Devanagari License Plate Detection, Classification and Recognition

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Abstract. This study presents a method for detecting, classifying, and recognizing Devanagari characters based vehicle's License Plate (LP) in Nepalese context. The IWPOD-NET model is used in the detection phase to extract the LP from a vehicle region. After post-processing for contrast adjustment, the extracted LP is fed to a nested classifier for vehicle classification. To reduce the noise around the LP area, several image-processing techniques are used. Finally, the Devanagari LP characters are predicted/recognized using two distinct CNN models. We built a customized LP dataset and character dataset to verify our method. The proposed system has been tested for both stationary and moving vehicles. The robustness of the proposed system is assessed in terms of LP detection, LP classification and character recognition accuracy.

Keywords: License Plate · Devanagari Characters · Convolution Neural Network · IWPOD-NET · nested Random Forest

1 Introduction

The use of vehicles as a mode of road transportation by various stakeholders (government, public, private, etc.) is growing by the day, and the necessity for a robust Automatic License Plate Detection and Recognition (ALPDR) has been a hot topic for each country for some years. The ALPDR includes employing a camera sensor to collect LP from a scene. To get the letter-digit combinations that make up the LP characters, a still image or a frame in which a vehicle is sensed is processed utilizing an image processing pipeline in conjunction with machine learning/deep learning based algorithms whenever necessary. Image acquisition, LP extraction, character segmentation, and character recognition are all steps in a typical ALPDR system [1]. The classification of extracted LP is introduced as an intermediary step before advancing to character segmentation in various ALPDR [2, 3]. The vehicle classification, which is based on an LP's foreground and background (FB) colour combination, confirms the vehicle's ownership by various stakeholders and also aids the researcher/developer in applying a proper image processing pipeline to threshold the LP mask before performing character segmentation. Variance in viewpoint, global and local illumination, occlusion, scaling, and intra-class variation all wreak havoc on the detection, classification, and segmentation phases. The ALPDR process is made

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more complex by the use of non-standard LPs, such as fluctuating LP size, confusing letter-digit combinations in a specific order to encode a vehicle registration number, writing style, fonts, and the use of different font sizes in several horizontal parts of an LP.

1.1 Devanagari (Nepalese) License Plate

The Nepalese government has classified LPs into seven categories based on vehicle ownership. This is seen in the colour combination of an automobile LP's background and foreground. The vehicles are further sub-classified into groups based on the weight of the load they carry. Also, three types of LP structures are seen; 1-row LP, 2-row LP, and 3-row LP; as vehicle's LP. In DLP, LP characters are read from left to right then from top to bottom in a LP. Figure 1 depicts the sample DLPs used in Nepalese vehicles.

The LP characters arrangement in different LP structures is shown in Table 1. Province is a fixed letter that represents Province (प्रदेश), PN is the 3 digits province identifier, PS is the plate status, L is the three-digits lot number, LD is the load type, and X is one-to four-digits vehicle identity. In 3-row Red (private) LP, the first (top) row has four fixed positional characters.

Province (letter), PN number (a digit), and two digits PS (01 for old registration, 02 and onwards for new registration). The L (3 digits) followed by LD (a letter) are both fixed positional characters in the second (middle) row. Only 1 to 4 digits are used in the final (bottom) row. The first and second rows of the 3-row LP structure contain exactly 4 characters (letter and digits) while the last row contains 1 to 4 numbers. In the case

Fig. 1. DLP characteristics based on ownership, LP structures, fonts, and font size

Table 1. Characters arrangement in DLP

LP Structure	First Row	Second Row	Third Row
3-row	PROVINCE PN PS	L LD	X
2-row	Z LT LD	X	**
	PROVINCE PN PS LT LD	X	
	PROVINCE PN PS	LT LD X	
1-row	Z LT LD X	**	**
	PROVINCE PN PS LT LD X		

**Not Applicable

of zonal format LP for 1-row and 2-row LP structure, Z indicates any fourteen zones (a letter) and LT denotes 1 or 2 digits lot number. Similarly, the province format 2-row LP structure includes either 4 positional characters on the first row and 5 to 8 characters on the second row, or 8 characters on the first row and 1 to 4 digits on the second row. In 2-row LP, the first row of the zonal format comprises 3 to 4 characters, and the second row has 1 to 4 digits as a vehicle identity. The maximum number of characters in a 1-row structure is found to be 12 for both province and zonal format. We should expect a minimum of 4 (zonal format) to a maximum of 12 characters (Province format) in all types of LP structures. In a 2-row (partial) or 3-row LP structure, the last row has just digits, whereas the other rows have both letters and digits in a specific order. For instance, a private truck has an LP with a red background and white foreground characters with load type letter "KA" that indicates a heavy vehicle. A Red LP vehicle with the characters BA (बा) 79 (७९) PA (प) 9544 (९५४४)is a private vehicle with zonal code Bagmati (BA), vehicle's lot no 79, a light vehicle (PA) representing either a motorbike or a scooter, and 9544 as vehicle's identification number. It should be noted that a vehicle that transport heavy load also use a letter "PA" as load type which is specifically seen in a tourist bus. In Nepal, same load type letters may be used to encode intra LP vehicles. For instance, a green BUS and green two-wheelers share same letter "PA" as load type. This ambiguity is also visible in inter LP as a red LP and a green LP share same letter "PA" as load type. The various properties of DLP are tabulated in Table 2.

Both the standardized and non-standardized LP is seen in vehicles. The non-standardized LP uses a variety of fonts to encode vehicle information; the characters may vary in size within the same row, and the space between LP characters varies due to the variety of LPs. Likewise, the space between two characters are not uniform in all kinds of LP. For instance, a minimum distance of 5 to 10mm between two characters within a row and the minimum 5 to 10 mm gap between characters between two successive rows is found to be missing. This lack of uniformity is due to the fact that the LP are written by local painters resulting in non-standard letter distance, font size, fonts, and even with some non-LP characters. Furthermore, we have difficulty recognizing characters due to the use of diverse fonts, as certain characters are too similar even though they belong to different classes. For example, the digits 5, 1, and 9 can be written in a variety of styles. Similarly, the characters (२- ३), (प-०), (बा- ना), (च- ज – ञं), and (मे - भे) might look similar and may mislead a character recognizer model.

To address these challenges, we proposed a technique for detecting, classifying, and recognizing Devanagari LP.

The following is a breakdown of the structure of this paper. We take a quick look at some related works in Sect. 2. The proposed ALPR system is described in Sect. 3. The dataset, results, and discussion of the experiments is discussed in Sect. 4. Section 5 wraps up our research work with conclusion.

2 Literature Review

The ALPDR is assumed to be a two-step process in which LP detection and localization is the process of locating a region in an image holding the LP, whereas LP recognition is the process of identifying the text written on it. Both localization and recognition need feature extraction and classification. Automated feature engineering for ALDPR approaches has recently been employed for feature extraction in addition to hand-crafted feature engineering. The hands-on feature engineering approaches use key computer vision algorithms to extract the features specifically. Automated feature engineering, on the other hand, learns features implicitly using machine learning/deep learning approaches.

For automated feature engineering, deep Convolution Neural Networks (CNN) and its derivatives have been widely utilized to detect, segment, and recognize vehicle's LP in recent years. The performance of CNNs in text and optical character recognition has already been demonstrated in [4–6]. One of the deep-learning-based systems for LP recognition is [7, 8] which generate LP region recommendations and perform final selection using a CNN as a binary classifier. Because of the high demand for robustness, some alternative methods use CNN-extracted features rather than hand-crafted features. To increase the character recognition rate, the authors supplement the character dataset with particular hierarchical data augmentation methodologies in [9]. The CNN is similarly trained for the whole character sequence to identify and recognize Malaysian LPs

Table 2. Devanagari LP characteristics

Background (Plate)	Foreground (Characters)	ownership	Load: Type	Load letters: English	Load letters: Devanagari	letters and Digits, Zonal Code: English	Zonal Code: Devanagari	Digits: Arabic	Digits: Devanagari
Red	White	Private	Heavy	KA	क	ME	मे	0	०
			Middle	CHA TA	च त	KO	को	1	१
			Light	PA	प	S	स	2	२
Green	White	Tourist	Heavy	PA	प	J	ज	3	३
			Middle	YA	य	NA	ना	4	४
			Light	PA	प	BA	बा	5	५
Yellow	Blue	Public/ National Institution	Heavy	GHA	घ	GA	ग	6	६
			Middle	YNA	ञ	LU	लु	7	७
			Light	MA	म	DHA	ध	8	८
Black	White	Public	Heavy	KHA	ख	BHE	भे	9	९
			Middle	JA	ज	RA	रा	**DLP characters used in proposed system	
			Light	THA	थ	KA	क		
White	Red	Government	Heavy	GA	ग	SE	से	**Characteristics of load type and zonal letters are identical within and between classes, 23 letters used	
			Middle	JHA	झ	MA	म		
			Light	BA	ब	**New Style (3-row LP)**			
Red Blue	White	Minister	Heavy Middle Light	** JHA **	 झ 	**English**	**Devanagari**		
Blue	White	Diplomat	Heavy Middle Light	** C D **	 सी डी 	**Province**	प्रदेश		

[10]. If LP and other general alphanumeric text exist, the algorithms described above will fail to detect them. Furthermore, the program is limited to standard LP due to the fixed-width enclosing box. To detect automobiles and localize LPs, Laroca et al. [11] employed two CNN models. This approach treats the LP as a fixed-length (seven-character) sequence and is only applicable to Brazilian standard LP. For recognition, Zhuang et al. [12] used semantic segmentation and counting refinement. This method works for LP with fixed length characters but not for those with variable lengths. Pant et al. [13] provides a method for detecting an LP in the context of a Nepalese vehicle using various image processing techniques, and the extracted histogram of oriented gradient characteristics (HoG) of DLP character is trained using a Support Vector Machine (SVM). According to the authors, the experiment was conducted on a small number of private LPs with low accuracy. The authors of [14] propose a deep learning method for LP detection and character recognition, but they leave out the full class of DLPs with different FBs, multiple horizontal segments, font, font size, and margin between LP characters. The DLP dataset [15] for private vehicles is also provided by the authors; however it is confined to the Bagmati zone and only for cars and two-wheelers. The approaches presented thus far for foreign LP have only dealt with detection and recognition for standardized designs and sizes. Standard LP is covered to some extent in the literatures that have been reviewed in relation to DLP, but the difficulty of recognizing non-standard LP remains a key gap. As a result, in this study, we propose a method for non-standard LP detection, classification, and recognition that used a variety of plate sizes, foreground and background colours, fonts, styles, and designs. A standard LP and characters dataset is also generated to test the proposed system's robustness.

3 Proposed Method

The details of detection and classification, segmentation and recognition are discussed in the respective sections.

3.1 LP Detection and Classification

The proposed method utilized an Improved Warped License Planar Object Detection Network (IWPOD-NET) [16] which can recognize vehicles in a range of capture scenarios and then rectify them to a fronto-parallel view. The IWPOD-NET is used as a fully convolutional network for recognizing an LP's four corners. The IWPOD-NET approach's network architecture, loss function calculation, vehicle detection, and resizing operation are all used in the proposed LP detection pipeline. Because IWPOD-unwarping NETs provide a nearly frontal image of the LP, it assumes a single FB color and the same size for each LP character, which is not the case with Nepalese LP. Because we expect multiple FB color LP, varying character counts in each segment of detected LP, and dissimilar character height in each segmented row of LP characters, this phase has to be modified. To address these issues, the detected LP is fed into the classification pipeline. To compensate for the low light, an image processing filtering is employed before passing the detected LP to the classification pipeline. The low light compensation process starts with determining whether the image is bright or dim by looking at the expected global average intensity of luminance components in YCbCr colour space and adaptively thresholding the image. The thresholded LP is then sent to the gamma correction filter, which corrects the brightness of the captured LP while leaving the other chrominance components alone. As the gamma value increases, the image transitions from black to white. The resulting image is an RGB colour space image that has been low light corrected. The LP image is resized to 240 pixels by 80 pixels and feed to the classification pipeline.

The initial step in the LP classification process is to determine which category a vehicle belongs to by examining the foreground and background (FB) colour of the LP. To accomplish this, the centre of extracted LP is computed using Eq. (1), where width refers to the width and height refers to the height of the extracted RGB LP. A 120 pixel by 40 pixel LP mask from centre is cropped from the low light compensated image using Eq. (2). The RGB LP mask is transformed into HSV mask. A random forest classifier is used as a FB classifier to determine the ownership of vehicles. The pixel values of hue, saturation, and value components for the cropped HSV image is fed to the random forest classifier. This classifier returns a class based on the hue, saturation, and value components of the LP mask. The returned class value is valid in most of cases except private and government LP. The private and government LPs use the same colour space, with the exception that the colours in the foreground and background are flipped. In such circumstances, another random forest classifier is nested at the end to reduce the ambiguity produced by private-government vehicle uncertainty and to improve vehicle classification results. Four corner patches are extracted as shown in Eq. (3) where TL, TR, BL and BR stands for Top-left patch, top-right patch, bottom-left patch and bottom-right respectively. Each extracted patch is transformed into HSV colour space, and trained with a second random forest classifier. These patches have colour components primarily dominated with the background colour; making it easier to classify the private-government LPs. Figure 2(a) depicts the classification procedure for a vehicle's LP.

$$center_x, center_y = \frac{width}{2}, \frac{height}{2} \tag{1}$$

$$img = img[centre_y - 20 : centre_y + 20, centre_x - 60 : centre_X + 60] \tag{2}$$

$$TL = img[0 : 20, 0 : 20], TR = img[0 : 20, 220 : 240],$$

$$BL = img[60 : 80, 0 : 20], BR = img[60 : 80, 220 : 240] \tag{3}$$

3.2 Character Segmentation and Recognition

Once the vehicles are classified the next task is to clean the noise around LP area and perform character segmentation task. We must apply numerous image processing filters in a sequential order to achieve this. The vehicle classification stage is a critical step for character segmentation since the final binary LP is acquired by applying the appropriate filtering pipeline that threshold the LP according to the class value (categorical) returned by FB classifier. Depending on the LP structure, we must first remove the noise, then segment the LP into a maximum of three vertically discontinuous sections, and finally extract the characters from each row.

The region that is attached to an LP but does not contain LP characters must be removed and the largest contour with LP characters must be acquired. So, the RGB LP is converted to HSV colour space and only the saturation component of the LP is processed. The saturation mask is passed into the Contrast Limited Adaptive Histogram Equalization (CLAHE) [17, 18]. AHE is good for increasing edge definitions and improving local contrast in specific sections of an image however it can enhance noise in more uniform areas. By restricting the amplification, Contrast Limited Adaptive Histogram Equalization (CLAHE), a subset of AHE, prevents this. The coordinates of four points of the thresholded largest contour (top, left, right, and bottom) is logged in this stage and four points perspective projection is applied to generate the actual LP region. The LP is then fed to next image filter which splits the LP structure into a maximum of three vertical segments (3-row LP) based on the numbers of character visible in each row. A Vertical Projection Profile (VPP) test is done in order to check the number of rows for each LP. For instance, the 3-row binarized LP has a valley at starts and later transition to a peak meaning we have encountered the first row LP characters. This process continues for another two rounds meaning the second row and last row LP characters are encountered. The VPP of each column is calculated as a sum along the vertical axis. The plate segmentation pipeline for a 3-row LP structure is shown in Fig. 2(b). The returned class value from nested random forest classifier is critical as the rest of the pipeline rely on FB colour combination of a given LP. We must note that this processing pipeline requires changes in several steps since we have seven types of LP based on vehicle ownership and three types of LP structure. For each vertically segmented binarized LP region the Connected Component Analysis (CCA) [19] is applied which filters out the unwanted blobs before the actual LP characters are segmented. The Connected Components are valid LP characters which must be retained in LP while other connected components must be filtered out. The valid connected component characters satisfy several features such as each candidate LP character must have specific height, breadth, area, aspect ratio and connectivity. At last, each character from vertical rows is segmented using Vertical Projection Profile.

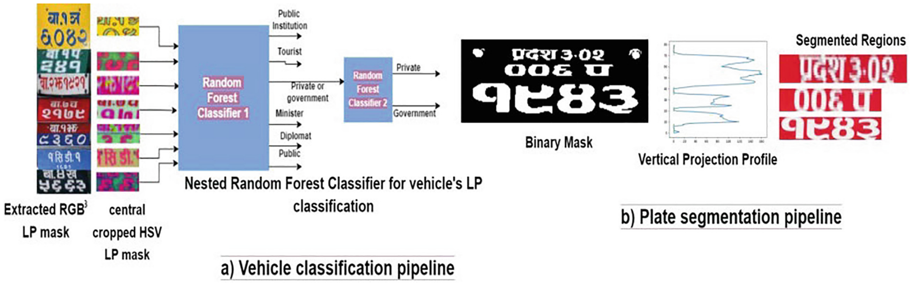

Fig. 2. a) classification pipeline b) vertical segmentation decision

Each segmented character is appended to a single character vector in a conventional character recognition system, which is then fed to a character recognition model for character predictions. We modify this technique by identifying each segmented character as a letter or a digit based on character position in an LP. These characters are then appended to the appropriate character vectors. For instance, the first row in 3-row LP structure has four positional characters where the first character is from the letter class and the remaining three characters are from the digit class. Similarly, the second row is made up of the first three characters from the digit class, followed by a letter from the letter class. In the final row, we expect 1 to 4 digits. Table 1 summarized the positional characteristics of LP. Two character vectors are employed in the proposed system, and all positional characters are merged into their corresponding categories. The Digit Recognizer Model (DRM) is an image container that stores positional digits segmented from each row from various LP structures. Similarly, when the position of the characters cannot be predicted, the letter-digit pair is stored into a Letter and Digit Recognizer (LRDM) model. For instance, because we may encounter zonal or province-based LP, the position of segmented characters in 1-row LP is difficult to predict. LDRM is used in this situation. The processing pipeline for character position decision is shown in Fig. 3.

In proposed ALPDR, each segmented LP character is a 32 × 32 feature vector that is used for Optical Character Recognition (OCR) and hence sent to the feature extraction subsystem. In the proposed method, the LRDM model has a total of 33 character classes, comprising 10 digits, 12 zonal letters, 10 load letters, and 1 province letter. The DRM model includes a ten-digit class that represents digits ranging from 0 to 9.

The LRDM and DRM are two Convolution Neural Network (CNN) models with identical architecture. The first two layers of LDRM and DRM have 60 filters with kernel size of 3 × 3. This step extracts the low-level features of LP characters. The 2 × 2 max-pooling operation down-sample the image input from previous layer. As we move progressively to upper layer of CNN model we capture higher-level image features.

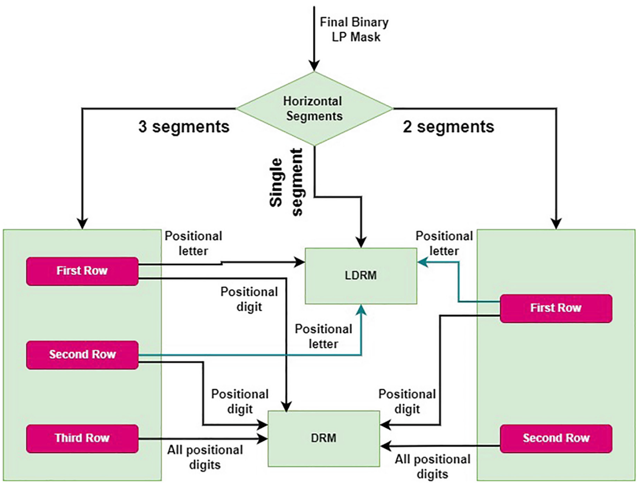

Fig. 3. Positional character decision for different LP structure

The image is further down-sampled in the second max pooling layer. Overfitting during the training is mitigated by introducing a dropout [20] operation once the vector is flattened as one dimensional vector with 480 neurons. A 50% drop-out is applied in the proposed method to prevent the models from overfitting. Later 1×500 one-dimensional feature vector is generated with another 50% drop-out to prevent overfitting. The Softmax activation function is used to predict the LP characters classes. The activation function predicts 33 LDRM classes and 10 DRM classes using the softmax function. Table 3 shows the architecture of proposed LRDM and DRM models.

4 Result and Discussion

4.1 DLP Dataset

The DLP dataset is divided into three parts: 1) the vehicle dataset (VD), 2) the LP dataset (LPD), and 3) the characters dataset (CD). VD, which consists of 3650 vehicles, is used as training data for the LP detection. Cropped LPs segmented during the LP detection, LPD, are used in the classification step for FB training in HSV colour space. The distribution of the VD dataset based on vehicle ownership is shown in Table 4. The VD images were taken in various locations, such as a road, a parking lot, a university, and so on. To avoid the training model from overfitting, the image augmentation technique based on Tensorflow-keras library [21] is used that increase the vehicle counts for vehicles with low vehicle counts. Similarly, the LP and CD dataset are also augmented using the same library to prevent the respective models from overfitting.

The LPs region is detected by IWPOD-NET from vehicles. The extracted LPs are divided into seven classes and then used as LP dataset. The LP dataset is utilized in

Table 3. LDRM and DRM

Layer Type	Parameters
Input	32×32
Convolution + ReLU	28×28, #filters:60, $k = 3 \times 3$
Convolution + ReLU	24×24, #filters:60, $k = 3 \times 3$
Max Pooling	k: 2×2, s: 1
Convolution + ReLU	10×10, #filters:30, $k = 3 \times 3$
Convolution + ReLU	8×8, #filters:30, $k = 3 \times 3$, p:1
Max Pooling	k: 2×2, s: 1
Flattened	#neurons: 480
Dropout	0.5
Dense	# neuron: 500
Dropout	0.5
Fully connected + Softmax	# neuron: 33 (LDRM), #neuron: 10 (DRM)

Table 4. VD for training (without augmentation)

Vehicle Type	Vehicle Ownership	Vehicle Counts
1	Private	1500
2	Tourist	500
3	Public	1000
4	Diplomat	50
5	Government	500
6	Minister	50
7	Public Institutions	50

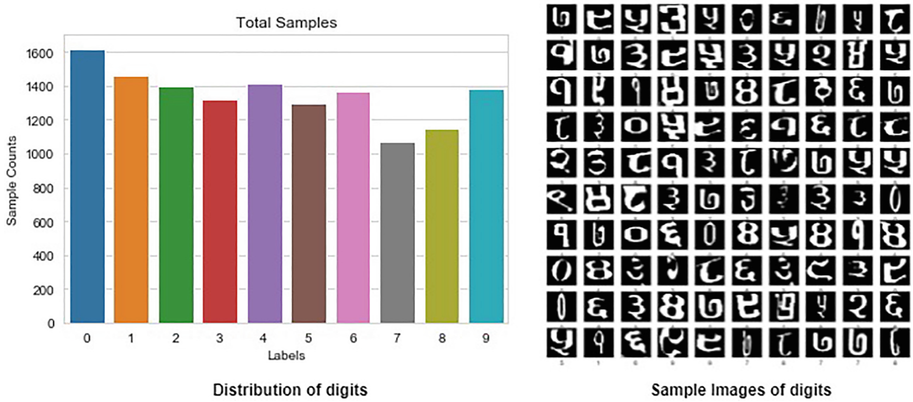

Fig. 4. Digit counts along with sample images

training by the nested random forest classifier for LP classification. During the testing, the extracted LP is fed into a nested random forest classifier, with the exception of government and private vehicles, where the first classifier successfully outputs the desired class. The LP is passed into the next classifier to resolve this ambiguity.

The CD dataset contains ten digits and twenty-three letters, which are used to train DRM and LDRM, respectively. These characters are cropped binary images acquired during the character segmentation stage and produced during the segmentation of characters from each rows of a LP. The characters are further classified as a digit or a letter, and each is saved in its own class folder. There are 13489 samples in the DRM model and more than 20000 images in the LDRM model. Each character has been scaled to 32 $\times$ 32 sizes. The characters that have low counts are augmented when needed in order to prevent the character recognition model from overfitting. Figure 5 shows the specifics of the number of sample distribution for the digit class. The number of digits with the highest number (0) is around 1600, and the number with the lowest number (7) is around 1100. A random sample of 100 Devanagari digits is also shown in Fig. 4.

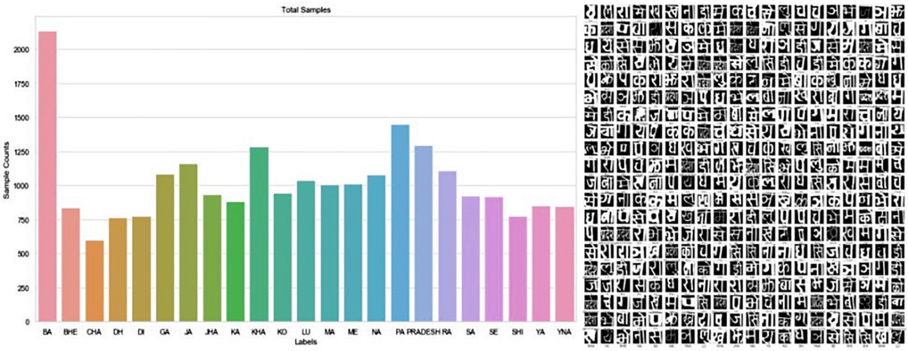

Fig. 5. Letter counts with sample image (digits not included)

The number of samples for each letter class is shown in Fig. 5. The highest number of letters (BA) was over 2200, while the lowest number of characters (SHI, DI) was approximately 800. Figure 5 also illustrates the 200 random letters used in Devanagari LP.

4.2 Detection and Classification Results

The 500 images with vehicle(s) in them are considered for testing, and they are further divided into seven classes based on ownership of the vehicle (FB colour). Because a test image may contain several vehicles, the IWPOD-NET model may detect many LPs in the test image. For each detected LP, the random forest classifier must classify each LP into suitable class.

The detection and classification results are shown in Table 5. The highest detection accuracy is achieved for private vehicles while minister's vehicle has the lowest detection accuracy. Similarly, 217 of the 225 accurately detected Red LPs have the highest FB classification. Overall, 493 LPs out of 537 were classified correctly using the proposed method.

4.3 Character Recognition Results

The character recognition step is performed for the LPs that are correctly classified in their corresponding class. Each LP's characters are split, and the prediction accuracy for each horizontal segment is measured. The character prediction accuracy of the entire (whole) LP is also assessed. For each LP, the entire LP accuracy is determined by correctly predicting the positional letters and digits on each horizontal segment. Table 6 shows the character prediction accuracy for the DLP. In 3-row LP, the availability of both letter and digit in the first and second rows results in lower character prediction accuracy than in the last row. However, in the first and second rows, the character-digit approximation of positional characters reduces prediction confusion, allowing for more accurate digit recognition. The overall LP accuracy for both the 3-row LP and 2-row LP structures is 86.5% and 83.5%, respectively. Because approximating position characters

Table 5. Detection and Classification Accuracy

Vehicle Type	Vehicle Ownership	Vehicle Counts	Ground truth (LP)	Detected LP	LP Detection Accuracy	Correct FB classification	FB Classification accuracy
1	Private	200	230	225	97%	217	96%
2	Tourist	120	130	125	96%	110	88%
3	Public	100	115	109	94%	100	91%
4	Diplomat	20	25	22	88%	20	90%
5	Government	20	22	20	90%	17	85%
6	Minister	20	21	18	85%	15	83%
7	Public Institutions	20	20	18	90%	14	77%
Total		500	563	537	95%	493	91%

Table 6. Character Prediction accuracy

LP Structure	LP Counts	First Row Accuracy	Second Row Accuracy	Third Row Accuracy	whole LP correctly recognized	Whole LP Accuracy
3-row	178	87%	91%	98%	154	86.5%
2-row	200	89%	97.3%	***	167	83.5%
1-row	185	82.7%	***	***	153	82.7%
Classifier	Accuracy					
DRM	97%					
LDRM	84%					

is challenging, and each character is predicted by the LRDM model alone, the 1-row LP structure has the lowest whole LP accuracy with just 82.7%. DRM achieves 97% character prediction accuracy, which is significantly greater than LDRM, due to lower intra-class variation in the digit class.

4.4 Real-Time Implementation Results

In addition, the resilience of proposed method is tested for moving vehicles in a parking lot. A scene in which vehicles are visible in the frame is taken into account. The various LPs from the vehicle with Bagmati zone make up the scene. A total of five videos in which a total of 30 vehicles are present are used to test the system's resiliency. Table 7 shows the results of the real time implementation. A frame with vehicle is captured when a vehicle cross a line. The captured frame is fed to the detection module which detect vehicle first and later a LP region is returned. With four LPs successfully recognized and

Table 7. Accuracy measurement in a dynamic environment

Scene	Vehicles present	Detected LP	Classified LP	Whole LP characters Recognized
1	5	4	4	4
2	8	7	6	5
3	4	3	3	3
4	8	6	4	4
5	5	4	3	3

classified, Scene 1 has the highest detection and classification accuracy whereas Scene 5 exhibits the worst performance.

5 Conclusion

This research presents LP recognition, classification, and character prediction system based on hybrid learning for vehicles with Devanagari LP characters. The IWPOD-NET is utilized as an LP detector and localizer, the nested random forest is used as an LP classifier that used the HSV FB color of an extracted LP region, and the two CNN models are used to predict characters. For LP classification, numerous image processing techniques and machine learning approaches are used. The classified LP is further processed to reduce noise before performing character segmentation. The binary LP is split into the number of rows applying horizontal projection profile. Two CNN models are used to train and predict the positional character: LRDM for letter-digit pairs and DRM for digits only. The Devanagari CD was developed which validate the resilience of the proposed method. In proposed system, total LP detection accuracy was 95%, LP categorization accuracy was 91% for the detected LP, and overall character prediction was over 83% for all LP structures.

In comparison to other DLP investigations [13, 14], this method is more advanced in a number of aspects. To begin, this study looks upon heterogeneous DLP with varying FB colour and plate structure. Second, in order to increase character prediction accuracy the characters dataset support various characters within and between the vehicle ownership classes. This research has included the method to tackle the problem of uncertainty in determining the letter and digit ambiguity and proposed two separate CNN model to improve recognition accuracy. At last, considering the heterogeneous nature of DLP, the overall accuracy in the detection, classification, and character recognition phases is comparably good when compared to available literatures [14] for DLP.

The results of the experiments showed that the proposed strategy could be employed effectively for both static and dynamic situations. This study's findings could be used to recognize an LP in a real-time situation. We intend to deploy this model in the future to detect, classify, and predict all sorts of DLP.

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