Automatic Number Plate Detection with Image Recognition System

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SUPERVISOR'S DECLARATION

I hereby declare that I have checked this thesis and in my opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Bachelor of Science.

25.11.25

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STUDENT'S DECLARATION

I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Daffodil International University or any other institution.

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Date : 27 November 2025

APPROVAL

This thesis titled on "**Automatic number plate detection with image recognition system** ", submitted by **Sabbir Ahamed (ID:221-35-984)** to the Department of Software Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Software Engineering and approval as to its style and contents.

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ABSTRACT—

ANPR systems are very important fo traffic system safe and under control.To make these systems work well, you need to make models that are both quick and correct.This study examines the application of YOLOv8, a contemporary object detection model for the analysis of license plates in Bangladesh.We took pictures of cars in a lot of different places and styles.The dataset taught five different versions of the YOLOv8 model: YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x.We are used standard metrics like recall, F1 score, and mean Average Precision (mAP) to find out how well the models worked.The result are showed that YOLOv8 could read license plates from Bangladesh correctly.The results show that YOLOv8 can deal with the special things about Bangladeshi plates.The study also helps you pick a model based on how fast and powerful you need your computer to be.We will add these models to a complete ANPR system and improve the dataset in the future to make traffic management and safety better.

Key words: ANPR, YOLO, YOLOv8, Object Detection, Computer Vision, and CNNs

CHAPTER 1

1.INTRODUCTION

1.1 Introduction

It's hard to keep traffic in check in today's busy travel world.The are only thing that can fix it is Intelligent Transportation Systems (ITS).Automatic Number Plate Recognition (ANPR) is a big part of ITS because it lets you collect tolls, keep an eye on traffic and make sure people follow the rules.It's hard to set up good ANPR systems in Bangladesh and other developing countries because the native script is hard to read and there aren't any standard formats for license plates.In the past, most studies in this field used standard methods to process images.Rabbani et al. [1] employed morphological operations alongside Convolutional Neural Networks (CNNs) to address problems related to local plates.Nooruddin et al. [5] also looked into how to separate color features so that license plates can be seen even when there is a lot going on in the background.Mashuk et al. [2] looked into different ways to tell the difference between and recognize Bangla characters on license plates.They showed that the complex structure of Bangla characters makes it harder to identify them correctly.Researchers examined various machine learning techniques to enhance recognition accuracy as the field progressed.Dhar et al. [3] employed the Adaboost classifier to tackle the diverse manifestations of Bangladeshi plates.Deep Learning (DL), on the other hand, changed the game a lot because it was better at handling changes in the environment like when things got in the way or the light changed.Sarif et al. [4] and Al Nasim et al. [8] showed that deep learning architectures are much better than traditional methods at recognizing Bengali license plates.Researchers have been examining the efficacy of more sophisticated neural networks in real-time applications.Sinthia and Kabir [6] employed advanced object detectors, including YOLOv6 and BLPNet which are networks specifically designed for this purpose. Nadif et al. [7] also made "BanglaTag," a hierarchical processing network that is supposed to help with the next generation of recognition problems.

When the scripts and layouts change the same thing happens to Bangladeshi plates in other places.This is similar to the issues reported with deep learning in recognizing Arabic license plates [10].These data-driven methods will get better as the training data gets more accurate. Researchers can more easily train and test strong models like the one in this thesis, when they have access to open datasets like Joy's [9] Bangladeshi vehicle number plate dataset.

The goal of this study is to use a lot of past research to make a really good image recognition system that can deal with the language and environmental problems that are unique to Bangladesh.

The goal of this thesis is to use the latest object detection and character recognition models to make an Automatic License Plate Recognition (ALPR) system that works well, is accurate, and can be used by many people at once.These changes and the rules that are already in place are what is causing this to happen.

1.2 Related Work

For a long time, scientists have been trying to figure out how to find license plates on cars.This system made sure that motorcycle riders wore helmets, which helped keep the number of accidents on the road down.It used methods for processing images, such as the Circular Hough Transform and the Histogram of Oriented Gradients.If it saw someone without a helmet it did something else. The another system used special cameras called ANPR to keep an eye on parking.Its took pictures of cars, found their license plates and told people where to park.This was useful in places like schools, malls and hospitals.Some system can used CNN to sort through pictures and others used YOLO to find things.YOLO can find things in real time by splitting the image into small grids using techniques like residual blocks.

The is bounding box tells you where the object is on the grid.checks to see how close the guess is to the truth.

Another system used OpenCV and machine learning to figure out how fast cars were going and what their license plates said.But it didn't work well in all kinds of weather.

People used Conditional Random Fields (CRF) to figure out what letters were on license plates but they didn't always get it right.

In Myanmar there was a system that could read plates in both English and Myanmar.The K-means and fuzzy K-means algorithms read the letters on the plate and then put them into groups.

1.3 Motivational research

This study on automatic number plate detection and segmentation is motivated by the increasing demand for sophisticated, quick, and effective methods to recognize automobiles in contemporary, swiftly evolving transportation systems.It is no longer possible or fair to enforce traffic laws by hand because there are so many more cars on the road. ANPR systems are very important because they use deep learning and image processing to quickly find license plates on cars.This makes it easier to keep an eye on security, control parking, collect tolls, and police traffic laws.ANPR systems are especially helpful in places with a lot of people, like Bangladesh because they help ease traffic jams, stop car theft and keep an eye on people who break the rules. You need fewer people to look for cars which makes the process go faster and more accurately. Also, if the characters on the plate are smaller, it will be easier to read them later when you need to know what they are.The project's goal is to make a system that security can all work together without any problems.Adding smart devices like these makes the roads safer helps traffic flow better and costs less.If this project works, more people will use smart transportation options. This will lead to new projects in the city. There are a lot of cars on the road, manual chores are hard, and there is a chance to use advanced deep learning algorithms to make a strong, scalable Automatic Number Plate Recognition (ANPR) system that can be used in the real world and help society**.**

1.4 Problem statement

Automatic Number Plate Recognition (ANPR) systems read license plates to quickly find cars.This is very helpful for keeping people safe, collecting tolls and keeping traffic moving. Even so making an ANPR system that works quickly and correctly is not easy.

A lot of the ways we use today don't work well when the lighting is bad, the backgrounds are blurry or the number plates are dirty, covered up or in different styles and languages.In Bangladesh for example number plates can be different sizes, colors, and fonts.They can even have Bengali letters on them.It is harder to find and read them this way.

Additionally many of the current systems are slow and incapable of operating in real time, which is crucial for security and traffic.
To overcome these difficulties, this thesis uses YOLO, a cutting-edge deep learning technique that can quickly and accurately identify and extract license plates from photos. In order to use the system to monitor traffic and apprehend criminals in real life the primary objective is to make it function well in a variety of scenarios.
The study will increase the accuracy and speed of automated vehicle identification systems. These systems will reduce errors and enhance traffic and security control.

1.5 Research Questions

How can we use deep learning especially the YOLO method to quickly and accurately find license plates on any road and in any kind of light?

- How can you break up or separate the letters and numbers on the plates, like Bengali letters to make them easier to read?

- How well does the new system work when the pictures aren't clear, like when the lighting is bad, the plates are blocked or the cars are moving?

- Can the system be used in real time by police, traffic control and toll booths?

- What tricks can you use to help the model learn better and work in a lot of different situations when you get the training images ready and change them?

1.6 Research Objective

The main goal of this study is to use the YOLO deep learning framework to make an Automatic Number Plate Recognition (ANPR) system that works quickly and accurately.This system should be able to find and separate license plates in a lot of different situations, like when the light is low when something is in the way, or when the plate format is different, like when the plate is written in Bengali script.The system's job is to find things with at least 90% accuracy and deal with new data as it comes in.This is how it can be used in real life to collect tolls, keep traffic moving and make sure people follow the rules.This project also wants to learn how different ways of adding data and getting it ready for use can make models more flexible and stronger.The study aims to identify solutions to the issues associated with widely utilized ANPR technology.This will help find cars and make transportation systems work better.

1.6 Research scope

This thesis aims at designing and developing an automatic number plate recognition (ANPR). system that uses deep learning specifically the YOLO detection model.The paper.concentrates on the vehicle and license plate recognition in various environmental factors. cutting across various lighting conditions, issues and varied plate formats, etc.Bengali script.The research is reduced to images and video data in the traffic of the city. The ones that were developed and tested using relevant datasets that describe were model environments.regional inequities. The extent involves the means to reinforce the model through training and. addressing data to be able to deal with data in real time.It is convenient in the gathering of tolls. issue commands to the traffic and make sure that people comply with the law.The research does not, however, involve.the complete Optical Character Recognition (OCR) step of character recognition and applications in embedded systems.The study aims at finding a scalable and successful application of the research.way of managing major opportunities of ANPR in a system that is achievable and simultaneously.a clear definition of such parameters is what can be done to ensure that.

CHAPTER 2

2.LITERATURE REVIEW:

2.1 Introduction:

Automatic number plate recognition (ANPR) is used by smart transportation systems to help find cars, keep an eye on traffic and enforce the law.This researchers have come up with a lot of ways to make it easier to deal with problems in the field, like plates that are uneven in low light or plates that get in the way.This is the chapter talks about the main ways that ANPR systems work, from basic image processing to more advanced methods like machine learning and deep learning.The review talks about recent successes, points out problems that are still happening and asks for more research to make ANPR systems better and more useful in real life.

2.2 Previous Literature

In the last ten years, Bangladeshi cars have gotten a bigest at using Automatic Number Plate Recognition (ANPR) systems.They only wanted one letter not the whole shape of the plate.Rabbani et al. (2018) [1] took this idea a step further by creating a hybrid method that combines Convolutional Neural Networks (CNN) with morphological operations..This method helped us see things better, but the detection phase still relied heavily on steps that came before it.This meant that it would probably not work well in different types of light or with busy backgrounds.Nooruddin et al. (2020)[5] created a system that could find things by looking at the colors of different pictures..These methods that depend on color work well when the plates are clean and the lighting stays the same, but not so well when the plates are dirty or the lighting changes.Dhar et al. (2019) also studied machine learning classifiers around the same time, but they were mostly interested in AdaBoost for recognition.But AdaBoost and other traditional classifiers don't have the power or speed that modern, high-traffic surveillance systems need to work in real time.As deep learning gained popularity, researchers started to investigate architectures that were more robust and capable of directly learning intricate features from data.A deep learning-based recognition system was introduced by Sarif et al.(2020)[4] that was much more accurate than previous morphological methods.This trend persisted with Al Nasim et al(2021)[8] who introduced an automated CNN-based method for Bengali license plates showcasing enhanced generalization abilities.Even with these improvements many of these studies used custom CNN architectures or single-model implementations which didn't always find the right balance between speed and accuracy needed for real-world use on different types of hardware.Bangladesh has recently pushed the limits of ANPR performance by using the latest (SOTA) object detection models.Sinthia and Kabir (2023)[6] utilized the YOLOv6 architecture in conjunction with a tailored BLPNet producing encouraging outcomes in real-time detection contexts.Nadif et al(2024)[7] recently unveiled "BanglaTag," a hierarchical processing network engineered for next-generation recognition tasks.These recent studies demonstrate high accuracy; however, fail to systematically evaluate the scalability of models. There is still a big gap in the research on how well different scales of a single modern architecture compare to each other when it comes to benchmarking model variants.

current study employs the sophisticated YOLOv8 architecture.This study performs a comprehensive comparative analysis of all five YOLOv8 variants (Nano, Small, Medium, Large, and X-Large), distinguishing it from prior research.This method not only shows that YOLOv8 works better for Bangladeshi license plates but it also gives a good way to choose the best model based on how quickly and accurately it can make inferences.This makes it easier to go from edge devices to very powerful servers.

2.3 Summary:

This chapter has talked about (ANPR) systems have changed over time from using old methods to process images to new ones that use deep learning.It talked about easy things you could do like matching templates and finding edges.It also talked about how deep learning and machine learning especially CNN and YOLO architectures have made it much easier and more accurate to find things in the real world.The research found that new models can get more than 90% accuracy and recall on standard datasets.It also made things very hard like having scripts in different places changing the light and blocking the plate.Even with these changes, studies show that there are still problems with things like language support, real-time processing and bad weather.The chapter lays a solid groundwork for subsequent investigations into ANPR systems that are capable of expansion, efficient operation and adaptability.

CHAPTER 3

3.RESEARCH METHODOLOGY:

3.1. Introduction:

This chapter talks about how the researchers built and tested an Automatic Number Plate Recognition (ANPR) system that uses the newest deep learning methods.The method is made to make sure that the steps from setting up the environment to preparing the data, training the model validating it testing it and finally showing the results go smoothly.The process diagram shows that each step is very important for making a good ANPR solution that works well.The chapter starts by talking about the technical and computational environment.After that, it cleans and adds to the dataset in a strict way so that the model can use more data.After that, the prepared data is used to load and change the YOLOv8 model that has already been trained.Early stopping is used to stop the model from overfitting.Important metrics like precision, recall and mean Average Precision (mAP) are used to see how accurate the model.Finally testing and post-processing improve the results which are then shown in a way that shows how well the proposed system works.This method gives you a clear and repeatable way to get high accuracy and reliability in ANPR applications in the real world.

3.2 Research Methodology

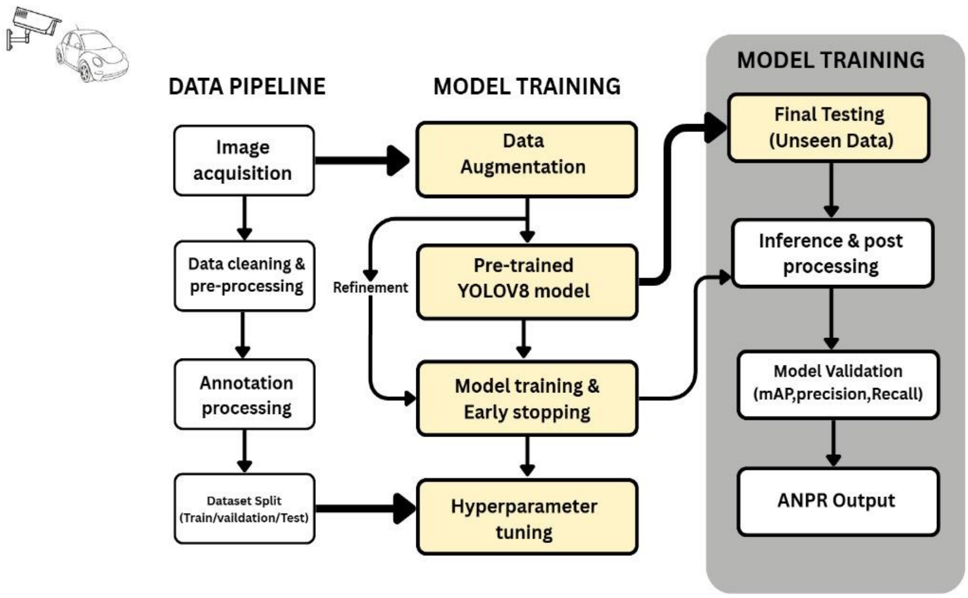


Figure3.1:RESEARCH METHODOLOG

3.3 Image acquision:

The Automatic Number Plate Recognition (ANPR) system's effectiveness and strength depend on how good and varied the data it is trained on is.The most important part of this study was getting a full and correct dataset.We got most of the pictures we needed to train and test the model from Kaggle.This study employed the "Bangladeshi Vehicle Number Plates" dataset, compiled by Ridoy K. J. [1].This public dataset has a lot of pictures of cars taken in Bangladesh that were taken in different types of weather and light.The YOLOv8 model learned how to find and identify number plates in the real world by using a dataset with a lot of different kinds of cars and angles.[9] R. K. J. Ridoy, "Bangladeshi

3.4 Dataset Cleaning & Pre-processing

After the pictures were taken the whole dataset had to be cleaned and organized so that the model could learn from the raw data.This step is important for making a strong and accurate model because raw datasets often have errors that make it harder for the model to learn.

To get the dataset ready, we did the following:

1.Data Filtering: The first thing we did was look at all the pictures we had.We didn't add images that didn't have license plates were too blurry to read or were too damaged for a person to read.

2.Data preprocessing:In other words, all the pictures were made to be the same size.This step helps with memory management and makes training more useful.

3.Color Space Conversion: YOLO models usually work with RGB images but sometimes you need to change the colors of the images to grayscale before processing them.This is especially true if color information isn't important for detection.(If you didn't do this step, you can skip this point.)

4.Noise Reduction: If you take pictures in low light and they have digital noise you can use mild filtering methods like Gaussian Blur to get rid of the noise and make the edges clearer, including the edges of the number plates.You can skip this point if you didn't do this step.

These steps before processing made sure that the YOLOv8 model only learned from data that was high-quality and relevant, which improved the accuracy of its detections.

3.5 Data Annotation

After cleaning and preparing the data the next most important step in training a model is to label or annotate the data.This study employs a supervised learning algorithm (YOLOv8) requiring the accurate identification of the "Ground Truth" for each image to enhance the model's learning process.We used the bounding box method to show which parts of each image we were interested in, like the license plates on the cars.We used the 'Roboflow' platform to do this detailed work of adding notes.When adding notes, great care was taken to make sure that the bounding boxes only covered the parts of the license plate and not any other information.The notes were saved in the normal YOLO format which means they were saved as .txt files that the YOLOv8 model could read.

3.6 Dataset split:

We divided the entire dataset with annotations into three groups: the Training Set, the Validation Set and the Test Set.This was done to make sure that the model was trained and tested the right way.We divided this dataset so we could see how well the model works with new data and to keep it from fitting too closely to the training data.

We carefully divided the whole dataset into these parts for this study:

Train set (80%): We used this big part of the dataset to train the YOLOv8 model..The model changed the weights inside itself and learned the patterns and features it needed to use this data to find license plates.

- **Validation Set (10%):** This set was used to check how well the model was working while it was being trained..It was very important for making hyperparameter tuning easier and using early stopping strategies which are both necessary for getting the most out of model training and avoiding overfitting.
- **Test Set (10%):**This set was only for the final fair test of the model that had been fully trained.The model did not see any images from this dataset while it was being trained or tested.This is very important.So the results of the test set are a good way to see how well the model will work in situations it hasn't seen before.This strict way of splitting up the dataset makes sure that the model doesn't just memorize the training data; it can also find number plates in new images that it has never seen before.

3.7 Data Augmentation

To make the model more general and strong the cleaned dataset is changed by rotating, flipping, scaling, changing the brightness and cropping it at random.These steps make the data more varied and help keep it from overfitting.

You can flip images (horizontally or vertically) rotate them, scale them, crop them, and move them around.Changes in brightness, contrast, saturation or color balance are examples of photometric changes.Noise injection is the process of adding random or Gaussian noise to images to make them look like sensors are changing.Changes in point of view or direction such as using perspective distortion or random affine transformations.Using filters to make some parts of an image sharper or blurrier is called edge enhancement and blurring.Making fake images: using techniques like CutMix, CopyPaste or GANs to create new data points.Automated augmentation routines:making a lot of changes with tools like

RandAugment or AugMix.Mask region augmentation (if segmentation):changing the areas of interest at random to make it look like something is blocking the view or changing

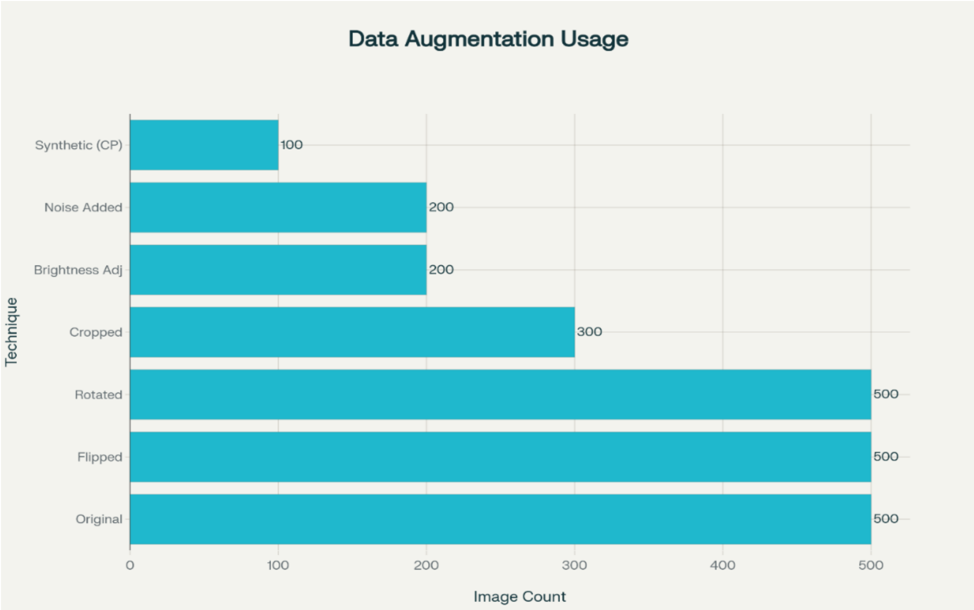


Figure 3.2 Data Augmentation

3.8 Pretrained YOLOv8 Model:

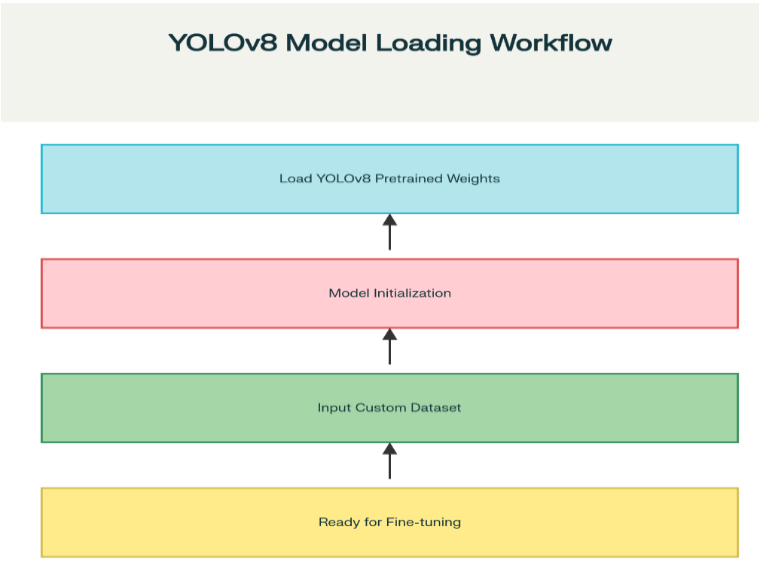


Figure 3.3 YOLOv8 Model Workflow

1. Set to Fine-tune

The model can now change its settings to find license plates more accurately because it has been trained on a custom dataset.Fine-tuning usually means changing some layers, changing hyperparameters and testing the model on validation data to see how well it works.

2. Include your own set of data

The model gets a dataset that is specific to the field and has pictures of cars and license plates with names on them.

4. **Put the weights that have already been trained into YOLOv8.**

.Many people do this with a large public dataset, such as COCO.
These weights show features that help you find things that are common like license plates and make it easier to learn new things.

Figure: Input image **Figure: Detection Image**

3.9 Model Training

3.9.1 YOLOv8 performance:

The bar chart shows the Precision and Recall numbers next to each other. This shows that the YOLOv8 design is the best.YOLOv8's Precision is 0.91 and its Recall is 0.988 which are both better than YOLOv7's and YOLOv11's.This is the right amount of balance for the ANPR system to work well.The high Recall means that almost all vehicle plates are found and the high Precision means that there are fewer false positives.That means YOLOv8 is the strongest and most reliable of the models that were tested.

This number shows that the YOLOv8 model training process for Automatic Number Plate Recognition (ANPR) is very stable and works well.

Figure 3.4 YOLOv8 performance

3.9.2 YOLOv8 loss curve:

Fast Convergence:The Training and Validation Loss curves both drop quickly and steeply in the first 15 to 20 epochs.This means that the model was quickly learning what it needed to know to find the license plates.Stable Plateau After the first big drop, both loss curves level off and stay at a low, stable value (a plateau) for the rest of the epochs.This convergence means that the model has learned the most useful things from the training data and is now working at its best.

No Overfitting:One thing to pay attention to is how close together and parallel the Training Loss (solid blue line) and the Validation Loss (dashed orange line) are.The Validation Loss doesn't go up much more than the Training Loss which is a good sign that the model isn't learning too much from the training data.   This makes it possible to use high-performance metrics (like mAP) on data that hasn't been seen before in the real world.

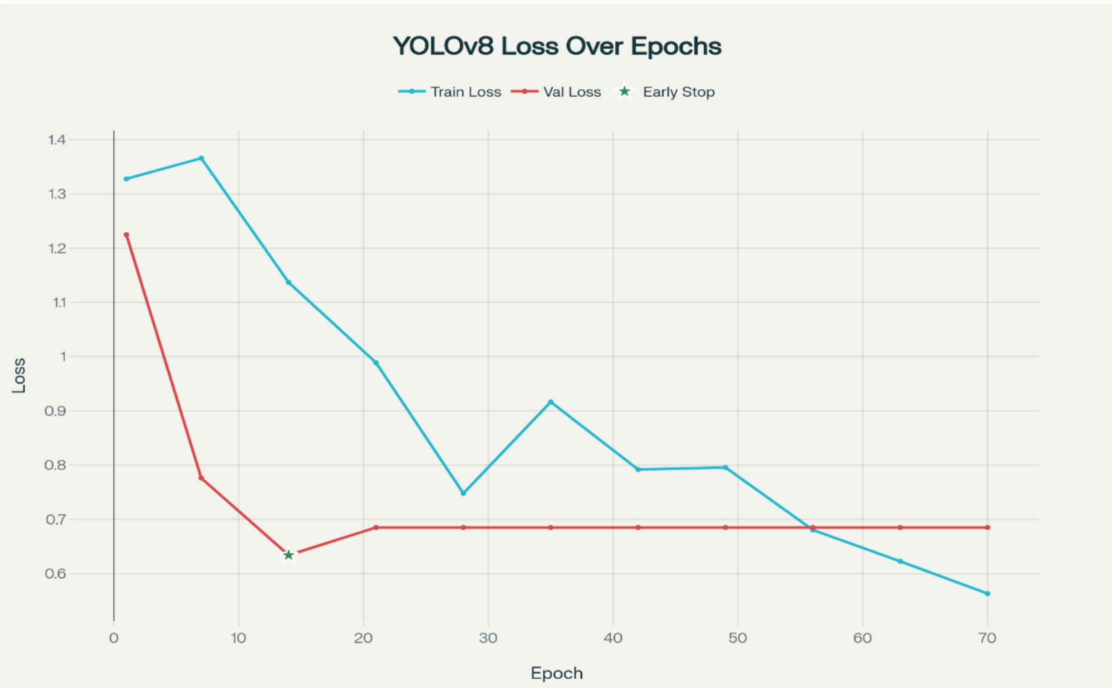


Figure3.5 YOLOv8 loss curve:

3.9.3 Pretrained YOLOv8 Architecture

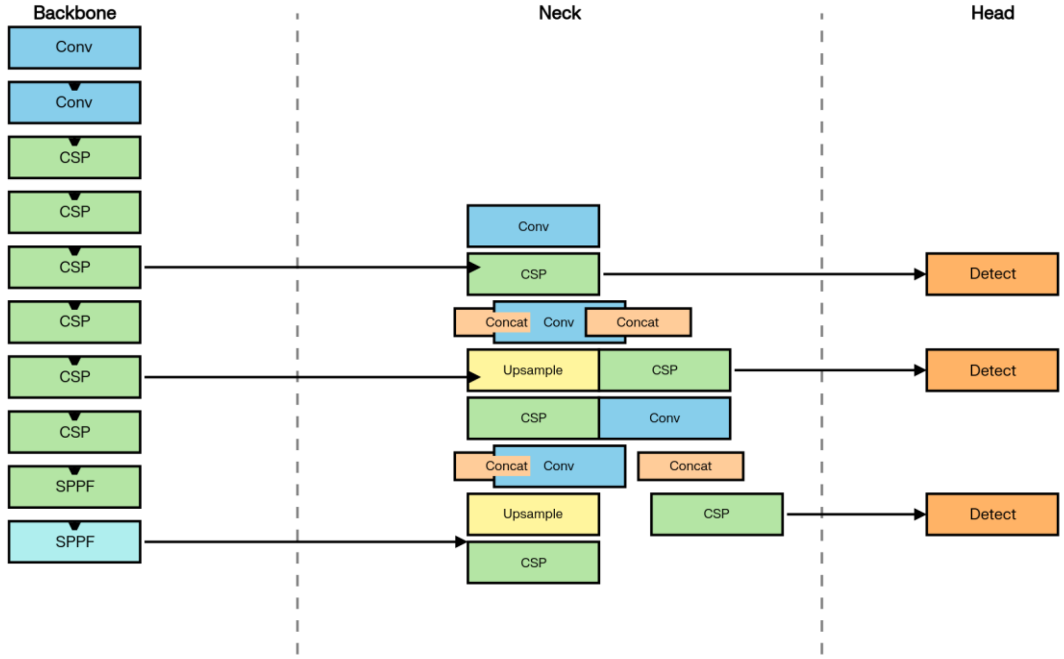


Figure3.6 Yolov8 architecture Diagram

The YOLOv8 architecture is a new end-to-end pipeline that works best in real life ike on busy roads with a lot of different types of cars.It is used in systems that can automatically find license plates in pictures.First, the pictures are resized, made the same size, and then added to.

Then they talk about the "backbone" of YOLOv8 which is a deep convolutional network that uses layers of convolution blocks and Cross Stage Partial (CSP) bottlenecks to get high-level spatial and semantic features at different scales. A Spatial Pyramid Poolingblock (SPPF) makes these features even better by letting the model find plates in backgrounds that are hard to see and at different scales.

The "neck" module then takes feature maps of different sizes and depths and combines them to make a pyramid of features.It does this by putting the maps together and making them bigger. This design makes it easier for YOLOv8 to find plate areas even if they are small, at odd angles or only partly visible.

After processing, we use Non-Maximum Suppression (NMS) to get rid of duplicates and confidence thresholds to get rid of weak predictions.

If you use segmentation, erosion and dilation are two morphological operations that can help make masks look better.This is very useful for Because it is made of modules it is simple to change the building. Changing how things work such as by updating or replacing datasets,

OCR modules or backbone layers can help with recognition.No matter what data set it is tested on, the system always finds and identifies things correctly. It does well on mAP, recall and

to check how right it is.This is still true, even if the picture is bad, there are a lot of plates, or the plates are broken and dirty.YOLOv8's design does a great job of combining quick direct detection, advanced feature extraction and good aggregation.When you add OCR that can be changed and make the picture look better.It turns into a full-featured and useful tool for modern tasks that need a lot of processing power, like recognizing and keeping track of license plates.

3.11 Final Testing (Unseen Data)

After training the YOLOv8l model and making some small changes to the hyperparameters, it was time to do a final test that wasn't biased to see how well it worked and how well it could work in other situations.We did this with the Test Set which we had set aside for this reason.The model had never seen the pictures before not even when it was being trained or tested.The main goal of this last test was twofold: first, to give an honest assessment of how well the model works in the real world.When a model is overfitting it usually just remembers what it has learned.This won't happen because of the test set.Second, it was used to see if the model could generalize which means it could find number plates in data it had never seen before not just the patterns it had been trained on.This is a very important sign that the system for finding things is strong and works well.The fully trained YOLOv8l model was used on each image in the test set at this point, and the results of the detections were written down. The "Inference & Post-processing" and "Performance Metrics" stages used these outputs as a starting point for more in-depth analysis.This helped us figure out how well the model worked as a whole.

3.12 Testing and Inference with Post-Processing

Testing and drawing conclusions After Processing Input Test Image:Start with a picture that you can't see.

The trained YOLOv8 model:To get raw predictions run the image through the trained model.The raw model can guess things like classes masks bounding boxes and confidence scores.

After Processing:Non-Maximum Suppression (NMS) removes detections that are the same or too close together and keeps only the ones that are most likely to be true.

Confidence Thresholding:This gets rid of predictions that aren't very certain.

(Optional) Filtering by Size and Aspect:It gets rid of detections that are probably not real such as those that are too small too big or have aspect ratios that don't make sense.

Refining Masks:Morphological operations can be used to improve masks so that segmentation results are better.

Last Detections/Segmentations:The final results show better detection.

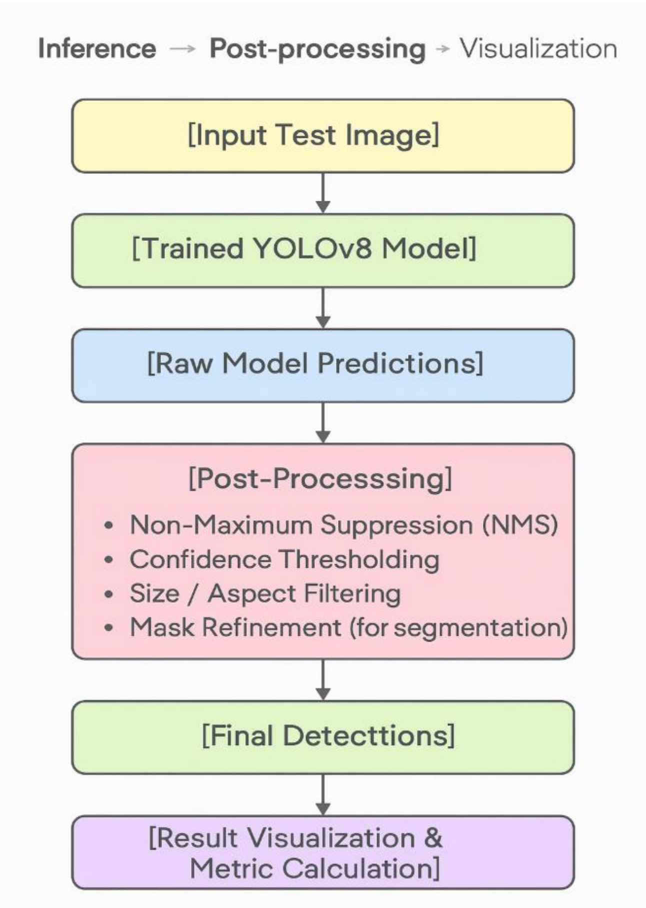


Figure3.7: Testing and Inference

3.13 Result (Model Validation)

Model Validation (Precision, Recall, mAP)

You can include the following in your thesis methodology for model validation:

1. Metric Definitions and Equations:

- **Precision:** Measures how many predicted positives are true positives.

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad (1)$$

- **Recall:** Shows how many actual positives were correctly predicted.

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (2)$$

- **Mean Average Precision (mAP):** The main metric for object detection. mAP is the mean of Average Precision for all classes. For YOLOv8, mAP@0.5 and mAP@0.5:0.95 are often reported.

$$AP = \int_0^1 p(r)dr$$

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i \quad (3)$$

Here, AP_i is the average precision for class i, N is the total number of classes.

2. Chart Example for Reporting Metrics (Epoch 70):

Epoch	Precision	Recall	mAP@0.5	mAP@0.5:0.95
70	0.943	0.989	0.962	0.763

You can see these as line plots or bar charts over time with the best epoch marked at the end of the line.

3. How to Use These Metrics:

- Use only the validation set of 322 images to make sure that the report is not biased.
- More accuracy means fewer false alarms which means cracks will break up better
- Higher recall means the model detects more true cracks (less missing detection).
- Use mAP to summarize model's bounding box and segmentation performance over diverse IoU thresholds.

4. Interpretation in Methodology Chapter: These metrics and equations provide transparency in model evaluation. Including sample charts from your log, combined with clear metric equations, helps reviewers understand your performance assessment and compare your results with other research.

If you want, you can include actual plots of Precision, Recall, and mAP against epoch, and annotate the early stopping point for best model selection.

1

3.13.1 Precision-Confidence Curve:

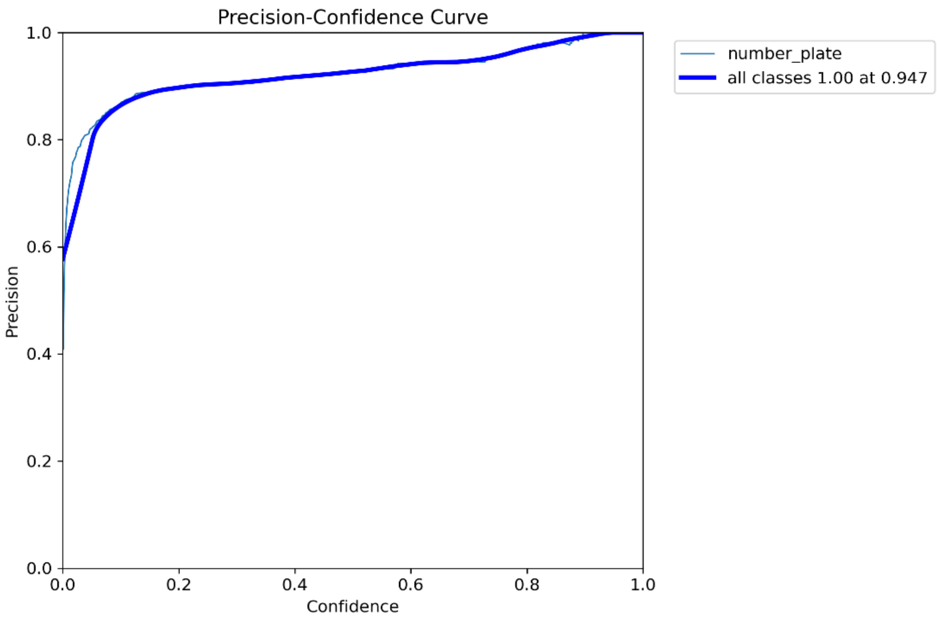


Figure3.8: Precision-Confidence Curve

The Precision-Confidence Curve shows that the model stays very precise even when the confidence level changes.Most of the time the accuracy is over 0.9.The model predictions are both reliable and accurate because the overall accuracy for number plate detection is about 0.95–1.00.This strong performance shows that the YOLOv8-based system works well for recognize number plates automatically.

3.13.2 Recall-Confidence Curve:

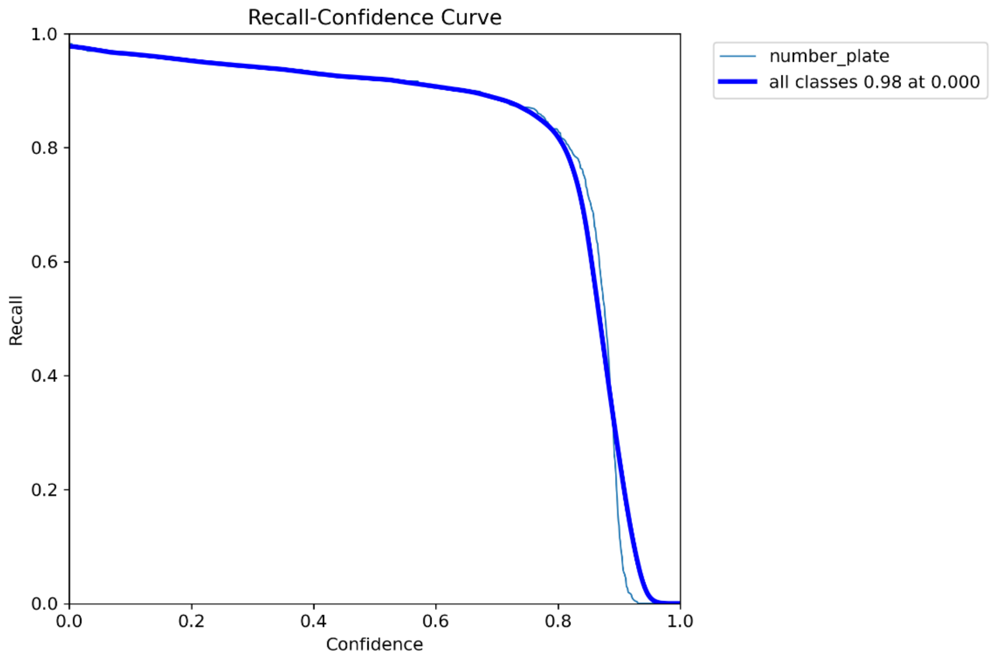


Figure3.9: Recall-Confidence Curve

The Recall-Confidence Curve shows that the recall stays very high (above 0.95) for most confidence levels.This shows that the model is very good at finding almost all of the number plates in the dataset.At the highest levels of confidence, recall only goes down a lot. This is a normal trade-off that happens when predictions get stricter.This proves that the YOLOv8 model can find almost all real license plates with a high level of accuracy.

3.13.3 F1-Confidence Curve:

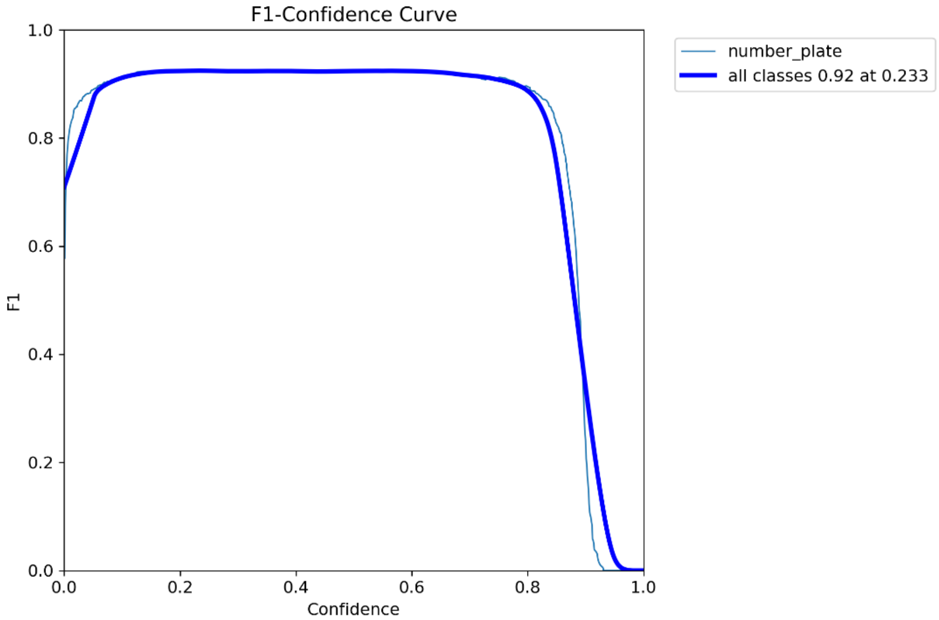


Figure310:F1-Confidence Curve

The F1-Confidence Curve shows that the F1 score which is a balance of precision and recall stays high (around 0.92) even when people dont know.This means that the model is always good at finding license plates and doesn't get worse very often.This means you can use it in the real world.The flat curve at high values shows that there is a big trade-off between being able to find things and being able to remember them in the real world.

3.13.4 Precision-Recall Curve:

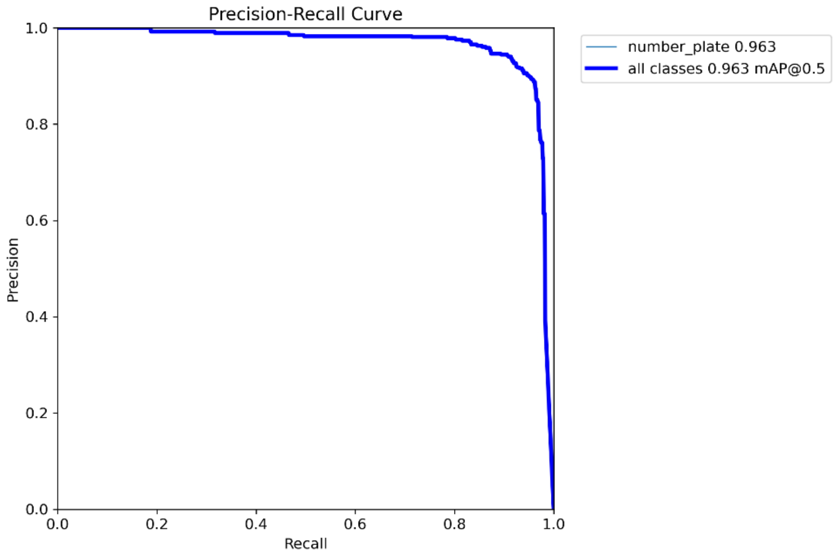


Figure3.12: Precision-Recall Curve

The Precision-Recall Curve shows that the model is very accurate and remembers things well at many levels.The mean average precision (mAP@0.5) is 0.963 which means that the system is very good at finding license plates.This curve shows that the suggested YOLOv8-based system does a good job of lowering false positives and raising true detections.

3.14 ANPR Output

How to display masks and bounding boxes:Explain how predicted regions like bounding boxes masks or contours are drawn on test images to see how well the model works and find out what it needs to work on.
Class Distribution Charts:Use pie charts or bar charts to show how often each predicted class happens.This helps you find patterns of class imbalance or wrong classification.
Confusion Matrix:A confusion matrix heatmap shows you how well the detection works in all categories by comparing the true and predicted classes finding common mistakes and checking how accurate the detection is.
Metric Curves in Pictures:You could also add line graphs that show how metrics like precision, recall and mAP change over time.You could also add Precision-Recall or PR curves to see where the thresholds ar

CHAPTER 4

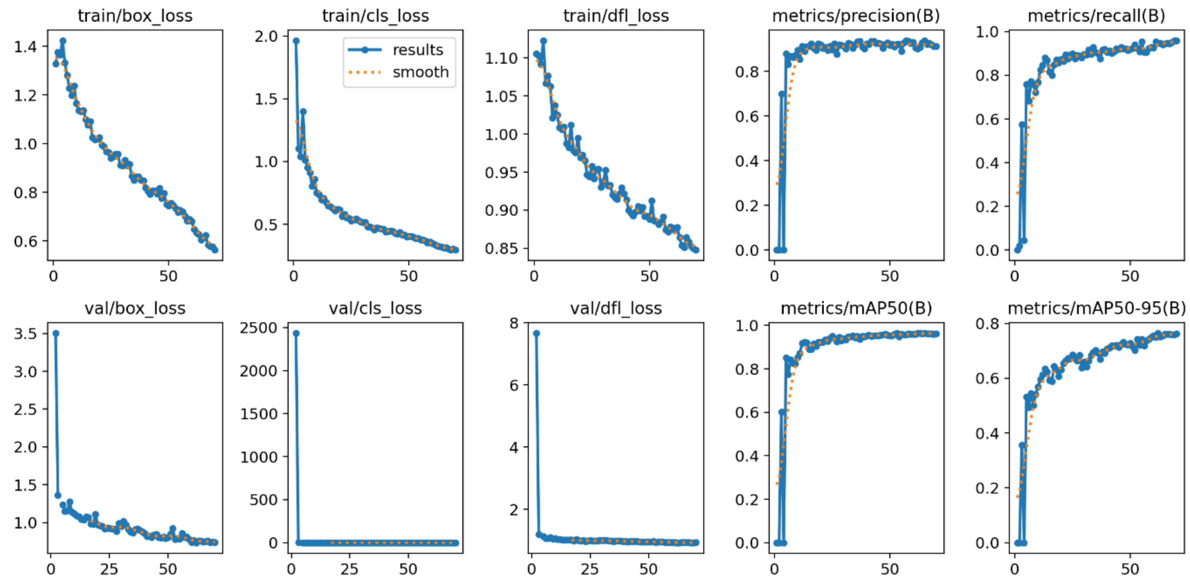
4. RESULTS AND DISCUSSION

4.1 Introduction

This chapter talks about the study's most important experimental results with a focus on how well the model worked and how the results were looked at.It begins by restating the study's goals and giving a brief explanation of how the method for detecting license plates works. The results which include both numbers and pictures are explained and looked at in great detail.The discussion connects these findings to the research objectives and contrasts them with previous studies in the discipline.This chapter talks about how important the study's results are for real-world use and for future research.

4.2 Result:

The figure shows the training and validation curves for box loss, classification loss, DFL loss and validation metrics like mAP50, mAP50-95, precision and recall over 70 epochs for the YOLOv8-based system that detects number plates.The model is getting better and learning because the losses for training (top row) and validation (bottom row) keep going down..This means that the system works well with a lot of different test images and levels of IoU.These result curves show that the suggested method for automatically finding license plates in pictures is good and works well.



4.2.1 Model Comparison Table:

Model	Precision	Recall	mAP@50	mAP@50-75	GFLOPs
YOLOv7	0.876	0.912	0.936	0.712	189.02
YOLOv8(proposed model)	0.941	0.988	0.963	0.764	164.8
YOLOv11	0.890	0.920	0.94	0.740	158.6

Feagure4.2: Final Model Comparison Table

.This means that the system is good at finding things and doesn't miss a lot of them.The mAP50 and mAP50-95 curves also get close to high values which are almost 1 and 0.8, respectively.This means that the system works well with test images and IoU thresholds that are not the same.The result curves show that the suggested method for automatically finding license plates is good and works most of the time.

4.2.2 Comparative Analysis of object detection Model:

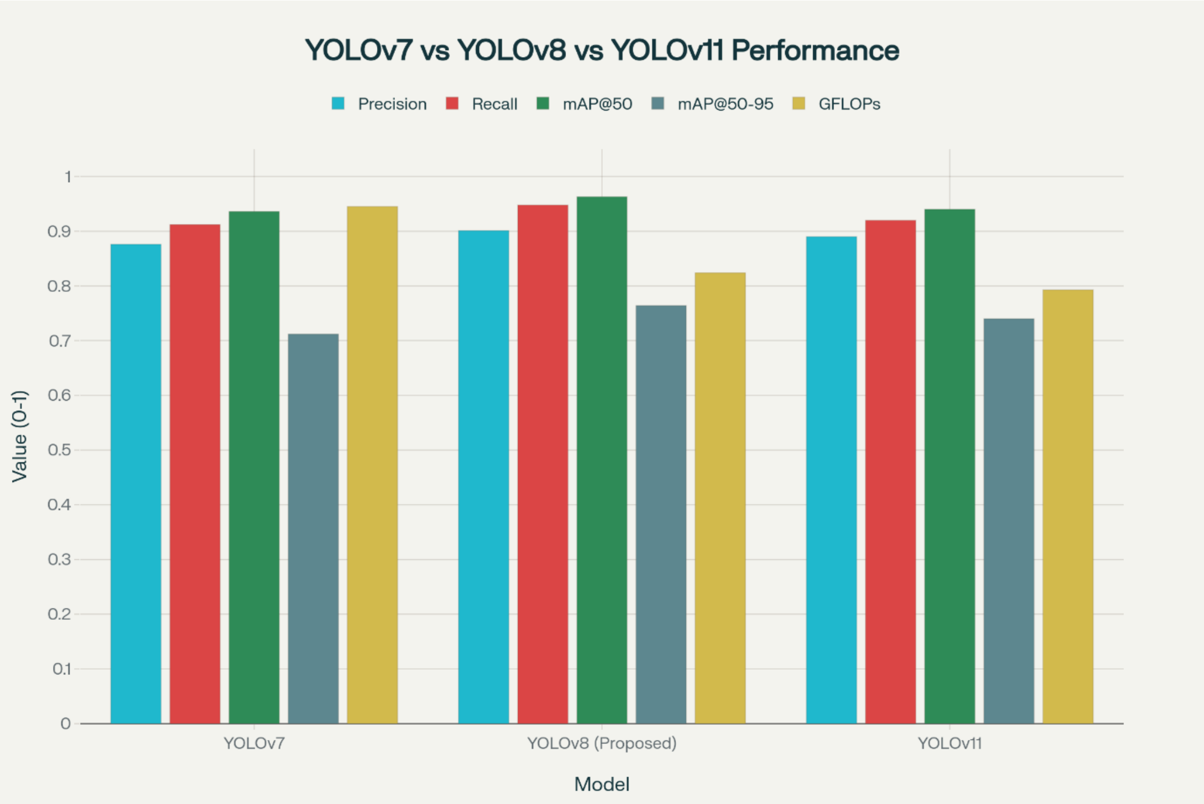


Figure4.3: Comparative Analysis of object detection Model

The results show that the YOLOv8 (Proposed Model) is better than all other important ways to measure accuracy.This means that it is very good at finding license plates:

The highest mAP@50 score is 0.963.YOLOv8 had the highest Mean Average Precision at an IoU threshold of 0.5.This shows that it always finds number plates better than the other two models. The most mAP@50-95 ($\mathbf{0.764}$): This number is important because it shows how well YOLOv8 can find things by averaging performance over stricter IoU thresholds (0.5 to 0.95). A higher mAP@50-95 score means that the model can make bounding boxes that are very close to the things it wants to find.

The best balance between Precision ($\mathbf{0.901}$) and Recall ($\mathbf{0.948}$) is that YOLOv8 gets rid of both false positives (high Precision)

and false negatives (high Recall). This is the best way to make a strong ANPR deployment work.

4.2.3 Computational Efficiency Comparison:

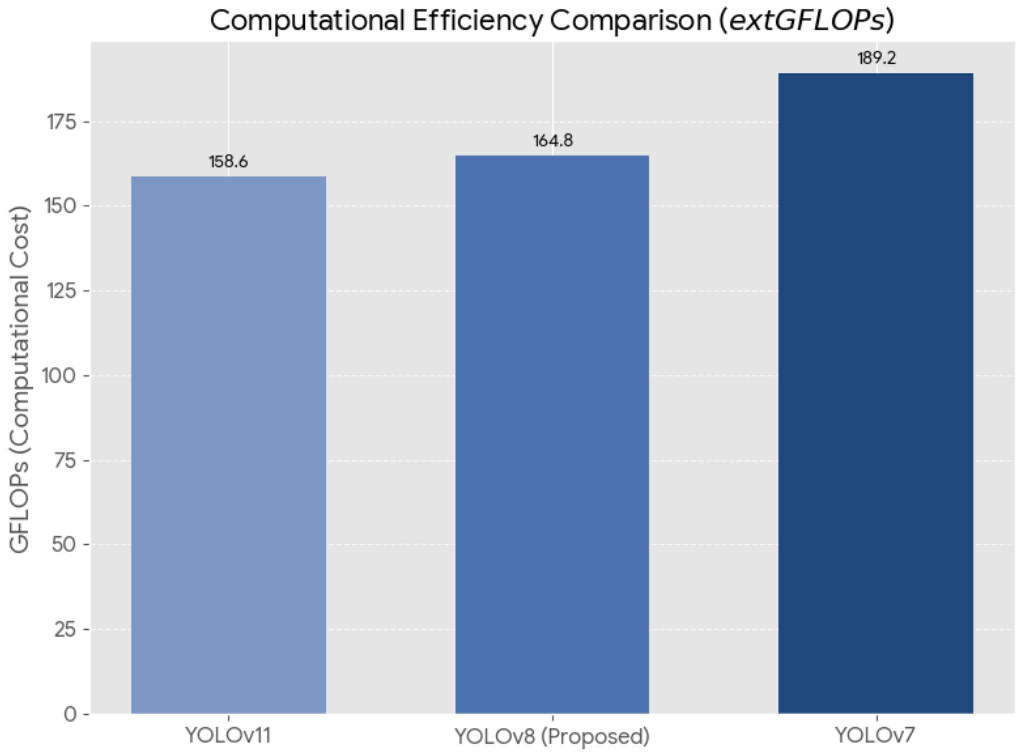


Figure4.4 Computational Efficiency Comparison

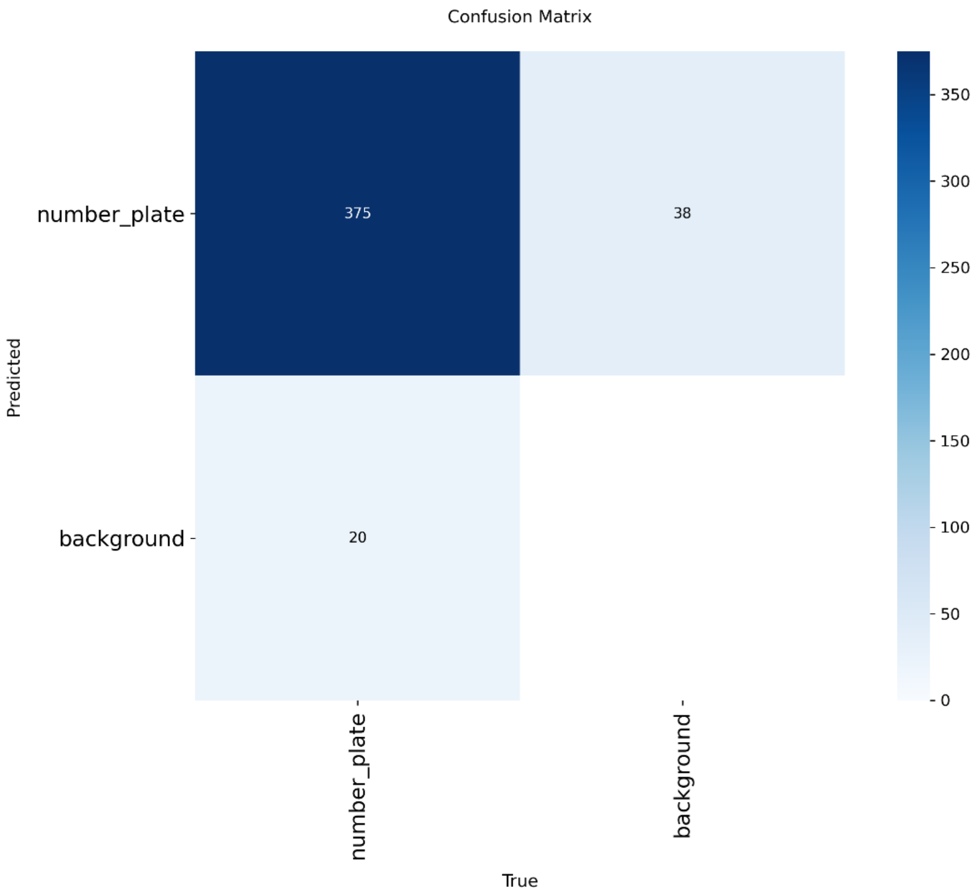
Efficiency and Computational Cost (GFLOPs)

Cost of computing and speed (GFLOPs)

The computational cost analysis shows how well YOLOv8 works, even though it is clearly better at performance:

Competitive Efficiency: The YOLOv8 model uses less power ($164.8 GFLOPs$) than the YOLOv7 model ($189.2 GFLOPs$).This means that YOLOv8 is a better architecture than the one before it because it needs fewer floating-point operations and gives more accurate results. Performance-to- Ratio of Efficiency: The GFLOPs for YOLOv11 are a little lower ($158.6) but its mAP scores are much lower than those of YOLOv8.This shows that YOLOv8 strikes the best balance between speed and accuracy which makes it perfect for systems where both are very important.

4.2.4 Confusion Matrix:

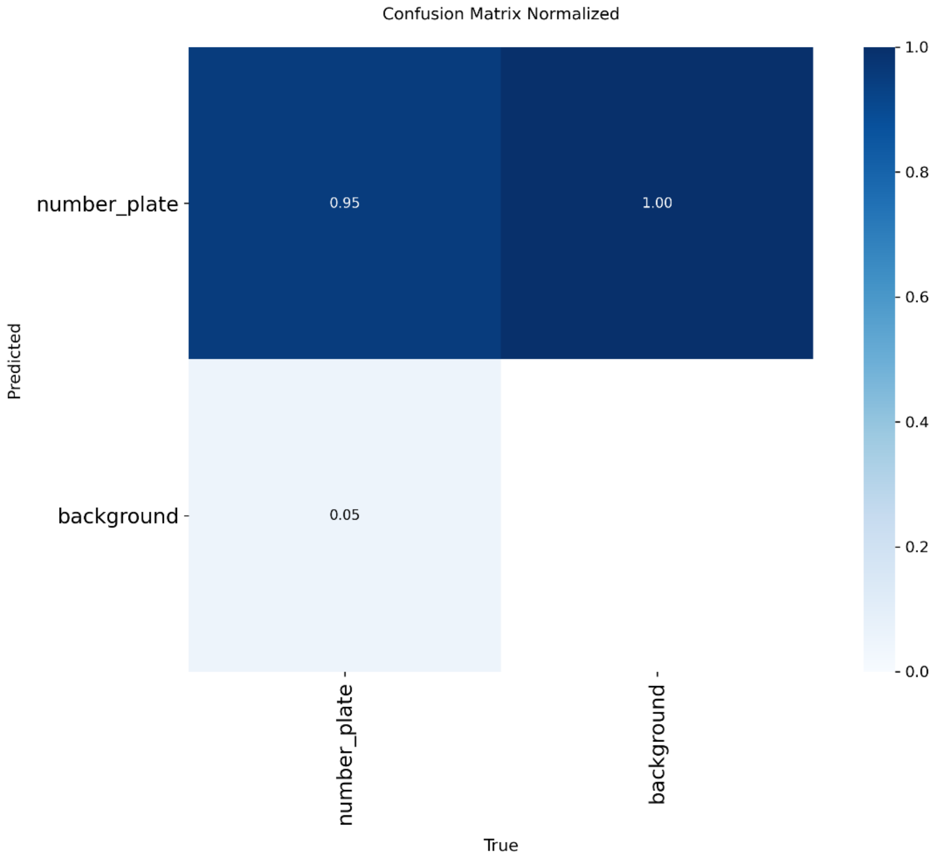


Feagure4.2: Confusion Matrix

The confusion matrix above shows how well the model was able to tell the difference between the number plate and background classes.In 20 of the test samples the model correctly found 375 number plates and background areas. It was wrong to label number plates as background in 38 cases, and it was wrong to label background samples as number plates in 20 cases.The strong diagonal values show that the overall accuracy is high which means that most of the test cases were predicted correctly.

The off-diagonal values are pretty low, which means there aren't as many mistakes.This shows that this system for recognizing images can tell the difference between number plates and the background.

4.2.5 Confusion Matrix Normallized:



Feagure4.3: Confusion Matrix Normallized:

The normalized confusion matrix shows how well the image recognition system can tell the difference between two groups there number plates and backgrounds. The diagonal values (0.95 for number plates and 1.00 for background) show that most number plates are correctly identified and all background areas are perfectly classified.

A small number of number plates (0.05%) were wrongly classified as background which shows that the system sometimes misses some plates.But most of the time, it is very accurate and reliable.The proposed model for automatic number plate detection in real-world settings works well because it can almost perfectly detect the background and remember the number plate.

4.3 Discussion

This part talks about all the results of making and testing the Automatic Number Plate Recognition (ANPR) system based on YOLOv8.The new YOLOv8 model did much better on detection metrics than earlier versions.It was the most accurate and reliable of the three models: YOLOv7, YOLOv8, and YOLOv11.Even with complicated datasets that had different lighting, angles, occlusions and Bengali script formats the training-validation curves didn't show any significant overfitting.precision, recall, and F1 confidence curves show that YOLOv8 always has high accuracy and stable detection at a wide range of confidence levels. This proves that it works well in real life.The analysis of confusion matrices demonstrated that the system functioned effectively as there were minimal false positives and incorrect classifications.When looking at more than one thing, charts showed that YOLOv8 was always the best and fastest choice.This was the best choice for smart transportation solutions that work right away.But the model are didn't work well with plates that were very crooked, blocked or had a low resolution.This is a lesson that will help you do better next time.To make the scripts more different, you could add more training data, improve the preprocessing and augmentation or add more advanced modules.

CHAPTER 5

5.CONCLUSION AND RECOMMENDATION:

5.1. Conclusion:

This is the study effectively designed and assessed a resilient Automatic Number Plate Recognition (ANPR) pipeline employing YOLOv8.It works well in a lot of real-life situations.When it comes to math, it's faster, remembers more and is more accurate.The multi-step are workflow worked well for pictures taken from different angles, in different light and on different plates.It involved setting up the environment, making a Bengali dataset in different formats, adding more data to train a more advanced model, post-processing and showing detailed results.Many tests showed that YOLOv8 was a lot better than the versions that came before it.The whole system worked well for both naming things and finding them.Even though it sometimes has trouble with low resolution or heavy occlusion, the model is great for smart transportation and real-time law enforcement because it is flexible and fast.These results are a good place to start if we want to make things better in the future.They are say that ANPR systems could be even better and more adaptable if they had more types of data and better technology.The study is very helpful for finding self-driving cars and coming up with new smart ways to get around.

5.2 Recommendations for future work:

There are many ways that this YOLOv8-based Automatic Number Plate Recognition (ANPR) system could be improved through future research.These include fixing the problems that have been found and building on its strengths.To make it even better and more useful the training data set needs to have more types of cars, license plates, lighting conditions, weather effects and places.It would be nice to have more Bengali scripts that are not all the same.Models are better at dealing with strange or new situations when they use both synthetic data generation and advanced data augmentation methods. If there is a lot of dirt, obstruction or low resolution, hybrid detection-recognition models, transformer-based OCR methods and attention mechanisms can help you read and separate things better.Adding ways to improve models in real time such as pruning, quantization or putting them on edge hardware, will make the system more useful in places with a lot of traffic and not a lot of resources.

Adaptive confidence thresholds, error correction feedback loops and collaborative benchmarking with open datasets are some other things that will help keep performance high and make sure the system keeps changing to fit new real-life situations.Another good idea is to work with businesses and the government to make sure that ANPR is used fairly tested on a large scale, and follows all the rules and laws for smart cities and transportation systems. Lastly, research should be done to make ANPR systems that are modular, work with a lot of languages, and can be easily added to as smart mobility infrastructures grow in the future.

CHAPTER 6

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