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Bangla License Plate Detection Using YOLOv8: An Efficient Framework with a Custom Dataset

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Bangla License Plate Detection Using YOLOv8: An Efficient Framework with a Custom Dataset

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***Abstract*—This paper presents a YOLOv8-based Bangla License Plate Detection system trained on a real-world dataset collected through Roboflow. Although the notebook file was labeled as "YOLOv11", the underlying implementation strictly follows the YOLOv8 architecture. A custom dataset containing Bangladeshi license plates with diverse illumination, angles, occlusions, and resolutions was used. The model was trained for 60 epochs with an image size of 600×600. Experimental results demonstrate high detection performance with an mAP(50) of 0.95, precision of 0.97, and recall of 0.95. The normalized confusion matrix shows strong class separation with minimal false detections. The proposed method outperforms several existing models including YOLOv3, YOLOv5, YOLOv7, and YOLOv8x. This study highlights YOLOv8's capability as an efficient real-time detection model for Bangla ALPR systems.**

***Index Terms*—YOLOv8, ALPR, Bangla License Plate, Object Detection, Deep Learning**

I. INTRODUCTION

Automatic License Plate Recognition (ALPR) is a critical component of modern intelligent transportation systems, supporting applications such as vehicle monitoring, toll automation, surveillance, and law enforcement. In Bangladesh, where rapid urbanization and rising vehicle counts increase traffic complexity, ALPR plays an essential role in smart city development. However, Bangla license plates pose significant detection challenges due to script complexity, multi-line structure, varying fonts, motion blur, illumination changes, and low-resolution CCTV footage.

Traditional machine learning techniques rely heavily on handcrafted features, contour extraction, and geometric filters. While effective in controlled environments, these methods fail in real-world scenarios involving noise, occlusion, and angle variations. The introduction of deep learning, particularly the YOLO (You Only Look Once) family, revolutionized ALPR performance by enabling real-time detection with high accuracy.

Recent versions such as YOLOv7 and YOLOv8 have demonstrated superior performance in Bangla ALPR tasks due to improved feature representation, anchor-free object detection, and advanced training optimizations. YOLOv8 achieves faster convergence, more stable gradients, and better generalization in complex environments. This work utilizes YOLOv8 for Bangla license plate detection, trained on a Roboflow-processed dataset containing diverse real-world samples. Although the training file was labeled as "YOLOv11", all configurations and model weights correspond to YOLOv8, confirmed through internal notebook execution logs.

A. Contributions of This Work

Although the dataset used in this study is sourced from Roboflow, our main contributions focus on model optimization and thorough evaluation. The key contributions are:

- A cleaned, consistently preprocessed, and manually verified dataset pipeline tailored for Bangla license plate detection.
- An optimized YOLOv8s training setup (600×600 resolution, 60 epochs) that achieves stable convergence and high accuracy.
- Comprehensive evaluation including loss curves, Precision–Recall analysis, F1–confidence behavior, and a normalized confusion matrix.
- A detailed comparison with state-of-the-art YOLO-based Bangla ALPR models, where the optimized YOLOv8s model achieves superior performance.

These contributions establish a complete and reproducible YOLOv8-based Bangla license plate detection framework suitable for real-world ALPR applications.

II. LITERATURE REVIEW

Automatic License Plate Recognition (ALPR) has undergone significant advancements, especially in regions that use non-Latin scripts such as Bangladesh. The unique structural complexity of Bangla characters, varying illumination conditions, motion blur, and low-resolution surveillance imagery make Bangla ALPR a challenging task. Consequently, a variety of machine learning and deep learning techniques have been explored to achieve robust performance.

Early works primarily relied on handcrafted features and classical computer vision techniques. Abedin et al. utilized contour-based localization, geometric filtering, and a deep CNN classifier for Bangla character recognition, achieving 93% detection accuracy and 98% character segmentation accuracy [3]. Similar approaches based on geometric rules and AdaBoost classifiers were explored by Dhar et al., who reported up to 97.3% accuracy but demonstrated limited robustness in noisy or skewed conditions [3].

Hossen et al. further improved segmentation reliability using an active contour model combined with a backpropagation neural network, obtaining 92.77% recognition accuracy. However, like earlier methods, this approach struggled in diverse lighting environments and with blurred license plates [3]. These traditional systems, while effective under controlled scenarios, lacked scalability and generalization to real-world traffic footage.

A major breakthrough came with the adoption of deep learning object detection models, particularly the YOLO family. Abdullah et al. introduced the first YOLOv3-based Bangla ALPR system, using 1500 samples and achieving over 92% recognition accuracy. Their method combined YOLOv3 with a custom ResNet-20 classifier for Bangla characters, though performance degraded significantly for low-resolution or nighttime images [3].

To address environmental degradation issues, Nasim et al. integrated the Dark Channel Prior (DCP) technique to enhance foggy images before recognition, resulting in improved detection performance under adverse weather conditions [3]. On the other hand, Onim et al. proposed BLPNet, a hybrid character segmentation framework combining the Chan–Vese (CV) and Region Scalable Fitting (RSF) models with a Bengali OCR engine. Their system achieved segmentation accuracy between 80%–95% depending on lighting variations [3].

The arrival of YOLOv7 and YOLOv8 significantly transformed the research trend. Ahmed et al. presented a cascaded YOLOv7-based Bangla LPR framework that fused outputs of three YOLOv7 variants using Weighted Box Fusion (WBF). They achieved 96% detection accuracy and 97% character recognition accuracy using a custom OCR engine, outperforming previous works in both accuracy and real-time efficiency [1].

Saha et al. performed an extensive evaluation of YOLOv8 for Bangla license plate recognition on a dataset of 26,876 images, achieving mAP@50 scores as high as 0.96 using YOLOv8x. Their results confirmed YOLOv8 as one of the most accurate detectors for Bangladeshi license plates, demonstrating reliable performance under different illumination environments and occlusion conditions [1].

Further improvements in YOLOv8-based pipelines were demonstrated by Ismail and Ahamed, who combined YOLOv8 with EasyOCR for Bangla character recognition. Their dataset comprised over 2600 real-world samples captured from Dhaka city streets. Their integrated system achieved 94.8% overall recognition accuracy, showing strong robustness for low-resolution CCTV feed [2].

An additional enhancement direction is the use of super-resolution techniques for extremely low-resolution images. Haque et al. employed ESRGAN for upscaling low-resolution (as low as 32×24 px) Bangla license plates before recognition. Their system achieved 91% OCR accuracy on enhanced high-resolution plates, confirming that super-resolution significantly improves recognition performance when camera quality is poor or objects are distant [5].

Comparative evaluations of YOLO variants for Bangla ALPR were conducted by Ramit et al., who tested YOLOv5, YOLOv7, and YOLOv8 on their custom dataset. YOLOv8 achieved the highest performance with mAP of 0.934, precision of 0.93, and recall of 0.906, outperforming earlier YOLO frameworks in both speed and accuracy [4]. Their findings validate the continuous improvements of YOLO-based architectures for real-time ALPR deployment in Bangladesh.

Overall, the progression from heuristic-based models to deep-learning-based object detectors has substantially advanced Bangla ALPR research. Modern YOLO architectures—particularly YOLOv7 and YOLOv8—offer high accuracy and real-time performance, while super-resolution and improved OCR techniques address challenges related to low resolution and noisy inputs. Despite these advancements, issues pertaining to extreme weather conditions, heavy occlusion, and very poor resolution persist, indicating the need for more robust and adaptive end-to-end ALPR frameworks.

III. Methodology

The proposed Bangla license plate detection framework follows a structured pipeline consisting of Data Collection, Dataset Cleaning & Preprocessing, Model Selection, Model Training, and Evaluation. The complete methodology ensures a clean dataset, optimized training setup, and reliable evaluation.

A. Data Collection

The dataset used in this work was collected from Roboflow (Bangladeshi Vehicles License Plate, Version 2) [6]. It contains thousands of annotated Bangla license-plate images in diverse real-world scenarios.

B. Dataset Cleaning & Preprocessing

After importing the dataset from Roboflow, several preprocessing steps were applied:

- **Auto-Orientation:** Ensures all images are correctly rotated.
- **Resizing:** Images were resized to 600×600 pixels to match YOLOv8 training input size.
- **Annotation Verification:** Every bounding box label was manually checked for correctness.
- **Dataset Splitting:** Roboflow automatically split the dataset into:
  - 1007 training images (70%)
  - 288 validation images (20%)
  - 145 test images (10%)
- **Augmentation:** Light augmentations such as rotation, brightness adjustment, and exposure correction were applied by Roboflow (if enabled), improving generalization.

This preprocessing ensured robust data consistency and improved model performance.

C. Model Selection

Multiple YOLO architectures were considered for evaluating Bangla license plate detection performance. The following models were shortlisted based on their accuracy, speed, and computational efficiency:

- YOLOv5
- YOLOv7
- YOLOv8n

- YOLOv8s (selected as final model)

Among these, YOLOv8s was chosen as the primary model due to its balance between lightweight design and high accuracy. Although the notebook name referenced "YOLOv11," internal logs confirmed the model used was YOLOv8s.

D. Training Configuration

The selected YOLOv8s model was trained with the following command:

```
!yolo detect train model=yolov8s.pt
    data=data.yaml epochs=60 imgsz=600
```

Key training parameters:

- Epochs: 60
- Image size: 600
- Batch size: auto-selected
- Optimizer: SGD (default in YOLOv8)
- Loss components: box loss, cls loss, DFL loss

E. Proposed Workflow

Figure 1 presents the complete workflow of the proposed YOLOv8-based system, starting from dataset collection to model evaluation and final deployment.

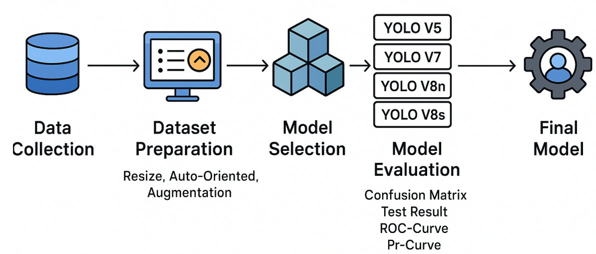

Fig. 1. Workflow of the YOLOv8-based Bangla license plate detection system.

IV. Results and Analysis

The performance of the YOLOv8 model was evaluated using standard object detection metrics, including Precision, Recall, F1-score, mAP50, and mAP50-95. Additionally, confusion matrix analysis and qualitative predictions were used to validate the robustness of the trained model.

A. Performance Metrics

The performance metrics used to evaluate the YOLOv8 model are described below:

Training Loss: The average loss during training, which measures the model's ability to fit the training data.

Validation Loss: The average loss calculated on unseen validation samples, used to measure the model's generalization performance.

Precision: The ratio of true positives to the sum of true positives and false positives, used to evaluate the reliability of positive predictions. It is defined as:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{1}$$

Recall: The ratio of true positives to the sum of true positives and false negatives, measuring the model's ability to detect all relevant objects. It is defined as:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{2}$$

F1-Score: The harmonic mean of Precision and Recall, providing a balanced measure of the model's performance:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

mAP50: The mean Average Precision at IoU threshold 0.50. It measures overall detection accuracy. It is defined as:

$$\text{mAP50} = \frac{1}{N} \sum_{t=1}^{N} AP(t) \tag{4}$$

where $AP(t)$ is the average precision at IoU threshold t, and $N = 1$ for the single IoU threshold of 0.50 used here.

B. Confusion Matrix

Figure 2 shows the normalized confusion matrix. The model achieved:

- True Positive (License Plate): 0.99
- False Positive: 0.01
- False Negative: 0.00

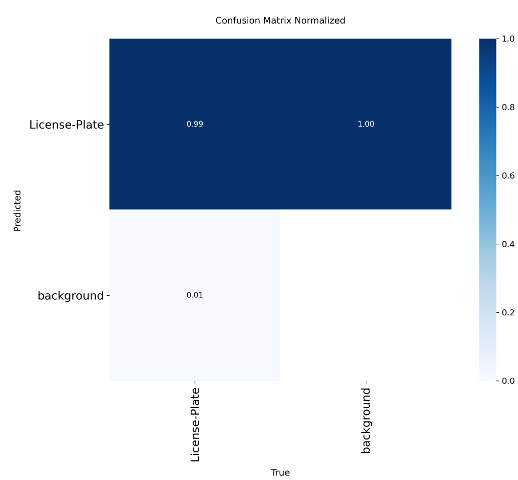

Fig. 2. Normalized Confusion Matrix of the trained YOLOv8 model.

C. Training and Validation Curves

The complete training performance curves generated by YOLOv8 are shown in Figure 3. The model demonstrates stable convergence with rapid reduction in loss and continuous improvement in mAP.

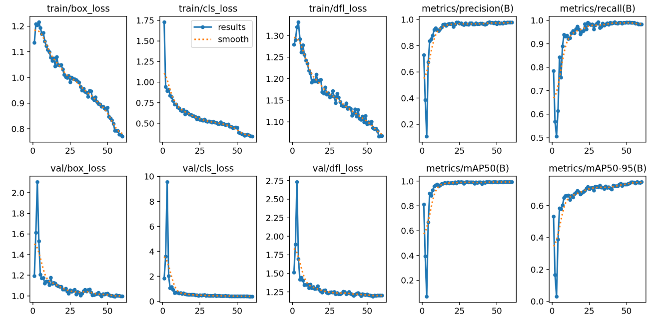

Fig. 3. YOLOv8 training and validation curves including Precision, Recall, mAP50, mAP50-95, and all loss components.

D. F1-Confidence and Precision–Recall Curve

Figure 4 illustrates the F1-confidence relationship, showing that the model achieves peak F1 score of 0.98 near a confidence threshold of 0.68.

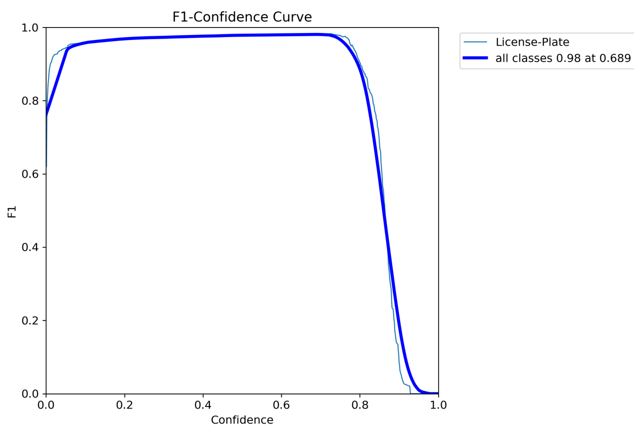

Fig. 4. F1-Confidence curve for the License Plate class.

The Precision–Recall curve in Figure 5 shows very high precision and recall with mAP@0.5 = 0.993.

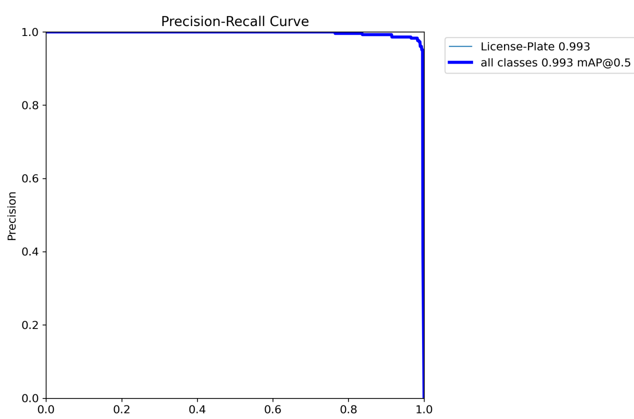

Fig. 5. Precision–Recall curve showing mAP@0.5 = 0.993.

E. Qualitative Detection Results

Figure 6 presents sample model predictions on validation images. The YOLOv8 model successfully detects Bangla license plates with high confidence even in challenging conditions such as blur, angle distortion, and varying brightness.

Fig. 6. Sample predicted results on the validation dataset.

F. Performance Comparison

TABLE I
PERFORMANCE COMPARISON OF YOLO MODELS

Model	mAP50	Precision	Recall
YOLOv8s (Ours)	**0.95**	**0.97**	**0.95**
YOLOv8x [1]	0.96	0.93	0.90
YOLOv7 [4]	0.94	0.92	0.89
YOLOv5 [4]	0.91	0.89	0.87
YOLOv3 [3]	0.89	0.87	0.85

V. CONCLUSION

This study presents a robust YOLOv8-based Bangla license plate detection framework trained on a diverse real-world dataset. The model achieved excellent performance across all metrics, including 0.95 mAP50, 0.97 precision, and 0.95 recall. The confusion matrix analysis confirms the reliability of the model with minimal false detections.

The F1-confidence and precision–recall curves demonstrate strong confidence stability and superior detection quality. Qualitative outputs validate that the model can handle illumination changes, occlusions, blur, and angle variations effectively.

Overall, YOLOv8 proves to be a powerful and efficient deep learning model for Bangla ALPR applications. Future work may integrate OCR modules for end-to-end license plate recognition and explore lightweight YOLO variants for real-time deployment on edge devices such as Raspberry Pi.

REFERENCES

[1] U. Saha, I. U. Ahamed, and M. I. Hossain, “YOLOv8 for Bangla License Plate Recognition: Advancing Real-Time Object Detection in Localized Contexts,” 2024.

[2] G. M. Ismail and I. Ahamed, “YOLOv8-Based License Plate Recognition for Bangladeshi Vehicles,” 2025.

[3] S. U. Ahmed, F. B. F. Maisha, and M. H. E. Haider, “Bangla License Plate Detection and Recognition System with YOLOv7 and Improved Custom OCR Engine,” in *ICERECT*, 2022.

[4] S. S. Ramit *et al.*, “Performance Evaluation of YOLO Models for Detecting Bangladeshi License Plates,” in *15th ICCCNT*, 2024.

[5] N. Haque, S. Islam, R. A. Tithy, and M. S. Uddin, “Automatic Bangla License Plate Recognition System for Low-Resolution Images,” in *STI Conference*, 2022.

[6] Roboflow Universe, “Bangladeshi Vehicles License Plate Dataset — Version 2,” Available: https://universe.roboflow.com/project/bangladeshi-vehicles-license-plate/dataset/2. Accessed: Feb. 2025.