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DESIGN OF A THREE-STEP FRAMEWORK FOR BENGALI LICENSE PLATE DETECTION AND RECOGNITION

MD. JULKER NAYEEM*
International Islami University of Science and Technology Bangladesh (IIUSTB), Bangladesh.
*Corresponding Author Email: julkernayeemt72@gmail.com

NAHID HASAN
Pundra University of Science & Technology, Bangladesh. Email: nahidpundra.cse@gmail.com

MD. ARIFUL ISLAM
Pundra University of Science & Technology, Bangladesh. Email: munirpundra.cse@gmail.com

SOHEL RANA
Chandpur Science and Technology University (CSTU), Bangladesh. Email: sohelranacse052@gmail.com

MST. FARJANA ALAM
Northern University of Business and Technology Khulna (NUBTK), Bangladesh.
Email: farjana.alam001@gmail.com

Abstract

Automated license plate detection and recognition systems are pioneering innovations in the field of computer vision with broad-reaching applications in traffic management, security, and vehicle tracking. Although several reliable systems for languages such as English, a dedicated license plate recognition system is not available for Bangla. This research aims to develop and evaluate an advanced Bangla license plate detection and recognition system, focusing on the linguistic complexity of the Bengali OCR and its reliability. Using cutting-edge YOLOv8 object detection algorithms to precisely identify and locate vehicles in video streams, EasyOCR with a fuzzy string-matching approach to find license plates on vehicle hulls, and a cutting-edge real-time system, this research presents a three-step plan to solve the problems of Bangla license plate detection and recognition. Our organized three-step plan works well, with an overall accuracy of 75.5%, a license plate detection rate of 99%, an OCR accuracy of 93.47%, and an F1 score of 96.6%. These outstanding results not only underscore the system's effectiveness in real-world scenarios but also represent a significant stride forward in the field of computer vision, particularly in addressing the linguistic complexities of the Bengali OCR.

Index Terms: Bangla License Plate, Real-Time System, YOLOv8, EasyOCR, Fuzzy String Matching.

1. INTRODUCTION

Automatic license plate detection and recognition (ALPR) is an advanced technology that automatically detects and recognizes license plates on vehicles via computer vision algorithms. Recent advancements in deep learning algorithms and the availability of extensive datasets have revolutionized computer vision, significantly increasing the accuracy and speed of automatic license plate detection and recognition systems. Several fields, including parking management, vehicle tracking, traffic management, and security surveillance, widely utilize this cutting-edge technology to enhance efficiency and security protocols. As of January 2026, the Bangladesh Road Transport Authority (BRTA) reported 6598320 registered vehicles in Bangladesh [1].

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Despite the substantial and continually increasing number of registered vehicles in Bangladesh, the absence of a dedicated license plate detection system for Bangla license plates is conspicuous.

While robust object detection algorithms such as YOLO and optical character recognition (OCR) technologies are prevalent, linguistic complexity arises in the context of Bengali license plates because they use a word-based numbering system rather than a character-based system. The proposed framework employs YOLOv8, EasyOCR, and a fuzzy string-matching algorithm to rectify and format OCR errors, ensuring a satisfactory result.

Furthermore, real-time Bengali license plate detection and recognition technology has become indispensable in addressing complex challenges in traffic management, law enforcement and security, vehicle tracking, and parking management. These tools, along with automated fuel stations and entrance and exit management, offer swift and precise identification of Bengali license plates.

Within this dynamic landscape, our research makes significant contributions by delving into the intricacies of ALPR technology, with an emphasis on precision. We focus on increasing the accuracy of the whole system in the case of the Bangladeshi license plate. This is complemented by a meticulous three-step methodology ensuring the system's unwavering reliability and robustness. By addressing linguistic complexities and enhancing detection and recognition processes, our research aims to advance state-of-the-art Bangla license plate recognition systems.

- We design a three-stage framework that effectively reduces false detections of license plates and avoids recognizing extraneous vehicle body texts outside the license plate. This framework demonstrates robust performance under various weather conditions and with angled license plates.
- Our string-matching algorithm is capable of correctly formatting license plate numbers, rectifying recognition errors in district names and the "metro" designation, and eliminating any unnecessary texts present on the license plate. This string-matching algorithm not only enhances the accuracy of our system but also offers a valuable tool for integration into other Bangla license plate detection and recognition frameworks, thereby reducing recognition errors.

The principal goal of this study is to increase vehicle identification, ensure public safety, and mitigate instances of traffic violations. License plates serve as pivotal tools for identifying vehicles entangled in criminal activities or traffic transgressions and facilitating the recovery of stolen vehicles.

Notably, the increasing frequency of road accidents in Bangladesh, which are frequently attributed to traffic law breaches, underscores the urgency of improved road safety measures. Police reports underscore that the preceding year (2021) witnessed a tragic toll of over 5088 fatalities in road accidents [8]. In light of these concerns, this research endeavors to contribute to the advancement of an intelligent traffic system by employing automated vehicle monitoring.

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2. RELATED ALPR SYSTEMS

The realm of automatic license plate recognition (ALPR) systems has undergone substantial development within the context of the English language. In contrast, the domain of Bangla ALPR systems remains relatively underexplored, despite Bangla being spoken by a population exceeding 282.9 million people worldwide [24].

However, noteworthy contributions have been made in this field of Bangla license plate recognition through previous studies, offering comprehensive investigations into various aspects of the topic. These studies have enriched our understanding by employing diverse research methodologies, encompassing experimental designs, statistical analyses, and theoretical models.

The existing body of literature underscores the importance and potential for further advancements in Bangla automatic license plate recognition (ALPR) technology. A. Ashrafee et al. explored a real-time Bangla license plate recognition system tailored for low-resource, video-based applications via MobileNet SSD v2 and the Google Vision API.

Their system achieved approximately 82.7% accuracy for license plate localization (LPL) and an OCR F1 score of 60.8% for license plate recognition [2]. M. H. Tusar et al. developed a real-time Bangla license plate detection and recognition system utilizing the YOLO model for plate detection and EasyOCR for Bengali character recognition, achieving 98% accuracy [3].

Similarly, M. N. I. Suvon et al. used the YOLO model to find license plates in real time and a convolutional neural network (CNN) to recognize characters. They obtained 91.38% accuracy, whereas Tesseract OCR achieved 90% accuracy [5]. H. H. Shomee et al. introduced a system for detecting and recognizing license plates from images of various Bangladeshi vehicles, contributing to the first extensive publicly available dataset, "Bangla LPDB-A," consisting of over 2,500 visible Bangla license plates.

Using YOLOv4, they achieved a mean average precision (mAP) of 98.35% for detection and 98.09% for recognition [22]. These studies highlight the efficacy of YOLO-based models in enhancing ALPR systems. A. A. Maruf et al. applied YOLOv4 for license plate detection and Tesseract for recognition, obtaining precision rates of 92.42% and 89.67%, respectively, across various datasets [28]. A recurring issue in these systems, whether for real-time video or static images, is the tendency to mistakenly detect license plate-like objects owing to their two-phase process of detection followed by recognition.

In contrast, S. Abdullah et al. leveraged transfer learning with a ResNet20-based CNN model for Bangla character recognition, achieving 92.7% accuracy, although the system relied on controlled hardware setups and was limited to vehicles registered in the Dhaka metropolitan area [21]. M. S. R. Tusher et al. further advanced the field by introducing a variational autoencoder (VAE) for deblurring Bangla license plate images, which uses convolutional neural networks (CNNs) and generative adversarial networks (GANs), significantly improving the precision and reliability of the ALPR system under diverse conditions [16].

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Table 2.1: Overview of Various Research Studies

Author	Paper Title	Methodologies	Accuracy
A. Ashrafee et al. (2022) [2]	Real-time Bangla License Plate Recognition System for Low Resource Video-based Application.	Mobile Net SSD v2, Google Vision API	LPL – 82.7% LPR – 60.8% (OCR F1 Score)
M. H. Tusar et al. (2022) [3]	Real-Time Bangla License Plate Recognition with Deep Learning Techniques	YOLOv5, EasyOCR	LPD – 98% LPR – 78% (OCR)
C. Tu and S. Du (2022) [4]	A hierarchical RCNN for vehicle and vehicle plate detection and recognition.	RCNN	LPD – 97% LPR – 85% (OCR)
M. N. I. Suvon et al. (2020) [5]	Real-time Bangla Number Plate Recognition using Computer Vision and Convolutional Neural Network	YOLOv3, Tesseract	LPD – 95% LPR – 91.38% (OCR)
N. A. Alam et al. (2021) [13]	Intelligent System for Vehicles Number Plate Detection and Recognition Using Convolutional Neural Networks.	CNN, Alexnet, Spatial super resolution	LPR – 98.1%
S. Abdullah et al. (2018) [21]	YOLO-Based Three-Stage Network for Bangla License Plate Recognition in Dhaka Metropolitan City	YOLOv3, ResNet-20	LPR – 92.7% (OCR)
Y. Shambharkar et al. (2023) [14]	An Automatic Framework for Number Plate Detection using OCR and Deep Learning Approach.	CNN	LPR – 96.23%
R. Laroca et al. (2022) [15]	On the Cross-dataset Generalization in License Plate Recognition.	RARE, R2AM, CR-Net, CRNN, Fast-OCR, YOLOv4, etc.	LPR – 82.4%
A. Pattanaik and R. C. Balabantaray. (2022) [6]	License Plate Recognition System for Intelligence Transportation Using BR-CNN.	BR-CNN, CNN	LPR – 98%
M. S. Zandi and R. Rajabi. (2022) [7]	Deep Learning Based Framework for Iranian License Plate Detection and Recognition.	YOLOv3, Faster R-CNN	LPD – 98% LPR – 98%
M. R. Amin et al. (2014) [23]	An Automatic Number Plate Recognition of Bangladeshi Vehicles.	Java (J2SE)	LPL – 88% LPR – 62% (OCR)

Despite these advancements, current systems face several limitations, including lower accuracy rates in detection and recognition and a shortage of comprehensive Bengali license plate datasets. The only widely recognized dataset suffers from a limited number of images and lacks representation across different vehicle types and geographic regions. Many systems that use cutting-edge YOLO models have performed well in other languages. For example, L. Wang et al. developed the YOLOv5-CBAM model for detecting license plates, which was 2% more accurate than RPNet and 2.7% more accurate with CBAM [17]. M. S. H. Onim et al. used GANs and YOLOv4 to achieve 89% accuracy for both daylight and nighttime images [18]. M. H. F. Afonso et al. compared the performance of YOLOv5 and YOLOv8, reporting accuracies of 97.83% and 97.98%, respectively [19]. H. Shi and D. Zhao employed an enhanced YOLOv5 along with a GRU

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and CTC, attaining a precision of 98.98% [20]. Additionally, M. Humayun et al. used YOLOv4 with a spatial pyramid pooling network to obtain an mAP of 81% under different weather conditions, which was better than that of a few other YOLO-based models [25]. Table 2.1 presents a summary of these studies, including their methodologies and results.

2.1 Limitations of existing works

The existing systems for ALPR face a variety of challenges and limitations.

- The current real-time Bengali license plate recognition systems exhibit a relatively low level of accuracy, with a detection rate of 82.7% and an OCR F1 score of 60.8% for recognition [2]. We have considered this paper our baseline because of the similarities between our working methods. They have worked with real-time video datasets to test model performance in a similar manner.
- The authors of [3] achieved remarkable recognition accuracy, but there are several limitations in their research. They have applied the EasyOCR approach only for a single district, Dhaka (ঢাকা). In their system, there is no string-matching technique. For example, if “ঢাকা মেট্রো” is incorrectly recognized as “চাকা মেট্রো”, then in their system, there is no approach to correct it. There is no handwritten number plate example in their research. In the case of handwritten number plate recognition, EasyOCR is able to correctly recognize the plate. However, if the system recognizes the number plate incorrectly for any unwanted reason, it will be unable to correct it due to the absence of a string-matching method. It is considered another base paper.
- These systems encounter difficulties in distinguishing license plates from vehicles with similar color schemes [4].
- There is a significant incidence of false detection by objects external to vehicles [4].
- There is a dearth of research on the performance of these systems under various weather conditions, such as fog, rainy, and sunny, as well as limited geographical areas or distinct cities [5, 21].

Our proposed system addresses these limitations by specifically focusing on overcoming false detections from objects external to vehicles and enhancing overall accuracy, primarily through the incorporation of a three-step strategy, notably the fuzzy string-matching technique. In addition, we consider various environmental conditions, including sunny and foggy conditions, as well as license plates from various geographical areas, including different districts in Bangladesh. Furthermore, we included both printed and handwritten license plates in our dataset to evaluate the performance of the model.

3. OUR PROPOSED SYSTEM

Our novel system represents a sophisticated three-step automatic Bengali license plate (BLP) detection and recognition framework. This system meticulously processes video frames through a structured sequence of operations.

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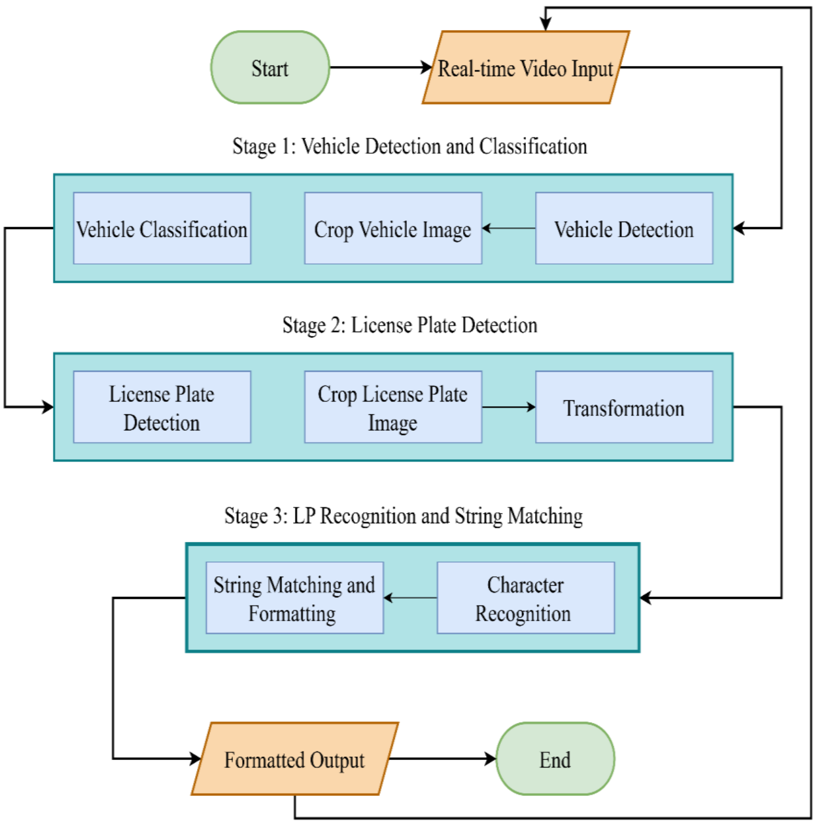

- ✓ In the initial step, vehicles are detected and classified within video frames via the YOLOv8 model. We then crop the vehicle images from the video frames, following the instructions in Section 3.1.
- ✓ In the second step, the system accurately identifies and crops the license plate image within the vehicle image obtained from the initial step. Additionally, the system performs specific transformations, particularly rotations, to increase the accuracy of the final recognition. This process is described in detail in Section 3.2.
- ✓ In the final step, the system uses EasyOCR to recognize characters from the license plate and applies a robust string-matching algorithm specifically designed for Bengali license plates. This whole process is described in detail in Section 3.3.

This comprehensive methodology, which is meticulously executed across three essential phases, underscores the system's ability to perform BLP detection and recognition effectively and accurately, promising significant advancements in the field shown in Figure 3.1.

3.1 Vehicle detection and classification

Our newly developed automatic license plate recognition (ALPR) system uses YOLOv8, specifically a pretrained compact variation known as YOLOv8s, to recognize vehicles inside video frames in the early stages of operation. The reason YOLOv8 was chosen

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over earlier iterations of the YOLO model is its positive characteristics, including improved speed, flexibility and efficiency. This decision is supported by its excellent ability to process a significant number of frames per second, making it suitable for real-time vehicle identification and classification tasks. Additionally, YOLOv8 performs well in a variety of weather circumstances, which greatly increases its usefulness and robustness in the context of our ALPR system. This strategic adoption of YOLOv8s serves as a fundamental cornerstone in our pursuit of accurate and efficient real-time vehicle detection, a pivotal component of the broader ALPR framework, as depicted in Figure 3.2.

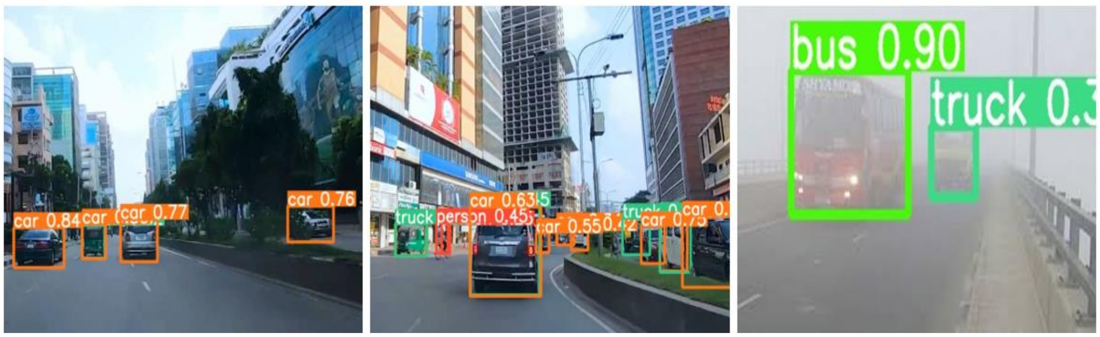

Figure 3.2: Vehicle detection and classification

3.2 License plate detection

In the second phase of our systematic approach, our ALPR system diligently undertakes the critical task of license plate detection, encompassing the precise cropping of the license plate section from the vehicle image and any requisite transformations. Within this detection phase, we continue to leverage the capabilities of YOLOv8, albeit this time employing a customized YOLOv8 small model that has been meticulously trained using a substantial dataset comprising 1544 vehicle images, each prominently featuring a visible license plate. The training process, as elaborated in Section 4.2, yielded commendable results. Upon successful license plate detection, as shown in Figure 3.3, our system adeptly proceeds to crop the relevant license plate segment from the image and, if necessary, execute image rotations.

Figure 3.3: License plate detection

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This rotation endeavor involves the detection of bounding boxes encapsulating the textual elements of the license plate through EasyOCR, followed by a meticulous calculation of the required degree of rotation. This determination occurs in two sequential steps: first, we ascertain the angles of all textual components with a character length exceeding 1 through an equation (eqn. 1), and subsequently, we compute the mean angle via an equation (eqn. 2). In instances where rotation is deemed unnecessary, the output from EasyOCR seamlessly integrates into the final phase of our innovative ALPR system, ensuring a comprehensive and effective workflow.

$$angle = \ atan2(y2 - y1, x2 - x1) * 180 \ / \ PI \qquad \text{(eqn. 1)}$$

Within this process, the coordinates (x1, y1) denote the lower-left point of the bounding box, whereas (x2, y2) corresponds to the lower-right point. Notably, angle measurement is selectively applied solely to bounding boxes encompassing more than one character.

$$mean\ angle = (\sum_{i=1}^{k} a_i \times l_i)\ /(\sum_{i=1}^{k} l_i) \qquad \text{(eqn. 2)}$$

Here, a represents the angle of BLP texts in degrees, l represents the char length, and k represents the total number of angles we calculated in the first step of the degree of rotation calculation.

3.2.1 Dataset

The dataset ‘Bangla LPDB-A’ utilized in this investigation comprises 4,597 photos, encompassing 2,668 cropped license plate images and 1,929 images featuring vehicles with visible license plates [12]. Notably diverse, this dataset captures images from various perspectives, angles, locations, and lighting conditions, encompassing a wide array of vehicle types and license plates representing various districts and classes. This inherent diversity renders the dataset highly applicable for comprehensive use throughout Bangladesh. Additionally, for testing vehicle detection, we utilize a real-world video featuring 100 moving vehicles, which include different types of vehicles, such as buses, trucks, and cars. We collected this video dataset from Bangladeshi highways, where each video clip contains a single or multiple vehicles from different districts of Bangladesh.

3.3 LP Recognition and String Matching

We use a pretrained Bengali script model from EasyOCR to recognize the characters on the license plate at the last stage of our system. After extracting the characters from the license plate, we methodically process them via fuzzy string-matching algorithms before formatting the final text according to Bangladesh's standard license plate number format. The final phase provides a precise and accurate illustration of the license plate numbers, resulting in a thorough recognition procedure.

3.3.1 Bangladeshi License Plate

In Bangladesh, a vehicle registration plate has a standard layout with four main parts: the district, the vehicle class, the class number, and the vehicle number. Figure 3.4 shows that there is also an option for a metropolitan indicator.

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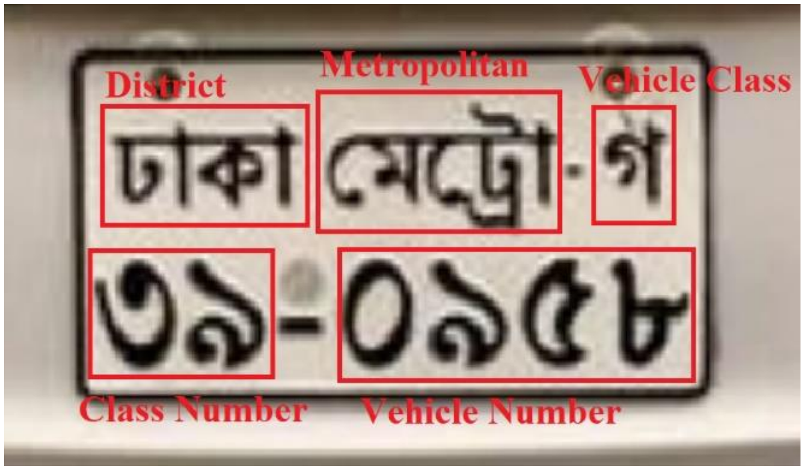

Figure 3.4: Demonstration of the BLP

- City Name: Written in Bengali script, this field designates the city or region of vehicle registration, e.g., "ঢাকা" for Dhaka [11].
- Metropolitan Indicator: Occasionally, the term 'মেট্রো' (Metro) is appended after the city name, signifying registration within a metropolitan area. [11].
- Vehicle Class: Utilizing the Bengali script, this field specifies the vehicle type, e.g., "হ", denoting a motorcycle [11].
- Vehicle Class Number: This field contains a 2-digit Bengali number to specify the precise class or category of the vehicle [11].
- Vehicle number: The fourth and final field, also with 4-digit Bengali numerals, represents a unique identifier assigned to each vehicle [11].

3.3.2 String Matching

In the context of the Bengali License Plates (BLPs), there are two parts: the Bangla script section and the numerical section. The primary challenge lies in the Bangla script, especially concerning district names and the presence of the word 'metro.' For example, optical character recognition (OCR) may often misinterpret 'ঢাকা' as 'ঢাক' or 'বগুড়া' as 'বগড়া', resulting in inaccuracies.

This misinterpretation is caused by the word-based number plate system and the linguistic complexity of Bangla. To address this, we first check for correct district names. If not found, we use 'fuzzywuzzy' for string matching, selecting the district with the highest similarity ratio. We perform a similar check for 'মেট্রো' and the vehicle class.

In the numerical part, we take the first 6 digits – 2 as the vehicle class number and 4 as the vehicle number. Once we have all the parts, we format them in the traditional Bengali license plate format. Algorithm 1 discusses the string-matching process.

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Algorithm 1: String Matching Algorithm

Input: Recognized text by EasyOCR

Output: A formatted string of Bangla

$output \leftarrow EasyOCR(blp\_image)$ //Read EasyOCR output

//Initializing Variables

$district \leftarrow ''$

$metro \leftarrow ''$

$class\_name \leftarrow ''$

$vehicle\_number \leftarrow ''$

//Split number and text part of output

foreach $char \in output$ **do**

  if $char$ is $digit$ **then**

    $number \mathrel{+}= char$

  else

    $text \mathrel{+}= char$

  end if

end foreach

//Find District Name

$district\_names \leftarrow$ ['ঢাকা', 'বগুড়া', ...] //Store all district names

foreach $district\_name \in district\_names$ **do**

  if $district\_name$ is in $text$ **then**

    $district \leftarrow district\_name$

    break

  end if

end foreach

// If the output does not accurately contain any district name, there might be misspellings. Therefore, string matching is required to determine the exact district name.

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if $district := ''$ **then**
  $max\_score \leftarrow 0$
  foreach $district\_name \in district\_names$ **do**
    $ratio \leftarrow fuzzy\_ratio(text, district\_name)$
    if $ratio > max\_score$ **then**
      $max\_score \leftarrow ratio$
      $district \leftarrow district\_name$
    end if
  end foreach
end if

//End of Finding District Name

//Find for Metro

if 'মেট্রো' is in $text$ **then**
  $metro \leftarrow$ 'মেট্রো'
else
  // In the absence of the accurate occurrence of the word 'metro' in the output, potential misspellings may exist. Consequently, string matching is necessitated to ascertain the presence of the term 'metro'
  $threshold \leftarrow 60$
  $district\_with\_metro \leftarrow district +$ 'মেট্রো'
  $score \leftarrow fuzzy\_ratio(text, district\_with\_metro)$
  if $score \geq threshold$ **then**
    $metro \leftarrow$ 'মেট্রো'
  end if
end if

//End of searching the presence of the term 'metro'

//Start finding the vehicle class

$vehicle\_classes \leftarrow$ ['ক','হ',...] //Store all vehicle class names

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```
foreach vehicle_class ∈ vehicle_classes do
    //    Adding white spaces before and after vehicle class to avoid unwanted matching
    vehicle_class_modified ← '' + vehicle_class + ''
    if vehicle_class_modified is in text then
        class_name ← vehicle_class
        break
    end if
end foreach
//    If the precise vehicle class is not identified in the initial search, a subsequent comparison will be conducted by sequentially matching the entire text with each potential vehicle class
if class_name := '' then
    max_score ← 0
    probable_text ← district + '' + metro + '' + vehicle_class
    foreach vehicle_class ∈ vehicle_classes do
        ratio ← fuzzy_ratio(text, probable_text)
        if ratio > max_score then
            max_score ← ratio
            class_name ← vehicle_class
        end if
    end foreach
end if
//End the finding of Vehicle class
//Set Vehicle Number as the first 6 digits from Number
if number.length <= 6 then
    vehicle_number ← number
else
    for i ← 0 to 6 do
```

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$vehicle\_number \leftarrow vehicle\_number + number[i]$
end for
end if
//End of getting all the components of the Bangla License Plate
//Format the number
$Output \leftarrow district + '' + metro + '' + vehicle\_class + '' + vehicle\_number$
Print Output

4. RESULTS

A license plate detection accuracy of 99% and a recognition accuracy of 75.5% are reached by our three-step Bengali License Plate (BLP) detection and recognition system. It also has an OCR F1 score of 96.6% and an OCR accuracy of 93.47%. The detailed results of our methods are described in sections 4.1, 4.2, and 4.3.

4.1 Vehicle detection and classification

We evaluated the pretrained YOLOv8 model within the vehicle detection component of our automatic license plate recognition (ALPR) system. This evaluation involved analyzing a video clip featuring 100 moving vehicles. This assessment yielded an impressive accuracy rate of 98%, which was calculated via Equation 3, with a precision of 0.98 and a recall of 1.00, as determined via Equations 4 and 5, respectively.

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \quad \text{(Eqn. 3)}$$

$$\text{Precision} = TP / (TP + FP) \quad \text{(Eqn. 4)}$$

$$\text{Recall} = TP / (TP + FN) \quad \text{(Eqn. 5)}$$

To provide comprehensive insight into the model's performance, we present the confusion matrix (Table 4.1) below:

Table 4.1: Confusion matrix of the vehicle detection part

		Actual	
		Positive	**Negative**
Predicted	Positive	TP = 98	FP = 2
	Negative	FN = 0	TN = 0

Here, this step is taken to prevent the license plate-like objects from being detected outside of the vehicle hull because the license plate is detected from the only cropped section in our following stage. Notably, while the pretrained model demonstrated high accuracy in detection, challenges emerged in the classification stage. Certain vehicle types commonly found in Bangladesh, such as CNG and Leguna, present classification difficulties. These challenges arose because of the limited capacity of the pretrained

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model to classify these specific vehicle types accurately. Notably, these classification difficulties did not significantly impact the overall accuracy of the system.

4.2 License plate detection

We conducted an evaluation of our automatic license plate recognition (ALPR) system in the second phase, using a dataset of 100 vehicle-cropped images randomly collected from a validation set of the 'Bangla LPDB-A' dataset, all containing license plates. In this test, our proposed system achieved amazing 99% accuracy, with a precision of 1.00 and a recall of 0.99, as calculated by equations 3, 4, and 5. A short diagram of the confusion matrix that accompanies this system can be found in Table 4.2.

Table 4.2: Confusion matrix of the LP detection part

		Actual	
		Positive	**Negative**
Predicted	Positive	TP = 99	FP = 0
	Negative	FN = 1	TN = 0

In addition to the evaluation using a 100-image dataset, the proposed model underwent validation with 385 images during the training phase. Throughout the training process, 30 epochs were executed, utilizing solely the vehicle image subset of the 'Bangla LPDB-A' dataset. We divide this subset into 80% for training, which includes 1544 images, and 20% for validation, which includes 385 images. The outcomes of this training process are detailed in Table 4.3 and Figure 4.1:

Table 4.3: Results of license plate detection

epoch	train/ box_loss	train/ cls_loss	train/ dfl_loss	metrics/ precision (B)	metrics/ recall(B)	metrics/m AP50(B)	metrics/m AP50-95(B)	val/ box_loss	vali/ cls_loss	val/ dfl_loss
5	1.474	0.902	1.392	0.912	0.888	0.946	0.512	1.501	0.780	1.485
10	1.405	0.728	1.325	0.935	0.951	0.971	0.526	1.497	0.652	1.460
15	1.365	0.663	1.316	0.979	0.961	0.990	0.608	1.343	0.535	1.333
20	1.309	0.599	1.277	0.977	0.974	0.992	0.617	1.340	0.500	1.337
25	1.260	0.496	1.277	0.965	0.980	0.991	0.605	1.384	0.502	1.390
30	1.186	0.450	1.236	0.979	0.985	0.990	0.644	1.318	0.450	1.321

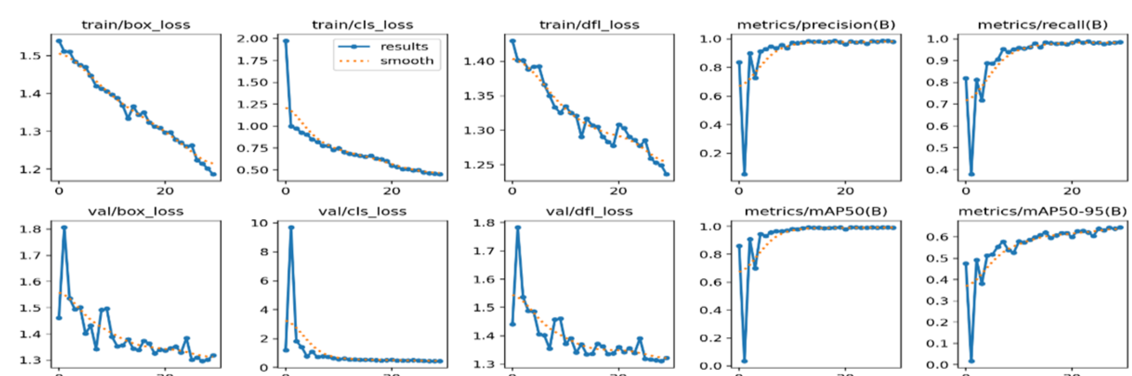

Figure 4.1: Results of license plate detection

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During the license plate identification phase, the YOLOv8 model, which is derived from the YOLO family, helps achieve minimal loss while retaining a precision of 0.979 and a recall of 0.985 at the best epoch during training. Additionally, it accurately detected 393 license plates out of the 396 in the validation dataset. Notably, there is a discrepancy between the number of recognized license plates and the total number of images in the dataset. This disparity arises from some vehicles that have more than one license plate. Furthermore, our system exhibited robust performance under challenging conditions, successfully detecting license plates even in scenarios where the vehicle and license plate share the same background color, as exemplified in Figure 3.3. This robustness of our system in the license plate detection phase is achieved by choosing YOLOv8, as previous research has demonstrated that the YOLO family is effective not only for object detection [9] but also for license plate detection [3, 5, 7, 17, 18, 19]. Additionally, in a prior study related to Bengali license plates, M.H. Tusar et al. [3] utilized YOLOv5 and EasyOCR and achieved notable results. Another study by M.H. F. Afonso et al. [19] indicated that YOLOv8 slightly outperformed YOLOv5 in terms of vehicle and license plate detection. Additionally, according to Augmented A.I., YOLOv8 offers superior speed and accuracy compared with YOLOv5 [10], rendering it more reliable for real-time applications.

4.3 BLP Recognition and String Matching

In the concluding phase of our system's implementation, we subjected the final results to rigorous testing. A set of 94 randomly chosen cropped license plate images from the "Bangla LPDB-A" dataset was used for this test, and our proposed system achieved impressive 93.47% accuracy, as shown in the formula (eqn. 3). Additionally, we performed an optical character recognition (OCR) test and obtained an impressive F1 score of 0.966. The precision score was 0.998, and the recall score was 0.936, which were calculated via formulas (eqn. 6, 4, and 5). Notably, during this testing phase, we treated the entire district name and 'metro' as a unified class while also considering the vehicle class and single digits as individual classes. The associated confusion matrix for license plate recognition is presented below in Table 4.4.

Table 4.4: Confusion matrix of the LP recognition part

		Actual	
		Positive	**Negative**
Predicted	Positive	TP = 731	FP = 1
	Negative	FN = 50	TN = 0

$$\text{F1 score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall}) \qquad \text{(Eqn. 6)}$$

However, within the context of license plate recognition, a single error in identifying a number plate can lead to misidentification of the entire vehicle. For example, if the system misidentifies the number '৬' as '৫' or a class 'হ' as 'ত', it can significantly impact the vehicle's identity. In this regard, we measured an additional performance metric, evaluating how accurately our system identified the entire number on the license plate. Our system

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correctly recognized 71 out of 94 license plates, demonstrating a 75.53% system accuracy, as calculated by the formula (eqn. 7).

System Accuracy = (Number of Correct Recognition) / (Total Number of Test) (eqn. 7)

The rotation process is very important in our automatic license plate recognition (ALPR) system because it is a key part of ensuring that the text extracted from Bengali License Plates (BLPs) through optical character recognition (OCR) is correct, as shown in Table 4.5.

Table 4.5: OCRs with and without rotation

Before Rotation	After Rotation
	
ময়মনসিংহ- ত -২৬৬৪ ১৫	ময়মনসিংহ- হ ১৫-২৬৬৪

In addition to rotation, the incorporation of fuzzy string matching is another vital contributor to the precision and accuracy of our system's outcomes. The results of recognition, considering both cases with and without string matching, are detailed in Table 4.6:

Table 4.6: Results with and without String Matching

Image	OCR Output	After String Matching
	ঢাকা মেট্রো গ ২২-৫৬২৭	ঢাকা মেট্রো গ ২২-৫৬২৭
	ঠাতুরগাং: ল ১১ ৪১১৪	ঠাকুরগাঁও ল ১১-৪১১৪

Our comprehensive process yields the formal recognition results detailed in Table 4.7.

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Table 4.7: Final outcomes of the ALPR system

Image	Recognized Text
	কক্সবাজার হ ১১-০১৫০
	নোয়াখালী ল ১১-০৩৫৮
	ঢাকা মেট্রো হ ৬৮-৮২৮
	সিলেট হ ১৩-৯৫০৫

In this step, we use EasyOCR, which supports over 80+ languages and uses their preprocessing technique [26]. EasyOCR is a GPU-supported, faster technique that uses the character region awareness for text detection (CRAFT) algorithm and ResNet+LSTM+CTC architecture [26, 27]. Compared with Tesseract OCR, EasyOCR has superior performance in handling noisy images [27]. Previous studies [3] have also demonstrated notable accuracy when using the EasyOCR for Bengali license plate recognition. However, because Bengali license plates are word-based and contain compound characters, EasyOCR is prone to character mistake detection within words. We employ a string-matching algorithm to mitigate this limitation.

4.4 Comparing our proposed framework with existing base papers

The structure of the Bengali license plate, as detailed in Section 3.3.1, significantly differs from those in other languages. Using YOLOv8 to find vehicles and license plates, we were able to find license plates more accurately than in our base papers by A. Ashrafee et al. [2] and M. H. Tusar et al. [3], as shown in Table 2.1. Ashrafee et al. focused on low-resolution video data, whereas Tusar et al. employed YOLOv5 and EasyOCR, which achieved commendable results. In contrast, our system incorporates image data collected under diverse conditions and employs YOLOv8 and EasyOCR along with a custom-designed string-matching algorithm. This three-stage methodology not only provides flexibility in removing false detections but also minimizes recognition errors. Compared

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with existing methodologies, our system achieves a license plate detection accuracy of 99%, surpassing that of previous studies. We further employ EasyOCR, which consistently provides accurate results for license plate recognition. During this phase, we apply the string-matching algorithm to enhance system performance by automatically correcting the district and metro components of the Bengali license plates. We have succeeded in enhancing license plate recognition compared with our base papers by A. Ashrafee et al. [2] and M. H. Tusar et al. [3], as mentioned in Table 4.8. In addition, in our system, we succeeded in overcoming the false detection problem by incorporating our proposed three-step strategy.

Table 4.8: Performance comparison between the proposed framework and existing methods for Bengali license plate detection and recognition

S. N.	Authors of the Paper	Methodologies	Results (%)
1	A. Ashrafee et al. (2022) [2]	Mobile Net SSD v2, Google Vision API	LPL Accuracy: 82.7% LPR: 60.8% (OCR F1 Score)
2	M. H. Tusar et al. (2022) [3]	YOLOv5, EasyOCR	LPD Accuracy: 98% LPR: 78% (OCR Accuracy)
3	M. N. I. Suvon et al. (2020) [5]	YOLOv3, Tesseract	LPD Accuracy: 95% LPR: 91.38% (OCR Accuracy)
4	S. Abdullah et al. (2018) [21]	YOLOv3, ResNet-20	LPR: 92.7% (OCR Accuracy)
5	M. R. Amin et al. (2014) [23]	Java (J2SE)	LPL Accuracy: 88% LPR: 62% (OCR Accuracy)
6	**Proposed Framework**	YOLOv8, Easy OCR, Fuzzy Wuzzy, string matching Algorithm	LPD Accuracy**: 99%** LPR Overall System Accuracy**: 75.5%** LPR OCR Accuracy**: 93.47%** LPR OCR F1 Score**: 96.6%**

In summary, the integration of YOLOv8 for enhanced detection and EasyOCR for the recognition phase has proven effective in our three-stage framework. The incorporation of image transformation techniques and a string-matching algorithm further enhances the accuracy of the results, addressing the unique challenges posed by Bengali license plate recognition.

5. CONCLUSION AND FUTURE RESEARCH

In this study, we presented a three-stage framework for a Bengali license plate detection and recognition system, addressing the linguistic complexity of Bangla. We achieve accurate recognition of Bangla license plate text via the state-of-the-art YOLOv8 object detection algorithm in the first two steps, vehicle detection and license plate detection, and EasyOCR with a string-matching algorithm in the third step. Our system demonstrates the ability to detect and recognize license plates with an accuracy of 75.5%,

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even under varying weather and lighting conditions, as well as in the case of handwritten number plates. The practical implications of our system extend across various domains, including traffic management, law enforcement, and security surveillance. By effectively addressing the linguistic intricacies of the Bengali OCR, our system holds promise for enhancing vehicle identification, promoting public safety, and mitigating traffic violations in Bangladesh. In our forward-looking endeavors, our team maintains a steadfast commitment to the continuous refinement of object detection methodologies. A primary emphasis is placed on confronting intricate challenges, notably the discernment between school buses and yellow trucks within the detection framework. Our strategic plan is to expand our dataset to include previously elusive vehicle types such as CNG and Leguna. Our continuous commitment also encompasses the continual advancement of our optical character recognition (OCR) technology. Our main goal is to seamlessly integrate this system into real-time applications, thereby increasing its influence and practical effectiveness within the fields of security and transportation systems.

Author Contributions

Md. Julker Nayeem (Corresponding), Nahid Hasan & Md. Ariful Islam: hold joint first authorship of this work; Conception or design of the work, Data collection; Data analysis and interpretation; Drafting the article; critical revision and Final approval of the version to be published.

Sohel Rana & Mst. Farjana Alam: critical revision of the article.

Conflict of Interest

The authors declare no conflict of interest.

Data availability statement

Available on request.

Ethic Approval

Not Applicable

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