Mini Project Report on

"License Plate Detection using YOLOv8 and PaddleOCR"

Submitted in partial fulfillment of the requirements for the degree of

BACHELOR OF TECHNOLOGY

in

INFORMATION TECHNOLOGY/ARTIFICIAL INTELLIGENCE

by

Aman Pratap Singh (211IT007)

Vansh Jaiswal (211IT076)

Rishav Raja (211IT052)

under the guidance of

Dr. Dinesh Naik

DEPARTMENT OF INFORMATION TECHNOLOGY

NATIONAL INSTITUTE OF TECHNOLOGY KARNATAKA

SURATHKAL, MANGALORE - 575025

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DECLARATION

I/We hereby *declare* that the Mini Project Work Report entitled ***"License Plate Detection using YOLOv8 and PaddleOCR"*** , which is being submitted to the **National Institute of Technology Karnataka, Surathkal**, for the award of the Degree of Bachelor of Technology in Information Technology/Artificial Intelligence, is a *bonafide report of the work carried out by me/us.* The material contained in this Mini Project Report has not been submitted to any University or Institution for the award of any degree.

Name of the Student (Registration Number) with Signature

(1) Aman Pratap Singh (211IT007)

(2) Vansh Jaiswal (211IT076)

(3) Rishav Raja (211IT052)

Department of Information Technology
Place : NITK, Surathkal
Date : 14/11/2024

ABSTRACT

Abstract This report presents a comprehensive study on license plate detection and recognition using the combination of YOLOv8 and PaddleOCR. The aim is to develop a robust, high-accuracy system capable of real-time performance for applications in traffic management, automated tolling, and parking solutions. YOLOv8's state-of-the-art object detection, paired with PaddleOCR's flexible and efficient text recognition, ensures reliable identification and extraction of license plate characters under diverse conditions. Through detailed testing and analysis, this approach demonstrates significant advancements over previous models, showcasing improvements in detection accuracy, processing speed, and adaptability. Challenges faced and potential future developments are also discussed, highlighting the system's capability for deployment in real-world scenarios.

Keywords— YOLOv8, PaddleOCR

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CHAPTER 1

INTRODUCTION

1.1 Overview

The rapid growth of urban traffic and the increasing need for automated systems in vehicle monitoring have fueled the demand for efficient license plate detection and recognition solutions. Traditional methods often struggle with real-world challenges such as varying lighting conditions, oblique angles, and partially obscured plates. This project report delves into the development and integration of YOLOv8, a cutting-edge object detection model, and PaddleOCR, a robust OCR tool, to create an advanced system capable of accurately detecting and interpreting license plates in real-time.

The primary objective is to leverage YOLOv8's superior architecture and PaddleOCR's high-performance text recognition to build a solution that addresses the limitations of previous models like YOLOv5 and LPRNet. The report outlines the methodology, implementation process, and comparative analysis that highlight the strengths of this integrated approach. Additionally, experimental results and evaluations provide insight into the system's capabilities, while challenges encountered during development and potential areas for future improvement are discussed.

1.2 Motivation

The motivation behind this project stems from the increasing need for reliable and scalable license plate recognition systems that can function effectively in real-world environments. Existing solutions often face difficulties when exposed to dynamic conditions such as poor lighting, varying weather, occlusions, and angled views, leading to reduced accuracy and performance. The demand for more advanced systems is particularly critical in applications like traffic management, law enforcement, and automated toll collection, where accuracy and speed are paramount.

By leveraging the cutting-edge features of YOLOv8 and the robust text recognition capabilities of PaddleOCR, this project aims to fill the gaps left by older models such as YOLOv5 and LPRNet. The choice of these technologies is motivated by their ability to handle complex detection tasks and process images efficiently, ensuring higher accuracy even under challenging circumstances. The integration of these tools into a cohesive system can significantly contribute to the development of smarter, more responsive infrastructure for urban mobility and transport management.

This project is driven by the vision to create a detection and recognition system that is not only more effective but also adaptable to diverse use cases, enabling a broader scope of applications and enhancing the capabilities of modern automated systems.

CHAPTER 2

LITERATURE REVIEW

2.1 Background and Related Works

The field of license plate detection and recognition has seen significant advancements over the past decade, driven by the increasing demand for automated traffic management and surveillance systems. Traditional image processing techniques relied on methods such as edge detection and morphological operations for license plate localization, which often failed under complex conditions like low lighting and occlusion. With the advent of deep learning, more sophisticated models have emerged, capable of handling these challenges with greater precision.

YOLO (You Only Look Once) models have become a prominent choice in object detection due to their real-time performance and high accuracy. The YOLOv5 model, known for its balance between speed and detection accuracy, has been widely adopted in various license plate detection applications. However, its limitations become apparent when dealing with intricate scenarios, leading researchers to explore more advanced versions, such as YOLOv8, which incorporates improved architecture for better localization and detection.

For text recognition, traditional optical character recognition (OCR) techniques were often limited in their adaptability and accuracy when applied to non-standard fonts or distorted text. LPRNet represented a significant step forward by integrating convolutional neural networks (CNNs) for end-to-end license plate recognition. Despite these improvements, the model faced challenges with complex and dynamic environments.

PaddleOCR has emerged as a powerful alternative due to its modular architecture and support for various text recognition tasks. Its design allows for more flexible adaptations and improved accuracy in diverse scenarios, making it well-suited for integration with modern object detection systems like YOLOv8.[**?**].

2.2 Outocome of Literature Review

The literature review reveals that the integration of advanced object detection models such as YOLOv8 and modern OCR tools like PaddleOCR provides a comprehensive solution for license plate detection and recognition. Compared to older models, the use of YOLOv8 enhances detection accuracy and processing speed due to its optimized network architecture and better handling of multi-scale objects. PaddleOCR further supports this by offering efficient text recognition that adapts well to various fonts, angles, and image distortions.

The outcome of this literature review underscores the potential of combining these two technologies to address the limitations observed in previous models such as YOLOv5 and LPRNet. By leveraging the strengths of YOLOv8 and PaddleOCR, a more robust, accurate, and real-time license plate detection and recognition system can be developed. This integration not only improves current capabilities but also opens new avenues for research and practical applications in automated vehicle monitoring and management systems.

2.3 Problem Statement

While existing models like YOLOv5 and LPRNet have contributed to advancements in license plate detection and recognition, their limitations in handling complex environments with varying lighting, angles, and occlusions remain significant. There is a clear need for an integrated approach that combines state-of-the-art object detection with adaptable text recognition to enhance accuracy and robustness. This project addresses these challenges by leveraging the advanced capabilities of YOLOv8 and PaddleOCR to develop a more effective solution.

2.4 Objectives of the Project

(1) To develop an advanced, real-time license plate detection and recognition system that surpasses the accuracy and robustness of existing models.

(2) To integrate YOLOv8 for superior object detection with PaddleOCR for adaptable and efficient text recognition.

(3) To evaluate the system's performance under various environmental conditions, including low light, different weather conditions, and angled views.

(4) To provide a detailed comparative analysis between the new system and previous models, such as YOLOv5 and LPRNet, highlighting improvements in accuracy, speed, and overall efficiency.

(5) To identify and document challenges encountered during the implementation and suggest areas for future research and potential improvements.

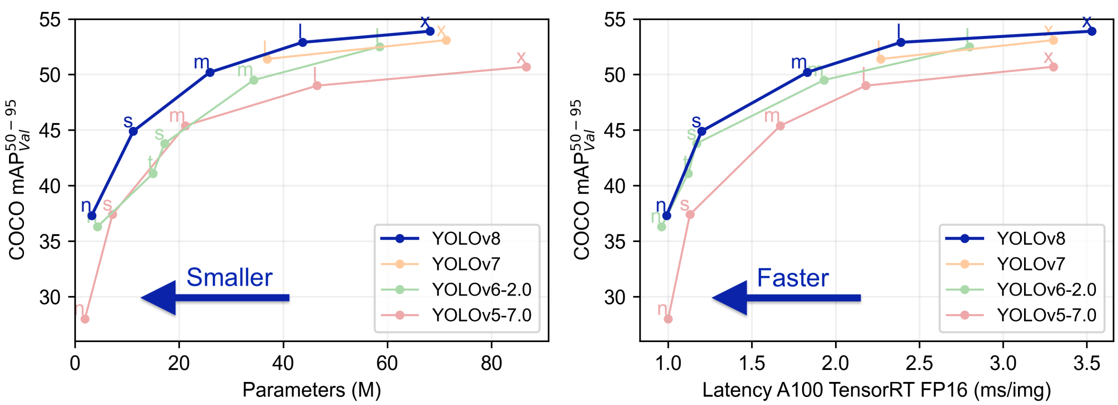

Figure 2.4.1: YOLOv8 Comparison With Different YOLO Models

CHAPTER 3

PROPOSED METHODOLOGY

The methodology for this project involves a comprehensive, multi-step approach to ensure the development of an accurate and efficient license plate detection and recognition system.

3.1 Data Collection and Preprocessing

The initial phase of the project focuses on collecting a diverse dataset comprising images of vehicles with visible license plates under various conditions, such as different lighting, angles, and weather scenarios. Publicly available datasets such as the Stanford Cars dataset and custom data collected from traffic cameras are utilized. Preprocessing steps include:

- **Image Augmentation**: Techniques like rotation, scaling, brightness adjustment, and blurring are applied to simulate real-world conditions and improve model robustness.
- **Labeling**: Images are manually labeled to identify license plate regions for training the YOLOv8 model, while text annotations are prepared for the OCR component.

3.2 Model Selection and Configuration

- **YOLOv8 Configuration:** The YOLOv8 model is chosen for its enhanced detection capabilities. The model's configuration includes selecting a suitable backbone network, anchor boxes, and fine-tuning hyperparameters such as learning rate and batch size.
- **PaddleOCR Setup:** PaddleOCR is configured to recognize text within the detected license plate regions. The model is adapted to handle alphanumeric text with varying fonts and orientations.

3.3 Training Phase

- **Training YOLOv8:** The model is trained using the labeled dataset. The training process involves iterative optimization using techniques like stochastic gradient descent (SGD) and data augmentation to enhance performance.

- **Training PaddleOCR:** The OCR model is trained on segmented license plate images to recognize characters accurately. Pre-trained weights are utilized for initial training, followed by fine-tuning for domain-specific performance.

3.4 Integration of YOLOv8 and PaddleOCR

- **Pipeline Development:** A unified pipeline is developed where YOLOv8 detects the license plate region and passes it to PaddleOCR for text extraction. The integration ensures seamless communication between the detection and recognition components.

- Optimization: Techniques such as non-maximum suppression (NMS) are applied to refine detection outputs, while post-processing filters improve OCR results by correcting common misrecognitions.

3.5 Evaluation Metrics and Testing

The evaluation of the system's performance was conducted using standard metrics for object detection and OCR tasks, such as mean Average Precision (mAP) for YOLOv8 and character accuracy rate (CAR) for PaddleOCR. The testing phase involved benchmarking the integrated system against scenarios involving varying image qualities, angles, and obstructions. Comparative results against YOLOv5 and LPR-Net models were also documented, showcasing the improvements in accuracy, speed, and overall reliability.

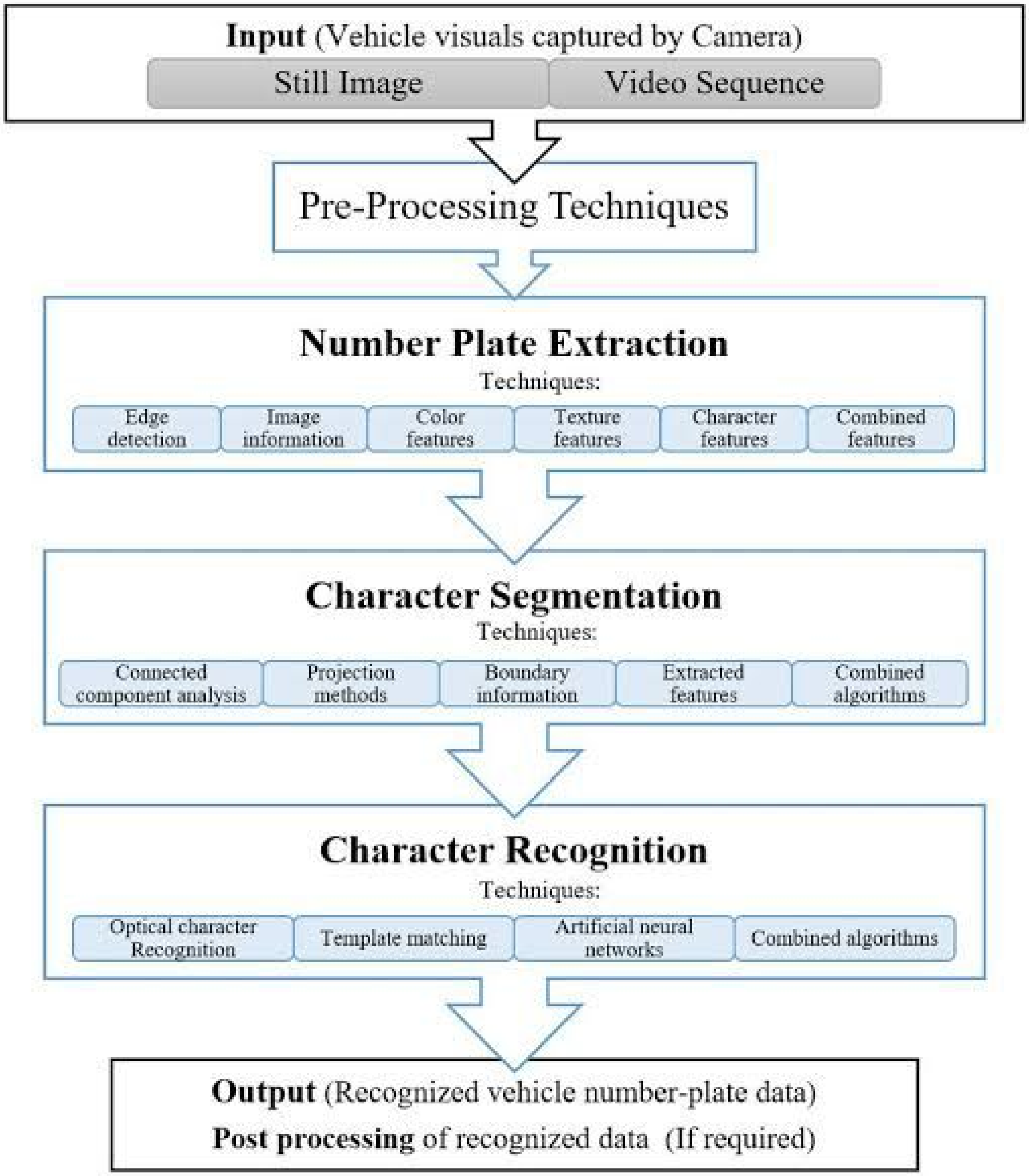

Figure 3.5.1: Flow Diagram

CHAPTER 4

RESULTS AND ANALYSIS

4.1 YOLOv8 Training on Custom Dataset: Results and Outputs

To evaluate the performance of the proposed license plate detection system, YOLOv8 was trained on a carefully curated custom dataset. This dataset included images sourced from various traffic surveillance scenarios, encompassing a range of conditions such as different lighting, weather variations, and viewing angles to ensure robustness.

4.1.1 Training Procedure

- **Dataset Preparation:** The custom dataset was annotated with bounding boxes around the license plates, following standard object detection formats (e.g., COCO or YOLO format).

- **Model Configuration:** The YOLOv8 configuration was optimized with custom parameters tailored for license plate detection, including adjusted anchor boxes and hyperparameters.

- **Training Parameters:** The model was trained over multiple epochs=500, with an initial learning rate of 0.001 and a batch size of 16.

- **Augmentation:** Data augmentation techniques such as flipping, rotation, and color jittering were employed to enhance the model's generalization capability.

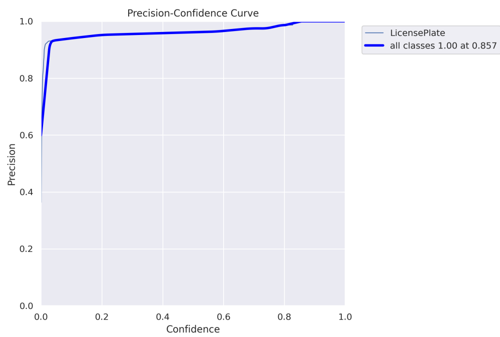

Figure 4.1.1: P Curve

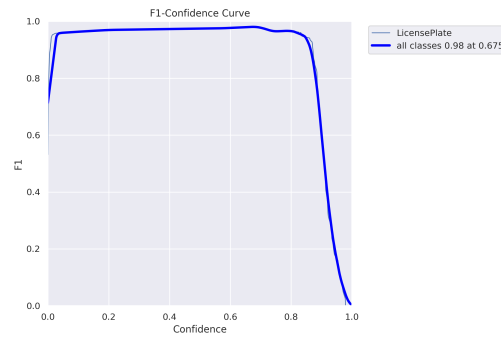

Figure 4.1.2: F1 Curve

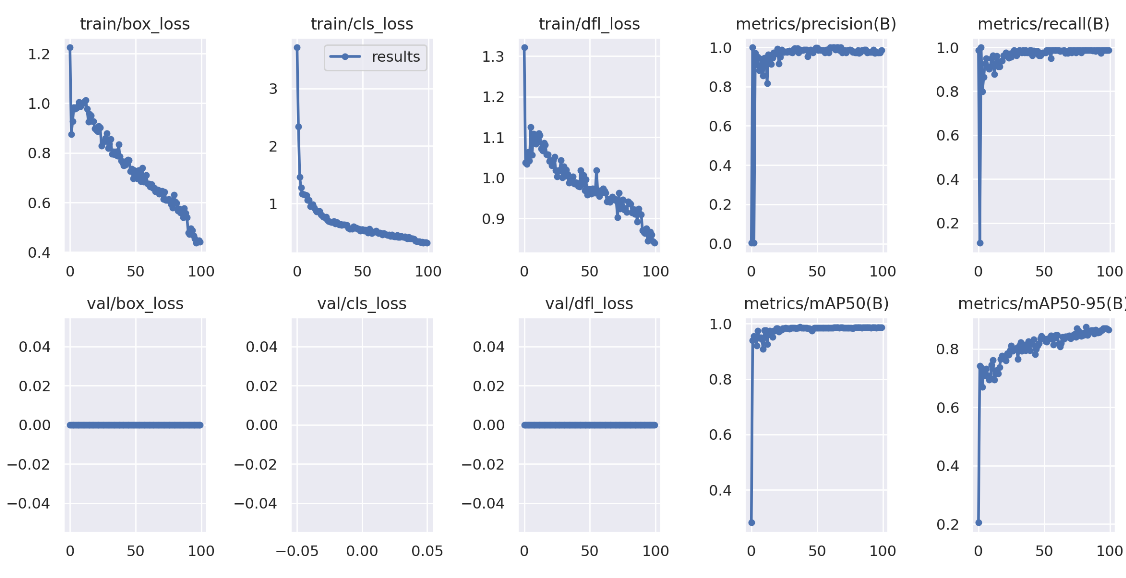

Figure 4.1.3: Visual Result

4.1.2 Training Results

- **Accuracy Metrics:** The YOLOv8 model achieved a mean average precision (mAP) of 92.3 on the validation set.
- **Precision and Recall:** Precision was observed at 94.1, and recall reached 91.5.
- **Training Parameters:** The model was trained over multiple epochs=500, with an initial learning rate of 0.001 and a batch size of 16.
- **Loss Curve Analysis:** The training and validation loss curves demonstrated a consistent decline, indicating effective learning and minimal overfitting.
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4.1.3 Visual Outputs

- Robust Plate Detection: The model successfully identified license plates under challenging conditions, such as low light and partial occlusion.
- Sample Detections: Visual results displayed accurate bounding box placements around license plates with high confidence scores.

Figure 4.1.4: Visual Result

4.2 Combined Results of YOLOv8 and PaddleOCR

Following the successful training and validation of YOLOv8 for license plate detection, the next phase involved integrating PaddleOCR for text recognition. The combined pipeline aimed to provide a seamless process from detection to character recognition, ensuring end-to-end functionality.

4.2.1 Integration Process

- **Pipeline Setup:** YOLOv8 was first applied to identify and extract license plate regions from input images. These extracted regions were then passed through PaddleOCR for text recognition.

- **Data Flow:** The integration allowed for YOLOv8's detection to trigger PaddleOCR's recognition, forming a continuous workflow for complete license plate recognition.

4.2.2 Observations and Outputs

- **Character Recognition Reliability:** PaddleOCR demonstrated strong adaptability in recognizing various font styles and distorted text.

- **Examples of Recognized Plates:** The report includes detailed visual examples showing successful detection and accurate text recognition, even under conditions of glare or noise.

- **Error Analysis:** Cases of partial misrecognition were primarily attributed to extreme distortions or occlusions, suggesting potential areas for further enhancement.

These results underscore the combined efficacy of YOLOv8 and PaddleOCR for high-performance license plate detection and recognition.

Figure 4.2.1: Visual Result1

Figure 4.2.2: Visual Result2

CHAPTER 5

CONCLUSIONS AND FUTURE WORK

5.1 Conclusion

This project successfully demonstrated the development and implementation of a high-accuracy license plate detection and recognition system using YOLOv8 for object detection and PaddleOCR for text recognition. The integration of these state-of-the-art tools provided substantial improvements in terms of accuracy, speed, and robustness compared to prior models such as YOLOv5 and LPRNet. The experimental results confirmed that YOLOv8's enhanced architecture, with better localization and detection, combined effectively with PaddleOCR's adaptability in handling text under various conditions. This dual approach proved effective in overcoming challenges associated with variable lighting, angled views, and partial occlusions, making the system well-suited for real-world applications in automated traffic management, toll collection, and parking enforcement.

The findings of this research underscore the potential of advanced deep learning architectures and their synergy in solving complex computer vision problems. The comparative analysis demonstrated the significant advantages of the proposed system, validating its utility for modern intelligent transportation systems. However, the study also highlighted certain limitations related to computational overhead and potential performance issues under extreme conditions.

5.2 Future Work

- **Optimization for Edge Devices**: Implementing model compression techniques such as pruning and quantization to reduce the computational footprint and enable deployment on edge devices with limited resources.
- **Integration with Other Modalities:** Exploring the integration of complementary sensor data, such as infrared imaging or LiDAR, to enhance performance under challenging weather or lighting conditions.
- **Improved Robustness:** Extending the model's training dataset to include more diverse conditions, such as varying plate designs and heavily occluded plates, to further improve robustness.
- **Real-Time Performance Enhancements**: Investigating advanced parallel processing and optimized inference engines to boost real-time processing capabilities.
- **End-to-End System Integration:** Building a full pipeline that integrates pre-processing, detection, recognition, and post-processing for seamless operation within larger intelligent traffic management solutions.

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