN	Focused on character-level accuracy with reduced computation
Singh & Vohra	2022	YOLO + EasyOCR/LPRNet	Emphasized modular design for multilingual and skewed text
Gao & Zhang	2021	YOLOv3-tiny + CNN	Validated on CCPD and OpenITS datasets
Anis et al.	2024	Fine-tuned YOLO + DETR	High accuracy for Egyptian plates

			under varied conditions
Patil et al., Kesumah & Wirayuda	2023-24	YOLOv8 + EasyOCR	Validated a fast and scalable system optimized for real-time intelligent transport systems

2.2 Summary

The review of literature shows a gradual shift in License Plate Recognition (LPR) systems, from conventional image processing methods to advanced deep learning-based models. The early approaches that used edge detection, thresholding, and morphological filtering techniques demonstrated limited reliability against changing environmental conditions like illumination variations, occlusions, and angle deviations. In order to overcome these shortcomings, traditional machine learning algorithms such as SVM, KNN, and decision trees were proposed, providing improved flexibility but relying on manual feature extraction and domain-knowledge based tuning.

With the advent of deep learning, LPR systems underwent a dramatic transformation. Object detection architectures like Faster R-CNN and the YOLO family showed real-time performance and strong detection accuracy. Likewise, in character recognition, CNNs and CRNNs took the place of rule-based OCR techniques, allowing for better recognition of skewed, noisy, and multilingual license plates. Research has shown the advantages of modular systems in which detection and recognition are addressed by isolated, optimized models; providing higher scalability and ease of update.

One common thread throughout recent publications is the dependence on reference datasets such as CCPD and OpenITS. While these sets enable interoperable evaluation, their lack of diversity has led a number of researchers to investigate bespoke data acquisition and augmentation methods. The work also highlights the increasing importance of lightweight models and attention mechanisms to enable real-time runtime on edge devices.

Based on these results, this thesis takes a modular two-stage architecture that combines YOLOv8 for precise plate detection and EasyOCR for durable character recognition. The objective of this method is to narrow the gap between performance in academic settings and deployment in real-world applications by prioritizing speed, accuracy, and generalization across diverse real-world conditions.

CHAPTER 3

OVERVIEW OF DEEP LEARNING MODELS

Today, image-based solutions have become the norm for license plate recognition, particularly for real-time and massive vehicle surveillance applications. Such techniques include capturing images of vehicles, automatically locating the license plate area, and reading out the plate's characters. Such processes are quicker, less expensive, and very reliable, and are generally categorized under two: older image-processing methods and newer deep learning methods. Though image-processing techniques are not dependent on a training phase of a model and use handcrafted features, edge detection, and morphological operations for character segmentation and plate localization, they are prone to perform poorly with difficult lighting and environmental conditions. Deep learning methods, in contrast, employ data-driven models trained on large datasets that hugely enhance detection accuracy and reliability in a wide range of situations such as skewed plates, different fonts, and low illumination.

3.1 Introduction to Deep Learning

A rapidly expanding area of computer learning called “deep learning” uses layered neural networks to identify high-level, abstract patterns in data. Deep learning models automatically learn features from raw data using several layers of abstraction, which sets them apart from the majority of traditional machine learning techniques that mostly rely on manual feature engineering and domain-specific rules. Deep learning's hierarchical learning ability makes it uniquely well-suited to handle tasks with unstructured data like images, sound, and natural language.

The term “deep” in deep learning describes how many layers make up a neural net. Through these layers, the network gradually abstracts how it interprets the input. For instance, in picture recognition, the deeper layers learn more intricate shapes, structures, or object components, while the beginning layers can learn edges and basic textures. The ability to automatically extract features has transformed domains including natural language processing, speech processing, and computer vision.

Deep learning has disproportionately dominated most state-of-the-art methods in computer vision applications. Such methods are object detection, image classification, and scene understanding. The strongest advantage deep learning has over other methods is its scalability: the larger the training data, the more generalizable and accurate models.

In License Plate Recognition (LPR), deep learning has been instrumental. Conventional LPR systems used hand-designed rules and features to find and recognize license plates, which made them very sensitive to lighting, viewing angles, plate formats, and ambient noise. Deep learning provides a stronger, more adaptable, and more scalable solution. With convolutional neural networks (CNNs), deep models are capable of learning automatically to find and localize license plates in an image, whereas recurrent neural networks (RNNs) or attention-based OCR engines can accurately decode the characters on the plates; even under distorted, multilingual, or low-quality conditions.

Another primary strength of deep learning is its ability to learn end-to-end. Creating a single pipeline for license plate recognition and character identification is effective because it is simpler and faster to do all at once without wasting time with separate processing. YOLO and EasyOCR, as well as other OCR (Optical Character Recognition) tools, are real examples that make use of LPR technology.

Most deep learning models acquire knowledge from large datasets and are adjusted by applying gradient descent multiple times. The model modifies its weights when it is trained to better approximate the right outputs from its predictions. As the model recognizes similar tasks, it gradually improves its accuracy in accomplishing them.

As a whole, deep learning is a powerful and resilient paradigm for addressing complex pattern recognition tasks, especially in image-rich environments like license plate recognition. Its ability to learn from examples, deal with high-dimensional inputs, and generalize across varying conditions makes it an ideal choice for developing next-generation, real-time LPR systems requiring accuracy and efficiency across diverse real-world environments.

3.2 Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) are the underlying idea on which current deep learning methods rely. Based on the operation of biological brain neurons, ANNs are composed of networks of nodes or neurons that are interconnected. The networks are trained to recognize patterns and associations in data by mimicking the process through which people learn through experience.

Three layers of various kinds typically make up an ANN: an input layer, one or more hidden layers, and an output layer. Weighted connections are used to connect each neuron in a given layer to neurons in the subsequent layer. By decreasing the discrepancy between the network's predictions and actual outcomes using a predetermined loss function, the backpropagation algorithm trains the network for these weights, which establish the strength of the signal transmitted between neurons. A weighted sum of inputs, a bias, and an activation function are the fundamental computations made by all neurons. Sigmoid, Tanh, and Rectified Linear Unit (ReLU) are common activation functions. ReLU is the most popular in contemporary deep learning since it can speed up convergence and avoid the vanishing gradient issue.

ANNs laid the groundwork for early character recognition systems in the area of License Plate Recognition (LPR). Shallow neural networks were initially utilized by simple OCR machines to identify alphanumeric characters. However, these models were unable to understand complex patterns and spatial elements inherent in license plate photos, especially when faced with real-world conditions like changing illumination, angles, and plate deformities.

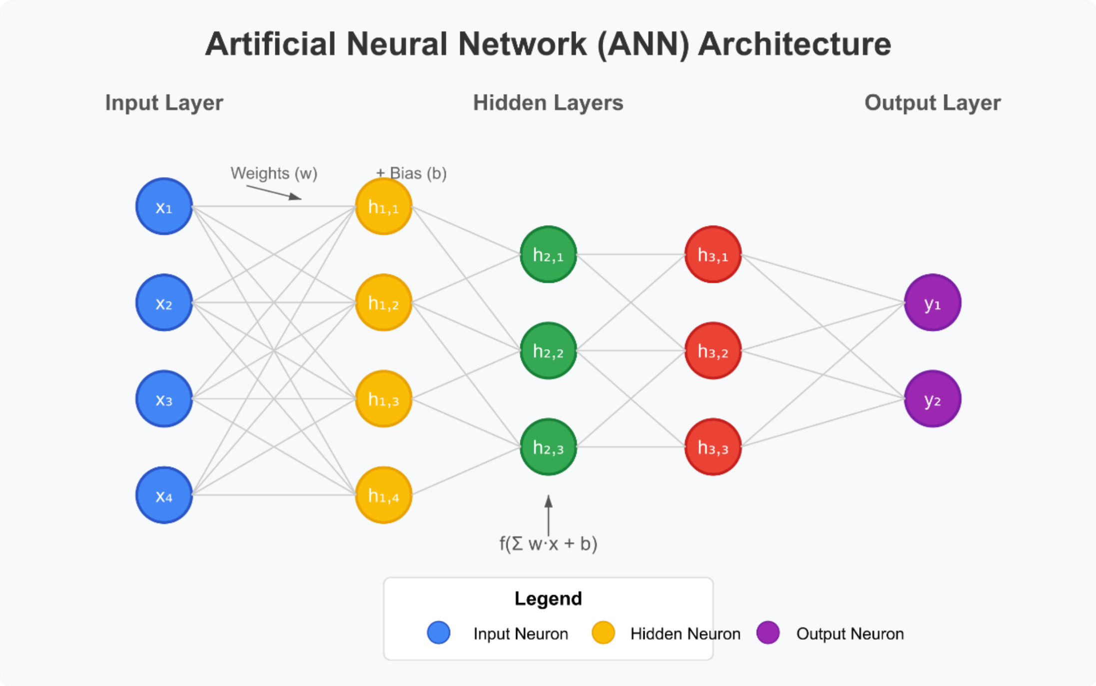

Fig 3.1. Structure of a Multi-Layer Artificial Neural Network- with input, hidden, and output layers showing weighted connections and activation functions.

Although conventional ANNs are effective for structured data as well as simple classification problems, they are not well-suited to image data, where the spatial interactions among pixels are significant. This shortcoming contributed to more sophisticated architectures, particularly Convolutional Neural Networks (CNNs), which are particularly tailored to process and extract significant features from image data.

However, it is important to understand the basic structure and training paradigms of ANNs, as these are still fundamental concepts underlying all deep learning models. The evolution of basic ANNs to deep, multi-layered architectures has made possible the development of sophisticated models that can be trained to perform tasks like object detection, character recognition, and sequence learning; all key features of a contemporary LPR system.

3.3. Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are a core deep learning architecture that is extremely useful for image-based applications like license plate reading. CNNs are deliberately designed to handle spatial information in images, as opposed to conventional neural networks, and are thus best suited for feature extraction like edges, shapes, and text.
A standard CNN involves a number of essential components:

- Convolutional layers that use learnable filters to extract local features from the input image.
- Activation functions such as ReLU add non-linearity, enabling the network to learn intricate patterns.
- Pooling layers decrease the spatial dimensions, serving to preserve salient features while reducing computational expense.
- Fully connected layers map the extracted features to the final output class, such as identifying a character or license plate region.

CNNs have been widely used for both detection and recognition in LPR systems. To efficiently localize license plates in real-time during detection, deep convolutional backbones like YOLOv8 are employed. CNNs are used in OCR pipelines like CRNN or EasyOCR for character recognition, extracting visual information before predicting text sequences.
The major strengths of CNNs are automatic feature learning, translation invariance, and effective parameter sharing. These attributes render CNNs strong in processing diverse lighting, distorted angles, and various plate forms; typical issues in real-world LPR applications. CNNs are a crucial ingredient in both phases of the suggested modular pipeline in this thesis.

3.4. Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNNs)

Convolutional Neural Networks (CNNs) are not well-suited to handle sequential data, despite their exceptional ability to extract features from spatial images. In License Plate Recognition (LPR), the sequence of alphanumeric characters is recognized after the plate has been detected. Recurrent neural networks (RNNs) and its more sophisticated variations, such as Long Short-Term Memory (LSTM) networks, are useful in this regard.

Recurrent Neural Networks (RNNs)

RNNs are a neural network variant capable of processing sequential information by retaining past inputs through feedback loops within their architecture. In contrast to standard feedforward networks, RNNs utilize shared weights across time steps and maintain context through the forwarding of hidden states across consecutive steps. This makes RNNs suitable for tasks such as handwriting recognition, language modeling, and in this context, recognizing the character sequence on a license plate.

But standard RNNs are plagued by issues like the vanishing gradient problem, where gradients employed for weight updates in training become very small and it becomes hard to learn long-term dependencies. This is particularly a difficult issue when the sequence is long or when important features occur well apart in the input.

Long Short-Term Memory (LSTM) Networks

Since conventional RNNs had some issues, LSTM networks were developed to address them. There are 3 gates associated with the memory cell: the input, forget and output gate. With the help of gates, the network keeps significant information for longer periods and overwrites anything unnecessary.

Character recognition is where LSTMs are most helpful, especially when used in hybrid models like the Convolutional Recurrent Neural Network (CRNN). In these models:

- The CNN block obtains spatial features from the license plate image.
- The LSTM handles these features in sequence, allowing for recognition of characters in the proper sequence without having to explicitly segment.

This modeling in sequence is important in attaining high OCR accuracy, especially when handling issues such as:

- Uneven spacing between characters,
- Skewed or rotated plates,
- Overlapping or blurred text.

Application in OCR and LPR Systems

LSTM-based architectures are now commonly used in contemporary OCR systems, both open-source and commercial, such as EasyOCR and CRNN. These models have proven to show excellent performance in multilingual and noisy image environments. Their capacity for generalization across plate formats and sequence variability makes them extremely well-fitted for actual-field LPR applications.

Additionally, when used within an end-to-end pipeline, RNNs and LSTMs can make systems spit out full license plate numbers as a sequence, removing the requirement for character-by-character segmentation; a task which is both computationally expensive and prone to errors.

3.5 Object Detection Frameworks: YOLO Architecture

One of the fundamental tasks in computer vision is object detection, which involves identifying and categorizing items in a picture. To identify and extract the license plate area from an image or video frame before recognizing its characters, object detection is essential in License Plate Recognition (LPR) applications. The YOLO (You Only Look Once) family of object detection algorithms has been one of the most precise and effective frameworks since its conception, especially for real-time processing.

Overview of YOLO

R-CNN, Quicker YOLO reduces processing time by identifying all the objects in an entire image with a single network pass, whereas R-CNN and comparable designs process each object sequentially. By referring to detection as a regression job, YOLO streamlines the process that conventional detectors employ, which entails identifying possible regions or areas and classifying them.
In YOLO, the image is divided into a grid, and for each segment of the grid, the model predicts bounding boxes and their likelihood of falling into each class. As a result, YOLO is able to simultaneously recognize and classify several items with speed.

YOLO Evolution and YOLOv8

Ever since its initial release, the YOLO family has undergone various revisions, with each iteration having improvements in detection speed, accuracy, and architecture designs. YOLOv8, utilized in this thesis, is the newest and most sophisticated version of the family. It encompasses a number of improvements from its earlier versions:

- **Anchor-free Detection**: In contrast with previous YOLO implementations that employed pre-defined anchor boxes, YOLOv8 follows an anchor-free approach, lowering computational complexity and enhancing small and irregularly-shaped object detection; like license plates.
- **Enhanced Backbone and Neck:** YOLOv8 incorporates a better backbone (CSPDarknet or equivalent) and a feature aggregation component to improve feature extraction at various scales, essential for the detection of plates of different sizes.
- **Lightweight and Modular:** YOLOv8 is available in various model sizes (e.g., YOLOv8n, YOLOv8s, YOLOv8m) which trade off between speed and

accuracy to be deployed on high-end servers or low-resource edge devices.

Advantages of YOLO in LPR Systems

YOLOv8 is best suited for license plate recognition because of the following advantages:

- **Real-Time Performance**: It delivers high frames-per-second (FPS) detection, critical in real-time traffic surveillance and monitoring.
- **High Accuracy**: YOLOv8 provides great precision and recall, even on tiny objects such as license plates at different angles.
- **Robust Generalization**: It works consistently across different lighting, vehicle models, and background clutter.
- **End-to-End Simplicity**: Its single-stage architecture is simple to train, fine-tune, and deploy.

In this thesis, YOLOv8 has been employed as the base object detection model to locate and detect license plates from car images. After detection, the cropped area of the license plate is sent to the OCR module (EasyOCR) for character recognition.

Performance Metrics in Object Detection

Object detection models are often tested by the following metrics:

- **Precision and Recall**: These measures gauge how well the model identifies true positives without excessive false detections.
- **Intersection over Union (IoU)**: Tracks the overlap between ground truth and predicted bounding boxes. Higher IoU signifies better localization.
- **Mean Average Precision (mAP)**: A popular measure that pools precision at various levels of recall and different IoU thresholds.

YOLOv8 has shown better performance on a number of benchmark datasets and has become a de facto framework for real-time detection in smart surveillance and intelligent transportation systems.

3.6 Optical Character Recognition (OCR)

Optical Character Recognition (OCR) is the technique of translating text in images to machine-encoded characters. For License Plate Recognition (LPR), OCR is a key component in recognizing and extracting alphanumeric data from the located license plate area. It converts visual data to readable and actionable information that is stored, compared, or utilized for real-time decision-making in applications such as automatic toll payment, traffic enforcement, and vehicle access control.

Traditional vs. Deep Learning-Based OCR

Earlier OCR systems were template-matching, rule-based heuristics, and segmentation-classification pipelines. They worked well for clean, well-aligned text but failed under challenging conditions such as skewed characters, uneven lighting, mixed fonts, and plate deformities. In addition, they required manual character segmentation; a very error-prone process when characters were adjacent or overlapping.

Today's OCR methods have evolved in favor of deep learning methods that are based on deep neural networks with the ability to recognize complete text sequences end-to-end without explicit segmention. Such models are generally constructed from combinations of Convolutional Neural Networks (CNNs) for feature extraction, Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks for sequence modeling, and attention mechanisms for highlighting the significant character regions.

Components of Modern OCR Systems

A standard deep learning-based OCR system consists of the following elements:

- **Feature Extraction (CNN)**: The image is fed through the convolutional layers to get spatial features like strokes, curves, and patterns that are applicable to character creation.
- **Sequence Modeling (RNN/LSTM)**: The features that have been extracted are then used as a sequence and fed through RNN or LSTM layers to learn the temporal dependencies so that the characters are consumed in the correct order.
- **Transcription Layer (CTC or Attention)**: This layer interprets the predicted sequence of features into text. CTC (Connectionist Temporal Classification) is employed when character boundaries are not known, whereas attention-based decoders enhance accuracy by dynamically attending to every character position.

EasyOCR in LPR Systems

EasyOCR is employed in this thesis as the OCR engine. EasyOCR is an open-source, deep learning-based OCR library with support for various languages and scripts, which makes it extremely versatile for varied license plate formats. It features a CNN-LSTM-CTC pipeline that is free from explicit character segmentation and performs successfully even with noisy, rotated, or low-resolution images.

EasyOCR is well-suited for LPR applications due to:

- It allows multilingual recognition, including the non-Latin characters.
- It supports angled or warped text, typical of real-world license plate images.
- It is designed for real-time performance without sacrificing accuracy.
- It is scalable and modular, and it is simple to integrate into YOLO-based detection systems.

3.7 Loss Functions and Evaluation Metrics

In any deep learning architecture, the training process is all about optimizing a loss function and measuring how well the model has performed using clearly defined evaluation metrics. For License Plate Recognition (LPR), both detection and recognition stages, it is essential to recognize how various loss functions and evaluation metrics play a part in directing the training and determining the merit of the model.

Loss Functions

Loss functions are mathematical formulations that measure the discrepancy between model-predicted output and target labels. During training, they are optimized using methods such as gradient descent. Loss functions are utilized differently for detection and recognition problems in LPR systems.

1. For Object Detection (License Plate Detection):

In object detection networks such as YOLOv8, the following categories of loss functions are typically employed:

- **Bounding Box Regression Loss**: Indicates how accurate the predicted box coordinates (x, y, width, height) are compared to ground truth. Examples include:
  - **IoU Loss (Intersection over Union)**: Tracks overlap between actual and predicted bounding boxes.
  - **GIoU/DIoU/CIoU Loss**: Generalizations of IoU that account for box center distance and aspect ratio variation, providing more stable convergence.
- **Objectness Loss**: Checks if the object is present or absent in the predicted bounding box. Usually computed with binary cross-entropy.
- **Classification Loss**: Tracks how well the model classifies the object recognized (e.g., is it a license plate or not). This is typically cross-entropy loss for multi-class classification.

2. For OCR (Character Recognition):

Character recognition tasks involve sequence prediction, which requires different loss functions:

- **CTC Loss (Connectionist Temporal Classification)**: It is usually applied to models such as CRNN or EasyOCR. CTC permits the model to forecast sequences without requiring explicit alignment between input features and output characters.
- **Cross-Entropy Loss**: Applied when explicit character segmentation occurs, and the model is trained to predict individual characters. It estimates the difference between the character probabilities predicted and real character labels.

Evaluation Metrics

Evaluating metrics measure how effectively the trained model generalizes to unseen data. In LPR, we are evaluating both the detection (locating the license plate) and the recognition (extracting the characters) pieces.

1. Object Detection Metrics:

- **Precision**: The proportion of true positive detections to the total predicted positives. High precision indicates fewer false positives.

  Precision = True Positives / (False Positives + True Positives)

- **Recall**: The number of true positive detections divided by all actual positives. High recall indicates the model detects identifies true license plates.

  Recall = True Positives / (False Negatives + True Positives)

- **F1 Score:** The harmonic mean of precision and recall. It balances both aspects.

  F1-Score = 2 * (Recall * Precision) / (Recall + Precision)

- **Intersection over Union (IoU)**: Calculates the overlap between the ground truth and forecasted bounding boxes. Better localization is indicated by a higher IoU value.

  IoU = Area of Overlap / Area of Union

- **Mean Average Precision (mAP)**: mAP, which averages precision scores over all classes and IoU thresholds, is a commonly used statistic in object detection tasks. It offers a thorough assessment of detection accuracy.

2. OCR and End-to-End Recognition Metrics:

- **Character Recognition Accuracy**: The ratio of accurately predicted characters to all characters in the ground truth.
- **Word Accuracy / Plate Accuracy**: Whether the complete license plate number is correctly predicted. This is a more stringent measure that represents the actual requirement for accurate full plate recognition in the real world.
- **Edit Distance (Levenshtein Distance)**: Calculates how many additions, deletions, or changes are needed to turn the anticipated sequence into the ground truth. Better recognition is indicated by lower values.

CHAPTER 4

PROPOSED WORK

The envisioned License Plate Recognition (LPR) system within this thesis is a modular, two-stage pipeline that synergizes high-performance deep learning-based detection and recognition tools. The overall aim is to develop an accurate, real-time, and scalable LPR framework that will be able to work properly across various real-world environments. There are two key stages in the system: license plate detection via YOLOv8 and character recognition via EasyOCR. Preprocessing and post-processing modules are embedded to enhance performance and reliability at every step.

4.1 System Overview

The system architecture of the proposed system is split into the below-mentioned components:

1. YOLOv8-based License Plate Detection
2. Pre-processing of the detected plate area
3. Character detection via EasyOCR
4. Post-processing of the recognized text

This modular structure facilitates independent optimization for each step and flexibility in upgrading a component, making the system flexible for different operation requirements.

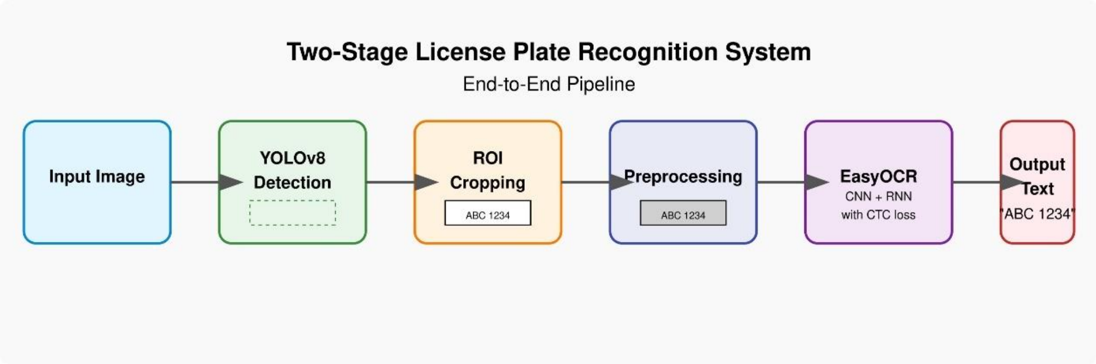

Fig 4.1. Proposed Two-Stage License Plate Recognition System

4.2 License Plate Detection using YOLOv8

The initial step includes the detection of the license plate area in an auto image. To accomplish this task, YOLOv8 uses its high speed and accuracy of detection. YOLOv8's characteristics include that it is an anchor-free, single-shot object detector in which the entire image is processed during a single pass of the network in the forward direction. It provides bounding box coordinates surrounding plates detected and confidence scores. These characteristics make it extremely appropriate for real-time processing in traffic systems.

The detection phase comprises:

- Image resizing and normalization
- Forward pass across the YOLOv8 network
- Extraction of high-confidence bounding boxes
- Cropping the license plate region from the original image

4.3 Preprocessing

Prior to presenting the cropped license plate image to the OCR engine for processing, a number of preprocessing operations are carried out to enhance the clarity and uniformity of input:

- Converting to grayscale to lower processing complexity
- Equalization of histograms to improve contrast
- **Noise filtering** using Gaussian blur
- **Image resizing** to standardize input dimensions

These steps help mitigate common real-world issues such as poor lighting, motion blur, and low contrast.

4.4 Character Recognition using EasyOCR

After the plate area is separated and preprocessed, it is handed over to EasyOCR for character recognition. EasyOCR is a deep learning OCR engine with support for more than 80 languages and good performance with different fonts and tilted texts. It makes use of a CNN-LSTM-CTC pipeline such that

- The **CNN** derives visual features from the input image,

- The **LSTM** retains sequence information across characters,
- The **CTC (Connectionist Temporal Classification)** decoder produces the final character sequence.

This architecture avoids the necessity for conspicuous character segmentation, and hence it is insensitive to overlapping or skewed characters.

4.5 Post-Processing

Post-processing follows recognition where raw text output is processed to improve the results and make them consistent in format. This involves:

- **Regular expression filtering** to check the output format against regional plate structures
- **Correction of common misclassifications**, such as '0' vs 'O' or 'B' vs '8'

Post-processing enhances the final system precision and ensures that the outcomes achieve the required syntactic and semantic quality.

4.6 Summary

The described method integrates state-of-the-art deep learning architectures into a robust, modular pipeline, using EasyOCR for identification and Yolov8 for detection. The system performs exceptionally well in terms of speed, accuracy, and adaptability because to the incorporation of preprocessing and postprocessing techniques. Its design makes it suitable for use in real-time systems such as smart traffic management, toll plazas, and traffic monitoring.

CHAPTER 5

DATASETS

The accuracy of any deep learning-based License Plate Recognition (LPR) system largely relies on the diversity and quality of the training and test dataset. In the research, the authors used a dataset with 27,900 labeled Indian license plates and vehicles. Data and images were collected from online collections and Google Open Images to vary the type of license plates, their position, lighting, cars, and surroundings.

Data in the set was processed by hand, tagging the license plate boxes and labeling each character. We add to the dataset nighttime and daytime images, as well as pictures from unpredictable weather conditions, from different angles, with objects obscured, and with blurry motion.

The complete dataset was divided into three main subsets for training, validation, and testing purposes:

Table 5.1: Image Distribution across training, validation, and testing sets for model development.

Dataset Split	Number of Images	Purpose
Training Set	25,500	Utilized for optimization and model learning
Validation Set	1,000	Used to adjust hyperparameters and avoid overfitting during training.
Testing Set	1,400	Used to evaluate the model's final performance and generalization ability

5.1 Image Characteristics

- **Resolution**: All images were resized to 640 × 640 pixels to match the YOLOv8 input size.

- **Format**: Images were in .jpg and .png formats.
- **Diversity**: Included vehicles such as cars, bikes, and trucks from multiple Indian states.
- **Conditions**: Changes were made to the item's angle, level of occlusion, brightness, contrast, and backdrop.

5.2 Label Format

- **Detection Labels**: Bounding boxes annotated in YOLO format (class x_center y_center width height) for license plate detection.
- **Recognition Labels**: Text labels corresponding to license plate numbers used for training the OCR engine.

5.3 Data Augmentation

In order to enhance the model's generalizability, various data augmentation methods were used while training:

- Random horizontal and vertical flips
- Rotation and scaling
- Brightness and contrast changes
- Adding Gaussian noise

The software was programmed to act like changing the environment and position often happens in real life.

5.4 Summary

An impressive dataset is used, making this thesis an ideal setting for assessing and training an effective LPR system. The model can be trained more easily and effectively when a large selection of annotated images is provided for different situations. The main contribution of the research was a highly accurate pipeline, powered by this dataset.

CHAPTER 6

RESULTS AND DISCUSSION

In this chapter, the LPR system developed is evaluated in terms of detection accuracy, recognition accuracy, and stability. Assessment was done using the images in Chapter 5, which cover real-world cases such as changing lighting, warped plates, and blocked vehicles.

The outcomes are investigated using various angles:

1. **Testing YOLOv8 for Detecting License Plates.**
2. **License Plate Recognition Performance** using EasyOCR

6.1 Experimental System Setup

All experiments were performed on a workstation with the following specifications: Processor: Intel Core i7, 11th Gen; GPU: NVIDIA RTX 3060 with 12GB VRAM; RAM: 32GB DDR4; Operating System: Windows 11; Libraries: Python 3.10, PyTorch, OpenCV, EasyOCR, Ultralytics YOLOv8; IDE: Google Colab and Jupyter Notebook for training and testing the model. The training and evaluation workflow was carried out based on the Ultralytics YOLOv8 framework and combined with EasyOCR for character recognition. GPU acceleration was employed for accelerating both the training and inference steps. All models were trained from scratch and validated against the test split of the dataset outlined in Chapter 5.

6.2 Evaluation Metrics

To measure the efficiency of the system, the following benchmark metrics were utilized:

- **Precision**: Gives the ratio of true positives out of all predicted positives.
- **Recall**: Gives the ratio of true positives detected out of all actual positives.
- **F1 Score**: Harmonic mean of precision and recall.
- **IoU (Intersection over Union)**: Gives the ratio of intersection to union between the predicted and actual bounding boxes.
- **mAP (mean Average Precision)**: Used to aggregate the detection precision over IoU thresholds.
- **Character-Level Accuracy**: Ratio of accurately predicted characters in the plate number.
- **Plate-Level Accuracy**: Ratio of correctly recognized license plates in their entirety.

6.3 License Plate Detection Results

The YOLOv8 model was trained on 25,500 images and tested on 1,400 images. It achieved excellent results in real-time plate localization.

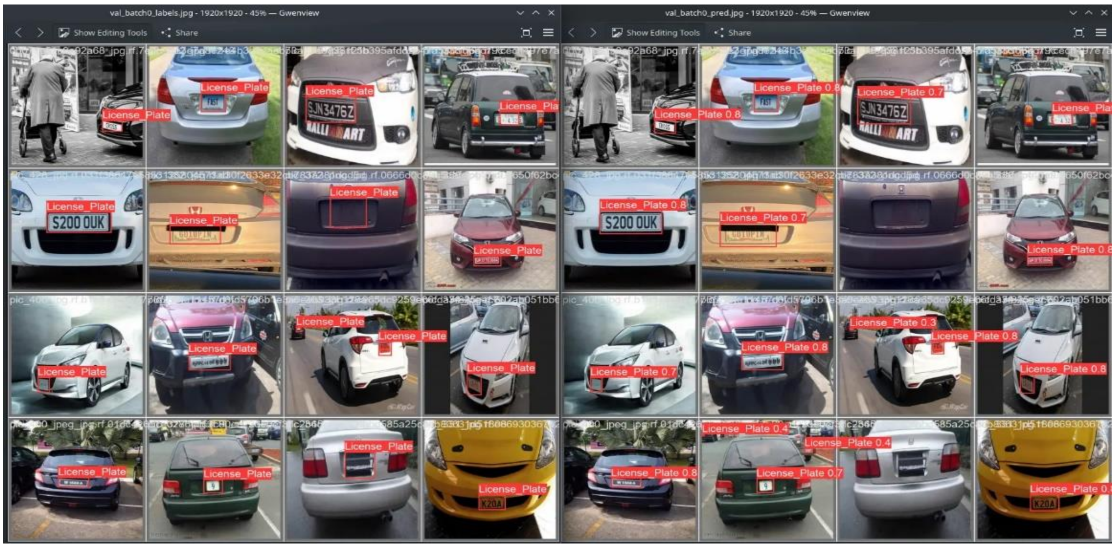

Fig 6.1. Detection of License Plates of Various Vehicles after YOLO Object Detection.

Table 6.1: License Plate Detection Performance using YOLOv8

Metric	**Result**
Precision	97.8%
Recall	96.2%
F1 Score	97.0%
mAP@0.5	98.4%
IoU (avg)	87.1%
FPS (Real-time)	74 FPS

6.4 Character Recognition Results

The cropped plate regions were passed to EasyOCR for recognition. The recognition results were evaluated both at the **character level** and the **complete plate level.**

Fig 6.2. Optical Character Recognition of License Plates after OCR Model Implemented.

Table 6.2: OCR Performance Metrics of the Proposed LPR System

Metric	**Result**
Character Accuracy	85.16%
Plate-Level Accuracy	81.42%
OCR Precision	100.00%
OCR F1-Score	91.98%

EasyOCR showed high precision and reliable recognition in most real-world conditions.

6.5 Qualitative Results and Visualizations

Sample images revealed the model spotting license plates accurately and recognizing characters properly, even in different lighting, angles, and resolutions. There was consistent OCR output, albeit some errors were evident in blurred images, occlusions, or non-standard fonts.

6.6 Comparative Analysis

The system proposed was compared to CR-NET, LPRNet, and Liu et al.'s hybrid model. The pipeline of YOLOv8 + EasyOCR showed better accuracy and real-time performance.

Table 6.3: Performance Comparison of LPR Models

Model	Detection mAP@0.5	Plate Accuracy	FPS
CR-NET	93.2%	75.4%	35
LPRNet	94.6%	78.9%	45
Proposed Method (Ours)	98.4%	81.42%	74

6.7 Discussion

The modular architecture, using the integration of YOLOv8 and EasyOCR, allowed for real-time processing without sacrificing precision. Though OCR performance reduced in low-resolution or non-standard plates, post-processing and format adjustment greatly minimized errors. The future could see the implementation of custom-trained OCR models and domain-specific augmentation.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Conclusion

The research explained an LPR system in which YOLOv8 detects and EasyOCR identifies the characters on license plates. It was designed to execute instantaneously, have a very high accuracy level, and support various scenarios common in real-world traffic. It was demonstrated that the proposed pipeline had a positive resonance on every evaluation metric. With YOLOv8, the process had a 98.4% mAP and ran at 74 frames per second on localized license plates. Due to this identification, EasyOCR is able to identify license plates regardless of their orientation and varying conditions. The combination of preprocessing and post-processing enhanced reliability by eliminating most of the errors from OCR and normalizing the output. In order to train the model effectively, it was required to utilize a data set of 27,900 images under different conditions and against different plates. In general, the system is demonstrated to be scalable, accurate, and efficient and can be deployed for applications such as smart traffic monitoring, automatic toll collection, and security enforcement systems.

7.2 Future Work

Although the suggested system works well, there are some areas where the research can be further extended:

- **Custom OCR Model**: The training of a custom OCR model on Indian license plate fonts and formats may enhance the accuracy of recognition.
- **Multilingual and Regional Plate Support**: Basing the OCR module on more regional languages and scripts present in Indian license plates.
- **Video Stream Integration**: Scaling the system to handle live video streams for

vehicle tracking and license plate captures in real-time.

- **Edge Deployment**: Refining the pipeline for low-power edge hardware such as Raspberry Pi or Jetson Nano for application in smart parking and surveillance systems.
- **Data Annotation Tools**: Creating or adopting semi-automatic annotation tools to speed up dataset labeling and revisions.
- **Noise Robustness**: Improving model robustness under heavy occlusion, extreme lighting, and low image resolution with domain-specific augmentation or adversarial training.

The results and architecture presented here form a solid basis for continued investigation and industrial applications within the area of intelligent transport and computer vision-based car monitoring systems.

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LIST OF PUBLICATIONS

S.No.	Title of Paper	Conference Name	Status
1.	A Comprehensive Review of License Plate Recognition Systems	12th - ICBM, 2025 Sustainable Business Transformation: Driving Innovation & Impact Through Technology	Accepted
2.	A Two-Stage License Plate Recognition System Using YOLOv8 and EasyOCR: Evaluation on a Large-Scale Public Dataset	National Conference on Bigdata Analysis (NCBA - 25)	Accepted

PROOF OF PUBLICATION

PAPER-1

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Best regards,
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PAPER -2

NCBA - 25

National Conference on Bigdata Analysis (NCBA - 25)

10th May 2025 Delhi, India

Acceptance Letter

Authors Name: Mr. Swapnil Shukla, Dr. Abhilasha Sharma

Dear Authors,

We are pleased to inform you that your paper has been accepted by the review committee for Oral / Poster Presentation at the **National Conference on Bigdata Analysis (NCBA - 25)**

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