AN END-TO-END EFFICIENT LICENSE PLATE DETECTION AND RECOGNITION SYSTEM USING DEEP LEARNING

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

13 JANUARY 2025

APPROVAL

This Thesis paper titled **"AN END-TO-END EFFICIENT LICENSE PLATE DETECTION AND RECOGNITION SYSTEM USING DEEP LEARNING"**, submitted by **Nushrat Jahan Bristi, ID: 221-15-4806** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 13 January 2025.

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Md. Sazzadur Ahamed, Assistant Professor,** Department of CSE Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ACKNOWLEDGEMENT

First, we express our heartiest thanks and gratefulness to almighty God for His divine blessing making us possible to complete the final year project/internship successfully.

We are really grateful and wish our profound indebtedness to **Md. Sazzadur Ahamed**, **Assistant Professor**, Department of CSE, Daffodil International University, Dhaka. Deep Knowledge & keen interest of our supervisor in the field of "*Deep Learning*" to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting them at all stage have made it possible to complete this project.

We would like to express our heartiest gratitude to **Professor Dr. Sheak Rashed Haider Noori**, **Professor & Head**, Department of CSE, for his kind help to finish our project and also to other faculty members and the staff of CSE Department of Daffodil International University.

We would like to thank our entire course mates in Daffodil International University, who took part in this discussion while completing the course work.

Finally, we must acknowledge with due respect the constant support and patients of our parents.

ABSTRACT

This research presents an enhanced license plate recognition system for real-time detection and recognition in transportation and security applications. YOLO object detection algorithms (YOLOv8s, YOLOv8x, YOLOv11s) enable accurate license plate localization, while EasyOCR ensures reliable alphanumeric identification in challenging situations, including low light and complex backgrounds. Testing on diverse datasets demonstrated high accuracy, with YOLOv11 and data augmentation achieving a peak F1 score of 98%. The system also addresses Bengali character recognition challenges, offering a foundation for region-specific improvements. These outcomes validate the system's effectiveness for law enforcement, traffic management and security.

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CHAPTER 1

Introduction

1.1 Introduction

Automated License plate detection and recognition is the crucial step for efficient traffic system and identified any legitimate vehicle without any disruption. License plate detection systems have showcased significantly over the years, but this method relied on manual methods which were expensive, labor-intensive and prone to errors. Therefore, digital technology invents computer vision, image processing techniques which brought significant improvement, end to end detection and recognition.

Hence, LPR system provide a plenty of benefits and very popular for such as traffic congestion prevention, digital parking management system, digital security system, traffic rules violation prohibition, transport identification of a specified organization, car park service, toll collection system. This model is vital for varieties security personnel section, educational institutions etc.

As well LPR solve the issue of kidnapping, any crime, vehicle theft, drunk driving, over speed control management, reckless driving, illegal vehicles, digital attendance system and so on. In our country, numerous vehicles rising day by day, but we are not using appropriate ALPR system.

Therefore, In Bangladeshi Road Transport Authority (BRTA) proposed the digital license plate have two lines decoration in one license plate while around the world have a single line decoration of the license plate. Bangladeshi license plate has three components on the initial row: The city name, the metropolitan area and Automobile category in Bangla such as Ka, Kha, Ha, Gha, La etc. The second line states that "number line" which is divided into two parts: class number and particular vehicle number. We have to do numerous tasks for instance preprocessing image, license plate detection and recognition.

Automatic Bangladeshi License plate recognition ALPR system typically consist of four phases: i) Data collection(vehicle), ii) License plate detection, iii) License plate segmentation, IV) Character recognition these are the major steps. In this paper, we have implemented robust ALPR technology to achieve more efficient and accurate Bengali license plate to determine the best performance of this technology.

Many existing algorithms are using different image processing and deep learning techniques. Moreover, the license plate detection system, we implemented popular object detection model the YOLOv5x and YOLOv8x models (You Only Look Once). As well we use Easy OCR (Optical Character Recognition) library for recognizing text from image. It is the best choice for extract the text from detected license plates. Yolov8x is best for real time detection of any vehicles license plate. In Bangladeshi context ensures a high accuracy and efficiency this is most challenging. The subsequent section we will delve the specific problem by this research, background study, the scope of limitations, outcome of the study.

1.2 Motivation

ANPR or Automatic Number Plate Recognition is considered a blessing in this era. The findings of this study therefore bring forth the important role that the ANPR plays in security systems as it relates to our daily life. This system hence smoothes the operations and efficiently modernizes them. Its important Key benefits are control over efficient traffic system management, enhanced security system, parking solutions, search and rescue efforts, law enforcement, prevention of crime, and so on.

Fundamentally, ANPR can reduce the problem of traffic gridlock since this problem wastes our valuable time.

The ANPR is closely associated with high potentials, for it enhances various causes: improved safety, better traffic regulation, and policing. Advanced technology such as ANPR enhances the after-effects of surveillance by promptly enabling the identification of vehicles that relate to unlawful activities. Moreover, the technology would allow for improved flow in traffic, which could be a great contributor to good urban planning and transportation. Its wide-reaching consequence is clear in applications such as parking management, border control, and rescue missions.

ANPR provides information not only that helps in the speedier course of action but also allows deep data analysis, giving well-informed decisions about public safety and growth. This research hopes to go beyond those boundaries toward a safer, connected society by discussing diverse benefits of ANPR.

1.3 Rationale of the Study

The ALPR system was created to the need to identify the problems with security, transportation systems, education, and law enforcement that exist today. As we are interconnected with society so reliable surveillance systems are most crucial. LPR technology improves security against criminal actions and any kind of threats by identification and tracking of vehicles. In addition, LPR lessens congestion, enhances urban accurate driving study, and transforms traffic management. In order to sustain crime prevention, the ALPR law enforcement guarantees an accurate reaction to events. In a nutshell, this study can create policies and systems, investigate valuable applications, and the consideration for the role of technology in the improvement of society.

1.4 Expected Output

This paper is expected to present expansion and impactful analysis for the ALPR systems in gaining optimization of accurate detection. It is supposed to highlight the benefits, drawbacks, and efficiency of license plate recognition evaluation while summarizing and synthesizing research papers, techniques, and technologies emphasizing our country. It generally includes identification for enhanced security, vehicle rescue and search, traffic management, and overall efficiency.

Therefore, the anticipated result is a source that informs us on how to enhance knowledge on ALPR while at the same time giving guidelines for hands-on policy making, urban planners, and technology in pursuit of exploiting the technology for societal benefit.

1.5 Report Layout

The distinctive features of our endeavors are as follows:

Chapter 1: The research topic's historical and contextual information is presented in the introduction, along with the investigation's challenge or query and the study's goals and relevance. This section includes the introduction of the paper in 1.1, the inspiration for the subject of the study in 1.2, the justification for the study's conduct in 1.3, the anticipated results of this article in 1.4, and the summary or format of the document in 1.5.

Chapter 2: An initial appraisal that provides a brief synopsis of the research conducted on this topic is included in the background study. The applicable intelligence technology research is described here. Moreover, the challenges we faced while doing this study demonstrated the size of the issue. The terminologies subsection is used to describe the areas we will investigate for the paper in 2.1, the related works that show the scientist's prior work in 2.2, the comparative evaluation and summary of the topic in 2.3, the overall goal of the paper in 2.4, and the difficulties we will encounter in 2.5.

Chapter 3: The main concepts of data set handling and model generation have been comprehensively covered in this section. In 3.1, the research approach is introduced; in 3.2, how the dataset is assembled; in 3.3, how the dataset is sterilized; in 3.4, the preliminary processing strategy of the dataset; and in 3.5 and 3.6, respectively, the recommended approach and the implementational prerequisites.

Chapter 4: This section assessed and looked into the output of our predictive framework. For ease of understanding, it incorporates all the results from the graphical description. This section comprises the evaluation of the paper and the experimental findings. The introductory part in 4.1, the result investigation in 4.2, the confusion matrix and classification report resemblance of the outcomes in 4.3 and 4.4, the precision of the validation and training in 4.5, and the discussion of the results segment in 4.6.

Chapter 5: The repercussions of marine life freshness on the community, the surroundings, as well as sustainability are briefly addressed in 5.1, 5.2, 5.3, and 5.4 accordingly.

Chapter 6: In accordance with 6.1, 6.2, and 6.3, an overview of the accomplished study, a conclusion, and potential future research are shown in this section.

CHAPTER 2

Background Study

2.1 Terminologies

The process for detecting license plates focuses on the advancement of deep learning techniques. Before dive into the evolution of Automatic license plate detection, we should know some basic primary terms these are discussed in this paper. ALPR system involve with detecting and analysis the license plate using sophisticated technology systems.

Traditionally, we rely on the manual method but the advancement of the technology we could performed CNN (Convolutional Neural Networks) such as YOLO, Faster R-CNN, SSD etc. These enable more accurate and efficient detection of license plate. Because security is most crucial against illegal activities, theft, potential threats, and so on. As well reduce traffic gridlock and improve efficient traffic management, rules of traffic and expert driving study. ALPR is also vital for preventing criminal offense, and investigation and policy maintain are needed for the society welfare. In this study, we prepare efficient model for the prevention of vehicles related problems.

2.2 Related Work

Sarif et al. (2020) implemented an ALPR license plate recognition system with YOLOv3 for license plate detection and custom segmentation, and CNN for recognition. ALPR system gained for Bangladeshi vehicles with 97.5% recognition accuracy with 2000 images dataset [1]. Sufiun et al. (2023) proposed ALPR systems used yolov5 and achieved 95.41% precision. The open dataset divided into training and testing. Then training images are two section which has images and labels for classes. after that level images are labeled with bounding box with different classes. In other words, testing images are used for utilized the accuracy level of the model.13 classes of license plates in Bangla words and letters are declared here. It would be the ideal if all classes are included in this study [2]. Gnanaprakash et al. (2021) developed a deep learning model that utilizing the ImageAI library with a training process. The performance of the system is analysis using Tamil Nadu license plates Images. For car detection gained accuracy 98.5% , 97% Number plate detection accuracy ,96.7% for Optical Character identification accuracy . This system uses Tesseract OCR engine [3]. The detecting license plate in real-life scenario is represented by Nasim et al. (2024) analyzed the effectiveness of Dark Channel Prior (DCP) for dehazing unclear images, analyzing its efficacy. This research provides comprehensive, step-by-step guidelines for DCP-based dehazing, encompassing stages like image enhancement and dark channel creation. Uses modern technology to improve the Bangla license plate detection in foggy conditions.98.5% license plate identification was accomplished with 2,754 samples from a supplementary dataset using OCR technologies for recognition, YOLOv8 object detection, and DCP dehazing techniques [4]. Alharbi et al. (2023) YOLO and blockchain enhance ALPR security with high accuracy ALPR system achieved 96.2% accuracy including approximately 150 films and 4500 frames. The grayscale conversion was performed to eradicate the number of input channels which is needed to build the model. The technique for noise reduction methods like Gaussian blur and median filtering were used [5]. Al-Batat et al. (2022) In this section, YOLO is used for vehicle and license plate detection with ALPR technology. Achieved 90.3% recognition accuracy across various datasets. For reliable ALPR performance, the YOLOv4 detector is used with data augmentation to provide robust ALPR performance [6]. Maruf et al. (2023) The vehicle detection and license plate recognition (LPR) system employs YOLOv4 to detect the vehicles, and recognition is done with OCR Tesseract ensuring high accuracy Single row and dual row number plates are detected. The system Achieved a mAP of 97 %. The earlier techniques abstracted and relied on primitive image processing, but the present methods are capable of real-time detection in various situations [7].Shi et al. (2023) presented this system minimizes information loss and improves feature extraction as well as high precision in complex environments is shown Experimental data. It detects license plates using an YOLOv5, for recognition it used a advanced technique Gated Recurrent Units (GRU), for decoding Connectionist Temporal Classification (CTC) is used. The model merges recognition and localization into one framework. This system enhances accuracy and decreases the training time. The average recognition precision of the model is 98.98% [8].The license plate detection system associated Aljelawyet et al. (2023) Detection is through the YOLO technique. The accuracy of detection is enhanced through a cascade classifier. The Images will be converted to text using the library EasyOCR(optical character recognition). Recognizing license plates with real-time video processing. analysis of how the accuracy is impacted by distances and angles. This system uses a Raspberry Pi device. The novel approach achieved promising results with 99% accuracy for close ranges when compared to previous tactics that were inadequate in the same situation [9].Alam et al. (2021) proposed Convolutional neural networks are utilized in an intelligent system to efficiently recognize and identify vehicle number plates. The system includes components of number plate detection and recognition. Supports applications for smart cities like traffic management and security. Number plates in Bengali are correctly identified by the system [10].Sultan et al. (2023) LPR is crucial for criminal searches and traffic tracking because Conventional LPR techniques depend on hand-crafted designs for detection. Robust features are automatically learned from data utilizing deep learning algorithms. license plate detection, Vehicle detection, and recognition are the three primary modules of the methodology. The Deep Learning Network identifies the license plate, Morphological operations determine the license plate area, and the Faster RCNN algorithm is used for vehicle detection.

Obtain High accuracy in real-life images is the main goal [11].Saif et al. (2019) proposed the system identifies Bangla license plates from automobile images. This method pre-processed the Image to 416 x 416 pixels and recognized the license plate using a (CNN). For accuracy testing, 200 images from Dhaka city were collected and added to the dataset. The model recognition accuracy is 99.5%. A single vehicle's speed was tested in a video at 9 frames per second. Specifically, It emphasized Bangla license plates. There is one drawback which is the limited dataset range, it is the most challenging. Furthermore, a diverse dataset would be needed to solve this issue and be crucial for better model performance [12].Rahman et al. (2021) An Automated License Plate Detection and Recognition system which has three primary phases Identification, segmentation, and recognition. The You Only Look Once (Yolov4) model is applied for detection. For character segmentation, segmentation utilizes a greedy graph-based method. Using a (CNN)model, recognition is achieved. The model achieved a 99.89% detection accuracy after training on a dataset of 5087 pictures. The system achieves 119ms average processing time for real-time processing. ALPDR recognizes vehicles and gives relevant data for intelligent applications. Now this model is ready to implement in the actual world [13].Ahmed et al. (2022) proposed that There are many ways to detect license plates using a cascaded architecture. The proposed model uses YOLOv7 to extract license plates. The detection accuracy was improved by Weighted Box Fusion (WBF). Initial segmentation of characters is done by the LoG-RSF model. A specifically designed Bangla OCR engine is developed for character identification. XGBoost and transfer learning are utilized to enhance OCR accuracy. The proposed system's detection accuracy is 96%. The dataset contains car images numbering to 1928. [14].Chowdhury et al. (2021) represent the license plate recognition focusing upon the vehicles in Bangladesh. It deals with the need for the identification of vehicles when the usage of automobiles is increased. It is going to provide protection and prohibit vehicle detection. The methodology includes the image preprocessing and character recognition stages. Morphological operations are used for character separation. It achieves 96 percent accuracy during the daytime. During nighttime, it is 92 percent accuracy. The system will verify whether the license plate is authorized [15]. Kumar et al. (2021) proposed The system accurately detects vehicle license plates. It employs mathematical morphological operations for image processing. Additionally, Image processing techniques also boost the speed and reliability of detection. The method reduces redundancy and errors in recognition Template matching and OCR enhance recognition accuracy Image improvement techniques include grayscale transformation and bilateral filtering. The system is aimed at accurate as well as rapid license number detection There might be added features of face recognition in the near future [16].Salimah et al. (2021) Successfully identify license plates using (OCR) technology. The system has achieved a 75% output accuracy with respect to reading number plates. The character reading achieved an accuracy of 97.36%. The method comprises image acquisition through the use of the camera of an Android smartphone. This pre-processing stage includes cropping the license plate from the background. Database connectivity for accessing data related to vehicle owners. The ML-Kit library extracts the number plate text from the images. Normalization scales pictures to a fixed resolution of 1024 x 960 pixel [17].Rahman et al.(2023) presented the model reached a 96.8% detection rate of the plates, which demonstrating that the model is capable of identify the license plates of vehicles in different scenarios. According to these findings, the system performance is ideal for vehicle tracking, charging parking fees and detecting vehicles not associated with the system. It is also difficult to recognize letters with different color and style of fonts in the license plates While recognizing the license plates, for recognizing the number plates the paper uses You only Look Once version 3 (YOLOv3) this is a common object recognition algorithm.[18].Shambharkar et al.(2023) proposed license plate recognition, the proposed model solution was tested with a high accuracy of 96.23% of recognition even when the license plates weren't large.The paper suggests a system for the real-time detection of number plates and uses the YOLO framework with the CNN layer to improve the result accuracy, though it does not operate properly except for India.The paper proposes an automatic framework for number plate detection that consists of four essential parts: of data set, license plate segmentation, license plate detection, Optical Character Recognition (OCR). regarding the performance has further been tested on a public dataset published on Kaggle database[19].Islam et al. (2023) created the methodachieves recognition accuracy using MATLAB software of 94.17%. The proposed model for the automated vehicle license plate recognition system consists of four sequential modules: preprocessing, license plate region extraction, character segmentation, and license plate character recognition [20].

2.3 Comparative Analysis and Summary

As for the comparison of license plate detection and recognition, there are quite significant enhancements in our proposed model to the existing technologies. Why the current models for number plate identification which are functional are sub optimal in terms of flexibility and robustness to different conditions such as lighting of the environment, angle of view, and various plate designs. The gender of the model employed in our study was a sophisticated vehicle number plate detection, optimized for Bengali number plates but trained on a wide variety of datasets with various types of vehicles such as cars, motorbikes, trucks, CNGs in different lighting conditions, and various angles. Such extensive coverage enabled the system to perform excellently in several cases demonstrating more flexibility and reliability than the earlier models. Another reason for the enhanced performance of our model is the utilization of superior deep learning techniques and highly developed neural network architecture. In contrast with previous implemented technologies, which can fail to adjust themselves to complex and dynamically changing scenarios while providing uneven quality, our model does not wane in accuracy and precision. This forms the foundation of the dataset which has been integrated into training thereby making the model more flexible when it comes to issues concerning disparate plate sizes, fonts, and differences in light and dark conditions as would be seen in actual and intense racetracks.

Further, we also provided a detailed analysis of the comparison made between the existing models and our proposed system to substantiate that the current model was the most efficacious due to its faster detection rate accompanied by accuracy and adaptability. This comparison of our work shows the benefits of using the proposed method for daily work, as well as revealing the weaknesses of the previously developed systems. In summary, the current study enhances our understanding of the fact that our approach to LPR systems not only boosts its detection performance but also opens the possibility of adaptive and cost-effective solutions for vehicle identification and traffic control.

2.4 Scope of the Problem

Hereby the range of issues in the license plate recognition systems defines numerous technological, operational, and ethical issues. Inconsistencies and incompatibility of different LPR systems are one of the most significant problems since the systems utilized in traffic management and security cannot share data between them. Thus far there has been no form of centrally imposed structure and as a consequence, the potential to build connected infrastructures appears to be restricted which in turn prevents attempts at increasing functionality and integration. Furthermore, the increase of traffic volume, particularly in metropolitan routes and regional roads, pose scalability issues. The complexity of data sets that LPR systems need to process is increasing, and they should remain equally accurate and fast. Other conditions such as poor illumination, severe weather conditions and partially hidden license plates make easier identification and recognition of illites even more challenging. Apart from these technical challenges, there are special social and legal problems regarding LPR systems. Safety concerns threaten collection and storage of data relating to vehicle identification while exposing the owner to increasing risks of data breaches. Such information once in their possession has no standard guidelines on how to handle such details hence the greater tendency to misuse the information thus eroding the public confidence that particular source. Solving such problems is possible only through the creation of stringent legal norms and ethical codes, capable of adequately regulating the relationship between advantageous functional features of LPR, including the ability to optimize the control of traffic flow and improve security, and threats to privacy This now requires the simultaneous application of the next technological advancement with careful consideration of the social and policy impacts.

2.5 Challenges

There were many difficulties in performing this research, as with nearly any endeavor. However, for this to be successful, we must all collaborate together to overcome the entire procedure.

- ❖ The first and biggest challenge is to collect or create a sufficient collection of data by which we can work.
- ❖ Another challenge of AVLPD systems is scalability and this is a continuous problem with regions such as urban centers experiencing rapid traffic growth.

- The lack of standardization and compatibility across the wide range of currently deployed AVLPD solutions is a significant obstacle that hinders effective collaboration and data sharing between various platforms and authorities.
- Ethical concerns constitute some of the most important obstacles facing AVLPD technology. Significant worries regarding data security and privacy arise due to the processing and gathering of sensitive data.

- It is the most time-consuming step for me because I need to operate in Colab, which has limitations on the sizes and speeds of my data set.
- Lacking sufficient information for training and not sufficient data to carry out the procedure.

Furthermore, the most difficult aspects of this study are the collection of data on a road and managing users for permission to capture the vehicle-sensitive license plate images as well as user scalability.

CHAPTER 3
Research Methodology

3.1 Introduction

The methodological section of our research aims to provide readers an in-depth overview of the approaches and strategies utilized in carrying out the research. It has been acknowledged that technological advancements in modern times have led to in significant improvements in their respective fields. One of these innovations is a new machine learning and computer vision application for automatic vehicle number plate identification (AVLPD). This technique uses the most recent image processing and artificial intelligence techniques to make identification and extraction processes of license plate information from any image or video stream easier by creating detection and recognition systems. In a variety of sectors where accurate and efficient vehicle identification is crucial, such as parking enforcement, law enforcement and traffic management, this technology has found significant uses. This chapter describes the development process which proceeds from the former to the latter, which is the actual reality of an AVLPD system. Implementation entails training the YOLO V8 model, creating an effective prototype, and occasionally performing strict tests to determine the system's reliability and performance. At the core of that endeavor is the creation and curation of high-quality datasets essential to model development.

The basis is the production and curation of high-quality datasets essential to model development procedures. Modern deep learning frameworks and the utilization of high-performance GPUs for improving training accuracy and efficiency are the factors analyzed in this study. The prototype system's development and design are thoroughly examined in addition to model training The part of integrating the YOLOV11 model with tools such as EasyOCR for text recognition is the basis for the detection pipeline. This also includes creating an easy-to-use layout and an operational workflow for the entire system functionality, ensuring that everything works together seamlessly. This is another aspect of research called system testing and evaluation, which methodically involves testing such as functional, integration, and unit testing with measurement metrics like precision, recall, and inference time with reference to the prototype. Such ongoing system improvement helps highlight solutions provided for enhancing flexibility in an adverse environment and real-time performance. It makes available cloud services to store cloud data. We used the Google Colab platform to save and utilize our data for future use This research includes an augmentation method, but there are instances that call for the need to use an augmentation strategy. AVLPD examines the above features regarding data security and explores encryption techniques. However, this research is more extensive, including ethical considerations and data privacy to ensure that AVLPD systems are able to keep up with modern security and responsible usage demands. To this end, insights can be gleaned regarding the transformational effect AVLPD may have and how it may redefine vehicle monitoring, future surveillance, and related fields within modern society.

The methodology of this research is demonstrated in figure 3.1 which is called the proposed system architecture. It briefly explains every step of the research, and how we conducted this at every point which we followed.

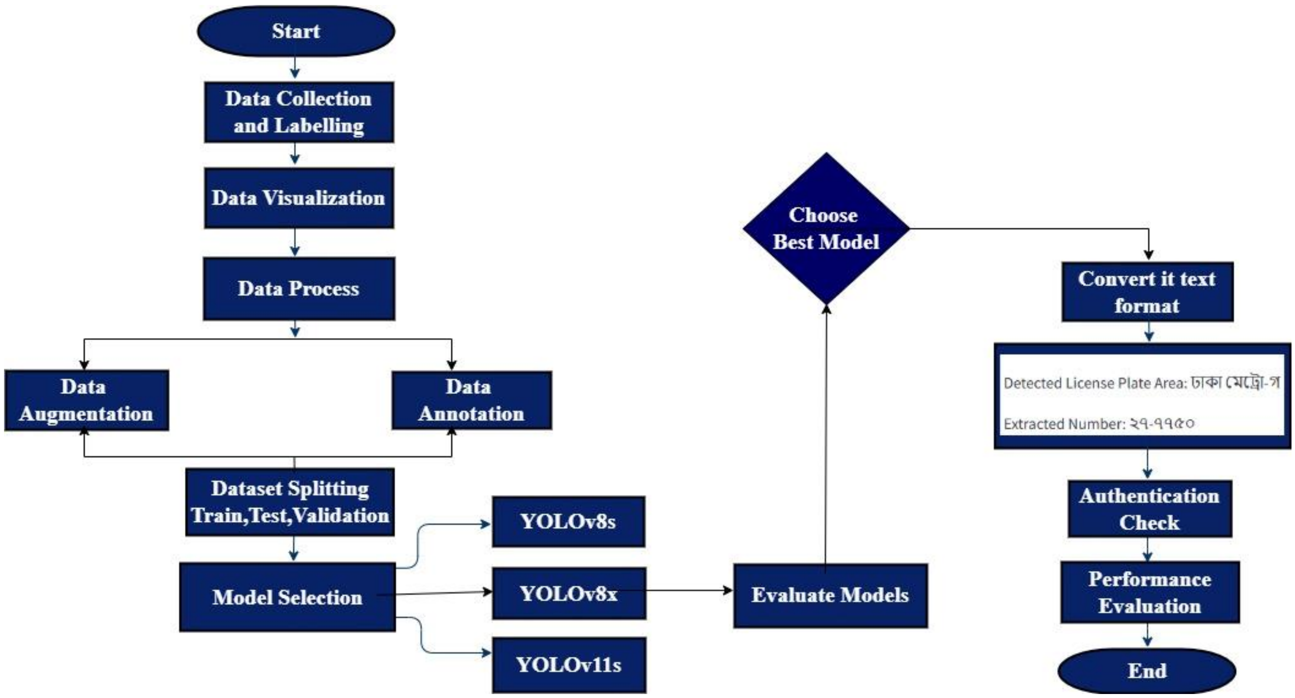


Figure 3.1.1: Proposed System Architecture

Implementation of this model using EasyOCR.

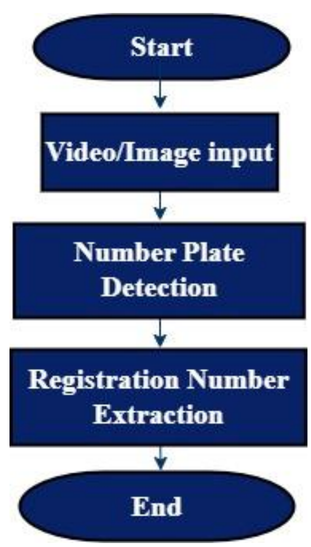


Figure 3.1.2: Implementation Architecture

3.2 Data Collection Procedure

Since data collecting is mandatory of every study, it is the most crucial component. In this study, we used 3500 images. License plates were collected across Dhaka, Bangladesh. In this study, there are numerous of images used. For instance, cars, buses, trucks, motorbikes, etc. But most of the images are cars.In Bangladeshi Road Transport Authority (BRTA) proposed that digital license plates have two lines of decoration in one license plate while around the world have a single line decoration of the license plate. The Bangladeshi license plate has three components on the initial row: The City name, the Metropolitan area, and the Vehicle category in Bangla such as Ka, Kha, Ha, Gha, La, etc. The second line states that "number line". For this study, we collected primary 500 data and took the rest of the data from the Online source Kaggle.

TABLE 3.2: TABLE OF IMAGE NUMBER

Class Name	Number of Original Images	Number of Augmented Images
Valid	1600	3500

Figure 3.2: Sample Dataset

3.2.1 Bengali Standard Number Plate Description

In this study, we implemented Bengali number plate detection and trained our model. As we know in Bangladesh licensed vehicles are categorized by a number plate. There are multiple cities in our country. The number plate text varies from city to city in our country. There are two parts to the number plate of Bangladesh. The initial part of the first line is for the city name and the car's chosen letter in Bengali number. The second line contains the number of serial of the car in the first two digits and then followed by a hyphen and then the rest of the part contains the number of the plate. With the help of the Figure 1, we can see it.

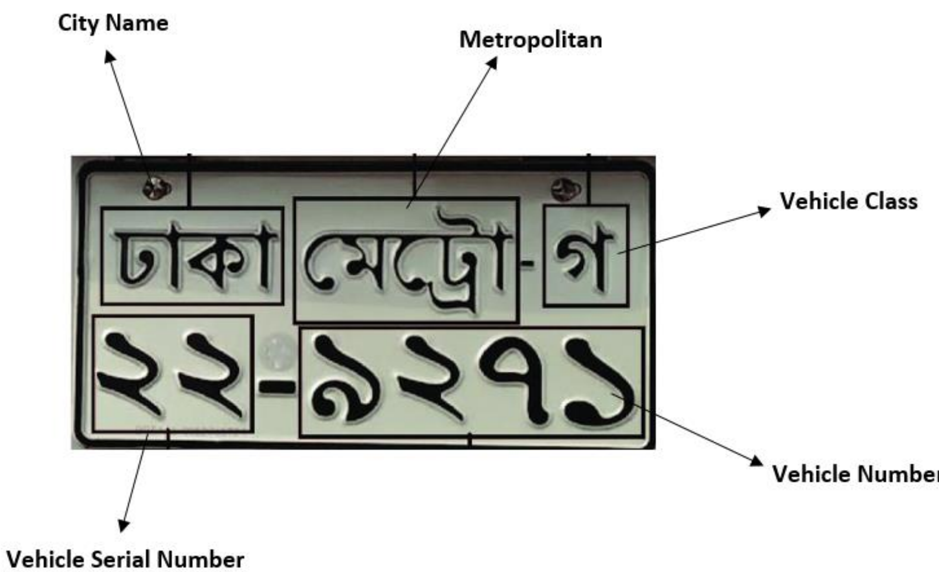


Figure 3.2.1: Bengali Standard License Plate classification

Here is the classification of number plate vehicle class according to vehicle type in Bangladesh.

3.3 Dataset Cleaning

We simply have to carefully review all of the photographs which have been taken mostly because our combined datasets from the road were constructed and we prefer to save just those pictures which have no issues and only focusing on the license plate and numbering section precisely. When choosing which of the intended photos would be relevant to the study, it was further realized that a few photos had exposure-related and ambiguous issues that could be detrimental to the simulation. For safety hazards, these photos were also removed from the data set and preserved locally and also on Google Drive. The databases which are final is after cleaning from the data.

Table 3.3 demonstrates the final dataset table:

TABLE 3.3: THE FINAL DATASET TABLE

License plate Condition	Classes	Numbers of Images
Valid	Valid	3500
Total	1 class	3500

3.4 Dataset Preprocessing

Data preparation is a crucial step in the data assessment section. It comprises cleaning, transforming, and organizing raw data in order to be ready for evaluation and model training. Here, YOLO was employed to gather trustworthy license plate information. A several procedures are utilized in constructing the dataset: labialized, bounding box, find classes, etc. for training the dataset, creating a tiny dataset with numerous varsities car number plates, then pre-processing those images. There are two categories for training datasets which are train and label images. In image classes, it is filled by images with various names whereas label classes are built by setting coordinates value using formulas of Xmin and Xmax.

The transformed images resize is preserved at 640*640. The images go through a number of steps, starting with image acquisition, which is followed by resizing to ensure consistent dimensions and enhancement to improve quality. Then, the images are normalized for consistency in color and brightness, and augmented through various techniques such as flipping the image horizontally, and vertically, rotating them 90 degrees in clockwise, counterclockwise, and upside-down directions, and applying grayscale to 15% of the image to expand the dataset diversity The images are then divided by [255,0] to normalize them to the range [0,1] The dataset photos are initially separated into two divisions (train and test) This was for maximum diversity of images with a proportion of 80 percent train and 20 percent test respectively Furthermore, the training (that 80% of data) descriptions get split into training and validation and this gets divided at 80-20 ratios as well for greater accuracy and diversity of the data Character segmentation: A character segmentation data set will be labeled first, wherein declared classes include 13 classes comprising car license plates written in Bangla words and letters. Thus, thirteen classes—including METRO, DHAKA, ONE, TWO, THREE, FOUR, FIVE, SIX, SEVEN, EIGHT, NINE, SA, ZERO) were declared. Then take the images one by one give them an accurate bounding box and afterwards label them appropriately according to the classes.

Table 3.4 demonstrate the size of the train, test, and validation data.

TABLE 3.4: THE NUMBER OF IMAGES IN EACH DATASET

Split Percentage	**Dataset Splitting**	**Number of Images**
80%	Training 70%	3130
	Validation 10%	302
20%	Testing	151

3.5 Proposed Methodology

In this study, we used the You (Only Look Once) version yolov8 and version yolo11 algorithms to detect the license plate from a vehicle. We used the algorithm to train our model. To identify the model, we proposed the labeling data with text format labeling for detection.

Here are the architecture of our models YOLOv8 and YOLOv11 –

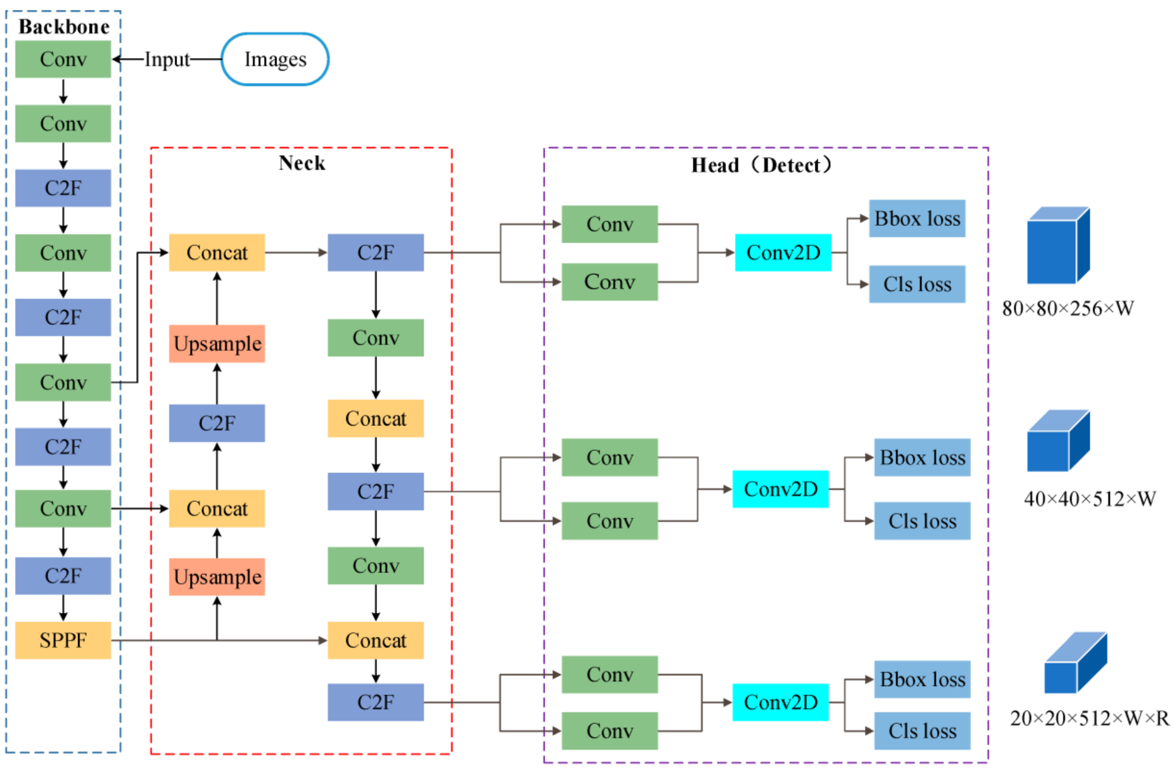


Figure 3.5.1: YOLO8 Architecture [21]

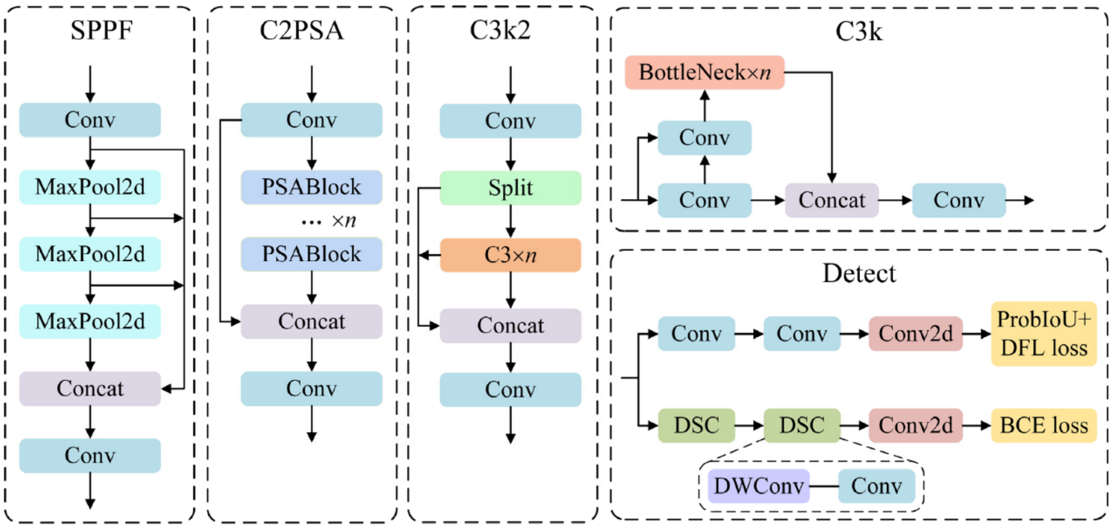


Figure 3.5.2: YOLO11 Architecture [22]

3.5.3 You Only Look Once (YOLO)

The YOLO (You Only Look Once) object detection model operates in a single pass through the network, making it a fast and efficient choice for real-time applications. Below is a detailed, step-by-step explanation of how YOLO processes an image for object detection, along with the necessary equations:

1. **Input Image Preprocessing:**

   The first step in the architecture of YOLO model is to prepare the raw picture. To make sure is that all the inputs are the same, the raw picture is resized with dimensions to a fixed size. is usually 640x640 pixels. This resizing makes the computations easier and allows It's also shown that the model handle images of different sizes appropriately. Following that, each pixel value has normalized to range from 0 to 1 by using the formula for conversion, that is dividing the value by 255. We can figure out this adjustment by:

$$I_{norm} = \frac{I_{pixel}}{255} \ldots\ldots\ldots\ldots\ldots\ldots \text{(1)}$$

The pixel intensity of the picture depends on the value of I pixel. Normalization makes sure that the network learns faster and does not have problems when the values entered are from different groups. Once the picture has been normalized, the normalized picture can be used to perform detection using the YOLO network to be found.

2.Bounding Box Prediction by Each Grid Cell

Each grid cell comes out with multiple bounding box predictions. In order to remain coherent for each bounding box, the following parameters are predicted:

(a) x and y: These actually denote the co-ordinates of the midpoint of the box which bounds the image. relative to the grid cell. The height and width of the image normalizes such coordinates.

(b) w and h: These two are the width and the height of the bounding box which are both in pixel and normalized by the image’s dimensions. These values enable the model for the ability to extend to other environments. object sizes.

(c) Pobj: This is the probable confidence that the bounding box is containing an object. This score needs to show the possibility of there being an object inside the box and this is computed as:

$$P_{obj} = sigmoid(C_{obj}) \ldots\ldots\ldots\ldots \text{(2)}$$

where Cobj is the raw prediction for the objects confidence. The sigmoid function scales down the obtained prediction to fall within the range of 0 and 1 a as a final step. The confidence score m is that a pobj is multiplied by the class probability to find out the chances of getting a particular object is within that box.

3. Final Bounding Box Prediction

For each bounding box, YOLO combines the confidence score pobj with the predicted class probabilities to generate the final output. The overall score for a bounding box is:

$$score_{final} = P_{obj}P_{class} \text{ ………. } (3)$$

The score reflects the likelihood that the bounding box contains an object belonging to a specific class. YOLO then filters out bounding boxes with low confidence scores, typically applying a threshold (e.g., 0.5) to keep only those boxes that are highly likely to contain an object.

4. Non-Maximum Suppression (NMS)

After predicting multiple bounding boxes for each grid cell, many boxes may overlap with each other, especially when detecting the same object. To resolve this, YOLO f ilters out redundant boxes using Non-Maximum Suppression (NMS). NMS retains the bounding box with the highest confidence score and removes all other boxes with a higher overlap (measured by Intersection over Union, IoU) than a defined threshold (e.g., IoU ¿ 0.5). This step ensures that only the most accurate bounding boxes remain. The IoU between two bounding boxes is calculated as:

$$IoU = \frac{Area\ of\ Intersection}{Area\ of\ Union} \ldots\ldots\ldots (4)$$

Bounding boxes with IoU values more significant than the threshold is discarded, leaving only the most relevant bounding boxes.

3.5.4 EasyOCR

EasyOCR is an enhanced open-source optical character recognition software designed to easily convert scanned images, PDFs and any other documents into editable and machine readable texts. It scans practically all types of novelties and through leveraging intricate approaches to algorithmic practice, it provides extremely professional text recognition hence an ideal choice for retrieving info from relevant types of documents. EasyOCR guarantees the ease of operation, which will fit even those users who are not very familiar with technology. It has multi-language options, common ones like English, Spanish, French, German and among others, which increases its flexibility and relevance to various customers in different areas of working. The aspect that distinguishes it, is its batch processing mode that enables processing of many files at once, which is useful for large projects. The fields which are benefited from EasyOCR are the finance, business, legal, healthcare, and educational fields because they can use EasyOCR for documentation, data entry, and improving work effectiveness. Its strengths of users through making data extraction procedures easier and increasing effectiveness.

3.6 Model Training

In detail, after training, all models are tested in terms of necessary indicators, including recal ,precision and mean Average Precision (mAP). These evaluation metrics are highly essential for determining the level at which the model will estimate the bounding boxes and at the same time effectively classify the items objects in the dataset. YOLOv11, the model under consideration, is characterized by a broader potential than the previous models because of the use of an improved organizational structure and new approaches to feature extraction. In all the evaluation stages, YOLOv11 receives high F1 scores while also obtaining splendid mAP indications of balancing precision and recall. This is beneficial for narrowing down false negatives and false positives and it makes the system very viable in an object detection system. It also allows achieving better computation efficiency for inference time while maintaining high accuracy. Once the evaluation is already done, then the most optimized version of YOLOv11 is ready for deployment.This model is ideal for applications that require fast identification like was in the case of license plate recognition in a car. Precision (mAP). These metrics are critical in determining the model's ability to accurately predict bounding boxes and correctly classify objects in the dataset. YOLOv11, as the proposed model, exhibits superior capabilities compared to its predecessors due to its advanced architecture and enhanced feature extraction techniques. During the evaluation process, YOLOv11 consistently delivers high F1 scores and achieves remarkable mAP values, maintain an excellent balance between the precision and recall of its detections. This ensures the model minimizes false positives and false negatives, making it a highly reliable option for object detection tasks. Its optimized computation efficiency also enables faster inference times without compromising accuracy. The yolo11 architecture will be thoroughly clarified in the statements that follow.

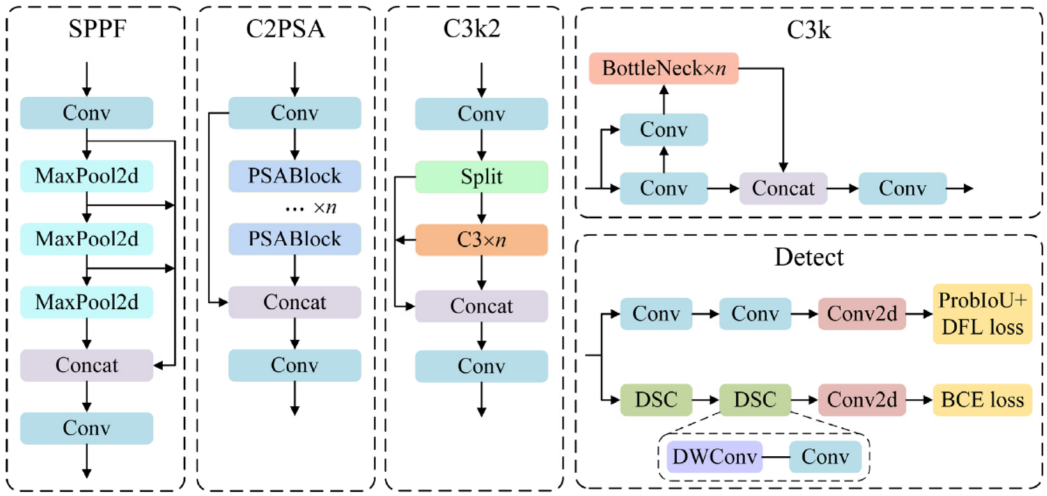


Figure 3.6: YOLO11 Architecture [22]

Once the evaluation is complete, the best-performing version of YOLOv11 is prepared for deployment. This model is tailored for real-time applications such as vehicle license plate detection, where quick and precise identification is crucial. Trustworthy in fixed as well as a changing environment making it effective in critical or complicated situations. Through the implementation of YOLOv11, users are able to solve the current problems with object detection with a level of accuracy and speed that is considered elite and premier within the current market.

3.7 Implementation Requirements

- Different Deep Learning Frameworks and Libraries
- Windows 11
- Google Colab with Runtime TPU

- Kaggle enabling TPU runtime
- Google Drive
- POCO x24 and iPhone 15pro max for Image Gathering

CHAPTER 4
Result Analysis and Discussion

4.1 Introduction

We deployed three distinct deep-learning models to achieve the highest level of precision on our custom-made dataset. By using CNN to construct YOLOv8s, YOLOv8x, and YOLOv11s individually on our unique dataset, the time required to build the model from scratch has been minimized. Here, utilizing the methodology of learning, we can develop models using our dataset while preserving the weights that have been previously trained for each model.

4.2 Experiment Results and Analysis

The experiment results and the analysis of the LPR system prove that the model synthesized performs well with adequate efficiency. In the initial phase of vehicle detection for our system, it was tested on 3500 images which returned a precision of 0.97 With 98 true positives and two false positives. It means that a recall value of 1 represents that all the vehicles present in the dataset were properly detected. Furthermore, the global percent accuracy of 98%(f-1score) proves the effectiveness and efficiency of the system.

Further training on 3500 images, using metrics such as precision, recall, mAP50, and mAP50:0.95 across several epochs and batch sizes, maintained the model further hence enhancing its performance during various epochs and batch sizes. Therefore, the confusion matrix and the classification reports comparison demonstrate that the model can optimize the outcomes in various cases successfully. These outcomes support the reliability of our work and serve as the groundwork on which precise license plate recognition can be launched.

The results of each model with the corresponding assessment grades are shown in the table below.

TABLE 4.2: THE EXPERIMENT RESULT OF THE EVALUATED MODEL

Transfer Learning Model	**Map50**	**f-1 score**
YOLOv8s	0.98	0.97
YOLov8x	0.98	0.97
YOLOv11s	0.98	0.98

We got good confidence in our validation dataset. We can see it in Figure 4.2.1

Figure 4.2.1: Validation Result

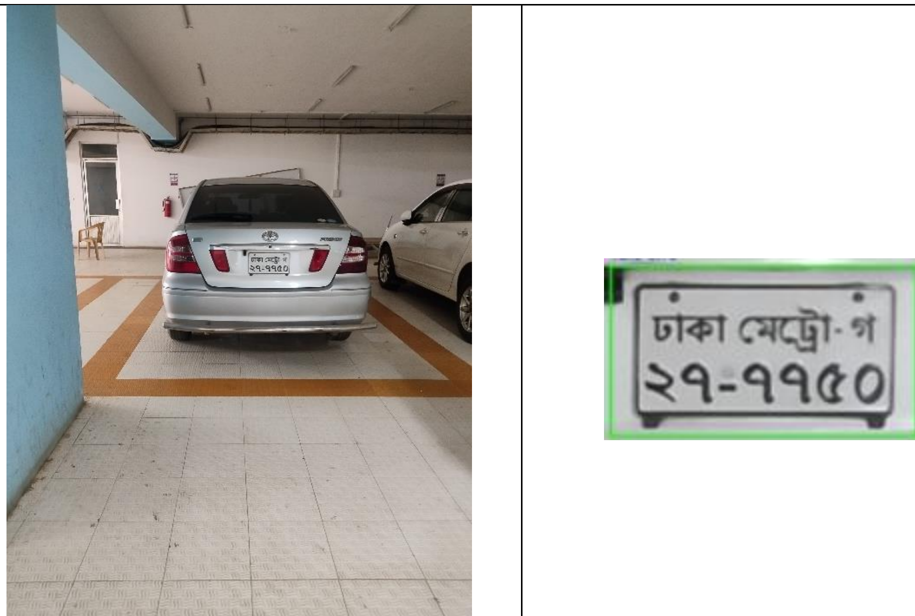


Figure. 4.2.2 Image to license plate Detection output.

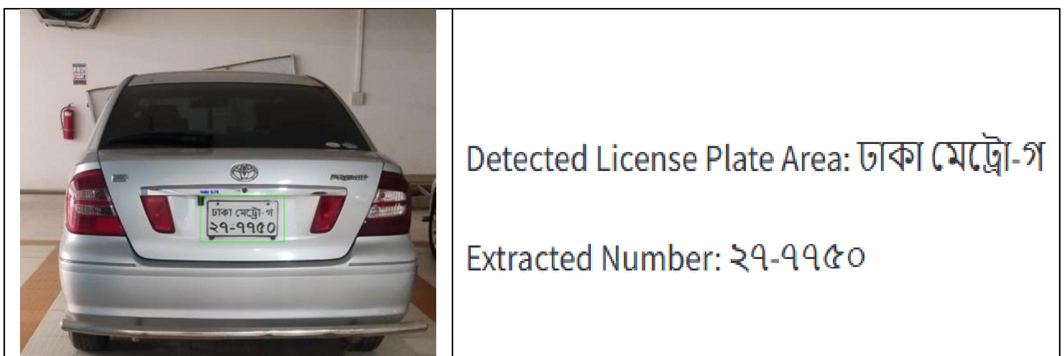
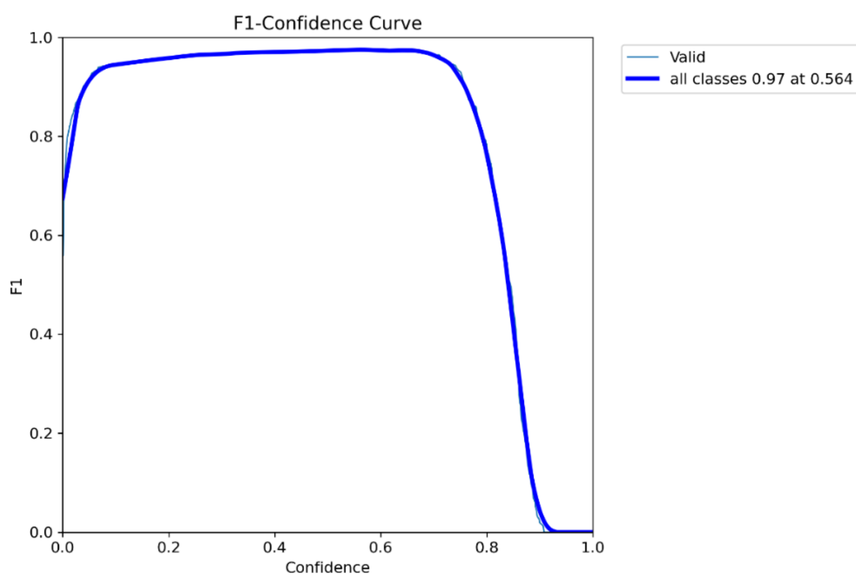


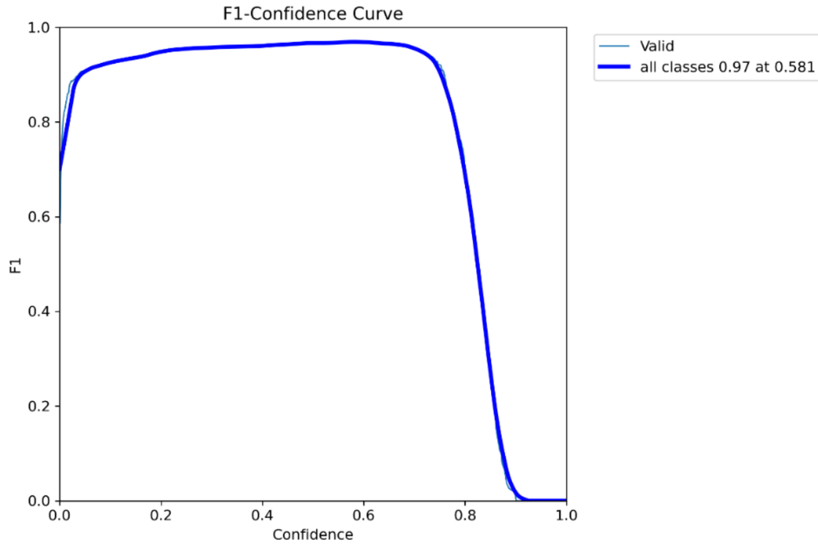
Figure.4.2.3 Image to license plate Extraction output.

4.3 F1 Curve Analysis

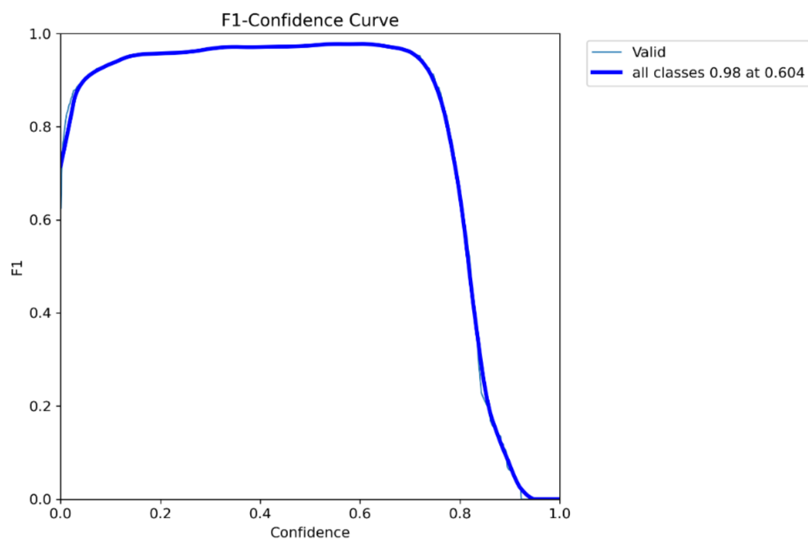
The F1-confidence curves are used to give a more comprehensive analysis of the relative false positive rate, true positive rate of the tested models when varying the confidence threshold. From the figure, talented YOLOv11 (small) achieves the F1 score of 0.98 which makes it the most suitable for the case where precision and recall are important. Superior to others and its performance can be confirmed because it has an approximate accuracy, which is 98 %. The YOLOv8 (small) model performs second with an F1 score of 0.97 of the capacity to distinguish between courses. This model remains substantively constant in its performance across confidence levels, making detection sound. The experiential outcomes highlight that it has a 97% accuracy approximation making it dependable towards multiple usages. For object detection, the F1 score is calculated to be 0.97 for YOLOv8 (x) the same as the YOLOv8 (small). This makes it highly competitive as it provides consistency to the processes it is used to render. From this comparative evaluation, the YOLOv11 (small) model is identified as the best performing instance to yield the optimal F1 score and real approximate accuracy. Thus, both YOLOv8 (small) and YOLOv8 (x) remain among the top contenders while trying to strike a reasonable compromise between detection accuracy and general versatility. The F1-confidence curves further re-iterate that of these models the consistent performance is achieved.



(a) F1 Curve of YOLOv8s



(b) F1 Curve of YOLOv8x



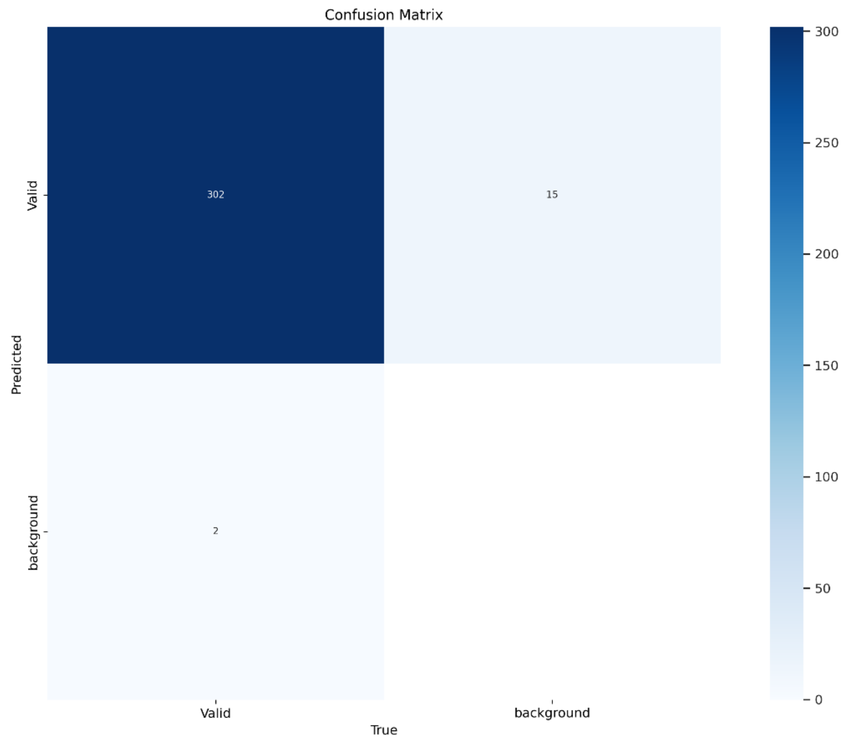
(c) F1 Curve of YOLOv11s

Figure 4.3.1: Fi-Confidence Curve

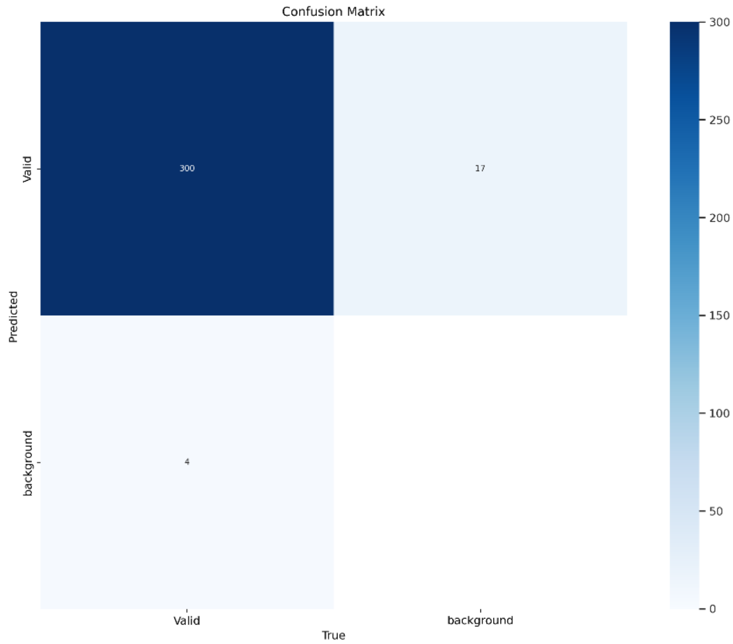
4.4 Generating Confusion Matrix

Thus, to measure the effectiveness of the proposed method, clustering of confusion matrices was done to cope with classification by checking character recognition, plate region detection, and error correction among different groups. These matrices are used to compare the various predictions made with actual values giving an understanding on the performance of a particular model. It explains how well the system for classification works at using a table called the matrix of confusion. These consist of True Positive cell or area, True Negative cell or area, False Positive cell or area and False Negative cell or area. YOLOv11 (small) worked on more errors due to dissimilar characters in remotely different fonts, or partially erasing license plates. YOLOv11 (small) encountered more errors, especially when differentiating visually similar characters or recognizing partially obscured plates. To attain high levels of reliability of these models, further optimization is needed. In conclusion, YOLOv8 (small) yielded relatively the most favorable mean average precision and standard deviation in principle for deployment, though need for improvement in consistency in classification were evidenced in YOLOv11 models. YOLOv8 (small) provided more remarkable results in terms of precision and recall of number and character sequences when tested in different circumstances. YOLOv8 (x) not only was fast, but also failed at moments distinguishing between visually similar characters. In general, the YOLOv8 (small) model offered the right blend of precision without compromising too much on run time and was therefore chosen for production, while the YOLOv11 variants require further development for reliable classification.

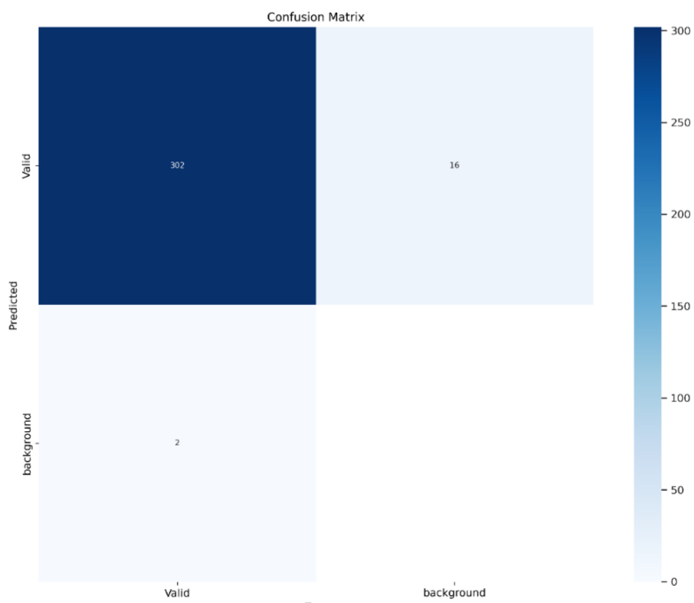
The confusion matrix of the models is illustrated in Figure 4.4.



(a) Confusion Matrix of YOLOv8s



(b) Confusion Matrix of YOLOv8x

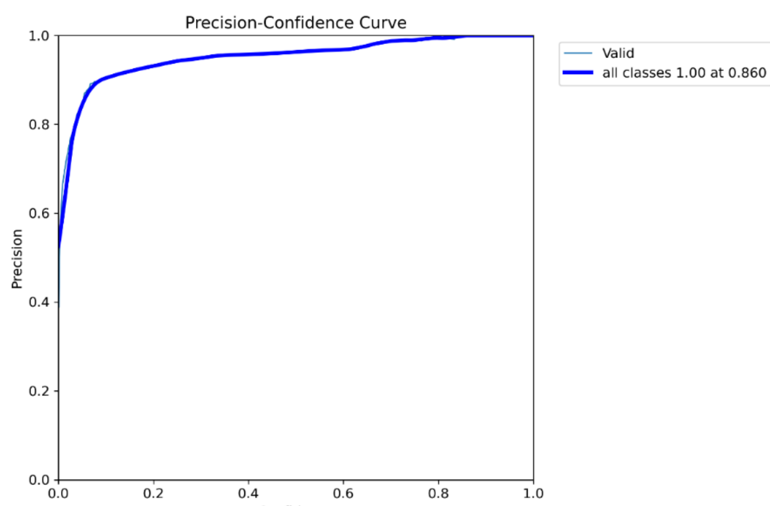


(c) Confusion Matrix of YOLOv11s

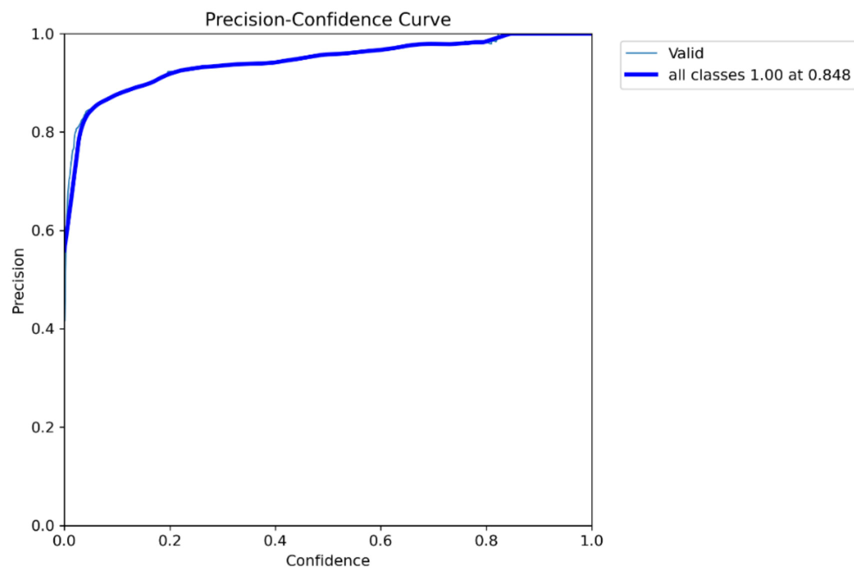
Figure 4.4: Heatmap of Confusion Matrix

4.4.1 Precision Curve Analysis

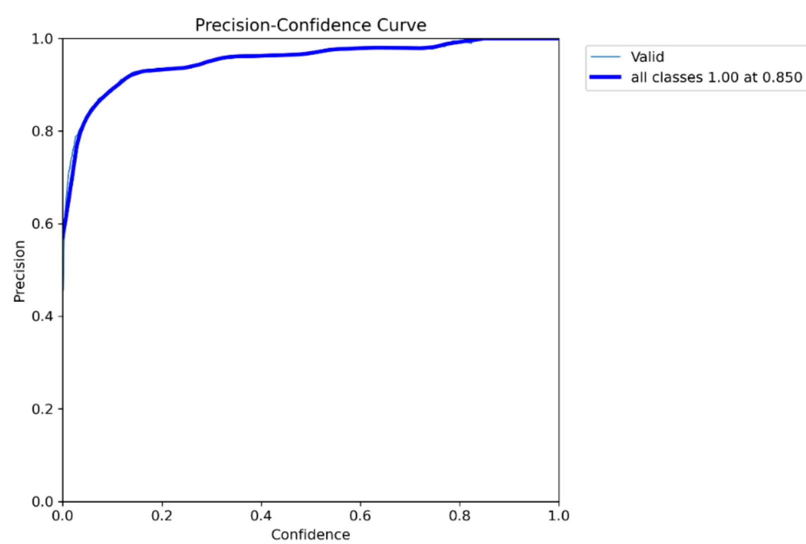
The analysis of precision curve for the assessed models, namely Yolov8s, Yolov11s, and Yolov8x exhibits high precision in all forms of cases. For precision measure, it shows that Yolov11(s) has the highest precision level of 0.97, emphasizing that it is accurate in predicting few false positives while predicting the actual positives accurately. Both Yolov8(s) and Yolov8(x) test at slightly lower accuracy at 0.96 meaning that they are comparable to Yolov11(s) but has a slightly higher false positive detection rate. All the models seen here have tight variations between precision and recall which proves that these models are reliable for classification problems, though Yolov11(s) has a marginal edge when it comes to precision it doesn't skimp on recall or F1-Score. This performance makes Yolov11(s) suitable for the application where high confidence is desired like the object detection where false alarms lead to large errors downstream. Lastly, the general trends depicted by precision curves also suggest that all the three models are highly optimized to deliver high precise detections, with Yolov11(s) doing slightly better than others making it the most reliable in event requiring high precision.



(a) Precision Curve of YOLOv8s



(b) Precision Curve of YOLOv8x

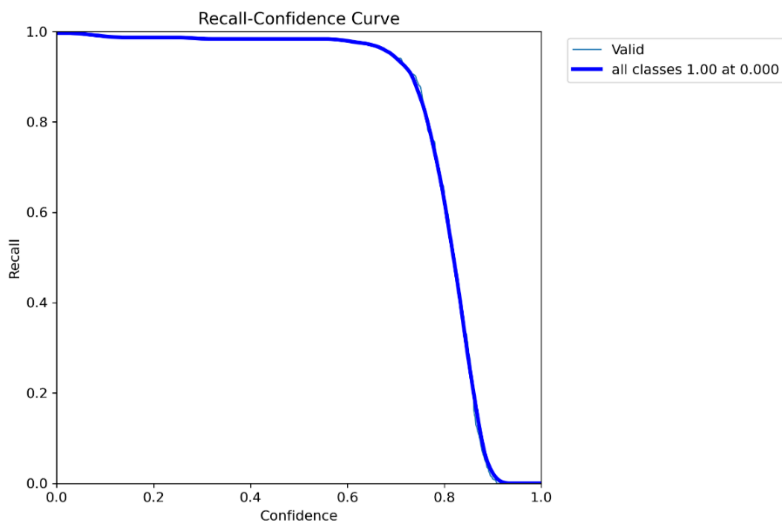


(c)Precision Curve of YOLOv11s

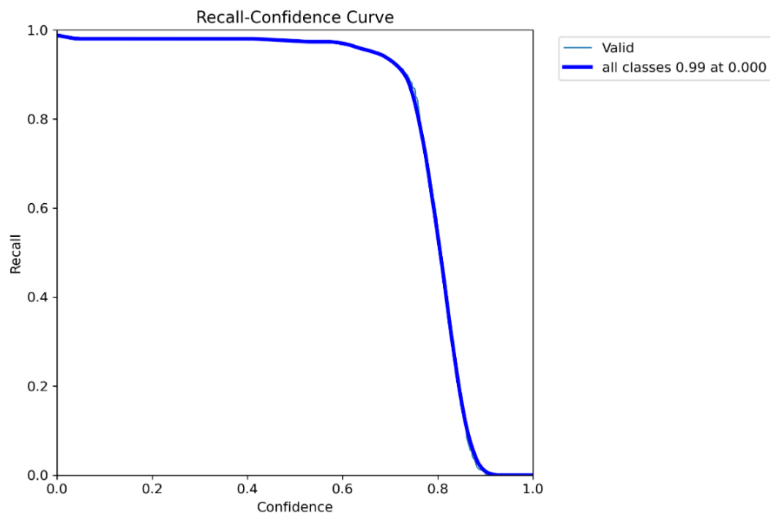
Figure 4.4.1: Precision Curve of YOLO Models

4.4.2 Recall Curve Analysis

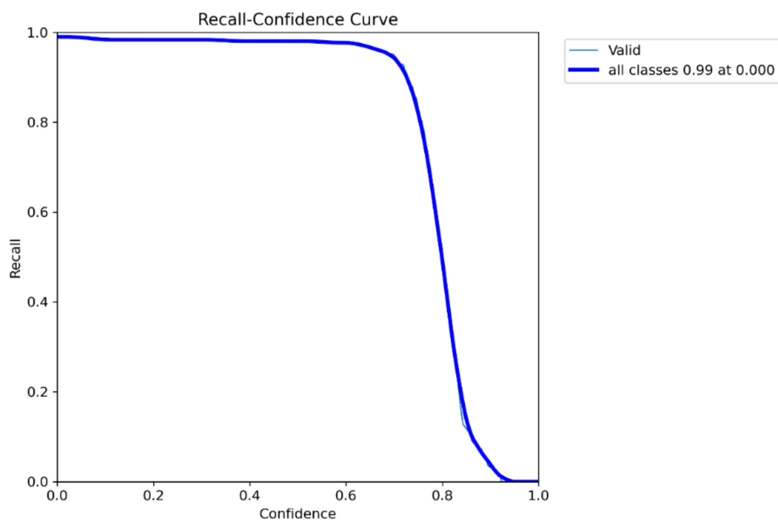
The F1-confidence curves gives an understanding of the models with precision and recall at different confidence levels. For the lower confidence range the YOLOv11 (small) performs the best and demonstrates the best F1 across the majority of confidence intervals, which means that the network is good at avoiding both false negatives and false positives across classes. At the same time, the F1-Score of Yolov8(small) and Yolov8(large) are slightly lower than the previous Yolov11(small) series. The results indicate that the YOLOv11 (small) is the most effectively balanced for recall and precision, suitable for applications that require a stable detection of objects in various situations.



(a) Recall Curve of YOLOv8s



(b) Recall Curve of YOLOv8x



(c) Recall Curve of YOLOv11s

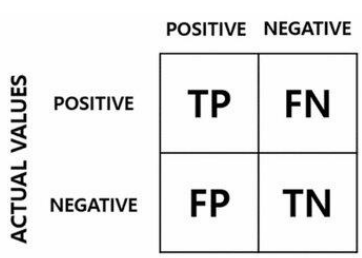
Figure 4.4.2: Recall Curve of YOLO Models

4.5 Generating Classification Report

More precisely, in the application of the license plate recognition (LPR) system, the generation of the classification report plays a vital role in the process of testing classification models where the assessment is based on their performances in the specified categories. The report includes information on the values of precision, recall, and mAP50-95 for each model, which will make it possible to analysis the performance of the system when recognizing the license plates in various conditions. It also has common averages such as the weighted average and the overall median that present an average of the model for all the models.

This is especially significant when dealing with altered data in case or even more significant when specific class values have a greater significance. Based on these measures, the classification report outlines the main advantages of the model and also provides an understanding of the need for further development in some areas in order to achieve a stable result in various scenarios.

The dataset is pre-processing, and experiment results were found from a CPU which is a core i5 processor with 8GB of RAM. ResNet50 generated the best result in our dataset. The calculation and quantitative analysis used Recall (R),Precision (P), F1-Score, mean Average Precision (mAP), Average Precision (AP), parameters, and Frames Per Second (FPS) for road pavement damage detection calculation. The formula of calculated accuracy, precision, recall, and F1-score, mAP50**-95** are shown in Table (4.5) respectively.



$$Precision = \frac{TP}{TP + FP} \qquad Recall = \frac{TP}{TP + FN}$$

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

In the model, True Positive (TP) is a positive sample and True negative (TN) is a negative sample both are predicted the better the classification level of accuracy. In, False Negative (FN) The predicted value gives a false prediction where the actual value is true, but the predicted value is false. In False Positive (FP), The predicted value gives a false prediction where the original value is positive, but the predicted value is negative. Here, the Intersection ratio IoU) indicates whether the prediction is correct or not.Accuracy is associated with how many true predictions occur in this model. The calculation predicted how many things are positive which is correct is called precision and Recall is correct predicted values. Therefore, In the f1-score the harmonic mean of recall and precision were calculated accurately which gives the overall performance of the system.

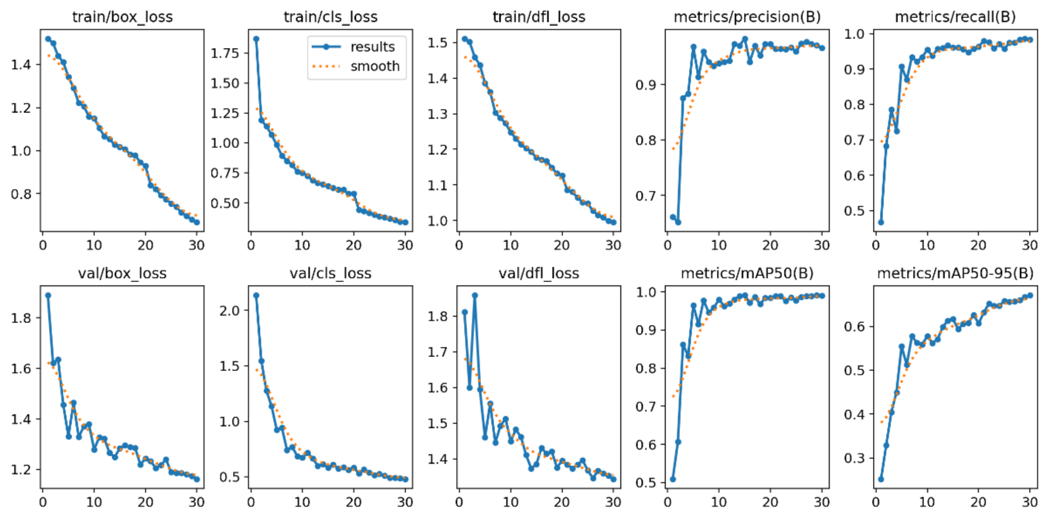
TABLE 4.5: CLASSIFICATION REPORT FOR DIFFERENT YOLO MODELS

Model	Precision	Recall	f-1 Score	mAP50-95
Yolov8(s)	0.96	0.98	0.97	0.67
Yolov11(s)	0.97	0.97	0.98	0.67
Yolov8(x)	0.96	0.97	0.97	0.64

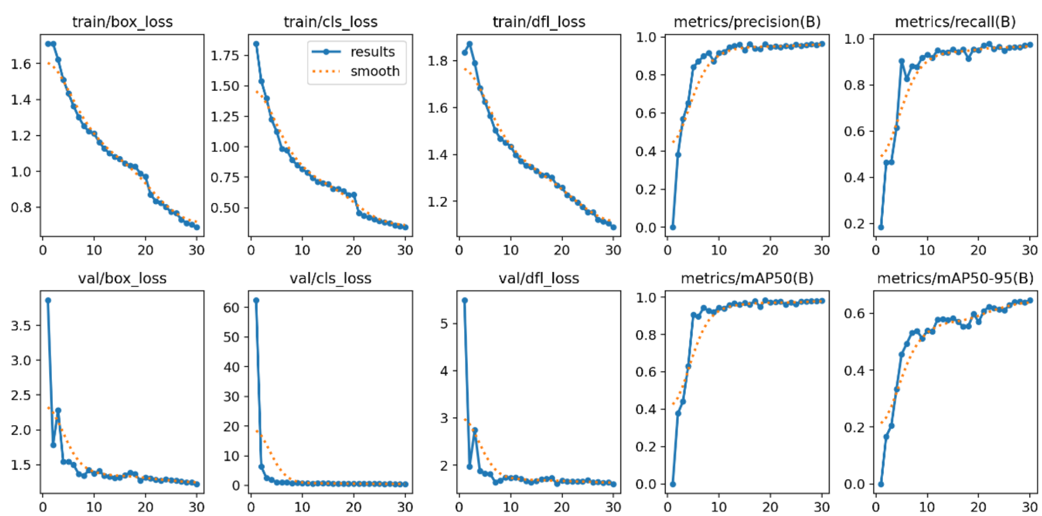
4.6 Training and Validation Accuracy and Loss Curve

We initially ran YOLOv8x for 30 epochs using the PyTorch training loop with custom callbacks. Figure 4.5 presents the training and evaluation curves after 30 training epochs.

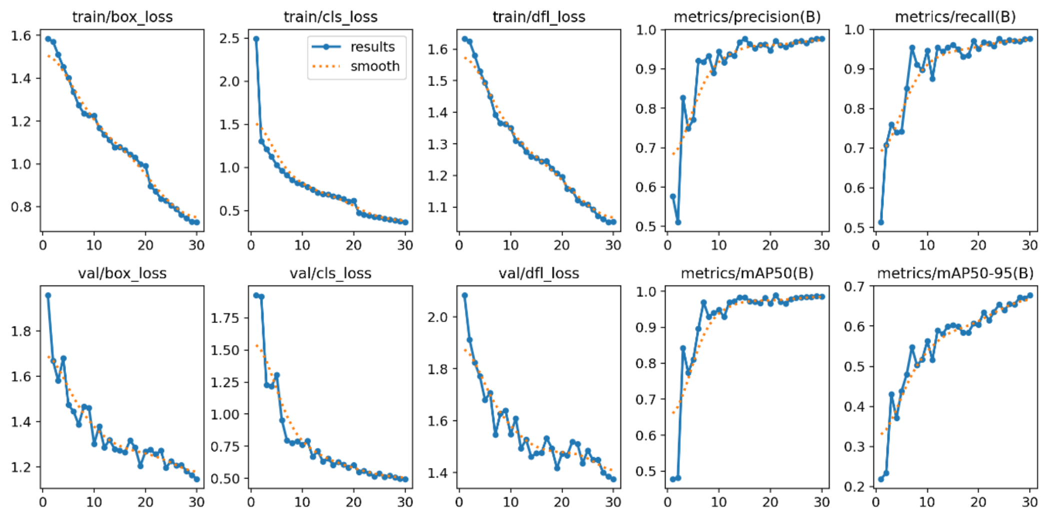
The best epoch, possessing almost 100% of preciseness both during the training and validation process, was determined to be epoch 30.



(a) Training and Validation Loss of YOLOv8s



(b) Training and Validation Loss of YOLOv8x



(c) Training and Validation Loss of YOLOv11s

Figure 4.6: Training-Validation Curve with 30 Epochs

4.7 Discussion

In the current work, four deep-learning YOLO version have been recommended to the license plate detection system We show the entire workflow of our attempt as also our work's accuracy in the study findings and analysis outcomes to be specific, yolov8s, yolov8s, yolov911s version of yolo each got an accuracy of 97%, 97% ,98% respectively once our trial was over. In particular, it should be noted that during the trial, the yolov911s model showed better results among all the other suggested simulations. The model came up with good detection precision when benchmarked against other appliances.

CHAPTER 5

Impact on Society, Environment, and Sustainability

5.1 Impact on Society

This study on number plate detection and recognition systems is of great significant to society in as much as safety and efficiency of transport systems are concerned, and economic productivity in general. In helping police forces identify vehicles accurately such systems play a crucial role in preventing and deterring crime such as vehicle theft and unauthorized use to improve societal security. The technology also includes functioning as a traffic master by collecting toll diligently, enforcing laws which prevent traffic offenses and managing parking facilities to decrease traffic hold-ups and improve transportation operations. Moreover, it also provides economic advantage through less paperwork, low operational expenses and reliable service for industries depending on vehicle tracking like logistics and pick up services. The establishment of such systems also enhances regulatory compliance because it guarantees that all vehicles that are registered within these regions legal and tax compliant constructing legal enforcement. Furthermore, technology development in number plate recognition contributes to the development of machine learning and artificial intelligence technology, which in turn contribute to the technological development of the society, effectively relevant sectors. In general, this research tackles some of society's most important objectives by enhancing protection, increasing effectiveness, and enhancing technology.

5.2 Impact on Environment

This research finds that the application and deployment of automatic license plate detection and recognition(ALPDR) systems significantly affect the environment because it reinforces sustainable and environmentally sound urban practices. Quite importantly, the management of traffic is known to lower congestion and therefore, fuel consumption and Green House Gas Emissions. Transportation is one of the leading sources of emissions, which are especially unhealthy when auto drivers delay for hours in traffic-congested areas; AVLPR mitigates these occurrences by reducing congestion and emissions in cities. This serves to help fight climate change around the world and decrease the dangers of air pollution from vehicles for the general populace. Furthermore, these systems have a critical function in compliance with environmental standards. They thus provide information on vehicles that do not conform to emission standards or break environmentally friendly policies thus promoting a shift towards environmentally friendly modes of transport including going for electric or hybrid cars. This not only makes efficiency in the use of individual vehicles a reality but also promotes a culture of legal compliance in sustainable practices. Furthermore, such systems ensure optimum application and management of transport operations, thus reducing unnecessary movements, improving routes, and subsequently, decreasing energy and emissions.

Smart technology implementation within such systems takes the environmental advantage to another level. For instance, the use of automatic tolling systems eradicates man-powered toll collection and automatic parking thereby erasing the time wasted at toll stations or parking spaces resulting in reduced energy consumption of the services. The systems also allow real-time monitoring of traffic hence appropriate responding to traffic build-up or incidences thus improving traffic flow and reducing fuel usage. Yet the factors that decide the systems' degree of impact on the environment need to persue the energy and carbon needs of the infrastructure necessary for its processing and storing. When the following challenges are addressed and energy-efficient designs and automatic license plate detection systems are installed, they maximize utilization of the technology in the environment and open up a brighter future for the ambience.

5.3 Ethical Aspects

The application of automatic license plate detection and recognition systems brings significant ethical questions that cannot remain unanswered while using the systems. The first of them is related to privacy as vehicles through technology are captured and processed, and one way or another someone may abuse the obtained data. Therefore, maintaining individual identities will be crucial, data protection should always be regulated, and privacy laws remain in place to avoid unlawful use of the information of others. The public will only be assured if there is a better understanding and realization of the extent and ability of the system. Another ethical issue is linked with the fairness or otherwise of the system in relation to its operations. The pedestrian used in license plate detection must be trained on diverse data because it is wrong to tag people from certain regions or ethnicities as criminals. This is important particularly to ensure that developers come up with solutions that are not biased to the parties involved and that will address issues that relate to the application of the system in a non-prejudice manner. Moreover, accountability and responsibility are essential elements of the ethical deployment process. The step that one should understand and has perhaps no clear answer as to who is responsible for putting into use the technology is to ensure there are clear standards that can be followed and be able to counteract the misuse or any other undesirable effects. Such operators and the stakeholders should be answerable to guaranteeing that the applied system stays in its intended capacity without violating the rights and causing harm to the user. Finally, things should come to the so-called externalization effects that relate to the contribution of the specific technology for reaffirming society's safety without invading personal rights and liberties. Such ethical considerations help to guarantee that optimized Automobile Tag

Recognition technologies fertilize society's benefits and respect fair-squeaky first principles.

5.4 Sustainability Plan

There is clearly a need to have a realistic long term sustainable development strategy for an ALPR system because the concept of sustainable development requires much more than a simplistic understanding of how the system evolved, how it will operate and in what ways it can be useful to the environment and society. On this basis, the focus of this plan is placed on the further improvement of system efficiency and energy characteristics.

Frequent Maintenance and Updates:

Users should be able to make updates of new algorithm and software to accommodate new database and new technologies. There is a need to address emerging requirements set by the changing environment laws. Optimize the model in order to keep good results when using on different data sets.

Scalability:

It has to be designed to incorporate new coverage territories as well as progressively increasing volumes of information Ensure that there is potential for the integration of more numbers of camera counts, data input and output besides the aspects of processing performance. Modate additional numbers of camera counts, data input and output as well as processing performance. Design it flexibly because nearly all these designs will be changed in future or when integrating the technologies into use.

Efficiency of Energy:

Design low power consuming hardware and use efficient algorithm for lesser power consumption. Integrate energy-saving in data centers and go virtual for a small carbon footprint. They should consider other kinds of energy to power the system by using, may be solar or wind energy.

Stability of Finances:

Establish organizational funding mechanisms like government sponsorship through grants, PPM, or Through user charges for business operations. Maintain a reliable funding stream for the continuous costs of maintenance and capital improvements without gaps.

Eco-Friendly Materials and Their Disposal:

The use of sustainable and environmentally friendly was also advocated when manufacturing system components. Set proper procedure for disposing off old or obsolete equipment.

Building Capacity and Training:

Ensure that human resource develop a culture of constant updating and include the latest technologies and practices for the personnel. Teach staff members how to use and support the system as fairly as well as efficiently as possible. Provide capability for addressing large and growth-based infrastructure management.

Investigation and Invention:

Continued research must be made in a bid to enhance the durability of the systems as well as the efficiency with which they perform their tasks. Pay more attention to utilizing technological advancement is to cut down even more environmental effects. Consult with environmental specialists to conform the above system with environmental conservation measures.

This broad strategy guarantees the appropriate consistency, flexibility, and sustainability of the ALPR system as a society's great advantage in the long term.

CHAPTER 6

Overview of the Study, Conclusion, and Future Work

6.1 Overview of the Study

This research pays more attention to an optimization model for the Automatic License Plate Detection and Recognition System(ALPDR) that will improve the detection rate for license plates. The most important discovery of the work was to develop a finely tuned structure for the successful detection of the license plates depending upon the distance of vehicles, the angle of the captured image, and variations in the color of the license plates. The model was fine-tuned on high-quality images of various vehicle types and settings to reproduce it for various real-world applications. For this study, used the YOLO algorithm, which is considered optimal for object detection. This system could be enhanced by the real-time image processing feature included in this algorithm. In this research, the activities of the developed model was assess in the process of license plate recognition for Bengali cars through training and testing it. Consequently, the conclusions of this study reveal the possibility of improving vehicle detection technologies using deep learning techniques. The model originated in this paper is a reliable and highly efficient one with various applications in transportation and surveillance systems such as police cars, traffic monitoring mechanisms, and so on. This study provides a basis for enhancing and optimizing the ALPR system in different context-dependent fields and underlines its function in promoting operational efficacy and enabling more MOS-equipped advanced automotive technologies.

6.2 Conclusions

This study successfully developed and evaluated an Automatic License Plate Detection and Recognition (ALPR) using modern technologies including YOLO

V8 and Easy OCR. From the results obtained from this work, the proposed system achieved high levels of accuracy and saved time when identifying vehicle number plates under different situations. With the help of those trends, the ALPR system offers reliable performance for traffic management, police, automobile, and other administrative purposes such as electronic tolls and identification of automobiles for registration, etc. The research is rich in the ethical issues of the use and application of the technology in particular and the concept in general All the issues regarding data privacy and Use of the technology in a fair way have been addressed. The resilience of the system also establishes the versatility of the presented proof for practical applications and future adaptations, including enhanced performance in unfavorable environments and integration with AI-related improvements. This work extremely benefits the application of ITS and promotes the contribution of computer vision for contemporary smart city facilities.98.00% accuracy is achieved using Yolov8x's unique input layered model on our custom dataset of 3500 images.

6.3 Limitations

This present article made quite a few strides towards the development of a system for automatic number plate detection, yet there are several challenges and conflicts that will need to be addressed. Generalization is likely to be reduced due to the limitation in quantity and diversity of the annotated datasets and this would severely limit the performance of the system as no generalization will be possible across vehicle models or local norms. A bias in the detection algorithm also may create a problem of misidentification, either on vehicle colors or on types, therefore it points to the need for frequent audit and correction for accurate and just results. Other issues are privacy and security, as they can demand very strong protocols for data collection, storage, and utilization with regard to legal standards and the protection of user data. Moreover, Unsatisfactory computational or infrastructural provisions would prevent a system from performing real-time data processing. Thus, optimization and investment would have to be continuous. The solutions to these problems would hold the grounds for claiming the system's reliability, fairness, and ethical application in the future. Furthermore, this study utilizes images from Dhaka city only and needs to collect images from other districts. Improve image quality using CLAHE and pursue black-and-white imaging. YOLOv8 (x) also performed well but showed occasional errors with visually similar characters, such as 'O' and '0'. Further optimization could address these issues.

6.4 Future Work

In this study, we implemented AVLPD for detecting license plates with an outperforming result. We overcome the result of the previous license plate detection model. Our model is to implement real-world applications. However, in the future, we will include other systems in this research. We will aim to Develop a smart toll management process by using YOLO-based number plate recognition models coupled with OCR and IoT technology. The system will detect its number plate using a YOLO-based model then the OCR-extracted text will be stored against a pre-registered database containing vehicle IDs and owner details. If a match is found, the toll fee will automatically be deducted toll from the linked account. and the access barrier (belt) will open for the vehicle to pass.

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