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***Abstract*—This research paper presents a comprehensive investigation into the effectiveness of YOLO (You Only Look Once) models, namely YOLOv5, YOLOv7, and YOLOv8, in the domain of Bangladeshi license plate detection. With the escalating demand for precise license plate recognition systems to facilitate efficient traffic management and bolster law enforcement efforts, this study conducts an in-depth evaluation of these models. Central to our methodology is the development of a specialized dataset comprising Bangladeshi license plate images, reflecting the unique characteristics and challenges prevalent in this geographical context. Through meticulous dataset curation, model training, and rigorous testing procedures, we ascertain the performance metrics of each YOLO variant. Notably, our findings reveal YOLOv8 as the most proficient model, achieving a remarkable mean average precision (mAP) score of 0.934 with precision 0.93 and recall 0.906 . The insights gleaned from this research contribute significantly to the advancement of intelligent transportation systems and public safety initiatives in Bangladesh, offering tailored solutions for license plate detection challenges in this specific locale.**

Keywords*— License plate, License plate detection, YOLO v5, Yolo v7, dataset, Annotation

I. INTRODUCTION

Bangladesh's economy and technology have grown, which has increased demand for automobiles and related issues like parking management and finding stolen cars that violate bans [1]. License plate recognition is crucial in many aspects of modern life, including traffic control, surveillance, and law enforcement [1], [2]. When authorities can swiftly and precisely identify license plates, they can monitor vehicle movement, enforce traffic laws, and enhance public safety. Robust license plate recognition systems are particularly crucial in Bangladesh, where a growing urban population density poses major challenges to the nation's transportation infrastructure and security. Conventional techniques for detecting license plates frequently depend on manually designed features and heuristics, which may not be able to adjust to different types of vehicles and different environmental conditions. Nonetheless, object detection tasks have been completely transformed by recent developments in deep learning, especially with the introduction of convolutional neural networks (CNNs)[3]. Among these, the YOLO (You Only Look Once) models have shown to be effective and accurate real-time tools for object detection. While YOLO models are extensively employed in various domains, their appropriateness for specific scenarios, such as Bangladeshi license plate recognition, remains unclear. This paper aims to bridge this gap by methodically assessing multiple YOLO variants, such as YOLOv5, YOLOv7, and YOLOv8, in the context of Bangladeshi license plate detection.As part of the study's methodology, a specialized dataset of Bangladeshi license plate photos is gathered and arranged to represent the range of characteristics and challenges that occur in daily life. After being trained on this dataset, the YOLO models are evaluated using standard performance metrics such as inference speed and mean average precision (mAP). This study aims to clarify the benefits and drawbacks of each YOLO variant in the context of Bangladeshi license plate detection, providing valuable information that can direct the development of more specialized and effective solutions. Ultimately, the findings of this study may have a significant impact on public safety initiatives and the development of intelligent transportation systems in Bangladesh and around the world.

II. Literature Review

Chi-Hung Chuang et al. [1] challenges of different video resolutions, distances, and lighting conditions, including shadows, are highlighted by concentrating on car license plate identification, recognition, and super-resolution algorithms. These issues are intended to be addressed by a novel technique to license plate recognition in Taiwan. Upcoming projects involve improving the accuracy of license plate recognition. By increasing video resolution, the study is able to detect license plates with a higher degree of accuracy—46.52% for Rank 1 and 93.87% for Rank 10. Using a dataset of 10 test data samples with blurry license plates, the research uses digital camera-captured photos of license plates.

Murat Peker [2] Through a comparative analysis of object detection networks, the paper explores license plate localization. It details various techniques and network structures, such as ResNet50, Inception, MobileNet, and ResNet101, with an emphasis on improving performance. Two sets of data were used: a test dataset with 100 images from different fixed cameras with a similar resolution and 200 photographs at 480x360 resolution from Adana, Turkey. MobileNet outperforms other networks when tested on the second test dataset, obtaining F1 scores of 0.680 and 0.980 for license plate localization and car detection, respectively

SORIN DRAGHICI[3] presents the Visicar system, an application for license plate recognition based on neural networks. By changing contrast change scanning parameters, plate location accuracy is increased and plate location and segmentation success rate is increased to 99%. The accuracy of character recognition is 98%. Only 80% of registration plates can be recognized completely, though.

SP Jainaveen et al. [4] The study focuses on an Automatic License Plate Detection (ALPD) system that uses Wavelet Packets, K-Means Clustering, and the Adaptive Neuro-Fuzzy Inference System (ANFIS). The results of the experiments highlight the need for more research to guarantee that the system can accommodate license plates from other nations.

Zuwena Musoromy et al.[5] used The Rothwell algorithm, along with Canny and Sobel, is known for its accuracy in edge identification. Canny shows effectiveness with an accuracy of 98.2% in plate detection. Among the difficulties are false positives brought on by intricate lighting. The study is based on a collection of 45,032 photos with a resolution of 720x288.

Shahid Uddin Ahmed et al.[6]Contour properties aid in both license plate (LP) detection and Bangla character recognition, while backpropagation neural networks assist in character classification and segmentation.. Integration of Optical Character Recognition (OCR) engines enables multilingual license plate recognition. A cascaded architecture utilizing YOLOv7 versions is employed for LP detection, achieving a 96% detection accuracy for Bangla License Plates (BLP) and 97% accuracy for Bangla characters.

Muhammad Rizwan Asif et al.[7]Techniques for License Plate Detection (LPD) prioritize pixel connection, color spaces, and edge information. Research targets both single and multiple vehicle scenarios, obtaining an accuracy of 93.86% and a precision rate of 87.15%, despite computational time constraints impeding real-time viability for some LPD approaches. With 460 photos taken at night and 1051 during the day, the dataset presents difficulties because of variations in lighting, weather, and illumination.

Z Jeffrey et al.[8]The goal of research is to improve edge detection parameters by studying LP detection techniques for both HD and SD images. Compared to the original algorithm, the suggested one exhibits a 10.1% increase in accuracy and a decrease in false positives. HD photos have a success percentage of 97.2%. The method combines techniques for eliminating background noise, leading to notable gains for noisy SD and HD photos alike. Jiri Matas et al. [9] proposes a new class of locally threshold separable detectors and focuses on techniques for detecting license plates and traffic signs. These machine-learning-adapted detectors deliver great accuracy under a range of circumstances. Furthermore, morphological operations-based detection has been previously proposed and achieved great accuracy in segmentation difficulties with an FPFN1.6 metric and 95% detection accuracy on a license plate dataset.

Nazmus Saif et al. [10] Systems and methods for ALPR are extensively employed worldwide, including in Bangladesh. Patel et al. achieved 99.5% accuracy on a dataset of 200 photos by classifying ALPR solutions according to accuracy and speed. Accuracy using five-fold cross-validation ranged from 94.5% to 97.01% on a dataset including 1050 training and 200 test photos. Using 200 test photos, their CNN model recognized and detected license plates with 99.5% accuracy at a pace of 9 frames per second. Other improvements are proposed, such as identifying more vehicle classifications and employing a more varied dataset.

MS Al-Shemarry and Y Li [11]For comparative reasons, the study paper's Section II examines comparable work on license plate detection, or LPD. It proposes expanding the LPD system with additional databases to address a wider range of circumstances. Furthermore, it is advised to investigate novel classifiers in order to raise detection accuracy rates. Additionally, there's interest in examining how deep neural networks can be integrated for feature learning in LPD systems. The article notes that there is an English automobile database with 510 photos and an expanded version with 1540 photos. Shefali Arora [12] published Intelligent transport systems are required due to the increasing usage of vehicles, and computer vision techniques such as license plate recognition (LPR) are essential. With the help of convolutional neural networks (CNNs) for feature extraction and bilateral filtering and Canny edge detection for localization, this work presents a strong deep-learning framework for LPR.These results highlight how well the suggested system works and point to major improvements in automated vehicle tracking and management systems. Additional studies should improve dynamic system performance and include more variables. The method outperformed a state-of-the-art detector when tested on a benchmark with 4,070 plates in 1,829 images under varying weather conditions, achieving a precision of 0.87 and recall of 0.83. Because these results were obtained without the use of temporal integration or preprocessing, they are remarkable [13]. Adaboost classifiers are used in the first stage to identify potential character regions on license plates. After that, an SVM trained on Scale-Invariant Feature Transform (SIFT) descriptors refines these candidates in order to remove false positives. The precision was 0.90185 and the recall rate was 0.920792 for the method. In order to increase efficiency, future work will concentrate on clustering detected characters and classifier optimization [14]. New developments in license plate detection (LPD) [15] have improved automated vehicle verification systems significantly, which is important for security and traffic monitoring applications. This paper presents a two-stage LPD approach that combines support vector machine (SVM) and Adaboost classifiers. 36 Adaboost classifiers are used to initially identify possible characters for license plates. The effectiveness of law enforcement has significantly increased, according to recent studies on Automatic License Plate Reader (ALPR) systems. This study looks at the efficiency of the Cincinnati Police Department's (CPD) ALPR systems [16] and finds that, in comparison to more conventional techniques, there has been a noticeable increase in follow-up arrests. According to these results, police departments can effectively allocate resources and improve their efforts to prevent crime by investing in ALPR technology.Advancements in convolutional neural network (CNN) [17]architectures have been applied to automatic license plate localization in recent times. The usefulness of various TensorFlow-based object detection models for Turkish license plates is investigated in this work.. The following four network configurations were assessed: region-based fully convolutional networks (R-FCN) with Resnet features, faster region convolutional neural networks (Faster R-CNN) with Inception layers, and single shot multibox detectors (SSD) [18] with MobileNet and Resnet50 features.

III. Methodology

We will go into more detail about our suggested methodology in this section. It covers the steps of data collection, annotation, augmentation, model training, and evaluation. Figure 1 displays a diagram of the entire methodology, and the ensuing subsections go into further detail about each step of the process.

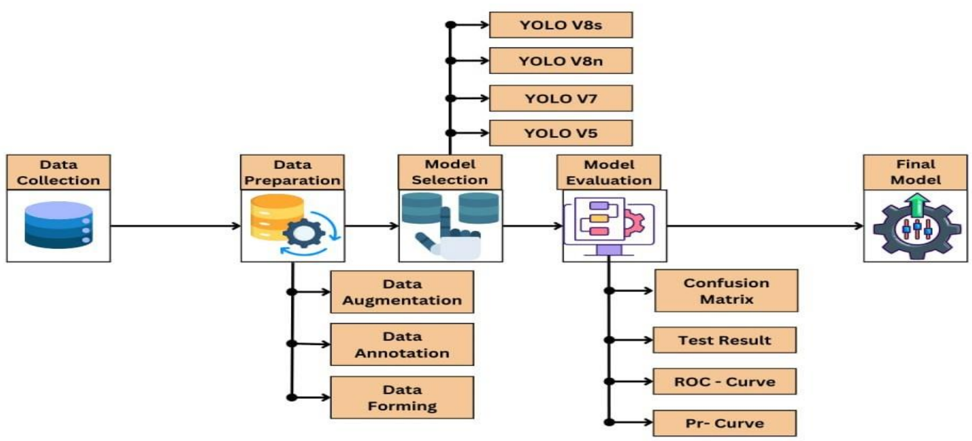

Fig. 1. Workflow Diagram of the Full Model

A. Data Collection

The process of gathering data involved visiting several bustling locations in Dhaka to obtain vehicle images. To guarantee that the data set included environmental factors and real-world scenarios, direct field collection was conducted. Pictures were taken using a variety of mobile devices, the majority of which used a Sony IMX689 48 MP 1/1.43 sensor, 1.12m, 23 mm-equivalent f/1.8-aperture lens camera. In total, over a thousand pictures were

B. Dataset Cleaning & Preprocessing

The majority of the massively gathered images were superfluous, grainy, or overexposed, which could have interfered with the model's training. These photos were taken out of the main dataset in order to improve the dataset's precision. The high resolution 1080x2400 pixels of the images taken from the open scenario are appropriate for use in our testing models. To ensure that the images contribute more equally in the event of a loss, we rescaled the images using (1/255), which changes the pixels' range from (0, 255) to (0, 1). The preprocessed photos maintain a 640 x 640 pixel resolutionSplit Dataset In total, 2273 images are stored in local storage as well as in cloud storage (Google Drive) for future usage. All of these images are used for training, testing and validation the model. For training we used 87 % (1979) of the images .In the same procedure of preparing the training dataset, to avoid

Fig. 2. Sample images of the data set

biasing the model, the testing dataset and validation dataset are generated separately by splitting the training dataset. The validation portion consists of 9% (197)of the images and the testing dataset portion consists of 4% (97) images for the model to predict.

C. Model Selection

choosing license plate detection models for Bangladesh, it is important to take into account a number of factors, such as adaptability to regional nuances, computational efficiency, and performance. The selection of YOLO variants—YOLOv5, YOLOv7, YOLOv8n, and YOLOv8s—for our study is explained in this section. Yolo Models has signify noteworthy progressions in the field of real-time object detection. YOLOv5, created by Ultralytics. It has a neck and a CSPNet backbone. Different versions are good for various trade-offs between speed and accuracy. YOLOv7's enhanced feature pyramids and head designs. The recent, YOLOv8, sets a new benchmark for accuracy and efficiency. An architecture diagram for version 8 of the YOLO (You Only Look Once) object detection model, which makes use of a Feature Pyramid Network (FPN) for enhanced multi-scale feature extraction, is shown in Figure 3. This is a thorough analysis of the architecture:

Backbone: C1 through C5: The convolutional layers of the network's backbone. Feature maps are extracted from the input image by the backbone network, which is usually a convolutional neural network (CNN). Conv Block: Convolutions, activations, and possibly normalization layers make up these fundamental convolutional blocks. Conv 3x3, C, 2C: A 3x3 convolutional layer with an additional channel count of 2C from C.Conv 1x1, 2C, C: Lowers the number of channels from 2C to C using a 1x1 convolutional layer.Upsample x2: An upsampling layer that increases the feature map's spatial dimensions by two

Feature Pyramid Network (FPN): Feature maps at various scales (C3, C4, C5) are improved by the FPN through the combination of high-resolution and low resolution feature maps. This makes it easier to detect objects of different sizes.The combination of feature maps from various backbone levels and the information flow are shown by the arrows.

Feature Pyramid: P3, P4, and P5: These are the feature maps that the FPN produced at various pyramidal levels. They line up with various feature scales. Conv 1x1, 512, 512: Prior to merging feature maps,

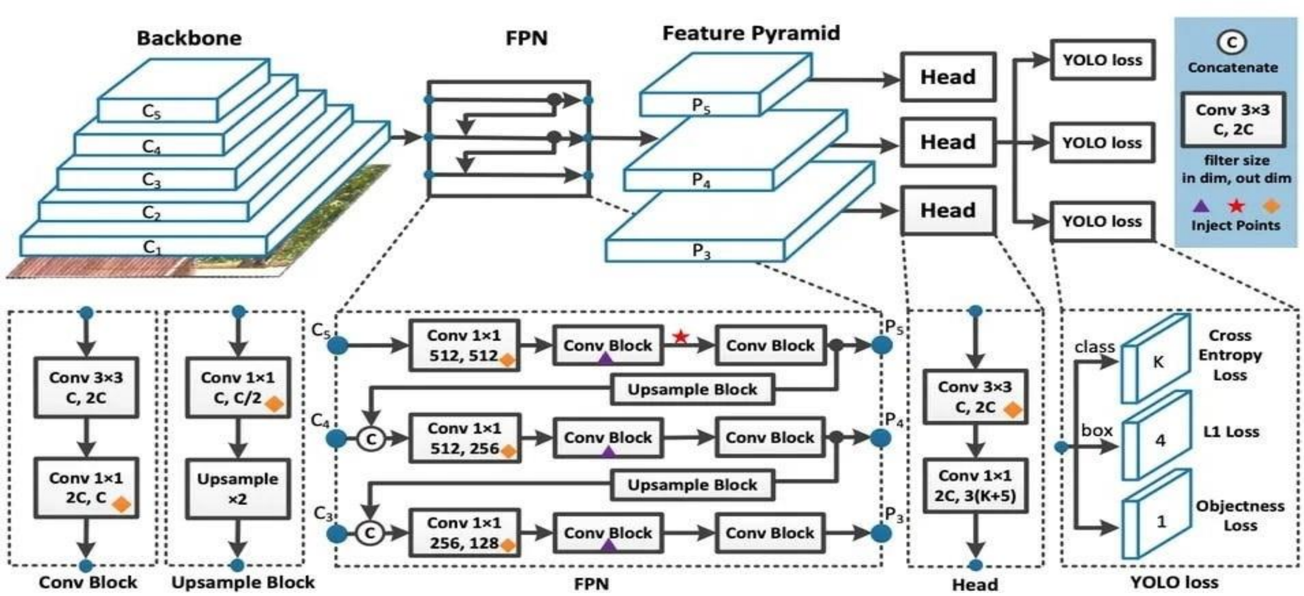

Fig. 3. Architecture of YOLOv8

1x1 convolutions are used to match the dimensions. Convolution Blocks and Up sample Blocks: To get the feature maps ready for the detection heads, additional convolutional operations and up sampling are carried out.

Head: The corresponding head processes each pyramid level (P3, P4, P5) and predicts bounding boxes, objectness scores, and class probabilities. Convolutions in the head for feature map processing (Conv 3x3, C, 2C). Conv 1x1, 2C, 3(K+5): Predictions (K classes, 4 bounding box coordinates, 1 objectness score) are output by the final layer.

YOLO Loss: Class (Cross Entropy Loss): Prediction loss for classes. Box (L1 Loss): Regression's bounding box loss. Objectness Loss: The inability to tell if an object is inside a box.

Thanks to this architecture, the YOLO model can more accurately and efficiently detect objects at various scales by utilizing multi-scale features that are taken from the FPN.

IV. RESULT ANALYSIS

To evaluate different models of license plate detection for Bangladesh, various methods and visualizations were employed to measure the performance of YOLO vari- ants—YOLOv5, YOLOv7, YOLOv8,. The evaluation metrics utilized include F1 curve, PR (Precision-Recall) curve, confusion matrix, and qualitative results analysis. At first let's see the comparison of different training losses .

TABLE I
COMPARISON OF TRAINING LOSSES OF YOLO MODELS

Model name	**train/box_loss**	**train/cls_loss**	**train/obj_loss**
Yolo V5	0.021512	0.0052642	0
Yolo V7	0.02221	0.003916	0
Yolo V8	1.0179	0.47726	1.0924

TABLE II
COMPARISON OF VALIDATION LOSSES OF YOLO MODELS

Model name	val/box_loss	val/cls_loss	val/obj_loss
Yolo V5	0.027566	0.0040377	0
Yolo V7	0.04151	0.007287	0
Yolo V8	1.2112	0.54486	1.1958

TABLE III
COMPARISON OF PERFORMANCE METRICS OF YOLO MODELS

Model name	Precision	Recall	mAP50	mAP50 95
Yolo V5	0.99097	0.93731	0.93703	0.61706
Yolo V7	0.8537	0.8599	0.8681	0.5416
Yolo V8	0.93702	0.90637	0.93461	0.62103

A. Model Evaluation

The YOLOv8 model's performance over several epochs of training and validation.

train/box_ loss: evaluates the bounding box predictions' accuracy. It is getting smaller, which suggests increased accuracy. Accuracy of classification is measured using train/cls_loss. It is declining and demonstrating improved classification performance.

train/dfl_loss: Bounding box distribution-related focal loss measurement. It's getting smaller, which suggests progress.

metrics/precision(B): Indicates how well positive predictions worked out. There will be fewer false positives as it rises.

metrics/recall(B): Evaluates how well the model locates all pertinent instances. It is rising, indicating improved true positive detection. Metrics for Validation Bounding box accuracy on validation data is measured by val/box_loss. It is declining, which suggests strong generalization.

val/cls_loss: Evaluates the precision of classification using validation data. It is declining, indicating better performance.

Measures focal loss on validation data (val/dfl_loss). It is declining, which suggests improved distribution forecasting.

metrics/mAP50(B): 50% IoU Mean Average Precision. It is rising, which suggests improved detection performance all around.

metrics/mAP50-95(B): Average Precision Mean across several IoU cutoff points. It is improving across a range of overlap levels and is growing. In brief

Enhancing Losses A decrease in training and validation losses suggests efficient learning and strong generalization. Improved Measures Metrics such as recall, mAP, and precision are getting better, indicating improved performance in detection and classification. By lowering data noise, the "smooth" dotted lines aid in the visualization of overall trends.

Now let’s see the confusion matrix for each model to see the summary of the model’s performance by showing how predictions compare to the actual labels.

Here the best results were given by yolo v8 model. The model has learned well and is not overfitting based on the notable decrease in both training and validation losses. The model’s predictions are found to be accurate and comprehensive due to its high precision and recall. A robust model across a range of IoU thresholds is confirmed by high mAP scores. According to these metrics, the model is operating effectively, detecting license plate accurately. At a glance all the results of Yolov8:

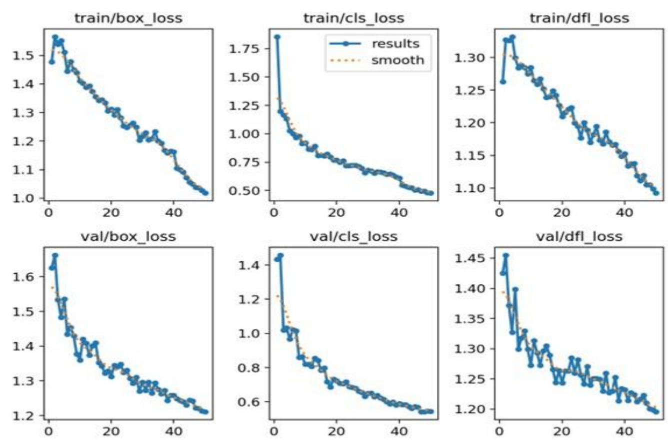

Fig. 4. Train and validation loss of YOLOv8

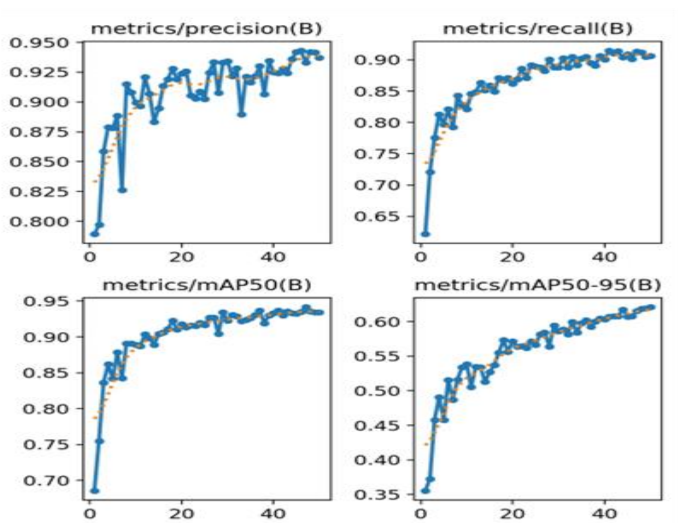

Fig. 5. mAP values of YOLOv8

Now let’s see the confusion matrix for each model to see the summary of the model’s performance by showing how predictions compare to the actual labels

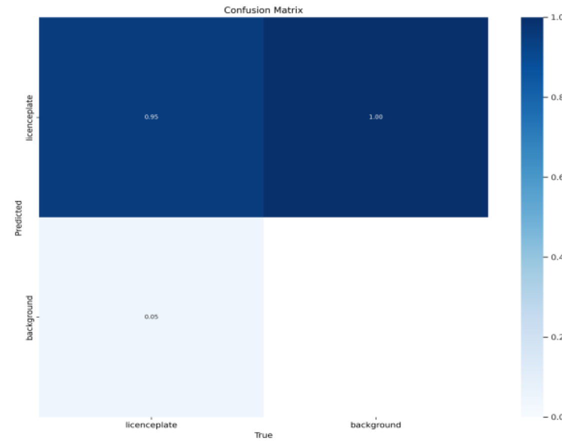

Fig. 6. Confusion Matrix of YOLOv5

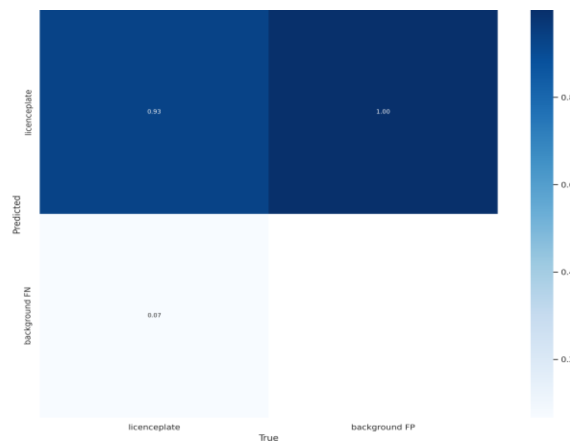

Fig. 7. Confusion Matrix of YOLOv7

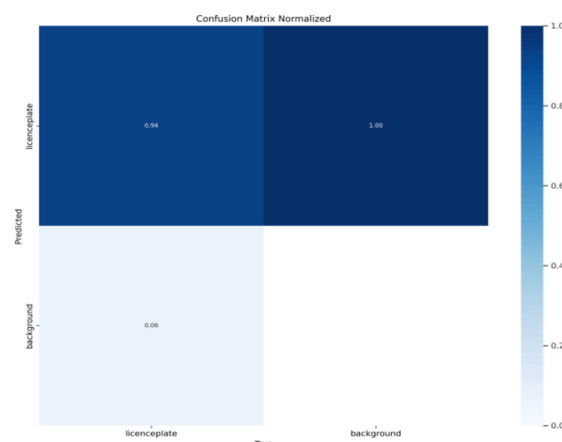

Fig. 8. Confusion Matrix of YOLOv8

F1 is harmonic mean of precision and recall score that goves a single metric that balances both also its confidence threshold used by the model to classify a detection as positive. Here we can see f1 curve for yolo models to compare among them.

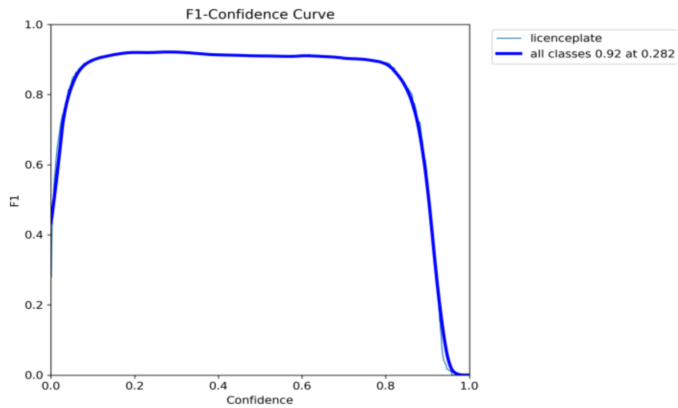

Fig. 9. F1 curve of YOLO v5

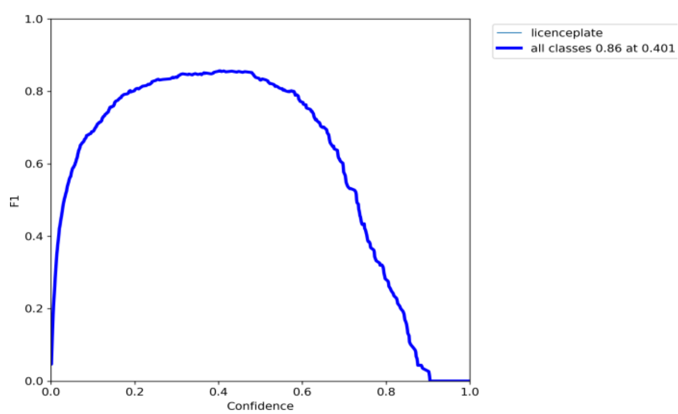

Fig. 10. F1 curve of YOLO v7

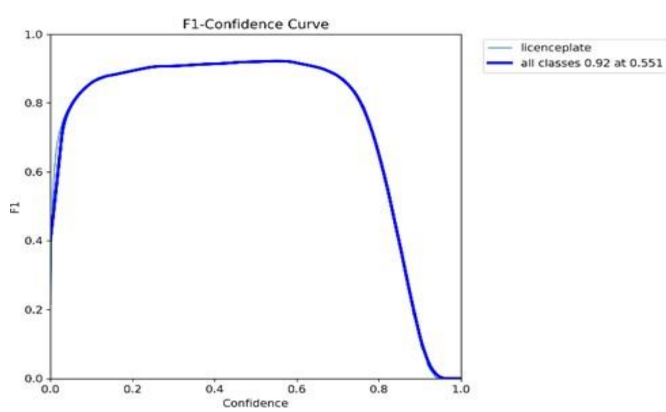

Fig. 11. F1 curve of YOLO v8

Fig. 12. Sample Output Images

V. Future Work

Seeing these promising results we thought of several goals for future research. One significant area is integration of Optical Character Recognition (OCR) to extract text from license plates. This would have applications like automated toll collection, traffic monitoring, and vehicle registration. Which will add significant value to the detection systems. Also using advanced data augmentation techniques and synthetic data generation can enhance model performance by creating a more diverse and representative training dataset. Additionally, using these models for real-time processing and deployment on devices is crucial for practical applications making it a scalable.

VI. Conclusion

We focused on optimizing and evaluating license plate detection models for Bangladesh using various YOLO (You Only Look Once) variants—YOLOv5, YOLOv7, YOLOv8. Facing unique challenges of this region like diverse environmental conditions, varying lighting, and specially non-standardized license plate designs a robust detection model is essential. Among the models, YOLOv8 gave the best performance. It has high accuracy and robustness in detecting license plates under diverse conditions. The F1 curve and PR curve for YOLOv8 showed a strong balance between precision and recall, and the confusion matrix shows effectiveness in fewer false positives and false negatives. Qualitative analysis confirmed that YOLOv8's capability to handle difficult scenarios, like bad weathered license plates, making it the most reliable model for practical use in Bangladesh.

REFERENCES

[1] C. H. Chuang, L. W. Tsai, M. S. Deng, J. W. Hsieh, and K. C. Fan, ”Vehicle licence plate recognition using super-resolution technique,” in Proc. 2014 IEEE International Conference on Advanced Video and Signal-Based Surveillance (AVSS), Seoul, South Korea, Aug. 2014, doi: 10.1109/AVSS.2014.6918703.

[2] M. Peker, ”Comparison of Tensorflow object detection networks for licence plate localization,” in Proc. 2019 1st Global Power, Energy and Communication Conference (GPECOM), Nevsehir, Turkey, Jun. 2019, pp. 101-105, doi: 10.1109/GPECOM.2019.8778602.

[3] S. Draghici, ”A Neural Network Based Artificial Vision System for Licence Plate Recognition,” International Journal of Neural Systems, vol. 8, no. 1, pp. 113-126, Feb. 1997, doi: 10.1142/S0129065797000148.

[4] S. P. Jainaveen, M. J. B. Reddy, and D. K. Mohanta, ”Automatic licence plate detection using adaptive neuro fuzzy inference system and wavelet packets,” Australian Journal of Multidisciplinary Engineering, vol. 13, no. 1, pp. 2-17, Jan. 2017, doi: 10.1080/14488388.2016.1274132.

[5] Z. Musoromy, S. Ramalingam, and N. Bekooy, ”Edge detection comparison for license plate detection,” in Proc. 2010 11th International Conference on Control Automation Robotics & Vision (ICARCV), Singapore, Dec. 2010, doi: 10.1109/ICARCV.2010.5707935.

[6] S. U. Ahmed, F. B. F. Maisha, and M. Hossam-E-Haider, ”Bangla License Plate Detection and Recognition System with YOLOv7 and Improved Custom OCR Engine,” 2022 International Conference on Advanced Computing and Intelligent Engineering (ICACIE), Bhubaneswar, India, Dec. 2022, doi: 10.1109/ICACIE.2022.10060446.

[7] M. R. Asif, Q. Chun, S. Hussain, and M. S. Fareed, ”Multiple licence plate detection for Chinese vehicles in dense traffic scenarios,” IET Intelligent Transport Systems, vol. 10, no. 8, pp. 535-544, Oct. 2016, doi: 10.1049/iet-its.2016.0008.

[8] Z. Jeffrey and S. Ramalingam, ”High definition licence plate detection algorithm,” in Proc. 2012 IEEE International Conference on Sensing, Communications, and Networking (SECON), Seoul, South Korea, Mar. 2012, doi: 10.1109/SECON.2012.6196912.

[9] 9. J. Matas and K. Zimmermann, ”Unconstrained licence plate and text localization and recognition,” in Proc. 2005 IEEE Intelligent Transportation Systems, Vienna, Austria, 2005, pp. 225-230, doi: 10.1109/ITSC.2005.1520111.

[10] N. Saif, A. Mannan, T. Haque, F. Ahmed, and M. A. H. Akhand, ”Automatic License Plate Recognition System for Bangla License Plates using Convolutional Neural Network,” 2019 International Conference on Sustainable Technologies for Industry 4.0 (STI), Dhaka, Bangladesh, 2019, doi: 10.1109/STI47673.2019.8929280.

[11] M. S. Al-Shemarry and Y. Li, ”Developing Learning-Based Preprocessing Methods for Detecting Complicated Vehicle Licence Plates,” IEEE Access, vol. 8, pp. 170951-170966, Jan. 2020, doi: 10.1109/ACCESS.2020.3024625.

[12] S. Arora, R. Mittal, D. Arora, and A. K. Shrivastava, ”A Robust Approach for Licence Plate Detection Using Deep Learning,” Inteligencia Artificial, vol. 27, no. 73, pp. 129-141, Feb. 2024, doi: 10.4114/intartif.vol27iss73pp129-141.

[13] F. D. Kurpiel, R. Minetto, and B. T. Nassu, ”Convolutional neural networks for license plate detection in images,” in Proc. 2017 IEEE International Conference on Image Processing (ICIP), Beijing, China, Sept. 2017, pp. 3395-3399, doi: 10.1109/ICIP.2017.8297014.

[14] W. T. Ho, H. W. Lim, and Y. H. Tay, ”Two-Stage License Plate Detection Using Gentle Adaboost and SIFT-SVM,” in Proc. 2009 First Asian Conference on Intelligent Information and Database Systems (ACIIDS), Dong Hoi, Vietnam, Apr. 2009, doi: 10.1109/ACIIDS.2009.25.

[15] J. W. Hsieh, S. H. Yu, and Y. S. Chen, ”Morphology-based license plate detection from complex scenes,” in Proc. 2002 16th International Conference on Pattern Recognition (ICPR), Quebec City, QC, Canada, Aug. 2002, doi: 10.1109/ICPR.2002.1047823.

[16] M. Ozer, ”Automatic licence plate reader (ALPR) technology,” The Police Journal: Theory, Practice and Principles, vol. 89, no. 2, pp. 117-132, May 2016, doi: 10.1177/0032258X16641334.

[17] M. Peker, ”Comparison of Tensorflow Object Detection Networks for Licence Plate Localization,” in Proc. 2019 1st Global Power, Energy and Communication Conference (GPECOM), Nevsehir, Turkey, Jun. 2019, doi: 10.1109/GPECOM.2019.8778602.

[18] G. R. Gonçalves, S. P. G. da Silva, D. Menotti, and W. R. Schwartz, ”Benchmark for license plate character segmentation,” Journal of Electronic Imaging, vol. 25, no. 5, p. 053034, Oct. 2016, doi: 10.1117/1.JEI.25.5.053034.