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A Bangladeshi License Plate Detection System Based on Extracted Color Features

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***Abstract*— As the number of motorized vehicles is increasing rapidly in Bangladesh, Automatic License Plate Detection and Recognition (ALPDR) systems have become a necessity for proper management of vehicles on roads. The first phase of an ALPDR system is the detection and localization of number plates from vehicle images. In this paper, we introduce a dataset of 630 images that were manually captured. The dataset represents various real-world scenarios. We propose the use of color histograms with MinPool and MaxPool features for license plate detection and localization. The detection system was tested in multiple color spaces to observe their effect on the detection phase. The proposed and developed system is very effective and achieved high levels of correctness in the detection phase according to different metrics.**

Keywords*— *automatic license plate detection; image processing, color histograms; horizontal and vertical histograms, random forests.

I. INTRODUCTION

Automatic License Plate Detection and Recognition (ALPDR) is the process of detecting a license plate (LP) region from an image, localizing and cropping the license plate, and recognizing the contents of the license plate [1]. Due to an increase in both commercial and private vehicles, automated systems such as automatic traffic control systems, ALPDR systems have become a necessity for proper management of vehicles in the road [2]. ALPDR systems enable law enforcement agencies to properly monitor the vehicles in the road and swiftly take actions against responsible parties in case of an accident. Applications of ALPDR systems include automated parking systems, access control systems, automated tolling systems, automated traffic control systems, border control systems, etc. [3]–[5].

According to the records from the Bangladesh Road Transport Authority (BRTA), a total of 34,19,884 registered motor vehicles exist in Bangladesh. Among these, there are around 1,35,081 trucks, 3,35,660 private cars, and 44,374 buses [6]. There is also a huge amount of non-registered vehicles that are unaccounted for. The sheer number of vehicles on the roads in Bangladesh requires automated management systems for proper management, however, very few such systems exist. Traffic jams, road accidents, hit and run incidents, etc. are among the numerous effects of a large number of vehicles and manual control systems [6].

Various notable methods have already been explored for number plate detection and recognition, such as deep learning based methods [7]–[9], image processing based methods [10], [11], fuzzy logic based methods [12], etc. Various ROI descriptor features such as Histogram of Gradient Orients (HOG), Features from Binary Robust Independent Elementary Features (BRIEF), Accelerated Segment Test (FAST) combined with machine learning techniques have also been successfully used for license plate detection. Various automated ALPDR systems have been developed in the context of Bangladesh [13]–[16]. Deep learning based fall detection systems do not require implicit feature extraction techniques. The deep learning models perform feature extraction, detection, and localization tasks internally. Deep learning based detection systems are very robust, as larger models can have millions of parameters and can extract sophisticated features from images. Image processing based systems mostly depend on various edge detection and morphological operations for license plate area detection and recognition.

Datasets are the most crucial part of any computer vision system and are mandatory for future incremental improvements. In this paper, we present the first-ever open-access Bangladeshi vehicle license plates dataset. We also propose a novel combination of features namely color histogram with MinPool and MaxPool for license plate detection and localization in the context of Bangladesh.

The rest of the paper is organized as follows: Section II provides information on Bangladeshi license plate regulations set by BRTA. Several related research works have been briefly discussed in Section III. Section IV presents the methodology of the detection system. The implementation details and experimental results are analyzed in Section V. Finally, Section VI concludes the paper.

II. LICENSE PLATES CONVENTION IN BANGLADESH

The registration numbers and the license plates that are used in vehicles are generally issued by BRTA in Bangladesh. Fig. 1 represents a typical Bangladeshi license plate. Bangladeshi license plates generally use Bangla numerals and characters to form the registration numbers. Currently, 33 letters and 10 numerals of the Bangla language are permitted for use in the registration plate. The permitted Bangla characters and numerals can be used to represent all valid license plate combos. The use of English characters and numerals are not permitted.

Bangladeshi license plates are generally printed on metal sheets. Most commercial vehicles such as buses and trucks are required to present a metal-sheet license plate with green background and black text for ease of detection and recognition.

Fig. 1. A typical Bangladeshi license plate.

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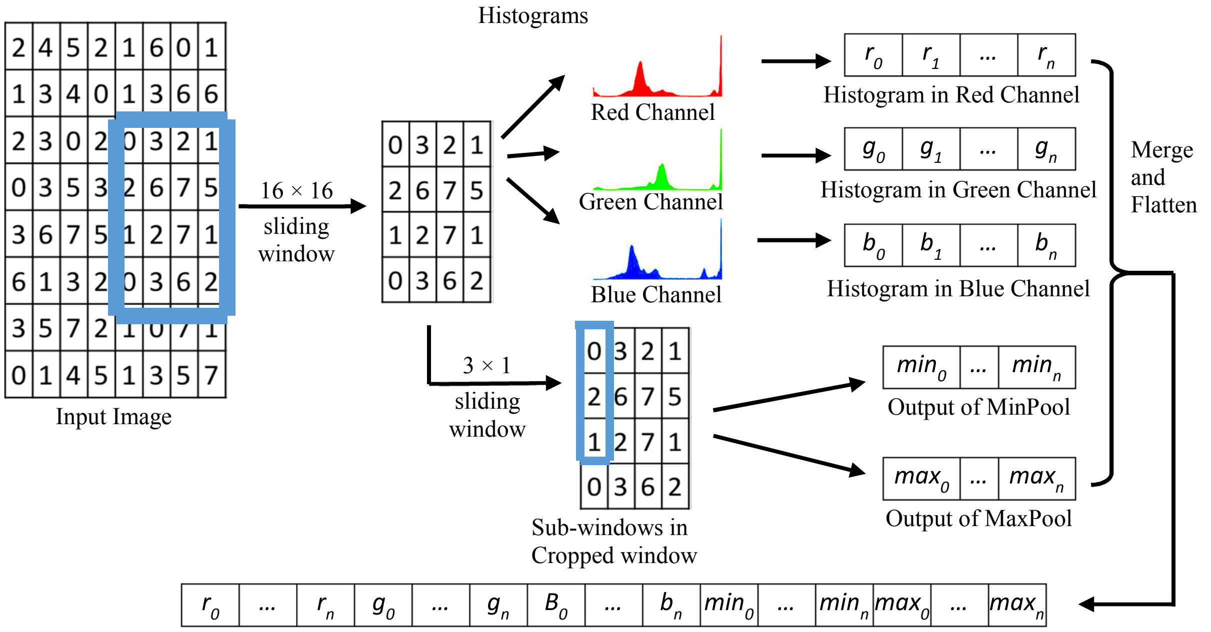


Fig. 2. The input image and extracted features.

The license plates must contain two lines. The standard format is “City Name -Vehicle Class Letter” in the upper line and “Vehicle Class Number – Registration Number” in the lower line. In the illustrated case “গাজীপুর” (Gazipur) is the city name. “জ” (Ja) is the vehicle class letter. “০৪” (04) is the vehicle class number and “০০২৬” (0026) is the registration number. According to BRTA, these have to be written in Bengali numerals and character, printed on a flat metal plate, and the total plate dimension must be 524 mm × 112 mm. The plate must be put both in front and in the back of the vehicles.

III. Literature Review

This section provides a descriptive summary of existing relevant ALPDR systems in the context of Bangladesh.

Siddique et al. [13] used a modified Sobel Edge Detector for horizontal and vertical edge detection and a size-specific search based on Bangladesh Road Transport Authority (BRTA) standards for license plate localization. Morphological operations and neighborhood connectivity were used for character segmentation. Horizontal line (মাত্রা), vertical line, closed loops and upper extension properties were utilized for character recognition and perspectives and curvature properties were used for numeral recognition. However, this system requires a consistent connection to the national database for license plate approximation. The system is also less robust as it performs a size-specific search based on BRTA standards for license plate detection.

Uddin et al. [14] used Sobel edge detection, vertical histograms, and morphological closing to detect and localize the license plate region. After performing adaptive thresholding on the localized license plate region, after noise removal, connected component analysis and aspect ratio of bounding boxes were used to segment the characters. After segmentation, a two-dimensional Gabor filter was used for feature extraction. The dimensionality of the extracted features was reduced using the Kernel PCA method and two separate SVM models for numbers and alphabets were trained using the features.

A YOLOv3 deep learning model for license plate detection and ResNet-20-based deep Convolutional Neural Network (CNN) for character recognition was used by Abdullah et al. [15]. The system is able to detect the license plates and recognize the characters in very complex scenarios and angles as generally state-of-the-art models were used.

The color properties of license plates, namely standard deviation and mean values of intensity were used by Deb et al. [16] to detect probable license plate regions from vehicle images. The images were represented in the HSI color model. After the morphological closing operation of the probable license plate regions, connected component analysis was performed. Then geometric properties such as aspect ratio, area, and intensity histograms are used to output the final license plate. This reviewed work does not perform any license plate recognition task.

IV. Methodology

In the license plate detection and localization stage, preprocessing steps such as image rescaling and color space conversions are performed. After preprocessing, a window of fixed size is slide across the image, and features are extracted from the sub-windows. The features are then used for training a machine learning model. Later, in test images, the trained model is used for determining whether a window is part of the LP region or not. The probable windows are then merged to generate probable license plate regions. The probable LP regions are finally filtered based on their area and aspect ratio to detect, localize, and output the license plate.

A. Preprocessing

1) Image scaling: Image resizing or image scaling refers to changing the size of an image. We used the Bilinear Interpolation method for scaling the images. All landscape images in the dataset were resized to (height, width, channel) = (480, 640, 3) and all portrait images were resized to (height, width, channel) = (640, 480, 3) for ease of calculation.

2) Color space conversions: A color space refers to the specific organization of colors. A color model is an abstract mathematical model that describes the representation of colors as tuples of numbers. We used three color models namely RGB, YCbCr, and LAB to research whether the color models affect the performance of the feature extraction method.

B. Feature Extraction

Color histograms represent the distribution of colors in an image. Color histograms can generally be represented in a 1D array whose length is equal to 2^N, where N corresponds to the bit depth. As color images in RGB color space contain three channels: Red, Green, and Blue, it is possible to calculate a total of three histograms (one histogram per channel). These color histograms can then be used as feature vectors.

Pooling is a general technique for reducing dimensionality, computational complexity, and variance. In the sliding window approach, in the case of MinPool or minimum pooling, the minimum pixel value among all the pixel intensities in the sliding window crop is selected. MinPool can be used to highlight the darker regions in a window. In the case of MaxPool or maximum pooling, the maximum pixel intensity value in a sub-window is selected. MaxPooling can be used to highlight the brighter regions in images. Eq. 1 and Eq. 2 represents the equations for minpooling and maxpooling.

In theory, MinPool and MaxPool are essentially identical to minimum filtering and maximum filtering. We calculated 3 color histograms (1 for each channel) and used a filter of size (height, width) = (3, 1) to calculate the MinPool and MaxPool features from each sliding window. The extracted features were then concatenated to generate the feature vector for the color histogram with MinPool and MaxPool based feature extraction method. While using a window size of 16 × 16, a total of 984 features are generated. The histogram bin size was set to 256. Fig. 2 represents the sliding window based feature extraction process.

$$I'(u,\ v) \leftarrow min\ \{\, I(u+i,\ v+j) \mid (i,j) \in R \}\qquad (1)$$

$$I'(u,\ v) \leftarrow max\ \{\, I(u+i,\ v+j) \mid (i,j) \in R \}\qquad (2)$$

C. Model Training

We trained a Random Forest machine learning classifier on the extracted features. Random forests are ensemble learning methods that are generated by constructing numerous decision trees each working with a random subsample of the entire dataset. The final output is generated by taking the mode of all the classes of the individual trees in case of classification. Information gain was used to decide which feature to use as a basis for splitting in the decision trees. The best feature is the one that provides the most information gain. Information gain is based on entropy and is calculated as follows where $H(T)$ represents the entropy. The equations of information gain and entropy are presented in Eq. 3 and Eq. 4.

$$IG(T, a) = H(T) - H(T/a)\qquad (3)$$

$$H(T) = I_E(p_1, p_2, \ldots, p_N)\qquad (4)$$

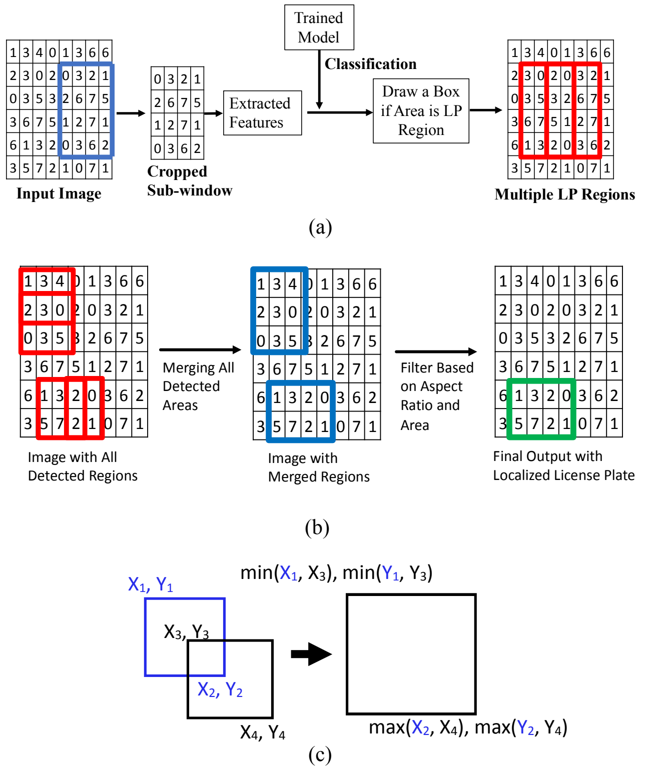


Fig. 3. The detection and localization process.

Fig. 4. Sample images from our dataset.

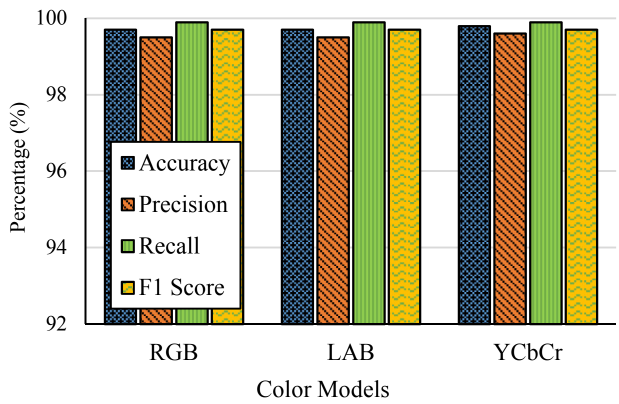


Fig. 5. Performance metrics of the developed models in different color spaces.

Random forests can overcome the overfitting tendency of decision trees by limiting the maximum number of trees used or the depth of the trees and by providing random subsamples of the dataset to each tree.

D. Detection and Localization

The sliding window approach used in the feature extraction method is used in the detection and localization phase. The features are first extracted from the cropped images from the windows, then standardized and sent to the pre-trained random forest classifier for classification. If the window is classified as part of a license plate, the co-ordinates are recorded and a bounding box is drawn. After the entire image has been classified, the overlapping bounding boxes are merged to get the probable license plate region. The probable license plate regions are then filtered based on area and aspect ratio. The one with the largest area and aspect ratio within 1.5 to 2.5 is output as the license plate region.

Fig. 3 illustrates the detection and localization process. Fig. 3(a) shows the candidate license plate region detection process. The yellow box represents the sliding window. The areas identified by the classifier as part of a probable LP region is represented by Red bounding boxes. Fig. 3(b) shows the final license plate selection process. Overlapping initial bounding boxes are combined using the formula presented in Fig. 3(c). If the coordinates of the top left corner and bottom right corner are known for each of the two overlapping bounding boxes, coordinates for a larger bounding box can be calculated that contains the object detected by the initial small bounding boxes. Probable LP regions are generated by merging the red bounding boxes. Probable license plate regions are presented by blue bounding boxes. After filtering the probable LP regions based on the Aspect Ratio and area, the final license plate region is selected. The final license plate region is represented by the green bounding box.

V. Experimental Results

The results and robustness of the automatic license plate detection system are presented in this section. The system was executed on a computer with 2.8GHz dual-core Intel Core i7 (Turbo Boost up to 3.3GHz) processor with 4MB shared L3 cache, and Intel Iris Graphics, and 16GB 1600MHz DDR3L onboard memory running Ubuntu 14.04.5 LTS. Python was used to develop the system and scikit-learn was used for the machine learning models.

A. Dataset

We have created a custom dataset containing manually captured images that represent various real-world scenarios. The dataset contains a total of 630 images. The portrait and landscape images had a resolution of 3120 × 4160 pixels and 4160 × 3120 pixels, respectively. As the original images have very high resolution, the license plate regions can be cropped to build a high-quality dataset for the recognition task. However, as image processing based methods are computationally extensive, the images were resized to 640 × 480 pixels in case of landscape images. The portrait images were resized to 480 × 640 pixels.

Blurring and depth effects were not used while capturing the images. Thus, a lot of the images contain multiple objects in the background. However, it was made sure that there is only one license plate visible per image. All the images were captured with express permission from the owners of the vehicles.

A smartphone containing 13MP Sony Exmor RS sensor with f/2.0 aperture, and pixel size of 1.12μm was used as the capturing device. The captured images were divided into six categories based on the position of the vehicle relative to the camera. These categories are: Back, Back-Left, Back-Right, Front, Front-Left, Front-Right. For example, in the case of Front-Right, the front side of the vehicle is in the right side of the camera. Fig. 4 presents some representative images from each type in the dataset.

TABLE I. Hyper Parameters for the Random Forest

Parameter Name	Value
bootstrap	True
class_weight	“balanced_subsample”
criterion	“gini”
max_depth	50
max_features	“sqrt”
min_samples_leaf	5
min_samples_split	12
n_estimators	100

TABLE II. Performance Measures (in %) of Detection and Localization

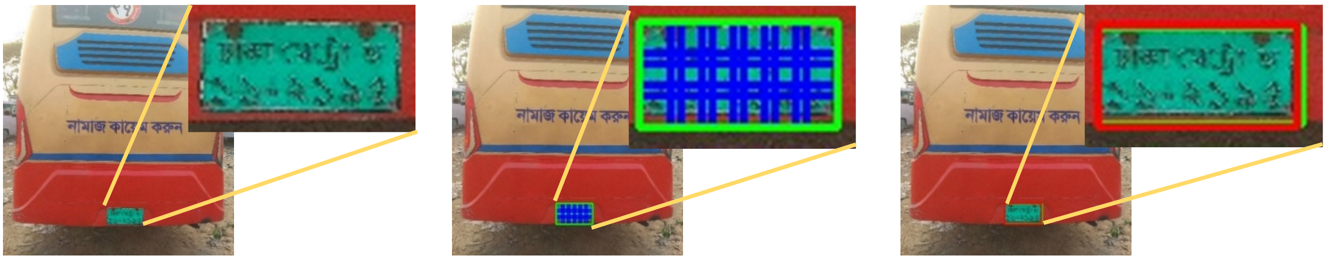
Color Space	Performance Metrics	IoU = 30%	IoU = 50%
RGB	Accuracy	89.9	80.1
	Precision	98.0	97.9
	Recall	91.5	81.6
	F1 Score	94.6	88.6
LAB	Accuracy	87.8	76.2
	Precision	96.5	95.6
	Recall	90.3	78.2
	F1 Score	93.2	85.7
YCbCr	Accuracy	89.3	76.5
	Precision	95.7	94.9
	Recall	92.7	79.3
	F1 Score	94.2	86.3

TABLE III. Categorical Performance Metrics in RGB Color Space

Category	Metrics (IoU = 50%)		
	Accuracy	*Precision*	*Recall*
Back	86.6	97.5	88.6
Back-Left	82.8	92.3	92.3
Back-Right	60.0	90.0	60.0
Front	83.3	97.6	87.0
Front-Left	91.3	100.0	90.9
Front-Right	77.7	100.0	76.4

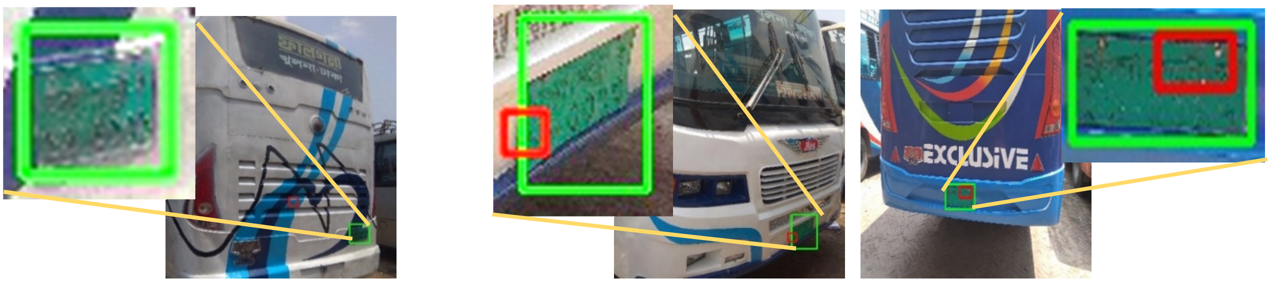
TABLE IV. Experimental Results on PKU Dataset for License Plate Detection

Methods	Subset					
	G1	*G2*	*G3*	*G4*	*G5*	*Avg.*
Zhou et al. [17]	95.4	97.8	94.2	81.2	82.0	90.2
Li et al. [18]	98.8	98.4	95.8	81.1	83.3	91.5
Yuan et al. [19]	98.7	98.4	97.7	96.2	97.3	97.6
Li et al. [8]	99.8	99.8	99.8	100	99.3	99.8
Selmi et al. [20]	99.5	99.4	99.4	99.6	99.1	99.4
Our System	90.5	91.1	98.6	76.5	87.9	88.9



(a) (b) (c)

Fig. 6. Sample detection and localization process.



(a) (b) (c)

Fig. 7. Some missed detection and localization samples.

B. *License plate detection and localization*

We used a Random Forest classifier model with the number of decision trees set to 100 and the maximum number of splits for each tree set to 50. This optimal specification was found after testing several combinations using the Grid Search technique. The features were extracted from images in three different color spaces: RGB, LAB, and YCbCr. Separate random forest models were trained for each color space. The performance metrics for the trained models are illustrated in Fig. 5. In all the cases, hyperparameters were tuned to optimize the model performance. The optimal hyper-parameter names and their values are presented in Table I. Almost all of the models achieved accuracy, precision, recall, and f1 score of 99.7%, 99.6%, 99.9%, 99.7% on average. So, it is evident that the used color space does not affect the proposed feature extraction method for detection and localization. It is also evident that the features of the two classes are highly separable and unique.

The percentile localization result of the detection and localization phase with respect to Intersection over Union (IoU) is provided in Table II. It is evident that the proposed feature extraction method for license plate detection and localization performs similarly in different color spaces. However, the best performance was achieved in the RGB color space. When IoU was set to 30%, the accuracy, precision, recall, and f1 score of the detection and localization system is 89.9%, 98%, 91.5%, and 94.6%, respectively. When IoU was set to 50%, the accuracy, precision, recall, and f1 score of the detection and localization system is 80.1%, 97.9%, 81.6%, and 88.6%, respectively. Fig. 6 illustrates a complete detection and localization output from an example image. The respective license plate region is zoomed and presented inset in all the images. Fig. 6(a) represents the input image. In Fig. 6(b), the windows that were detected as part of a license plate region by the classifier are represented using blue bounding boxes. The green bounding box was generated by merging all the blue bounding boxes. As there was only one probable region detected by the system, the region bounded by the green bounding box is output as the license plate region. In Fig. 6(c), the output from the system is presented using the green bounding box while the ground truth is marked using the red bounding box. The calculated IoU, in this case, is 0.93. Some example images where the system failed to detect the license plates are presented in Fig. 7. The images are from the Back-Right, Front-Right, and Back-Left category, respectively Lighting and the camera angles are one of the most important concerns in an automatic license plate detection system. In 7(a), due to the lighting angle and the deep color of the license plate, the license plate region is not easily discernable from the deep colored background. In 7(b) and 7(c), the output of the system is presented in a red bounding box and the ground truth is presented in a green bounding box. The calculated IoU is presented at the top of each respective image. In fig. 7(b), the system failed to detect the license plate due to the sharp camera angle. However, it was able to detect a very small portion of the license plate. In Fig. 7(c), the system failed to detect the license plate due to the discoloration of the license plate. The black coating of the license plate characters has peeled off and thus there are insufficient color features to identify potential license plate regions. The calculated IoU in are 0.0, 0.04, and 0.19, respectively. The percentile performance metrics on the 6 separate categories of the dataset in RGB color space are presented in Table III. The performance was calculated with IoU set to 50%. In all the cases, precision is consistently high, meaning the system is highly capable of detecting true license plates.

The performance and robustness of the detection and localization systems were evaluated on the PKU (Peking University) benchmark dataset [19]. The PKU dataset contains a total of 3977 images of Chinese license plates. The photos were captured under varying environmental and lighting conditions such as daytime, nighttime, nighttime with headlights on, daylight with sunshine glare, daytime with reflective glare, etc. The dataset is divided into 5 subsets: G1-G5. While the images in G1-G4 subsets contain one license plate per image, the images in the G5 dataset contains multiple license plates per image. The resolution of the images in the G1-G3 is 1082 × 728. The images in the G4 and G5 subsets have resolutions of 1600 × 1236 and 1600 × 1200. The images were resized to 640 × 480 pixels before applying our detection system. The comparison results of our method with other state of the art with other existing state-of-the-art license plate detection methods are presented in Table IV.

VI. CONCLUSION

Automatic License Plate Detection and Recognition (ALPDR) systems are one of the applications of Computer Vision that has revolutionized intelligent traffic control systems. Many developed countries use ALPDR systems for a multitude of purposes, from automatic centralized tolling, to law enforcement. In this paper, we have presented the first-ever open-access dataset containing Bangladeshi vehicles with license plates to facilitate further research. We have also proposed a novel feature extraction method for vehicle number plate detection and localization in the context of Bangladesh. The proposed system is very robust and can detect license plates regardless of their shape. Although our system performs very well in various scenarios, it has some limitations. One such limitation is that the selected window size for the detection phase is dependent on the distance of the capturing camera from the vehicle. If the vehicle is too close, the window size might be too small for detection and might miss license plate areas. Although there are set standards for Bangladeshi license plates, a lot of the vehicles use non-standard license plates such as license plates printed on paper instead of the color standard, single-line license plate instead of the multi-line standard, etc. In the future, shape features might be added with the existing features to get a robust detection system. Real-time ALPDR systems from video sequences in the context of Bangladesh might be developed. The Optical Character Recognition (OCR) system based on this dataset is currently under development.

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