A Minor Project Report

on

An Efficient and High Performing ALPR Model

submitted in partial fulfillment of the requirements for the award of degree

Bachelor of Technology

in

Computer Science and Engineering

by

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CERTIFICATE OF APPROVAL

This project work (E16) entitled " **An Efficient and High Performing ALPR Model** " by Ms. S Raga Divya of Registration No.21211A05T2, Ms. U Kavya Sree of Registration No.21211A05W3, Mr. T Kiriti of Registration No.21211A05V8, Mr. Y Sarthik of Registration No.21211A05Z1 under the supervision of Mr. D Abdus Subhahan in the Department of Computer Science and Engineering, B V Raju Institute of Technology, Narsapur, is hereby submitted for the partial fulfillment of completing Minor Project during II B.Tech II Semester (2022 - 2023 EVEN). This report has been accepted by Research Domain Computational Intelligence and forwarded to the Controller of Examination, B V Raju Institute of Technology, also submitted to Department Special Lab " Data Science" for the further procedures.

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DECLARATION

We, the members of Research Group domain **Computer Vision** under **Data Science** special lab , declare that this report titled: **An Efficient and High Performing ALPR Model** is our original work and has been submitted in whole or in parts for International conference or journal **International Conference on Recent Advances in Information Technology for Sustainable Development** . All sources of information used in this report have been acknowledged and referenced respectively.

This project was undertaken as a requirement for the completion of our **II B.Tech II Sem Minor project** in Department of **Computer Science and Engineering** at **B V Raju Institute of Technology**, Narsapur. The project was carried out between 31-March-2023 and 11-August-2023. During this time, we as a team were responsible for the process model selection, development of the micro document and designing of the project.

Automatic License Plate Recognition model aimed to recognise license plates. The project involved extensive research on the current ALPR models, identifying the key features required for the detection and recognition, and developing a prototype. The prototype was then tested and refined to ensure that it met the specified requirements.

We would like to express our gratitude to our project supervisor Mr.D Abdus Subhahan for his guidance and support throughout this project. We would also like to thank our Department Head Dr.CH.Madhu babu for his help and efforts. We also thank the experts who worked on ALPR project previously for providing valuable insights, which greatly assisted in the development of detection model.

We declare that this report represents Our own work, and any assistance received from others has been acknowledged and appropriately referenced.

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The experience of working on this project will surely enrich our technical knowledge and also give us hands on experience of working on a project and help develop our team's skill set to a great extent.

ABSTRACT

Utilising cutting-edge technologies for efficient automation in toll collecting, parking management, and related domains is the goal of the Automatic Licence Plate Recognition (ALPR) project.This is generally achieved by two basic steps that are detecting the license plate from the image or video footage and then recognizing the characters on it. The system accomplishes high-speed and accurate vehicle recognition, tracking, and precision licence plate identification by utilising the YOLOv8 and LPRNet algorithms. A specialised YOLOv8 model for licence plate detection allows accurate identification of licence plate regions, while the integration of YOLOv8 facilitates effective vehicle detection and tracking. The LPRNet method is used for further character recognition and text extraction from licence plates. By combining these elements, a robust ALPR system is created, allowing for the seamless automation of key toll collection and parking management activities. The project's precision, speed, and robustness open the door for many automated systems to operate more efficiently and reliably.YOLOV8 is the improved and updated version of YOLO algorithms which has shown improvement in recognition and recall rate and also has better recognition speed compared to other versions with an better accuracy rate.

Keywords: CNN,Deep Learning,License plate detection,Character recognition, YOLOv8, LPRNet

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LIST OF ACRONYMS AND ABBREVIATIONS

CNN Convulutional Neural Network

STN Spatial Transformers Network

YOLO You Only Look Once

GAN Generative adversarial network

CCPD Chinese City Parking Dataset

ALPR Automatic License Plate Recognition

HT (Hough Transform

CTC Connectionist temporal classification

CRN convolutional-recurrent networks

MAP Mean of average precisions

FPS Frames per second

TP True Positives

TN True Negatives

FP False Positives

FN False Negatives

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CHAPTER - 1

1. INTRODUCTION

In this report, we will explore the life cycle of our Automatic license plate recognition model to detect and recognise license plates from video tapes and real-time.This study aims to pave the way for enhanced automation and efficiency in traffic management, security, and various related applications.

1.1. Background

The background of this project lies in the intersection of computer vision, deep learning, and automation technology. Automatic License Plate Recognition (ALPR) systems have gained significant traction due to their potential to enhance various aspects of traffic management, law enforcement, and security. The project draws upon advancements in deep learning frameworks such as YOLOv8, specialized for object detection, and LPRNet for optical character recognition. The goal is to leverage these technologies to create an ALPR system that can streamline toll collection, parking management, and other related processes. By automating the identification of vehicles and their license plates accurately and swiftly, the project addresses real-world challenges in transportation and security, seeking to contribute to more efficient and automated solutions.[**?**].

1.2. Motivation

The motivation behind this project stems from the need to improve and automate processes related to vehicle monitoring, toll collection, and parking management. Automatic License Plate Recognition (ALPR) technology presents a powerful solution to streamline these processes, making them more efficient, accurate, and convenient. By automating the detection and recognition of license plates using advanced computer vision and deep learning techniques, this project aims to reduce manual intervention, minimize errors, and enhance the overall effectiveness of traffic and security systems. The potential impact of this automation includes smoother traffic flow, improved security measures, and enhanced resource management, driving the motivation to develop a high-speed and accurate ALPR system.

1.3. Problem statement

- The previous state-of-art models take large input sizes and process them using technologies like CRNet that use the segmentation method for character recognition which is a laborious task that results in low inference speed and does not perform well with small-scale data sets.
- Their accuracy decreases in unconstrained environments such as occlusions, bad weather, and oblique view as the image or video quality obtained will be of low resolution.

1.4. Objectives

1. Automatic license plate recognition using YOLOV8 and LPRNet.
2. Robust lightweight LPRNet framework to produce accurate results in less time

1.5. Scope of Project

To gain an insight into the scope of our project, let us first understand what the term scope of a project means in software development, the scope refers to the boundaries and limitations of a project. It also defines the features, functions, and requirements of the software being developed. The scope of a software project describes what the software will and will not do, and what is included and excluded from the project.

The Automatic license plate recognition Model will consist of two primary functionalities:

The project aims to deliver the following key features:

- Precise identification of license plate regions within detected vehicles using a specialized YOLOv8 model, a fundamental step in the ALPR process.
- LPRNet performed on detected license plate regions to accurately extract and interpret license plate characters, contributing to efficient vehicle identification.
- Aggregation and structuring of results, including vehicle tracking IDs, bounding boxes, and recognized license plate texts, in a coherent and organized manner for further analysis.
- Exporting the structured results to a CSV file for easy accessibility, sharing, and integration with other systems or applications.
- Flexibility to adapt and integrate with diverse use cases and environments, demonstrating versatility in potential applications beyond toll collection and parking management.

The boundaries and limitations of Automatic license plate recognition Model can also be defined by its scope, which also outlines the features, functions, and requirements of the system. Some of these boundaries and limitations are:

- **Data Quality and Quantity**: The performance of the ALPR model is significantly affected by the quality and resolution of the input video. Low-quality cameras or poor lighting conditions may lead to inaccurate vehicle and license plate detection.
- **Multiple formats**:The model may struggle with accurately recognizing license plates that deviate significantly from standard formats, including non-standard characters, different fonts, or non-standard plate sizes.
- **Processing Time and Efficiency**:The processing time required for each frame may be a limitation, especially for high-resolution videos. Enhancements in processing speed could further optimize real-time ALPR applications.
- **Environmental Factors**:Adverse weather conditions, extreme lighting variations, or complex backgrounds can impede accurate vehicle and license plate detection, affecting the overall performance of the ALPR system.
- **Generalization to Different Environments**:The model's performance might vary when applied to different geographical regions with distinct license plate formats, styles, or camera placements.
- **Privacy and Ethical Considerations**:As ALPR involves processing personal data (license plates), ensuring compliance with privacy laws and ethical usage is crucial. Proper anonymization and privacy protection measures should be implemented.

Addressing these limitations through ongoing research, collaboration with professionals, and continuous model refinement will be essential for maximizing the model's potential impact on License plate recognition and its applications.

Overall, the project report will provide a comprehensive understanding of the Automatic license plate recognition model using YOLOv8 and LPRNet. The report will serve as a valuable resource for Transportation authorities.

CHAPTER - 2

2. LITERATURE SURVEY

[1]This study provides an end-to-end deep learning model for licence plate localisation and identification in real settings. The model is divided into two sections: licence plate location and licence plate recognition. An upgraded version of the YOLOv5 algorithm is employed for licence plate location, which adds a unique attention mechanism in the Neck structure's down-sampling phase. This enhances the efficiency and accuracy of licence plate location. A GRU + CTC recognition network is used for licence plate recognition to complete the recognition of positioned licence plates. The model does not require pre-segmentation of licence plate characters, and the automated extraction of characters is performed by deep neural networks after learning by themselves[1].

[2]This research paper analyses the shortcomings of current licence plate detection and identification systems and offers LSV-LP, a new large-scale video-based licence plate dataset. The collection is more diversified and indicative of real-world circumstances since it includes 1,402 films, 401,347 frames, and 364,607 annotated licence plates. The research also introduces MFLPR-Net, a novel framework that investigates information across neighbouring frames to increase accuracy and efficiency. The suggested dataset and framework are examined using several cutting-edge algorithms, and the results demonstrate their efficacy. Finally, the study discusses the importance of the suggested dataset and methodology, as well as their possible applicability in real-world settings. In January 2023, the research was published in IEEE Transactions on Pattern Analysis and Machine Intelligence.

[4]A research paper on Car Licence Plate Recognition Based on Improved YOLOv5m and LPRNet is pre- sented . The research provides a unique approach for licence plate identification in complicated settings that enhances accuracy and real-time performance. Three components of the YOLOv5m algorithm have been improved: feature extraction, anchor box design, and loss function. In terms of accuracy and efficiency, the suggested technique surpasses existing target identification and licence plate recognition systems. The study includes experimental findings and analysis to back up the usefulness of the suggested strategy. Under various situations, the suggested approach achieves great precision in recognising licence plates.LPRNet is able to do thorough endto-end licence plate recognition. The 94 x 24 picture serves as the network's input, while the convolutional layer serves as its output.Overall, the research proposes a viable method for recognising licence plates.

[5]Image analysis of license plate analysis using generative adversarial neural networks is a research paper that proposes a new approach to LPR using deep learning techniques. The authors of the paper use a GAN to generate realistic license plate images, which are then used to train a recognition system.

The proposed approach is evaluated on a large dataset of license plate images and achieves superior results in terms of speed and accuracy. The paper begins by introducing the license plate recognition problem, which is a key project in many applications such as traffic control, parking management, and law enforcement. The authors then explain the limitations of traditional detection systems, which are based on hand-crafted features and require extensive image pre-processing. The proposed approach is based on the use of GANS, a type of deep neural network that can generate realistic images. The authors train a GAN to generate licenses similar to real licenses and then use these images to train a recognition system using a convolutional neural network (CNN). The CNN is trained on both real and synthetic images, allowing it to learn robust features for recognition. The results of the experiment show that the proposed strategy works. achieving peak performance across multiple benchmarks. In particular, it outperforms previous approaches in terms of accuracy and speed. The authors also analyze in detail the results showing that the proposed approach is robust to different types of noise and distortion. Overall, the paper presents a new approach to license plate recognition based on the use of GANS. This approach achieves state-of-the-art results and has the potential to improve many applications based on license plate recognition[5]

[3] Another method of automatic number plate recognition is using VSNet, it is a novel ALPR approach which is a cascaded framework that uses two Convolutional Neural Networks that are 1. Vertex Net To detects the License Plate 2. SCR-Net -To recognize the License plate. Experiments results indicate VSNet achieves better than 99 percent (99) accuracy on the AOLP and CCPD Datasets with an inference speed of 149 frames per second.It deals even with environmental conditions which makes it difficult to detect and recognise number plate using vertex net designed with small-resolution input. Both VertexNet and SCR-Net are designed with unique architectures to implement vertex-based operations. This system efficiently incorporates vertex estimation and LP rectification using a CNN structure, achieving optimal inference speed and accuracy. The output obtained by VertexNet is taken as input by SCRNet. It takes it as a classification problem rather than recognition like YOLO based detection methods and performs forward pass CNN[3]. VertexNet improves precision by 1.4 percent compared to state-of-the-art MTLPR obtaining the highest accuracy 99.1 percent and runs at a speed of 5.7ms per image with an accuracy of 98.8 percent it is also more effective than cutting-edge techniques. SCR-Net has the highest accuracy (99.5speed of 6.7ms per image which is a 43 percent improvement compared to RPNet of 11.7ms per image[3].

[6]This research publication describes an innovative technique to constructing a reliable automatic licence plate recognition system for Jordanian licence plates. The suggested method detects tiny LP elements and eliminates erroneous forecasts employing temporal information and a collection of arrays data structure using two-stage Convolutional Neural Networks based on the YOLO3 framework. This is Jordan's first end-to-end ALPR that analyses video streams in realtime, making it a noteworthy addition to the field of intelligent transportation systems and also collected a dataset exclusively of jordian license plates which also helps in better character recognition.The study also compares the proposed method to other current approaches and provides a full description of the dataset utilised for training as well as testing. There are no known conflicting financial interests or personal ties amongst

the authors that might have impacted the work presented in this study.

[7]This research preserve describes a real-time licence plate detection and identification system based on YOLOv7 and LPRNet that can recognise Chinese licence plates rapidly and reliably. To identify and recognise licence plates in complicated surroundings, the system employs a combination of deep learning models and image processing techniques. For licence plate detection, the YOLOv7 model is employed, while for character recognition, the LPRNet model is used. The technology has a higher average accuracy of 96.1% than standard licence plate detection and identification systems. This system's possible uses include intelligent security systems, roadway monitoring, and handling parking spaces. Overall, this system delivers a reliable and quick solution for real-time licence plate detection and recognition.

[8] The Squirrel Search Algorithm (SSA)-based Convolutional Neural Network (CNN) model is proposed in the research study as an optimum deep learning model for Vehicle Licence Plate Recognition (VLPR). Preprocessing, LP positioning and detection, HT-based (Hough Transform) character segmentation, and SSA-CNN-based recognition are the four primary operations in the proposed approach. Even in difficult settings such as fluctuating lighting and variances in standpoint, forms, colours, and patterns, this model is durable and efficient at recognising licence plates. The study also explores the difficulties encountered throughout the VLPR process and how the suggested deep learning model addresses them.

[9]Several phases are included in this work for licence plate identification and recognition utilising neural pattern matching. The technique is intended to overcome the issues raised by non-standard licence plates in underdeveloped nations such as Pakistan.For licence plate recognition, three distinct models are proposed here. These models comprise a red, green, and blue channel segmentation licence plate identification model, a multi-directional licence plate identification system relying on the MD-YOLO framework, and a fully convolutional network termed YOLOv3.It displays considerable gains in character recognition efficiency, which can have major repercussions for safety and traffic administration.

[10]This study presents a full ALPR system capable of detecting licence plates in a range of situations while also compensating for perspective-related errors. A vehicle detector and an ALPR module that can manage photometric and geometric fluctuations are included in the system.The authors offer an Improved Warped Planar Object Detection Network (IWPOD-NET) that can identify the four corners of a licence plate in a range of settings, allowing it to be warped to a fronto-parallel view and alleviating perspective-related distortions. The suggested detector outperforms state-of-theart approaches and earns top scores on many datasets.The possibility of tailoring Optical Character Recognition (OCR) technologies for different licence plate locations is also considered.The developed system is a promising solution for ALPR in unconstrained scenarios, and this study provides a detailed description of the system and its components.

CHAPTER - 3

3. REQUIREMENT ANALYSIS & SPECIFICATION

This section of the project report is the most critical element as, it provides a foundation for the entire project. It ensures that all stakeholders are aligned on the project's objectives, scope, and deliverables, and it provides a clear road map for the project team to follow.
This section is further divided into 3 sister sections:

- Feasibility Study
- Model Selection
- SRS

3.1. Feasibility Study

A feasibility study is the first stepping stone into the development of any project, including our ALPR model to recognise license plates. It involves assessing the potential for the project to be successful, which in turn includes evaluating the market, technology, financial aspects, and operational requirements.

3.1.1. Market Analysis

The ALPR market has been growing steadily due to the rising demand for enhanced security and traffic management solutions in various sectors, including law enforcement, transportation, parking, and toll collection.Governments and private organizations are increasingly adopting ALPR technology to enhance security, automate toll collection, monitor traffic violations, manage parking spaces, and improve overall public safety.Continuous advancements in machine learning, computer vision, and OCR technologies are enhancing ALPR accuracy, speed, and capabilities, making it more effective and efficient.The market is segmented based on components (hardware, software, and services), applications (traffic management, law enforcement, parking management, toll collection), and end-users (government, commercial, and residential sectors).Key market players include global tech companies, specialized ALPR solution providers, and startups. These companies compete in terms of technology innovation, cost-effectiveness, and customizability of solutions.

3.1.2. Technology Assessment

The ALPR model integrates YOLOv8 for robust vehicle and license plate detection, SORT for efficient tracking, LPRNet for precise optical character recognition, and OpenCV for image processing. The blend of these technologies allows real-time processing and accurate extraction of license plate information. However, sensitivity to varying license plate formats and potential privacy concerns necessitate careful consideration for broader deployment. Overall, the model showcases a promising balance of speed, accuracy, and scalability for automated license plate recognition.

3.1.3. Operational Requirements

The operational requirements include a computer with a powerful GPU is needed to efficiently run the deep learning models like YOLOv8 for real-time processing of video frames.The system requires Python and relevant libraries (e.g., PyTorch, OpenCV) for model implementation, along with necessary frameworks like SORT for object tracking.A stable internet connection is necessary for initial model setup, updates, and potential integration with cloud services or APIs for enhanced functionalities.Access to a video stream (live or recorded) is crucial for feeding frames into the model for vehicle detection and license plate recognition.

3.1.4. Financial Analysis

The financial analysis for this project should consider costs for hardware, software licenses, and potential cloud services for real-time processing. Initial investment includes GPU-enabled hardware and licenses for relevant software components. Operational costs encompass electricity, internet, and maintenance expenses. Potential revenue streams could come from offering the ALPR system as a service to clients, licensing the technology, or integrating it into existing traffic management solutions, with ROI expected over the long term. Monitoring and optimizing costs are crucial for ensuring the project's financial viability and sustainability.

3.1.5. Risk Assessment

The main risks for this project include potential privacy breaches due to license plate data handling, model biases leading to inaccurate detections, dependency on high-quality video sources for reliable results, and legal compliance regarding data usage. Addressing these risks involves stringent data privacy protocols, continuous model refinement to mitigate biases, ensuring compatibility with varied video sources, and staying updated with legal frameworks governing data collection and processing for ALPR applications.

3.2. Selection of Process Model

The software life cycle process model is a framework that outlines the various stages involved in the development of a software application. So, choosing a life cycle process model is the stepping stone into the development of a software product.

3.2.1. Process Models

The choice of a process model for automatic license plate detection, recognition depends on the specific requirements of the system, an iterative and flexible process model would be suitable. One such process model fits well with AI and Deep learning projects is the ”Agile Process Model”.

3.2.2. Why Agile

Here are some reasons why the Agile model is the best choice for developing automatic license plate recognition model:

- **Iterative Development:** ALPR models often require fine-tuning and continuous improvement. The iterative nature of Agile allows for incremental updates and enhancements, responding to changing requirements and emerging challenges effectively.
- **Customer Feedback Integration:**Agile emphasizes customer involvement and feedback throughout the development process. In the case of ALPR, involving law enforcement agencies, transportation authorities, or other stakeholders ensures the system aligns with their specific needs and priorities.
- **Adaptability to Changes:**ALPR technology is evolving rapidly. Agile allows the team to adapt to technological advancements, regulatory changes, or alterations in project goals, ensuring the model remains up-to-date and relevant.
- **Rapid Prototyping:**Agile methodologies enable rapid prototyping and early visualization of the ALPR system. This is crucial for stakeholders to understand the system’s functionality and make informed decisions, improving the end product.
- **Risk Mitigation:**Agile emphasizes identifying and addressing risks early in the development cycle. In a project like ALPR, which involves sensitive data and evolving technologies, proactive risk management is essential to ensure privacy compliance, accuracy, and system security.
- **Continuous Integration and Testing:**ALPR models require rigorous testing. Agile promotes continuous integration and testing, which is crucial to identify and fix issues promptly, ensuring a robust and reliable ALPR system.

- **Cross-Functional Collaboration:**ALPR development involves various aspects such as computer vision, deep learning, data processing, and system integration. Agile encourages collaboration among cross-functional teams, facilitating a holistic approach to ALPR development.

3.2.3. Why Not

Every coin has two sides thus, we can't forget to consider that the agile model has some limitations too such as:

- Complexity in Large Projects:Agile can face challenges in managing larger and more complex projects, particularly when the project scales beyond the capacity of a small, co-located team.
- Resource Intensive:Agile demands high involvement and collaboration, which can be resource-intensive, requiring dedicated team members and constant communication.
- Client Involvement:Agile heavily relies on continuous client involvement and feedback. If clients are unable to dedicate time and effort, the Agile process may be hindered.

While Agile offers many benefits, it may not be suitable for projects with fixed, rigid timelines or highly regulated environments, where extensive documentation and upfront planning are mandatory. In such cases, adopting Agile might require careful planning and adaptation to address the specific needs and constraints of the project.

3.3. Software Requirements Specification

3.4. Introduction

This project focuses on the development of an Automatic License Plate Recognition (ALPR) system, leveraging cutting-edge technologies like YOLOv8 for vehicle and license plate detection, SORT for vehicle tracking, and LPRNet for license plate text extraction. The objective is to automate processes such as toll collection and parking management by accurately identifying vehicles and extracting license plate information in real-time from a given video source. The integration of these components establishes a robust ALPR pipeline, emphasizing speed, accuracy, and efficiency to enhance automation and streamline various applications in traffic monitoring and security.

3.4.1. Purpose

The purpose of this document is to define the requirements and specifications for the development of the Automatic License Plate Recognition Model. The model aims to leverage modern technologies to improve traffic management, automate toll collection and parking processes, enhance security, and contribute to the development of smarter, safer, and more efficient urban spaces using YOLOv8 and LPRNet.

3.4.2. Scope

The Automatic License Plate Recognition Model will include the following functionalities:

- License Plate Detection:Identifies and localizes license plates on detected vehicles, a fundamental step for subsequent license plate recognition.
- License Plate Recognition (LPRNet):Performs Character Recognition on the detected license plate region, extracting alphanumeric characters to recognize and interpret the license plate number.
- Data Aggregation:Aggregates and structures the information obtained from vehicle detection, license plate detection, and recognition, organizing it for easy access and analysis.

3.4.3. Definitions, Acronyms and Abbreviations

- **Definitions:**
  AI:Artificial Intelligence

ALPR:Automatic License Plate Recognition
CNN:Convulutional Neural Network
YOLO:You Only Look Once
GAN:Generative Adversarial Network
HT:Hough Transform

- **Acronyms:**
  ALPR: Automatic License Plate Recognition
  CNN: Convolutional Neural Network
  OCR: Optical Character Recognition
  SSD: Single Shot Detector
  HOG: Histogram of Oriented Gradients
  RNN: Recurrent Neural Network
  CTC: Connectionist Temporal Classification
  GRU: Gated Recurrent Unit
  FPS: Frames Per Second
  IoU: Intersection over Union

- **Abbreviations:**
  DNN: Deep Neural Network
  LP: License Plate
  YOLO: You Only Look Once
  ROI: Region of Interest
  GPU: Graphics Processing Unit
  CPU: Central Processing Unit
  SSD: Solid State Drive
  FPS: Frames Per Second
  RGB: Red Green Blue
  LPR: License Plate Recognition

3.4.4. Overview

The document will mostly consist of two parts:

- Overall Description
- Specific Requirements

Overall description describes the major components of the system, assumptions and dependencies of the system, while specific requirements describes the functions of the system and their roles in the system and the constraints faced by the system.

3.5. Overall Description

3.5.1. Product Perspective

From a product perspective, this Automatic License Plate Recognition (ALPR) project offers a sophisticated and efficient system for automating vehicle identification and management. It provides an intuitive user interface for real-time monitoring and analysis, empowering users to make informed decisions in traffic management, toll collection, and parking operations. The robustness of its vehicle detection, license plate recognition, and data structuring features ensures a reliable and adaptable solution for improving urban infrastructure and security.

3.5.2. Product Functions

The main functions of the Automatic License Plate Recognition Model are as follows:

- **License Plate Detection:** Identifies and isolates the regions containing license plates on detected vehicles.
- **Character Recognition:**Extracts alphanumeric characters from license plates, recognizing and interpreting the license plate numbers.
- **Vehicle Tracking:**Tracks the movement and paths of vehicles across frames, enabling continuous monitoring and analysis.
- **Data Aggregation and Structuring:**Aggregates information from vehicle detection, license plate detection, and recognition, organizing it for ease of access and analysis.
- **Toll Collection Automation:**Automates toll collection processes by recognizing license plates and associating them with respective toll accounts.
- **Data Export and Integration:**Allows export of structured data to external systems or applications for integration and further processing.

3.5.3. User Characteristics

The intended users of the Automatic License Plate Recognition Model are Traffic management and researchers. They should have basic technical knowledge to interact with the model and understand the predicted results.

3.5.4. Constraints

The following constraints are considered for the development of the model:

- **Data Security and Storage:**Adhering to data security standards to protect sensitive information, including license plate data, is essential to prevent unauthorized access, data breaches, or misuse.
- **Accuracy and Reliability:**The model must strive for high accuracy and reliability to ensure effective vehicle and license plate detection, minimizing false positives and negatives which could affect its real-world applicability.
- **Hardware and Processing Constraints:**Considering the computational resources and processing power required for real-time performance, the model should be optimized for efficient usage of hardware, especially in resource-constrained environments.
- **Cost Constraints:**Considering cost-effectiveness in terms of hardware, software, and maintenance to ensure that the ALPR system is viable and affordable for deployment.

3.5.5. Assumptions & Dependencies

The Automatic License Plate Recognition Model assumes the following:

- Assumption that the input video feed is stable, well-captured, and of sufficient quality for accurate vehicle and license plate detection.
- License plates follow standard formatting rules and are legible, enabling reliable Character Recognition.
- system has access to camera feeds or video sources for real-time processing or analysis.
- Lighting conditions are suitable for optimal image processing and license plate detection.
- Project adheres to legal and ethical data usage principles, respecting privacy laws and obtaining necessary permissions for data collection and analysis.
- Dependency on sufficient computational resources (e.g., GPU, memory, processing power) to handle the processing demands of the ALPR system efficiently.
- Dependency on a diverse and relevant training dataset for training and fine-tuning the models to ensure accurate vehicle and license plate detection.

- Dependency on compliance with data privacy laws and regulations to ensure legal and ethical handling of data, protecting privacy and sensitive information.

3.6. Specific Requirements

3.6.1. External Interfaces

The Automatic License Plate Recognition Model may include the following external interfaces:

- Video Input Interface:The ALPR model interacts with video input sources, such as live camera feeds or pre-recorded video files, to capture the frames for vehicle and license plate detection.
- User Interface (UI):An interface that allows users to interact with the ALPR system, providing options to start/stop the process, configure settings, view results, and receive alerts or notifications.
- Data Export Interface:Enables the export of processed data, such as license plate information and associated details, to external systems or databases for further analysis, storage, or integration.
- Integration Interface:Facilitates integration with other applications, systems, or devices, allowing seamless data sharing, integration of ALPR functionality into existing systems, or leveraging external functionalities.

3.6.2. Functions

The primary functions of the Automatic License Plate Recognition Model are:

- **Vehicle Detection:**Detecting vehicles within a video stream or image, identifying their locations and boundaries accurately.
- **License Plate Detection:**Identifying and localizing the region of a detected vehicle where the license plate is located.
- **Character Recognition:**Extracting alphanumeric characters from the detected license plate, effectively recognizing the license plate number.
- **Data Structuring and Aggregation:**Organizing information obtained from vehicle detection, license plate detection, and recognition into a structured format for easy access and analysis.

3.6.3. Performance Requirements

The Automatic License Plate Recognition Model shall meet the following performance requirements:

- **Accuracy and Recognition Rate:**Achieve a high accuracy rate in vehicle and license plate detection, aiming for a recognition rate that exceeds a predefined threshold to minimize false positives and negatives.
- **Processing Speed and Real-Time Performance:**Process video frames in real-time or near-real-time to ensure timely detection, tracking, and recognition of vehicles and license plates.
- **Robustness to Lighting and Environmental Conditions:**Demonstrate robustness to varying lighting conditions, weather, and environmental factors to maintain consistent performance across diverse scenarios.
- **Privacy Preservation:**Implement mechanisms to anonymize or encrypt sensitive data to adhere to privacy regulations and protect personally identifiable information (PII).
- **Integration Compatibility**:Ensure seamless integration with existing systems, databases, or APIs to enhance the model's usability and facilitate interoperability.
- **Data Retention and Retrieval Time:**Optimize data storage and retrieval processes to ensure quick access to historical data for analysis and reporting purposes.

3.6.4. Logical Database Requirements

Implementing a logical database is crucial for this ALPR model. A logical database provides a structured and organized approach to store and manage the vast amount of data generated during vehicle detection, license plate recognition, and related activities. It allows efficient querying and retrieval of historical data, enabling data analytics for traffic flow analysis, identifying patterns, and optimizing operational strategies. Additionally, the logical database facilitates seamless integration with external systems and applications, enabling data sharing, reporting, and enabling the model to store and link data such as license plate numbers to relevant information like toll accounts or parking permits.

3.6.5. Design Constraints

The design constraints of the Automatic License Plate Recognition Model include:

- **Hardware Limitations:**Design considerations must account for varying hardware capabilities, ensuring the model can operate effectively across a range of devices and configurations.

- **Real-Time Processing:**The model must process video frames in real-time, necessitating efficient algorithms and optimized processing to meet this constraint.
- **Adaptability to Environments:**The ALPR model should adapt to diverse environmental conditions and lighting variations, requiring a robust design to handle challenging real-world scenarios.
- **Cost-Effectiveness:**Design choices should aim for an economical implementation, considering the costs associated with hardware, software, and maintenance.
- **Scalability:**The design should enable the system to scale efficiently, accommodating increased data volume and user demands as the application grows.

3.6.6. Software System Quality Attributes

The quality attributes of the Automatic License Plate Recognition Model include:

- **Accuracy:**The system should provide highly accurate results in vehicle and license plate detection, ensuring minimal false positives and negatives.
- **Reliability:**The ALPR model must consistently perform as expected, maintaining accuracy and functionality across different conditions and usage scenarios.
- **Efficiency:**The system should operate efficiently, utilizing computational resources optimally to process video frames in real-time while minimizing computational load.
- **Usability:**The system should have an intuitive interface, making it user-friendly and easy to operate for a range of users, including administrators and operators.
- **Scalability:**The ALPR system should be designed to scale effectively, accommodating increased data volume and usage demands without a significant drop in performance.

3.6.7. Object-Oriented Models

The Automatic License Plate Recognition Model can be represented using object-oriented models with the following key components:

- **ALPR System Class:**This class represents the ALPR system as a whole. It contains attributes like cameras for video input, modules for license plate and vehicle detection, LPRNet, and a database for data management. The methods allow starting, stopping, and analyzing frames.
- **Camera Class:**This class models the camera component. It has attributes for CameraID and Frame, and methods to capture a frame from the camera and retrieve the captured frame.

- **LicensePlateDetector Class:**Represents the license plate detection module. It uses a specific model and a confidence threshold for detection, and the detectLicensePlate() method executes the license plate detection algorithm.
- **VehicleDetector Class:**Represents the vehicle detection module. It uses a model and a confidence threshold for detection. The detectVehicle() method executes the vehicle detection algorithm.
- **Database Class:**Models the database component. It has attributes for a database connection and data storage. The saveData() method saves relevant data, while retrieveData() retrieves stored data.

3.6.8. Appendices

1. Glossary

- Automatic License Plate Recognition (ALPR): A technology that uses optical character recognition to automatically read license plate characters on vehicles.
- Convolutional Neural Network (CNN): A type of deep neural network that is commonly used in image and video recognition tasks.
- Histogram of Oriented Gradients (HOG): A feature descriptor used in computer vision and image processing for object detection.
- Single Shot Detector (SSD): An object detection algorithm that uses a single neural network to predict object classes and bounding boxes.
- You Only Look Once (YOLO): A real-time object detection system that uses a single neural network to predict object classes and bounding boxes.
- Region of Interest (ROI): A portion of an image that is identified as being of particular interest for further processing.
- Graphics Processing Unit (GPU): A specialized electronic circuit designed to rapidly manipulate and alter memory to accelerate the creation of images in a frame buffer intended for output to a display.
- Central Processing Unit (CPU): The part of a computer that performs most of the processing.
- Intersection over Union (IoU): A metric used to evaluate the accuracy of object detection algorithms by measuring the overlap between predicted and ground-truth bounding boxes.

2. References IEEE Std 830-1998, IEEE Recommended Practice for Software Requirements Specifications.

CHAPTER - 4

4. DESIGN SPECIFICATION

The design specification of a Tri-level segmented CNN involves identifying the requirements and functionalities of the system to be developed. In this section of the report we complete this very task by developing different diagrams.

The system should have an intuitive and user-friendly interface that is easy to use for odontologists. The system should be designed to handle complex shapes of teeth and should be scalable to accommodate growth in the number of teeth segmentations.

The system should also be designed to integrate with other systems such as gender predictions, age predictions and bitemark analysis.

We understand all these requirements better by developing the following diagrams of our system:

- Use Case Diagram
- Data Flow Diagram
- Class Diagram
- Sequence Diagram
- Activity Diagram
- State Chart Diagram

4.1. Use Case Diagram

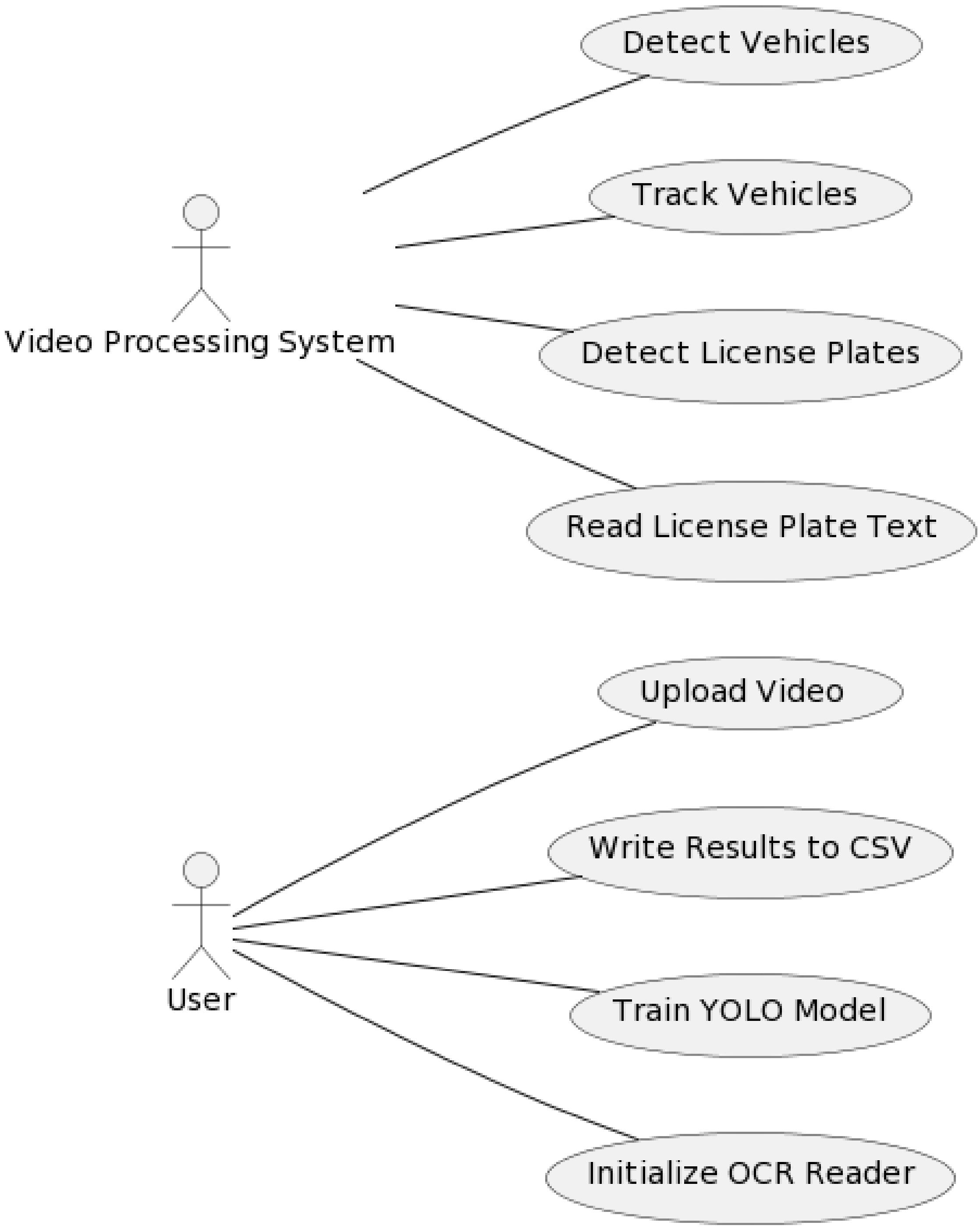

Figure 4.1: Use Case Diagram of Table ALPR

4.2. Data Flow Diagram-Level 0

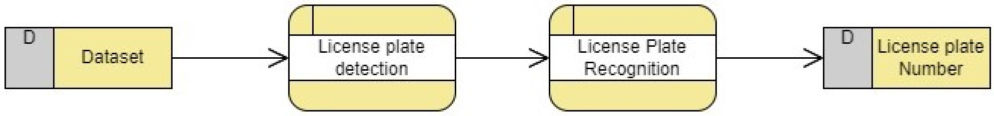

Figure 4.2: Level 0 DFD Diagram of ALPR

4.3. Data Flow Diagram-Level 1

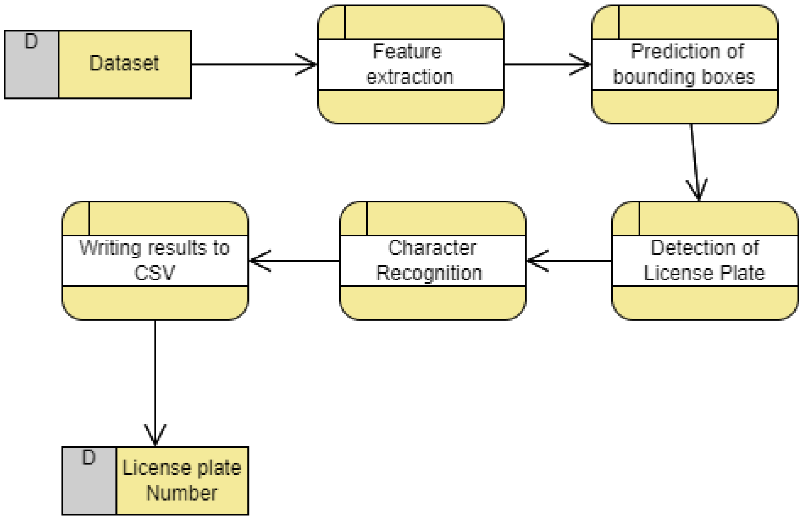

Figure 4.3: Level 1 DFD Diagram of ALPR

4.4. Data Flow Diagram-Level 2

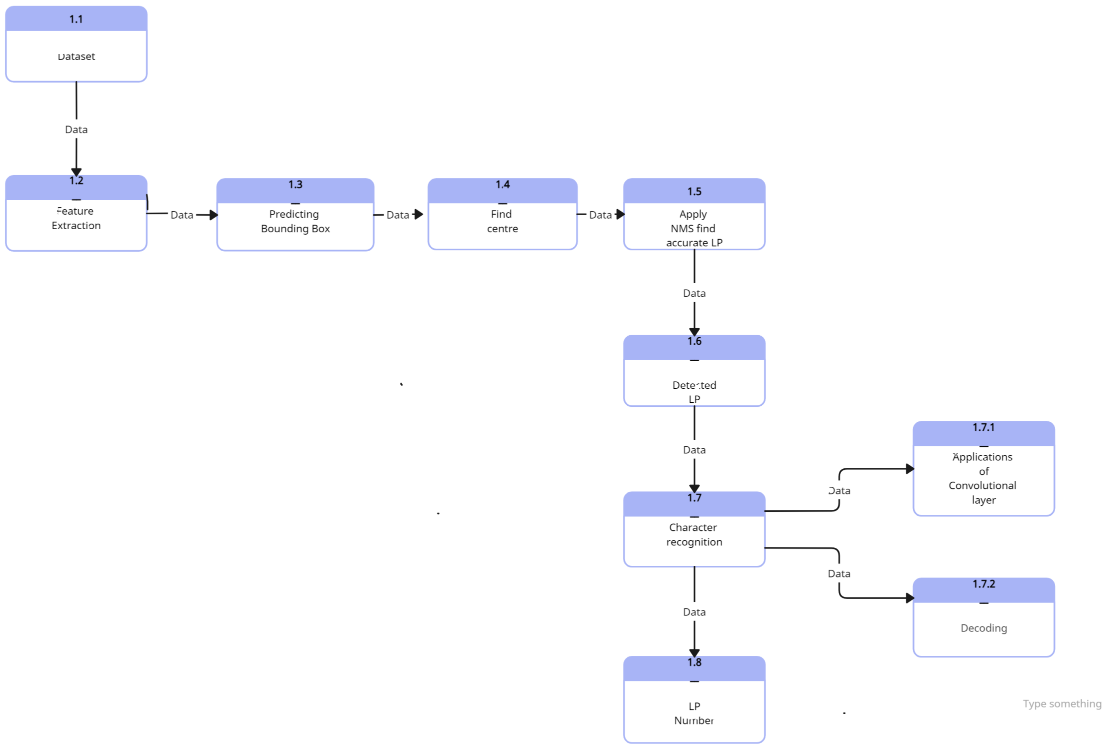

Figure 4.4: Level 2 DFD Diagram of ALPR

4.5. Class Diagram

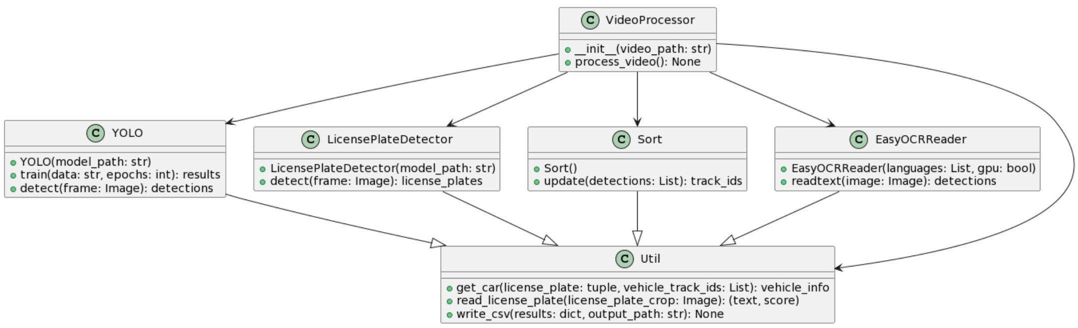

Figure 4.5: Class Diagram of ALPR

4.6. Sequence Diagram

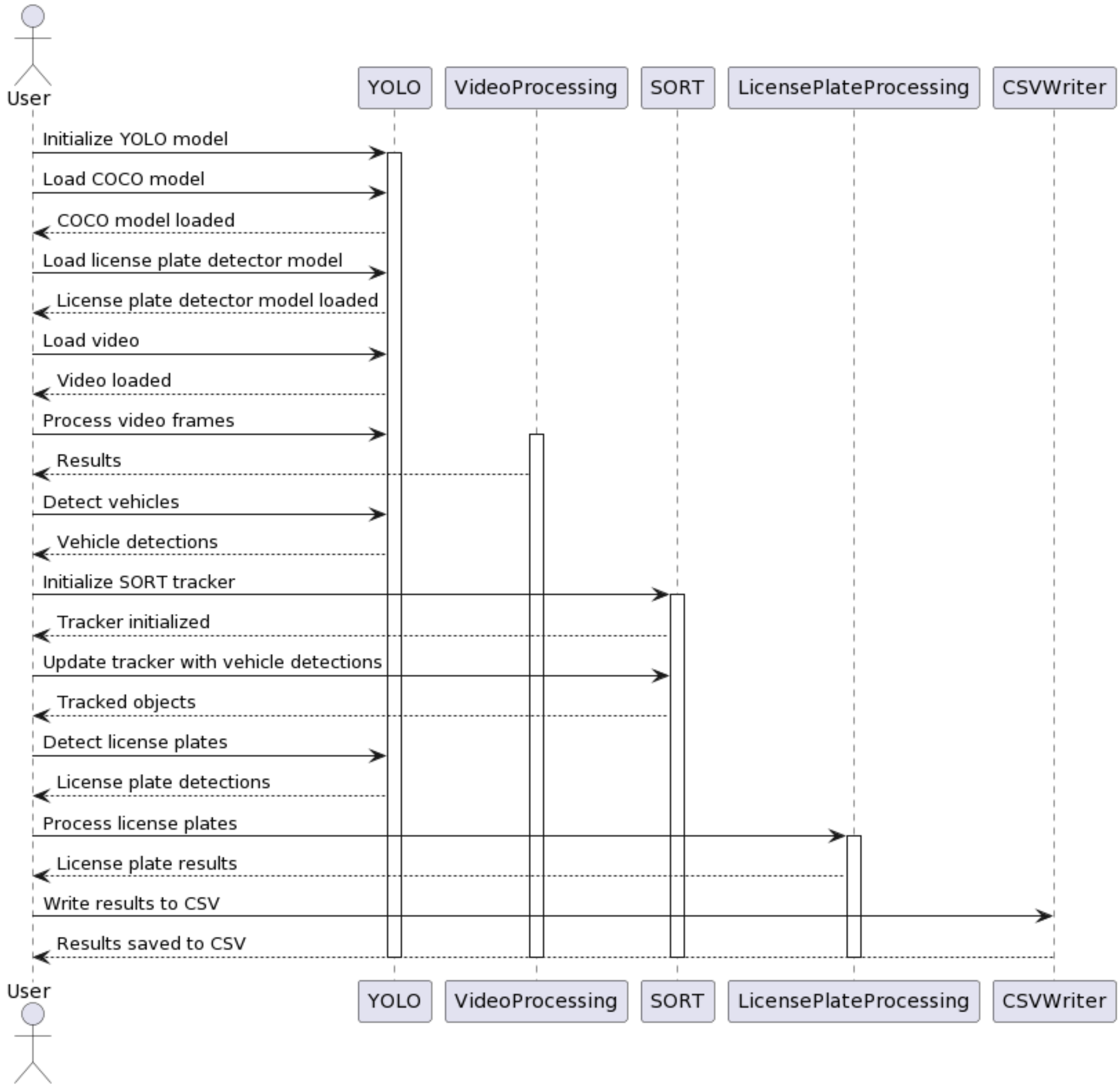

Figure 4.6: Sequence Diagram of ALPR

4.7. Activity Diagram

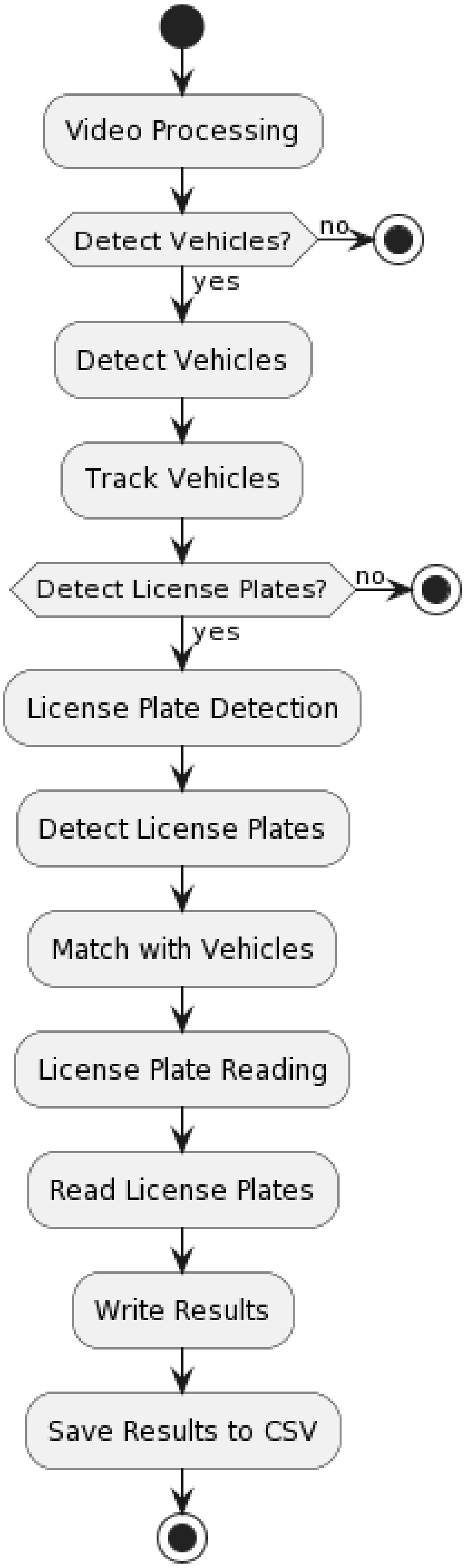

Figure 4.7: Activity Diagram of ALPR

4.8. State Chart Diagram

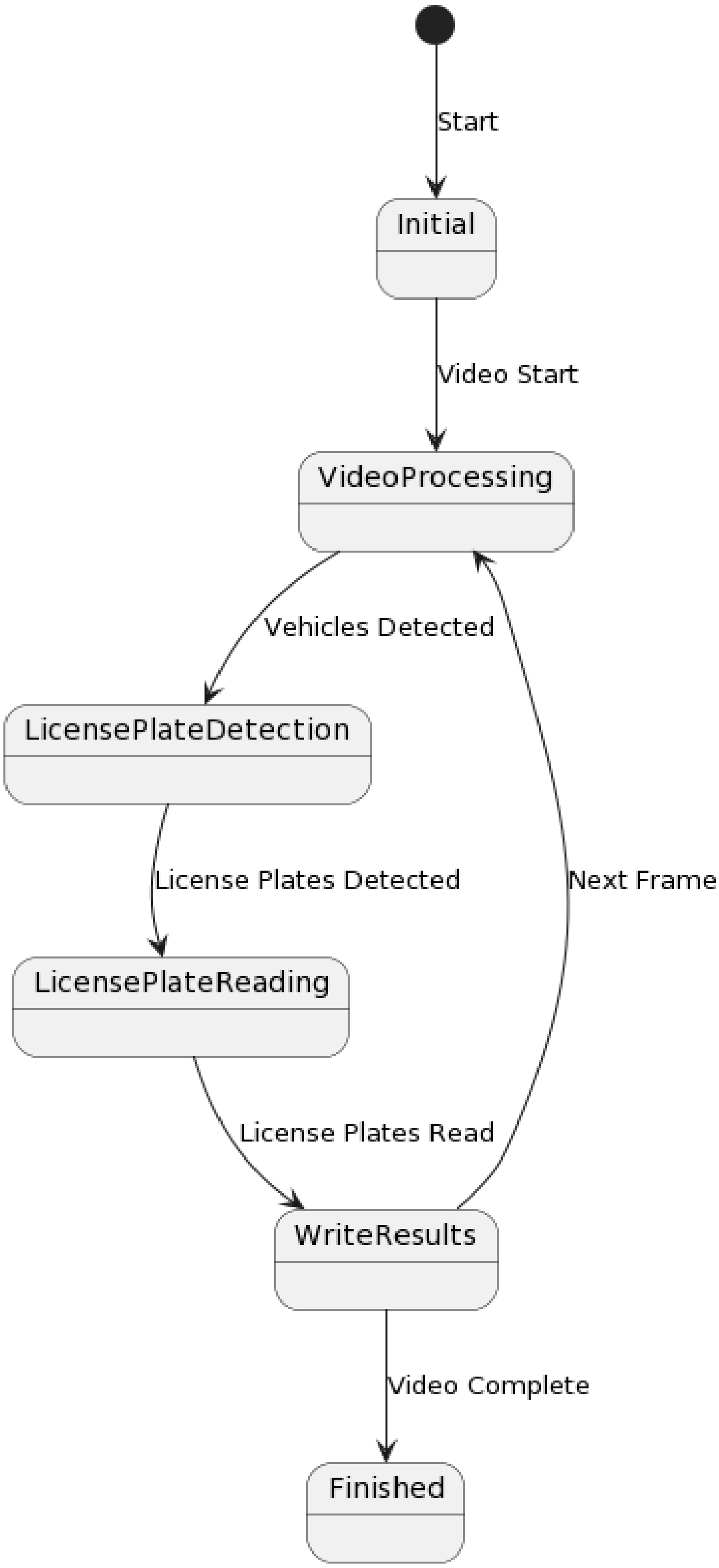

Figure 4.8: State chart Diagram of ALPR

CHAPTER - 5

5. METHODOLOGY

5.1. Modules

Data Collection We have collected a data set from Roboflow named a license plate for training the model for license plate detection. It consists of a total of 1680 images divided into two sets called to train and valid each consisting of 1530 and 150 images. The pictures of the license plate in this data set are from different angles and of different sizes which helps in the efficient training of the model. For LPR we need to train the model using the dataset consisting of license plates of the same country or region to avoid inaccuracy as different countries have different license plate formats. Hence we are choosing CCPD(Chinese city parking dataset) which also consists of different types like blurr, illuminated, tilted, rotated, and challenging license plate images for the efficient training of the model to get more accurate results

License Plate Detection We train the model using the collected dataset by importing modules called paralytics and basic code from Git Hub, after the training the model stores the results and will be ready to detect the license plate from any input image or video. Firstly, the input image of different sizes and pixels is given to the backbone of YOLOv8, feature extraction is done there inside the convolution layers. The output of this backbone is sent to the neck where the concatenation of all the features extracted undergoes followed by the head where the detection of the license plate is done based on loss metrics.

Data Preprocessing The output obtained from the YOLOV8 algorithm is given as an input for the LPRNet algorithm. Before that the output obtained from YOLOV8 must be pre-processed to give the best quality input image for the license plate recognition. To achieve this LPRNet uses STN(Spatial Transformer Network) and reduces the deformations of input images.

License Plate Recognition Number plate consists of multiple languages and numerics. these characters can be in different fonts and sizes,hence LPRNet is used which is specifically designed for licence plate character recognition.Once the Number plate is detected and processed using STN for deformations, the characters on the license plate must be recognized. To achieve this we use the LPRNet algorithm. The output obtained from STN is given as input for the backbone network of LPRNet which uses CNN to extract the features of the image and applies a kernel that gives the output result of a sequence showing the probability of the corresponding character. In the nest stage, it uses Beam Search to decode the sequence and finds the sequences with the highest probability based on which the characters of the number plate are recognized

5.2. System Block Diagram

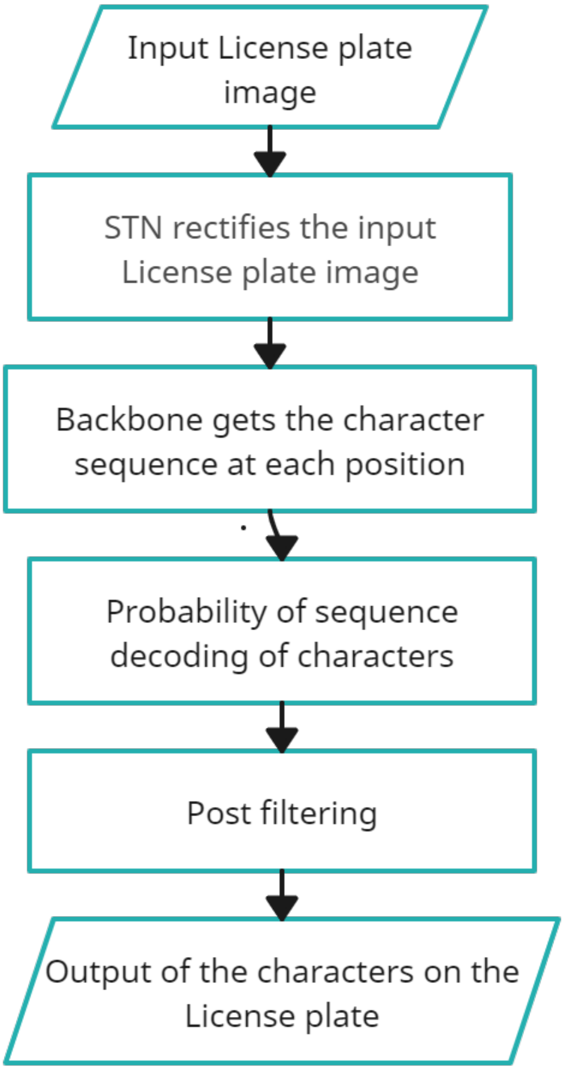

Figure 5.1: System Block Diagram

CHAPTER - 6

6. IMPLEMENTATION DETAILS

A ALPR Model is a computerized solution that simplifies recognition of license plates. It's main function is to automate the license plate recognition process. It is used to manage tasks such as Traffic Management,Toll collection, security and law enforcement agencies. Further in this section we talk about the implementation details to consider when developing ALPR Model using YOLOv8 and LPRNet.

6.1. Technology Stack

The technology stack for the Automatic License Plate Recognition Model may include Python as the primary programming language for its rich ecosystem of AI and machine learning libraries. Deep learning frameworks like TensorFlow or PyTorch can be utilized to build and train Convolutional Neural Networks (CNN) including YOLOv8 for vehicle and license plate detection. OpenCV is a crucial library for image and video processing, used extensively for tasks like reading frames from a video, image manipulations, and color space conversions.libraries like Ultralytics is used for YOLOv8 trainning and inference.The code can be developed and executed in various Python-compatible IDEs such as PyCharm, Visual Studio Code, or Jupyter Notebook.These technologies collectively enable the implementation of the ALPR system, incorporating object detection, tracking, OCR, and data handling for vehicle and license plate recognition in a video stream. The chosen technologies prioritize efficiency, speed, and accuracy to achieve the project's automation goals.

6.2. System Architecture

While making a decision about the architecture of our system we need to make sure that the system efficiency doesn't decrease in any way. So,The system architecture follows a modular and sequential flow, designed to automate license plate recognition efficiently. It begins with input from a video source, processed frame by frame. The vehicle detection stage employs YOLOv8, identifying vehicles through bounding boxes. Concurrently, a specialized YOLOv8 model is utilized to detect license plates within the vehicles. The identified license plate regions undergo image processing using LPRNet to extract the text.Finally, the results, including vehicle tracking IDs, bounding boxes, and recognized license plate texts, are structured and exported to a CSV file. This architecture showcases an organized pipeline integrating object detection, tracking, license plate detection, and recognition, ultimately achieving the desired automation for applications like toll collection and parking management.

6.3. User Interface

The user interface of YOLOv8 and LPRNet ALPR model will be user-friendly and intuitive. It will allow users to recognise the license plates in real-time or from a video quickly and easily, while also allowing LP recognition efficiently.
The user interface will not require a lot of technical acumen so that users are comfortable with such a user interface with minimal complexities.

6.4. Integration

The integration of models in this project involves incorporating two main components: the vehicle detection and tracking model (YOLOv8) and the license plate detection and recognition model (YOLOv8 + LPRNet).YOLOv8 is specialized for license plate detection, identifying license plate regions within the detected vehicles.Once the license plate regions are identified, they undergo further processing.This processed image is then passed to LPRNet, which recognizes and extracts the characters from the license plates.The results from these processes, including vehicle information, license plate information, and their respective confidence scores, are aggregated and structured. Finally, the integrated results are exported to a CSV file for easy access and further analysis.

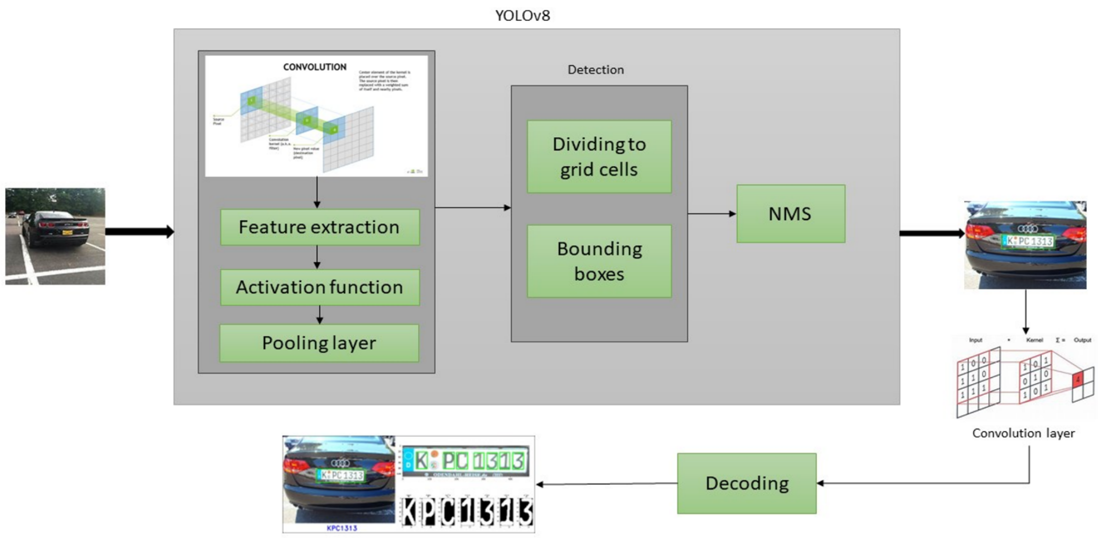

Figure 6.1: System Architecture of ALPR Model

6.5. Security

Security is a critical part of our model.ALPR systems capture and process sensitive information from vehicles, including license plate numbers. It's critical to ensure that this data is handled securely and in compliance with privacy regulations to protect individuals' privacy.

6.6. Testing and Deployment

ALPR model usin YOLOv8 and LPRNet will undergo rigorous testing in line with our Minor project curriculum; these tests will help us ensure that our model meets the functional and performance requirements as mentioned in the problem statement. We can also use continuous integration and deployment practices to streamline the development and deployment process.

Taking all the subsections into consideration, we were successfully able to develop a robust and efficient Automatic license plate recognition modelteeth that can reduce the manual work and enhance applications in various fields.

CHAPTER - 7

7. OBSERVATIONS

7.1. Time Domain - Gann Chart

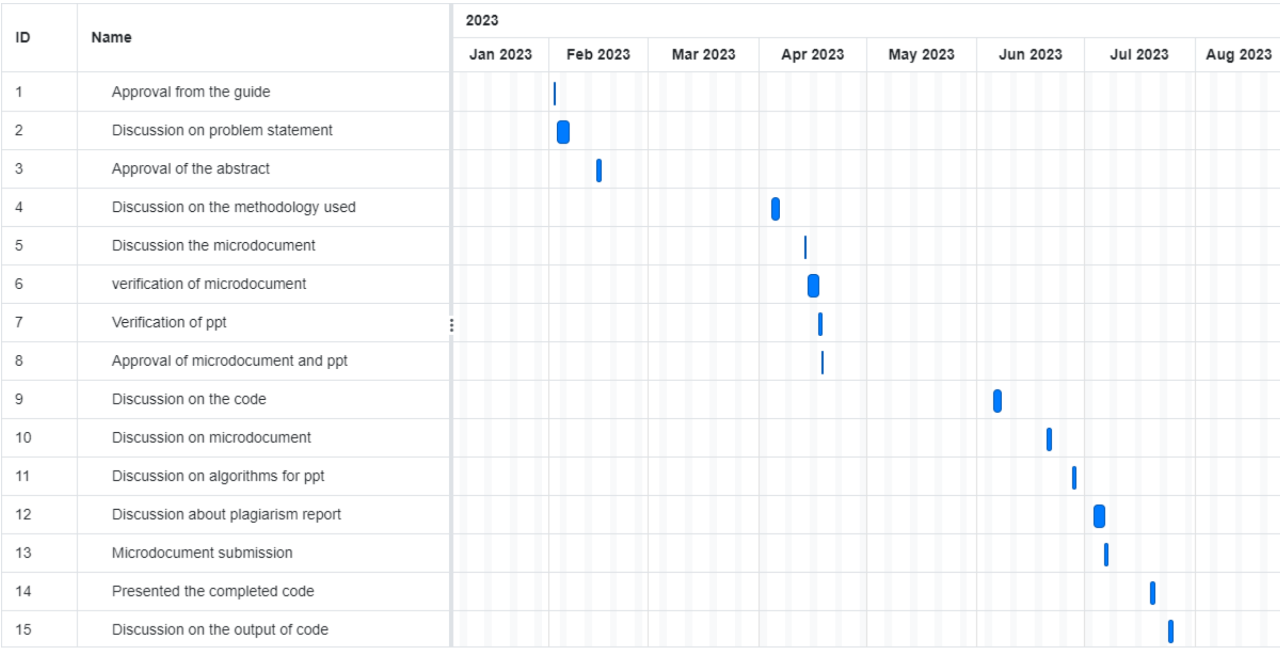

Figure 7.1: Gann Chart of Project Timeline

7.2. Results and Comparitive Study

In the landscape of license plate detection, SSD and HOG pioneered efficient object detection. R-CNN improved accuracy through a region proposal network but sacrificed speed with its multi-stage approach. YOLOv3 made a significant impact by combining real-time processing and accuracy in a single pass, addressing scale variations in license plates. YOLOv8, a streamlined version of YOLO, maintained high accuracy while enhancing speed, making it ideal for real-time license plate detection. Its efficient design and single-shot approach position YOLOv8 as a strong contender for modern ALPR systems, offering a compelling balance between accuracy and efficiency. YOLOv8's architecture is particularly well-suited for applications demanding rapid and precise license plate detection.

Among license plate character recognition algorithms, LPRNet stands out with its specialized design crafted specifically for this task. Its lightweight architecture and regression-based network prioritize real-time performance, a critical advantage for Automatic License Plate Recognition (ALPR) systems. Compared to traditional RNN-based approaches like GRU, LPRNet demonstrates enhanced efficiency in character discernment within license plates. The blend of accuracy and speed firmly positions LPRNet as a pivotal player in the modern landscape of ALPR technology.

When compared to previous models such as SSD, HOG , YOLOv3 ,this YOLOv8 algorithm has good accuracy and results. We have also minimised false positives and false negatives by providing larger dataset for training purpose. YOLOv8 shows promising results as it is leading and latest algorithm of object detection and it is a pretrained model which is trained over 80 different types of objects using coco dataset.The car license plate identification model experiment showcases impressive results in terms of recog- nition accuracy,recall,and Map(mean average precision).have all improved, reaching 98.49%, 97.9%, and 98.56%, respec- tively. Comparison of detected accuracy with various other algorithms: The model is able to accurately identify the license plate even in complex environmental conditions which improved its overall performance

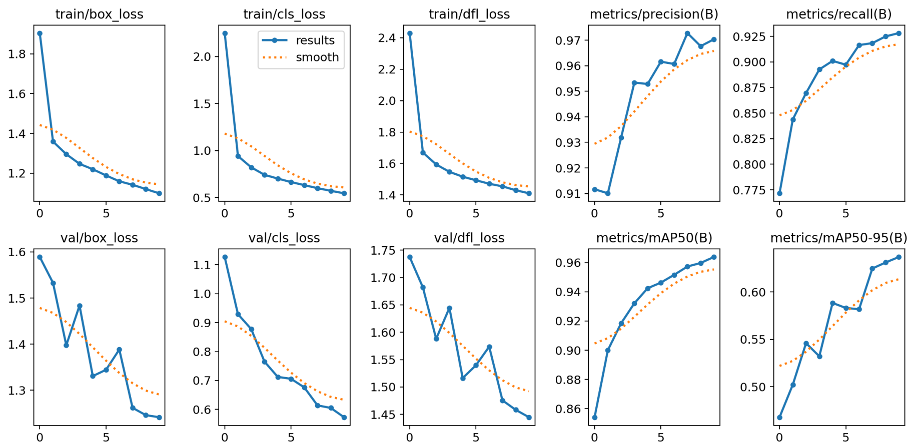

Figure 7.2: Loss Metrices

CHAPTER - 8

8. CONCLUSION

Automatic License Plate Recognition provides numerous benefits in applications like Toll Collection,Traffic Management. By automating various processes :

- Detection of License Plate
- Character Recognition

Transportation and Traffic Management department can use this model for License Plate Recognition which will reduce errors and manual work increasing time efficiency.

In the development of this project report, we have successfully worked as a team and as a team, we actually grasped the concepts of computer intelligence and the tasks that come hand in hand with the development of a model. The development stage helped us understand real world implications of the umbrella activities that come under a computer intelligence process model. All in all, the opportunity has allowed us to understand the importance of making documentation while developing a deep learning model.

Our system hasn’t yet been tested and evaluated in a real-world setting but we are very sure that the results will show that it can significantly improve the efficiency of License Plate Recognition, reduce errors, and increase accuracy. Overall, our Automatic License Plate Recognition Model CNN is a valuable tool for Transportation and Traffic Management,Toll Authorities who are looking to automating License Plate Recognition methods.

CHAPTER - 9

9. LIMITATIONS AND FUTURE ENHANCEMENTS

9.1. Limitations

This project is highly planned and acted upon from the beginning. Nevertheless, the project had to face some of the limitations due to various factors. Different aspects of the projects such as nature of data, visualisation methods, data storage method and so on have their own limitations. Some of the limitations faced by the project are:-

1. The accuracy and generalization of the model may be limited by the size and diversity of the training dataset. A more extensive and diverse dataset could enhance the model's ability to handle a broader range of scenarios and license plate variations.

2. Adverse weather conditions, poor lighting, or occlusions can significantly affect the model's performance, leading to reduced accuracy in detecting and recognizing license plates.

3. The project relies on pre-trained models (YOLOv8, LPRNet) which may have limitations based on their training data and may not generalize well to specific regions, fonts, or languages.

4. The model processes each video frame independently, without considering temporal information. Incorporating temporal analysis could enhance vehicle tracking and further improve accuracy.

5. The model's performance may vary based on the camera angle and perspective. It might face challenges in accurately recognizing license plates in non-standard orientations.

6. The model may produce false positives (detecting a license plate when there isn't one) or false negatives (missing a license plate) depending on the complexity of the scene or the quality of the pre-trained models.

9.2. Future Enhancements

Future enhancements for the Automatic license plate recognition Model can be planned to further improve its capabilities and address emerging needs. Some potential areas for enhancement include:

1. Enhance the model's accuracy and generalization by training it on a more diverse dataset that includes various license plate formats, fonts, and styles from different regions.

2. Fine-tune the ALPR model to adapt to specific regions with unique license plate formats and characters, making it more versatile and applicable globally.

3. Integrate multiple ALPR models specialized for different regions or license plate styles, dynamically selecting the appropriate model based on the context to improve recognition accuracy.

4. Incorporate temporal analysis and tracking algorithms that utilize information from multiple frames to enhance vehicle tracking, particularly in challenging scenarios with occlusions.

5. Implement additional security measures to ensure secure storage and transmission of data, meeting the highest standards of privacy and regulatory compliance.

6. Develop a user-friendly mobile application that allows users to access and interact with the ALPR system, providing notifications, alerts, and on-demand access to license plate recognition results.

A. APPENDIX

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A.1. Project Timeline

An Efficient and High Performing ALPR Model project timeline: 31 March 2023 to 11 August 2023

Table A.1: Project Timeline

Date	Topic Discussion	Action Taken
02-02-2023	Received approval from the guide to work under his supervision	The guide approval form has been signed
03-02-2023	Discussion of problem statement	Discussed and clarified the project's problem statement with the team.
14-02-2023	Approval of abstract	Abstract was approved by the project supervisor.
04-04-2023	Discussion of the methodology used	The methodology has been confirmed
13-04-2023	Discussion of microdocument	Collaborated on drafting the microdocument.
15-04-2023	Verification of microdocument	Reviewed and verified the microdocument for accuracy and completeness.
17-04-2023	Verification of ppt	Checked and verified the content of the project presentation.
18-04-2023	Approval of microdocument and ppt	Both microdocument and presentation were approved for the project.
05-06-2023	Discussion on the code	Conducted discussions regarding the project's code implementation.
20-06-2023	Discussion on Microdocument	Held a team meeting to discuss and refine the microdocument.
27-06-2023	Discussion on algorithm for ppt	Collaborated on determining the appropriate algorithms for the presentation.
03-07-2023	Discussion about plagiarism report	Discussed and addressed any potential plagiarism concerns in the project.
06-07-2023	Microdocument suggestions	Received and incorporated suggestions for improving the microdocument.
19-07-2023	Presented the completed code	Received and incorporated suggestions for improving the performance.
24-07-2023	Discussion on the outputs of code	Collaborated on adding relevant comparison table and images to the project's code.

A.2. Coding

https://github.com/Kiritia05v8