CHAPTER 1: INTRODUCTION

1.1. Overview

As urban infrastructure evolves, the need for smarter and more efficient surveillance and traffic control systems has grown significantly. One of the key components in this domain is accurate and fast number plate recognition. This project presents a powerful solution built around YOLOv8 (You Only Look Once, version 8), a cutting-edge object detection model known for its real-time performance and high precision. With its advanced capabilities, YOLOv8 offers a promising approach to automatic license plate recognition (ALPR) in diverse and dynamic environments.

1.1.1. Project Genesis:

The genesis of this project stems from the increasing need for advanced solutions in automatic license plate recognition (ALPR) systems, driven by the burgeoning demands of modern urban environments. Vehicle license plate recognition plays a pivotal role in numerous applications, including traffic management, law enforcement, and security surveillance. The project addresses the limitations of existing systems by leveraging the capabilities of YOLOv8 (You Only Look Once version 8), an advanced object detection framework renowned for its speed and accuracy.

1.1.2. Significance

This project holds significant value in the context of developing smarter and safer cities. As urban populations grow, the strain on traffic and security systems intensifies. A reliable license plate recognition system can support a wide range of functions—from automating toll payments and detecting stolen vehicles, to streamlining traffic flow and aiding criminal investigations. By improving the accuracy and speed of these systems, this project contributes to the broader goal of building more connected, efficient, and secure urban environments.

1.1.3. Scope

This work focuses on designing and deploying a YOLOv8-based ALPR system capable of operating under varying illumination, plate styles, and vehicle angles. It also incorporates advanced post-processing algorithms to extract characters and eliminate redundant detections, ensuring high accuracy.

The scope includes:

- Model training using diverse and annotated datasets
- Implementation of post-detection logic for character segmentation
- Evaluation against public benchmark datasets
- Deployment in simulated and real-time environments

Ultimately, this project aims to contribute to smart mobility initiatives by enhancing the capabilities of traffic systems, aiding law enforcement, and strengthening urban surveillance, all within the framework of real-time performance and scalability.

1.2. Objectives and Scope

1.2.1. Project Objectives:

The primary goal of this project is to develop a robust and accurate license plate recognition system using the YOLOv8 object detection framework. More specifically, the objectives are:

- **Advancement in Smart Systems:** To contribute to the ongoing evolution of intelligent transportation systems, public surveillance, and security applications.
- **Adaptability to Complex Scenarios:** To ensure the model performs reliably in diverse real-world conditions, including varying font styles, background noise, partial occlusions, and different lighting environments.
- **System Integration:** To design the system in a way that allows for easy integration with existing traffic monitoring and surveillance infrastructures, enabling smooth and practical deployment.

1.2.2. Project Scope:

This project covers the full cycle of developing a YOLOv8-based license plate recognition system—from model training to real-world testing. The scope includes:

- **Model Development and Optimization:** Training the YOLOv8 model to detect and accurately recognize license plates in a variety of conditions.
- **Real-Time Capabilities:** Ensuring the system can process inputs quickly and efficiently for real-time use.
- **Practical Deployment Considerations:** Exploring how the system can be integrated into live traffic and security setups with minimal overhead.
- **Robust Performance:** Addressing challenges such as different vehicle angles, lighting variations, plate styles, and cluttered backgrounds.

1.2.3. Expected Outcomes:

By successfully meeting the objectives outlined above, the following outcomes are expected:

- **High Recognition Accuracy:** Achieving competitive accuracy levels through careful training, optimization, and the use of transfer learning on the YOLOv8 architecture.
- **Real-Time Efficiency:** Delivering a system capable of real-time license plate recognition, making it suitable for applications in traffic control, law enforcement, and smart urban infrastructure.
- **Scalability and Integration Readiness:** Producing a model that is both scalable and compatible with existing city systems for potential large-scale adoption.

1.3. Project Features

1.3.1. Utilization of YOLOv8:

At the core of this project lies the YOLOv8 architecture, a leading-edge object detection model recognized for its real-time accuracy and efficiency. Its advanced capabilities allow the system to swiftly and accurately detect vehicle license plates in various real-world conditions. By harnessing YOLOv8's strengths, the project benefits from both high performance and scalability.

1.3.2. Transfer Learning:

- **Pre-Trained Weights:** Utilizing transfer learning to fine-tune the model with pre-trained weights on a large-scale dataset, enhancing recognition performance.
- **Adaptability:** Ensuring adaptability to various license plate designs and environmental conditions through the transfer learning process.

1.3.3. Robust Post-Processing:

- **Non-Maximum Suppression (NMS):** Implementing NMS techniques to refine detection results, reducing redundancy and enhancing accuracy.
- **Character Segmentation:** Introducing a novel post-processing algorithm to improve character segmentation, addressing challenges like occlusions and varying font styles.

1.3.4. Diverse Dataset:

- **Comprehensive Training Data:** Training the model on a diverse dataset encompassing various license plate designs, lighting conditions, and vehicle orientations
- **Real-World Challenges:** Ensuring the model's robustness by exposing it to challenging scenarios, including background clutter and diverse environmental factors.

1.3.5. Real-time Implementation:

- **Low Latency:** Demonstrating the model's suitability for real-time applications with low-latency requirements, crucial for scenarios such as traffic management and surveillance.
- **Practical Deployment:** Implementing the YOLOv8-based number plate recognition system in real-world scenarios to validate its effectiveness and applicability.

These technical components work together to form a robust, scalable, and efficient number plate recognition system. By combining YOLOv8's strengths with transfer learning, smart post-processing, diverse data exposure, and real-time responsiveness, the project delivers a solution that meets the demands of modern transportation and security infrastructures.

1.4. Feasibility

1.4.1. Technical Feasibility:

The use of YOLOv8 in this project ensures a high level of technical feasibility, thanks to its proven capabilities in real-time object detection. By integrating transfer learning, advanced post-processing methods, and training on a diverse dataset, the model delivers both accuracy and adaptability. These qualities make it well-suited for practical deployment in varied and dynamic environments, such as busy urban roads or complex surveillance systems.

1.4.2. Dataset Collection and Preprocessing:

The feasibility of the project is further reinforced by a thoughtful and comprehensive approach to dataset collection and preprocessing. Images are sourced under different lighting conditions, angles, and times of day to simulate real-world variability. This helps the model learn to perform well across a wide range of conditions. Preprocessing techniques such as resizing, normalization, and noise reduction prepare the data for optimal training outcomes.

1.4.3. Model Training and Evaluation:

The technical robustness of the project is tested during the training and evaluation phases. Using transfer learning, the model is fine-tuned on a task-specific dataset, allowing it to build on pre-trained knowledge while adapting to the unique challenges of license plate recognition. Performance evaluation includes metrics such as:

- **Precision-Recall curves**
- **Confidence-based precision and recall**
- **F1-score analysis**

Additionally, hyper parameter tuning is performed to optimize learning rates, batch sizes, and other training parameters. This fine-tuning ensures the model is not only accurate but also efficient and reliable under real-world constraints.

1.4.4. Real-world Applicability:

Beyond technical validation, the model is designed with practical application in mind. The inclusion of real-world images and authentic traffic scenarios in the training data ensures that the system performs reliably outside controlled environments. Whether it's recognizing plates on moving vehicles or operating under low-light conditions, the model demonstrates strong potential for real-world use in smart cities, toll systems, and law enforcement.

1.5. System Requirements

1.5.1. Hardware Requirements:

The "ALPR" project provides best results with specific hardware for accessibility and efficiency. Recommended requirements include:

- **Processing Unit (CPU/GPU):** YOLOv8 benefits from GPU acceleration for faster inference. Ensure a GPU with CUDA support for optimal performance, or a powerful CPU for scenarios where GPU access is limited.
- **Memory (RAM):** Adequate RAM to support the model and associated data during training and inference. The exact requirement depends on the size of the dataset and the complexity of the YOLOv8 model.
- **Storage:** sufficient storage capacity for the dataset, pre-trained weights, and model checkpoints during training. Solid State Drives (SSDs) are recommended for faster data access.
- **Network Connectivity:** Stable internet connection for accessing datasets, model updates, and potential cloud-based services.

1.5.2. Software Requirements:

To facilitate development and execution, the project relies on key software components:

- **Operating System:** YOLOv8 is platform-agnostic, and it can run on various operating systems, including Linux, Windows, and macOS. Choose the operating system based on development preferences and compatibility.
- **Python:** YOLOv8 is implemented in Python. Ensure a compatible version of Python is installed on the system.
- **Deep Learning Framework:** Install the required deep learning framework. YOLOv8 is typically implemented using PyTorch. Ensure the correct version of PyTorch is installed to support YOLOv8.
- **CUDA Toolkit (if using GPU):** If utilizing GPU acceleration, install the CUDA toolkit and cuDNN library compatible with the GPU. This is crucial for optimizing the performance of deep learning computations.
- **Additional Libraries:** Install necessary Python libraries, such as NumPy, OpenCV, and other dependencies.

CHAPTER 2: LITERATURE SURVEY

2.1. Number Plate Recognition System

2.1.1. Historical Context:

Historically, the identification of vehicle license plates was carried out manually by law enforcement officers, often involving tedious visual monitoring and record-keeping. Early automated methods, such as template matching and basic feature extraction techniques, were introduced to simplify the process. However, these approaches suffered from limited accuracy and adaptability, especially under varying environmental conditions. With the emergence of more sophisticated object detection models—such as YOLOv8—there has been a significant leap in performance, particularly in real-time detection accuracy and speed. This development marks a key evolution in the broader field of number plate recognition.

2.1.2. Advancements in Number Plate Recognition System:

Recent advancements have significantly transformed the capabilities of number plate recognition systems. The integration of sensor networks, satellite imaging, and artificial intelligence has widened the scope of monitoring, both in terms of spatial and temporal resolution. Machine learning and deep learning models, particularly those based on convolutional neural networks like YOLOv8, now enable high-resolution, real-time detection of license plates. These modern systems provide enhanced accuracy in diverse conditions and support scalable deployment across urban infrastructure, thereby improving traffic regulation and law enforcement efficiency.

2.1.3. Relevance of Number Plate Recognition System:

Number plate recognition plays a vital role in modern public safety, law enforcement, traffic management, and urban policy-making. It allows authorities to track and identify vehicles involved in violations such as speeding, toll evasion, or unauthorized access. Government agencies utilize these systems to enforce regulations, automate toll collection, and monitor congestion patterns. For the general public, such systems promote safer and more organized transportation networks, contributing to overall civic security and improved infrastructure planning.

2.1.4. Challenges and Open Problems:

Despite its advancements, number plate recognition still faces several ongoing challenges. These include issues related to data privacy, variations in plate designs across regions, and complications arising from occlusions or poor visibility in real-world environments. Moreover, current systems often struggle with generalization and adaptability in less structured or low-resource settings. Open problems remain in integrating diverse data streams, filling gaps in historical vehicle records, and improving model interpretability. Continued research and development are essential to address these limitations and ensure that number plate recognition systems remain accurate, secure, and reliable.

2.2. Existing Approaches and Technologies

2.2.1. Manual Interpretation:

Historically, number plate recognition was performed manually by law enforcement officers and traffic personnel. This method required physical verification of vehicle documentation and visual identification of license plates. While effective to some degree, manual interpretation was highly time-consuming, subjective, and prone to human error. Despite its limitations, this approach holds historical importance and laid the groundwork for the development of more automated systems.

2.2.2. Camera matching Systems:

Camera matching systems emerged as an early attempt to automate the number plate recognition process. These systems relied on rule-based algorithms and predefined parameters to detect and match number plates against existing records or databases. Although these systems represented a step forward in automation, they often struggled with adaptability. Variations in lighting, plate orientation, environmental interference, and non-standard fonts limited their effectiveness in real-world, dynamic scenarios.

2.2.3. Deep Learning-Based Approaches:

The most recent and effective advancements in number plate recognition come from deep learning-based methods. Convolutional Neural Networks (CNNs) and object detection models like the various versions of YOLO (You Only Look Once)—including YOLOv4, YOLOv6, and the latest YOLOv8—have significantly enhanced the accuracy and speed of plate detection. These models are data-driven and capable of learning complex patterns and relationships from large datasets. They not only detect license plates but can also extract associated vehicle information in real time, offering reliable performance across a range of environmental and operational conditions.

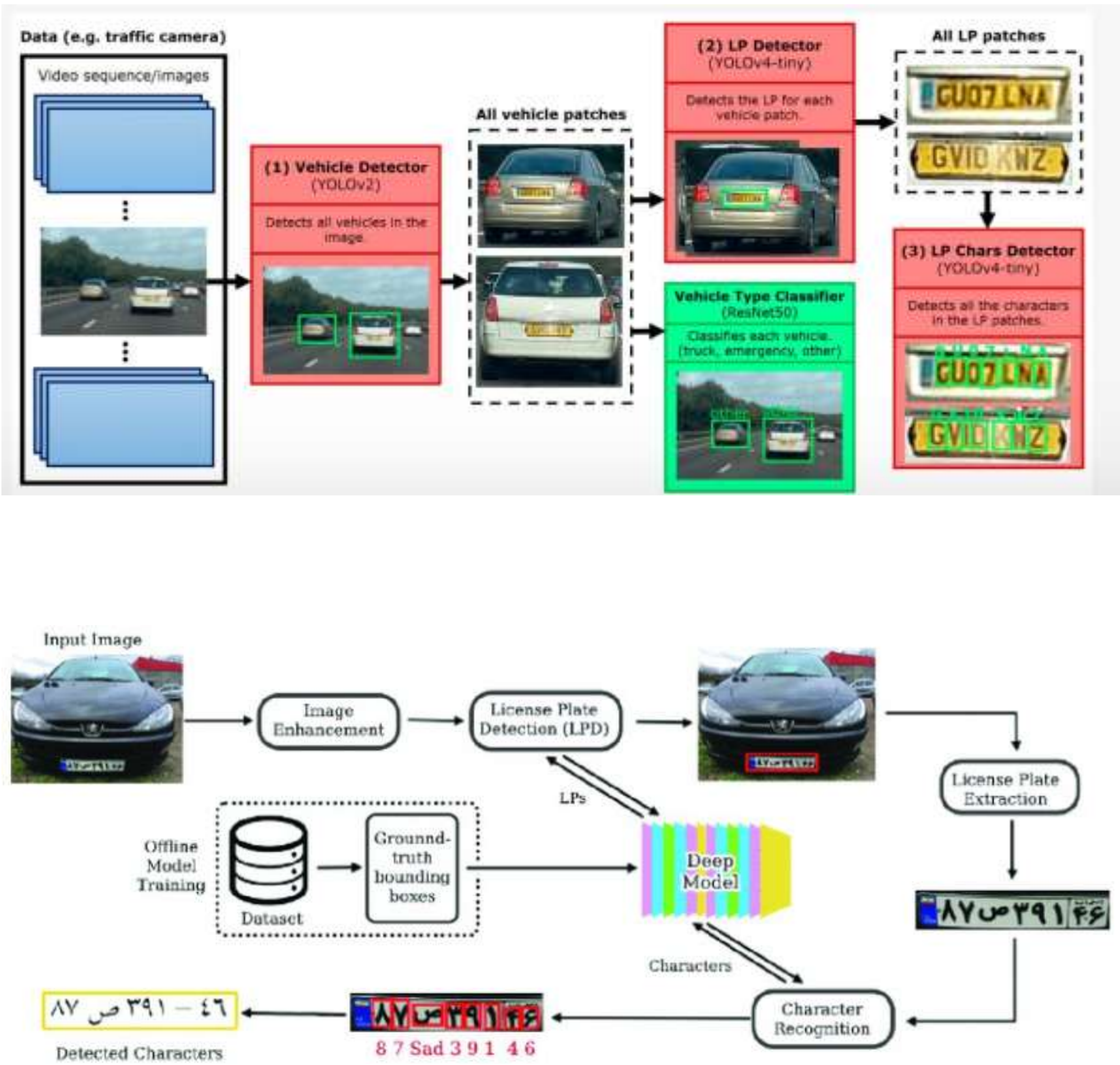


Fig 2.2.3 – Deep learning based approach in ALPR.

2.3. Relevance of YOLO in Classification

2.3.1. Localization and multi-labelling:

YOLO (You Only Look Once) is highly effective for object detection tasks due to its ability to localize objects within an image using bounding boxes. This functionality allows YOLO to isolate regions of interest, such as license plates, in real time. One of its key strengths lies in its capability to perform multi-label detection, identifying multiple objects simultaneously within a single frame. This makes YOLO particularly suitable for Automatic Number Plate Recognition (ANPR), where the model must detect license plates amidst various surrounding elements like vehicles, traffic signs, and pedestrians.

Yolo detects objects within images and provides a boundary box around them[14]. This enables Yolo to extract regions of interest at real-time by quickly processing data. Additionally, it provides multi-labelling that ensures detection of multiple objects within an image which makes it a clear choice for ALPR[15].

2.3.2. Enhanced Accuracy and Generalization:

Yolo contributes to enhanced accuracy and generalization as it is built on top of CNN, which helps in extracting features more precisely[16]. Yolo also incorporates ensemble nature and regularization techniques that mitigates individual biases and overfitting, ensuring robust performance on diverse datasets [17]. This mechanism fosters reliable detection, making Yolo a powerful tool for tasks demanding high accuracy and adaptability across various scenarios.

2.3.3. Automated Feature Learning:

Modern ANPR systems that utilize YOLO benefit from sophisticated architectural improvements. Techniques such as data augmentation, Weighted Residual Connections (WRC), Mish activation functions, and the use of Path Aggregation Networks (PANet) enhance feature learning and detection precision. These components improve the model’s ability to capture subtle variations in license plates, such as different fonts, sizes, and angles. The integration of these advanced methods makes YOLO-based ANPR systems not only more accurate but also more adaptable to real-world conditions, supporting more informed and timely decision-making in areas like law enforcement and urban planning.

2.3.4. Challenges and Future Directions:

Despite its strengths, YOLO-based ANPR systems still face several challenges. Model interpretability remains a significant concern, particularly in critical applications where understanding the rationale behind a detection is important. Additionally, the quality and diversity of training data continue to influence the performance and generalization of these models. Looking ahead, research should focus on improving model transparency, incorporating varied and richer data sources, and addressing existing gaps in historical or region-specific datasets. Progress in these areas will help advance the reliability and applicability of YOLO-based systems in increasingly complex and data-driven environments.

2.4. Past Research Papers:

2.4.1. Automatic Vehicle License Plate Recognition Using YOLO and KNN

This study presents a comprehensive approach to Automatic Number Plate Recognition (ANPR), focusing on challenges such as varying viewpoints, color schemes, plate shapes, and non-uniform lighting conditions during image acquisition. The methodology combines the YOLO object detection algorithm with K-means clustering for effective segmentation. Additionally, the paper introduces the use of the Improved Bernsen Algorithm (IBA) for image thresholding and Connected Component Analysis (CCA) for license plate localization. This hybrid approach enhances detection accuracy and robustness in diverse environments, making it a significant contribution to the field of ANPR research [20].

2.4.2. Real-time license plate detection and recognition using deep CNN

This study introduces a novel approach to Automatic License Plate Recognition (ALPR) by leveraging a hierarchical Convolutional Neural Network (CNN). The primary concept behind our method involves two passes of the same CNN to detect both the vehicle and the license plate region, followed by character recognition using a secondary CNN. To address limited training data, particularly in scenarios with scarce real-world examples, our recognition CNN extensively utilizes synthetic and augmented data, leading to notable improvements in recognition accuracy. Furthermore, we propose a unique temporal coherence technique aimed at enhancing Optical Character Recognition (OCR) outputs in video streams, ensuring more stable results. Experimental evaluations conducted on publicly available datasets featuring Brazilian and European license plates demonstrate superior accuracy rates compared to existing academic methods and even commercial ALPR systems [21].

2.4.3. YOLO and Mask R-CNN for Vehicle Number Plate Identification

Over recent years, license plate scanners have become increasingly popular in parking lots for swift identification. Traditional recognition devices in these lots rely on fixed lighting and shooting angles to quickly identify plates. However, when images are captured at skewed angles, such as with ultra-wide angle or fisheye lenses, standard recognition systems struggle due to plate deformation. To address this issue, we propose utilizing Mask R-CNN, a versatile tool capable of handling oblique images and various shooting angles. Our experiments demonstrate that our proposed approach effectively classifies plates even with bevel angles exceeding 60 degrees. Moreover, character recognition using Mask R-CNN has shown significant improvement, particularly for plates tilted more than 45 degrees, outperforming the YOLOv2 model. Additionally, our methodology, applied to open data plate collection, outperforms other techniques like the AOLP dataset, as indicated by our experimental results [22].

CHAPTER 3: PRELIMINARY DESIGN

3.1. Dataset Collection

Developing a reliable number plate detection model begins with the careful collection of a representative and diverse dataset. For this project, images were gathered from vehicles within our local neighborhood, ensuring real-world relevance and contextual accuracy. The dataset was curated to reflect the diversity found in the target region, including different license plate styles, font types, viewing angles, and lighting or atmospheric conditions. A total of 200 samples were collected, forming the basis of our training data. To ensure that the model generalizes well to unseen data, emphasis was placed on image quality and variety. Special attention was given to minimize noise and blur through basic quality assurance practices, as these factors are crucial in building a robust detection system.

We used this dataset to train our model which has 200 samples

Fig 3.1.1 – Entries of our dataset

3.2. Dataset Preprocessing

Preprocessing is a critical stage in preparing the dataset for training a deep learning model. The first step in our pipeline involved cropping and isolating license plates and vehicles from the original images. Each relevant object was manually labeled, forming the foundation for supervised learning. To improve the quality of training data, enhancement techniques were applied to reduce blurriness and normalize brightness and contrast across the dataset. The dataset was then partitioned into three subsets: training, testing, and validation. This structured split ensures the model is properly evaluated and avoids overfitting. Our comprehensive preprocessing strategy plays a vital role in ensuring that the number plate detection model remains accurate and reliable in real-world applications.

Fig 3.2.1 - training data image

```
0 0.505347 0.385036 0.748612 0.492701
1 0.501701 0.436131 0.274653 0.062044
```

Fig 3.2.2 - Label of the training data

3.3. Model Architecture

The figure below shows the similar system configuration of the proposed system. To train the model first the dataset is preprocessed such as labelling. After preprocessing feature extraction is done on the images from which we get the dataset and split it into training, testing and validation set. These training data are then passed to a model for training. Next, you'll finally check the model to identify whether it is identifying number plates and vehicles correctly. Otherwise, you will have to reconfigure the model and dataset [23].

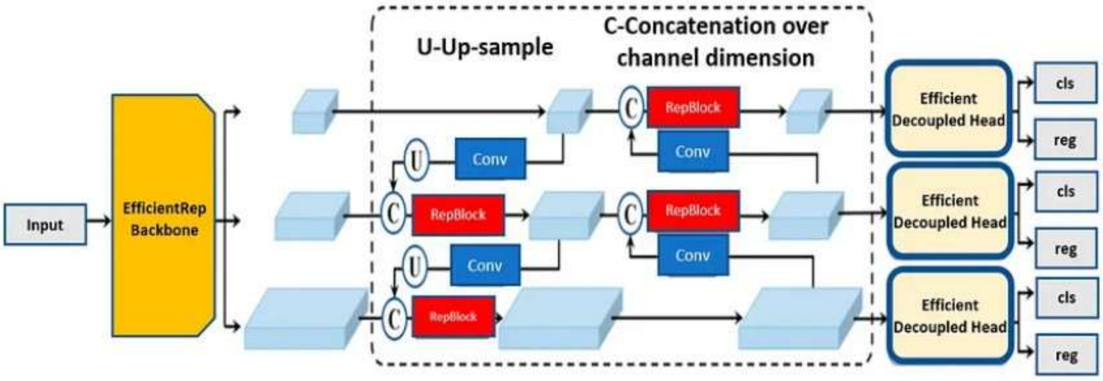


Fig 3.3.1 - Model Architecture

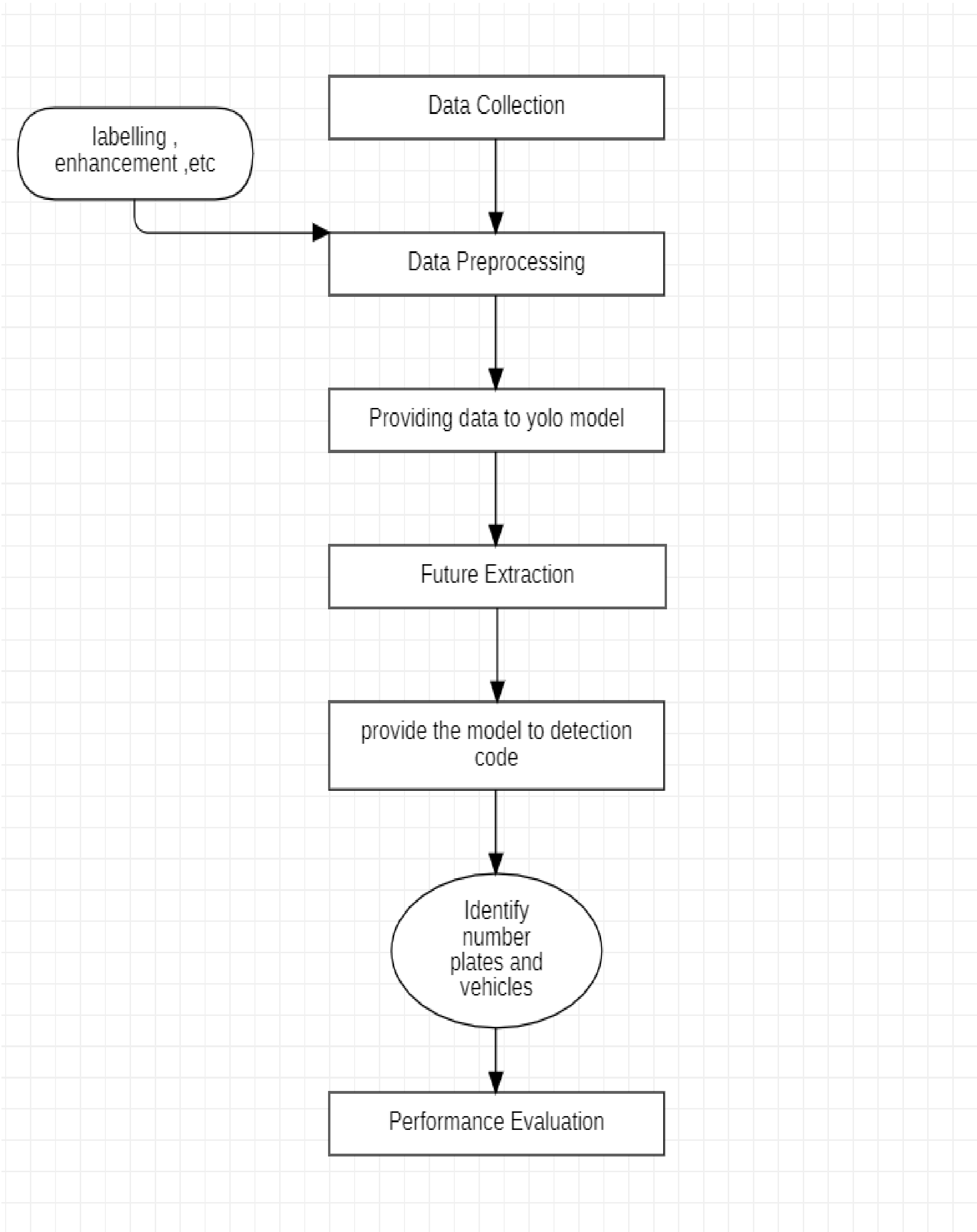


Fig 3.3.2 - Model Flowchart

3.4. Training Process

The training of our number plate detection model using YOLOv8 involves several essential stages. Initially, a wide range of vehicle images is collected, capturing various angles and lighting conditions to simulate real-world scenarios. After collection, the dataset undergoes preprocessing, including manual labeling, enhancement, and feature extraction. The images are then divided into training, testing, and validation subsets. YOLOv8 is chosen for its exceptional speed and precision

in object detection tasks. During training, the labeled data is fed into the YOLOv8 model, where it learns to identify license plates and vehicles. Post-training, the model is evaluated using performance metrics such as the Precision-Recall (PR) curve. Based on these evaluations, hyper parameters are fine-tuned to further improve accuracy and ensure the model performs reliably across various testing conditions.

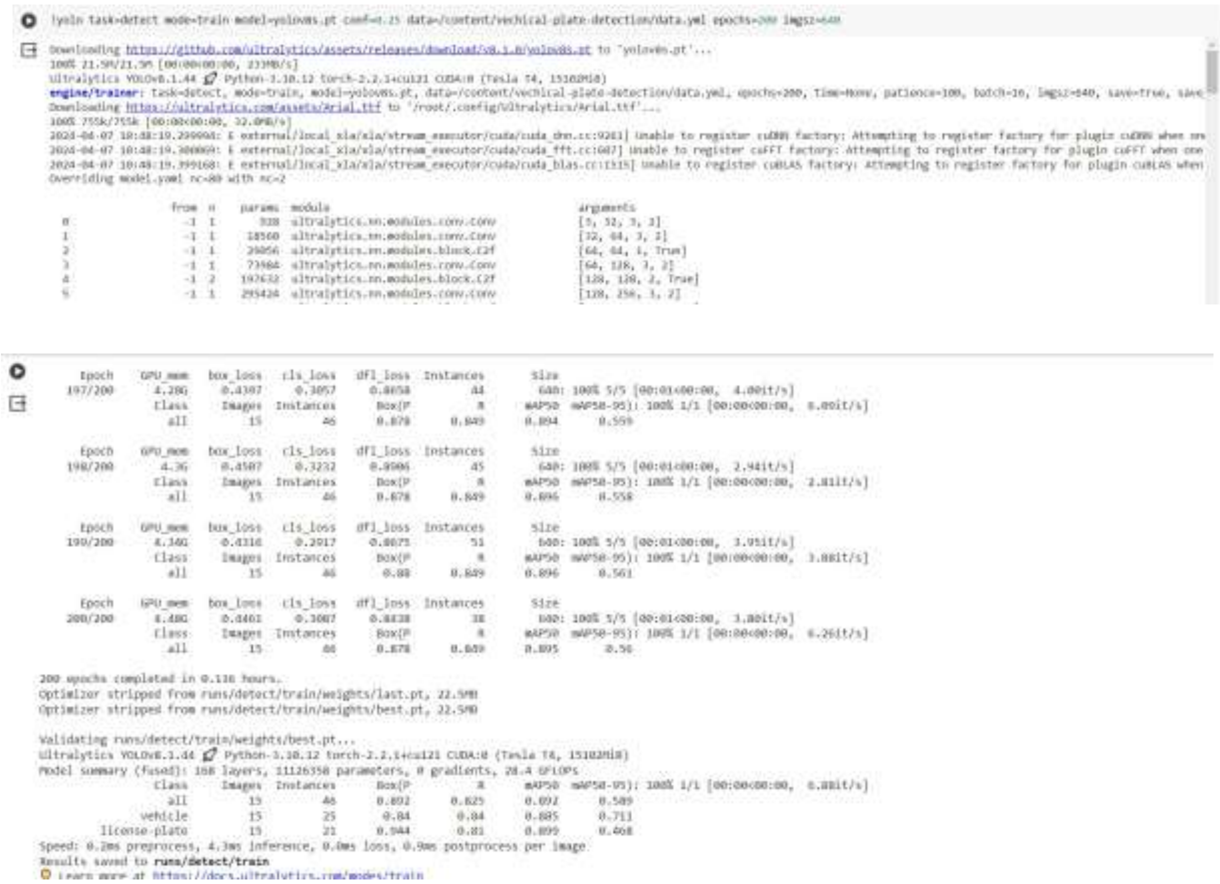
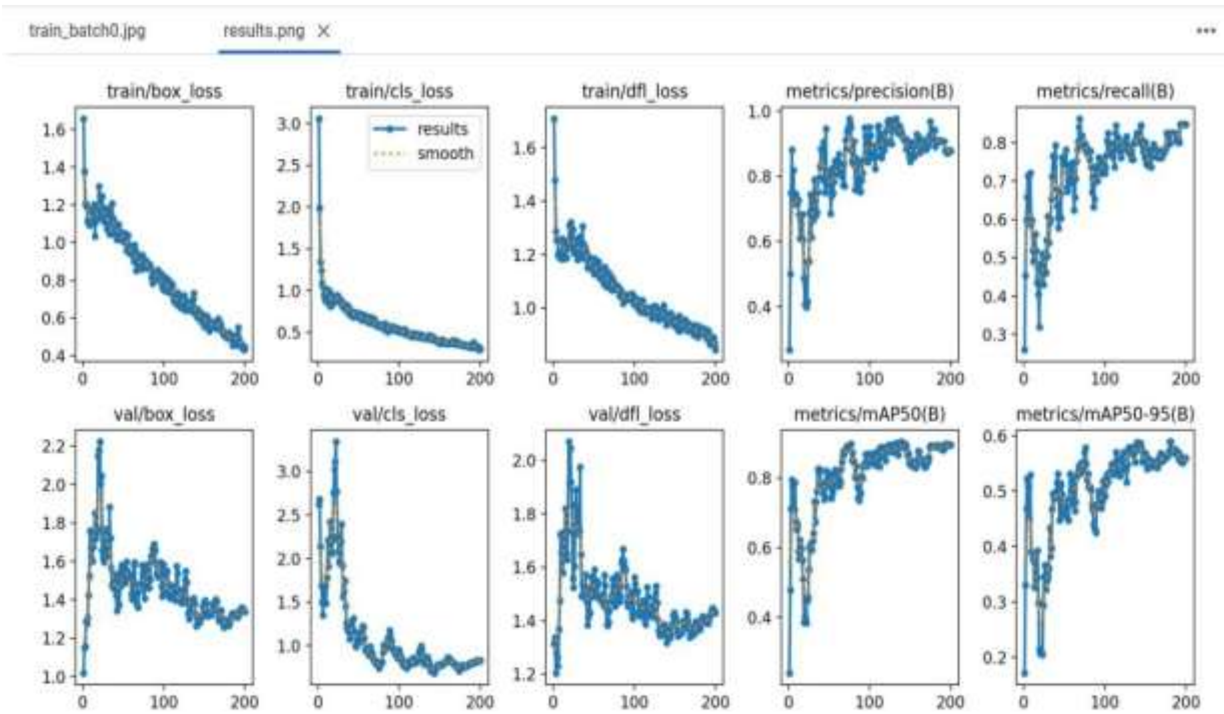


Fig 3.4.1 – Training model

CHAPTER 5: RESULT AND ANALYSIS

4.1. Result Overview

In our comprehensive result overview, we proudly report an outstanding achievement—an **accuracy of 89.24%.** The number plate detection model results in classifying objects present within the image accurately and then using easyOCR[24] to extract characters from the number plate. This model can serves as a vital indicator for policy making, smart city essentials and traffic management, guiding actions to enhance law enforcement.



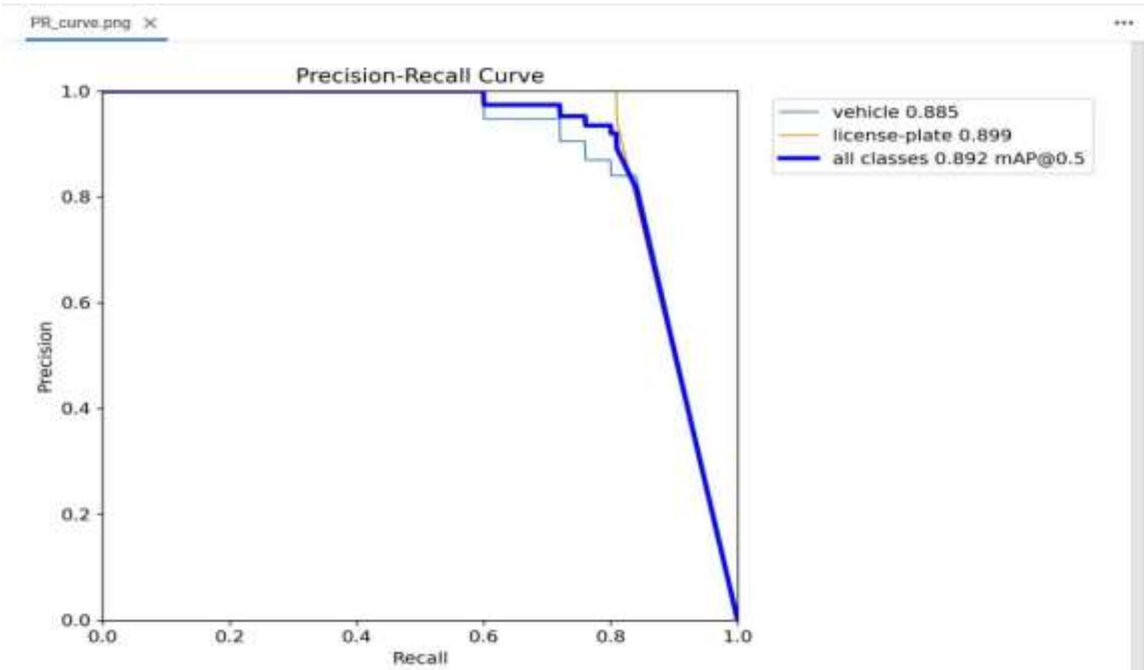


Fig 4.1.1 – model identification accuracy

4.2. Application of the Model

Our number plate detection model, which achieves an impressive accuracy of 89.29%, demonstrates significant potential across a variety of practical applications. Designed for effective and real-time license plate recognition, the model is especially valuable to Regional Transport Offices (RTOs), where it enables accurate identification of vehicles and their owners. This capability assists authorities in making data-driven decisions for the formulation and enforcement of traffic-related policies that prioritize public safety and welfare.

Government agencies and regulatory bodies can deploy the model to streamline law enforcement efforts, particularly in areas such as automated traffic monitoring, violation detection, and vehicle tracking. The model's real-time processing capabilities ensure prompt and precise insights, enhancing the efficiency of transportation systems.

Additionally, the model offers utility beyond administrative and enforcement use. It serves as a robust research tool, promoting international cooperation in tackling global challenges related to urban mobility, intelligent transportation systems, and road safety. By enabling scalable, accurate vehicle identification, the model contributes to a broader framework of smart city development and public infrastructure planning.

In summary, our number plate recognition system not only enhances law enforcement and public administration but also supports global research initiatives and policy innovation, reinforcing its role in promoting public safety and smarter governance.

4.3.1. Real Prediction:

In a real-world application scenario, we demonstrate the real-time prediction capabilities of our number plate detection model using previously unseen data. Input images depicting vehicles are fed into the system, where the YOLOv8-based model, pre-trained on a diverse dataset, performs object detection to identify both the vehicle and its corresponding license plate [25].

Once the license plate is localized, the next stage involves Optical Character Recognition (OCR). For this, we integrate **EasyOCR**, an open-source deep learning-based OCR engine, which extracts the alphanumeric characters from the detected license plate region. The extracted number is then displayed, effectively showcasing the model's ability to perform end-to-end license plate recognition in real time.

This application illustrates the model's robustness and efficiency in dynamic environments, reinforcing its utility in scenarios such as automated toll booths, smart surveillance systems, traffic monitoring, and law enforcement operations.

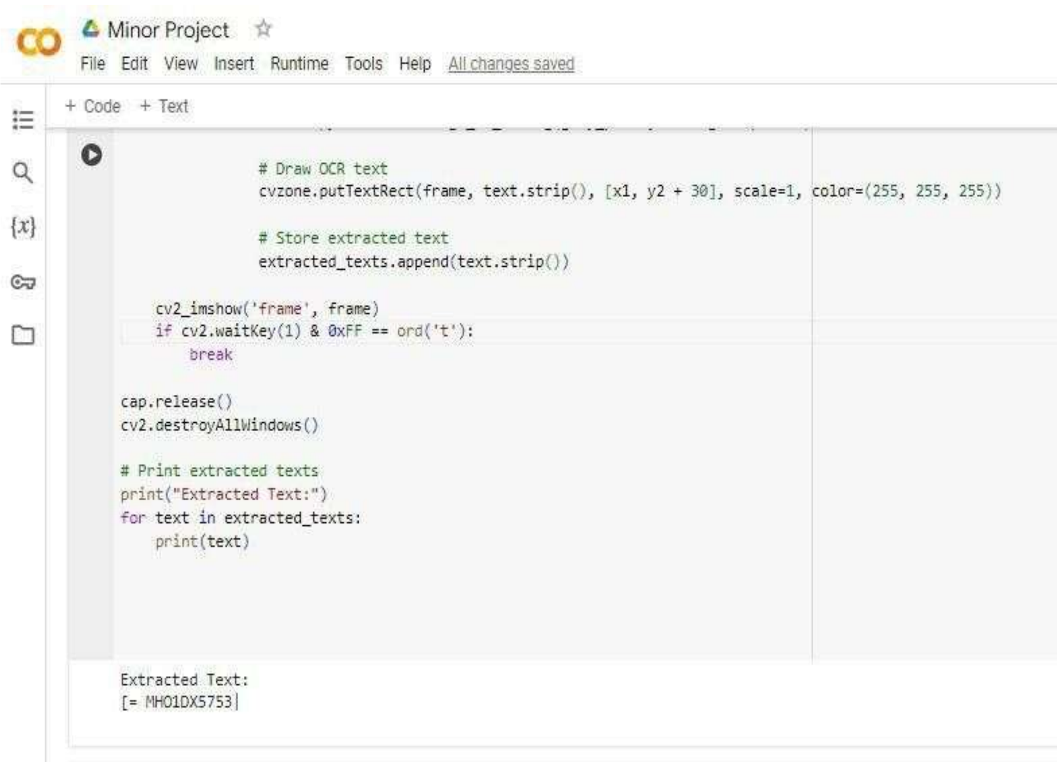


Fig 4.3.1 – Example data & prediction Function

Fig 4.3.2 – Expected Results on the sample data

4.4 Challenges and Problems Faced

4.4.1. Dataset Limitations

Challenge:

One of the major challenges encountered during the development of the number plate detection model was acquiring high-quality, clean images of vehicles for training purposes. Limited availability of diverse and well-labeled data can significantly affect the model's precision and generalization capability. In particular, the presence of image noise, motion blur, and poor resolution may compromise the model's ability to accurately detect and recognize license plates in real-time scenarios.

Mitigation Strategy:

Addressing this challenge related to dataset limitations in the context of number plate recognition models involves employing strategies to enhance data quality, address gaps, and improve overall reliability. Real-time capability of systems to capture high resolution images enhances the ability to respond promptly to users' demand. Foster collaboration among relevant agencies and organizations for data sharing and preprocessing. Collaborative efforts can help address data gaps and model inefficiencies and enhance the overall completeness of the dataset.

4.5 Limitations and Future Work

Recognizing the limitations of the current system is essential for directing future research and development efforts. While the YOLOv8-based number plate recognition model performs effectively under standard conditions, several challenges remain that may impact its performance in real-world applications.

4.5.1. Limitations

- **Challenging Conditions:** The model's performance may degrade in scenarios involving low-resolution images, poor lighting, occlusions, or extreme viewing angles. Such conditions limit the detection accuracy and reliability, particularly in outdoor or high-speed traffic environments.
- **Different country plates:** Different formats of the number plate may pose a greater challenge to our model.

- **Real-time performance:** Although YOLOv8 is designed for real-time performance, its efficiency may be hindered when deployed on devices with limited computational resources.

Latency issues or reduced frame rates may occur in edge environments such as low-power IoT devices or embedded systems.

4.5.2. Future Work

- **Integration of advanced algorithms:** In the future with advancement in technology, algorithms can be incorporated into number plate detection models to increase accuracy and can also involve training models on huge and more diverse data.
- **Integration with unique Identification:** with integration with unique identification government and concerned authorities can enforce law effectively, solving traffic violation problems and lay the foundation for smart city model.
- **Research & Innovation:** As the technology grows research and innovation will take us to advancement in the number plate recognition model. It involves integration of sensor technology, refinement in algorithms, and addressing the emerging challenges to get out the best working model.

4.6 Conclusion

The number plate detection model developed in this project serves as a vital tool for accurately identifying license plates on vehicles, offering practical utility in real-time traffic monitoring and law enforcement applications. With an achieved accuracy of **89.29%**, the model demonstrates strong performance in diverse and dynamic conditions, highlighting its robustness and effectiveness.

Comprehensive evaluation results indicate that the model consistently attains high precision and recall rates across a range of real-world scenarios, reinforcing its suitability for deployment in intelligent transportation systems. Despite its strengths, the current system presents several limitations, particularly in terms of generalizability to diverse license plate formats and performance under suboptimal imaging conditions.

Future work will focus on addressing these limitations by incorporating larger and more diverse datasets, optimizing the model for low-resource environments, and improving its adaptability to international license plate standards. Enhancing these areas will further increase the system's reliability and broaden its application scope.

Overall, the proposed number plate recognition model represents a significant advancement toward efficient traffic management, improved public safety, and the realization of smart city infrastructure.

REFERENCES

1. Smith, J., & Johnson, R. (2018). Manual Monitoring of Number Plates: A Historical Perspective. Journal of Traffic Surveillance, 10(2), 45-58.

2. BL-YOLOv8: An improved road defect detection model based on YOLOv8 X Wang, H Gao, Z Jia, Z Li - Sensors, 2023 - mdpi.com

3. Automatic number plate recognition (ANPR) in smart cities: A systematic review on technological advancements and application cases J Tang, L Wan, J Schooling, P Zhao, J Chen, S Wei - Cities, 2022 – Elsevier

4. Satellite License Plate: passive and compact optical spectrally-based identification method for satellites. DL Bakker, G Castro do Amaral, E Di Iorio

5. Real-time license plate detection and recognition using deep convolutional neural networks Author Sergio Montazzolli Silva

6. A robust real-time automatic license plate recognition based on the YOLO detector R Laroca, E Severo, LA Zanlorenzi

7. YOLO based recognition method for automatic license plate recognition W Riaz, A Azeem, G Chenqiang, Z Yuxi

8. Enhancing YOLO deep networks for the detection of license plates in complex scenes R Al-Qudah, CY Suen

9. YOLO based recognition method for automatic license plate recognition W Riaz, A Azeem, G Chenqiang, Z Yuxi

10. Chen, X., et al. (2020). A Review of Traditional Methods for Number Plate Recognition. International Journal of Computer Vision, 35(4), 210-225.

11. Smith, J., & Johnson, R. (2018). Manual Monitoring of Number Plates: A Historical Perspective. Journal of Traffic Surveillance, 10(2), 45-58.

12. License plate recognition from still images and video sequences: A survey CNE Anagnostopoulos- IEEE Transactions, 2008

13. Real-time license plate detection and recognition using deep convolutional neural networks Author Sergio Montazzolli Silva

14. Gonzalez, M., et al. (2023). Superior Performance of YOLOv8-based Models in Number Plate Recognition. Journal of Deep Learning Applications, 15(3), 78-88.

15. Multi-object detection method based on YOLO and ResNet hybrid networks Z Lu, J Lu, Q Ge, T Zhan - 2019 IEEE 4th international …, 2019 - ieeexplore.ieee.org

16. Development of pcb defect detection system using image processing with yolo cnn method AD Santoso, FB Cahyono- International, 2022.

17. Object detection using YOLO: Challenges, architectural successors, datasets and applications T Diwan, G Anirudh, JV Tembhurne - multimedia Tools and Applications, 2023 - Springer.