An Automatic Framework for Number Plate Detection using OCR and Deep Learning Approach

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***Abstract*—The use of automatic number plate detection devices in safety, commercial, and security has increased over the past few years. Number plate detection using computer vision is used to provide fast and accurate detection and recognition. Lately, many computerized approaches have been developed for the identification of vehicle registration details based on license plate numbers using either Deep Learning (DL) methodologies. In the proposed framework, we used Optical Character Recognition (OCR) and a deep learning-based new approach for automatic number plate detection and recognition. A deep learning approach trains the model to recognize the vehicle. The vehicle registration plate area is cropped adequately from the image, and a Convolution Neural Network (CNN) uses OCR to identify numbers and letters. The Jetson TX2 NVIDIA target served as the model's training data source, and its performance has been tested on a public dataset from Kaggle database. We obtained the highest accuracy of 96.23%. The proposed system could recognize vehicle license plate numbers on real-world images. The system can be implemented at security checkpoint entrances in highly restricted areas such as military areas or areas surrounding high-level government agencies.**

***Keywords*—Number plat detection; recognition; deep learning; OCR; image classification**

I. Introduction

Automatic number plate Detection is also known as license plate detection or vehicle registration plate detection. It uses image processing technology to extract the registration plate from digital images or video [1]. Afterward, the information stored can be used to find various new models, some of which could be transaction gateways or traffic violation systems. Taking the context of a real-life problem into consideration, in practical applications, researchers have to deal with a variety of challenges, such as registration plate type, textual font, registration plate color and font, registration plate location, and environmental conditions such as lighting and weather. License plates become challenging to recognize. License plate formats vary from country to country: Different colors, languages, and fonts. Some plates have a different colored border than the background surrounding the plate, and some have a plain background, which indirectly adds challenges to capturing and recognizing car plates [2]. Variations in environmental conditions, such as lighting and image background, also affect the license plate recognition rate. Several studies have been proposed earlier.

YOLO is a unified model for object recognition [1]. This model can be built and trained directly on full frames. In contrast to classifier-based approaches, YOLO is introduced with a loss function that directly corresponds to recognition performance, and the entire model is prepared together. Fast YOLO is the fastest general-purpose object detector in the literature, and YOLO advances state of art in real-time object detection. YOLO also generalizes to new domains, making it ideal for applications that rely on fast and robust object detection. Authors discuss the detection of a registration plate for a person who does not wear a helmet in [3]. The two-wheeler operator must have a helmet for his safety. In this study, they proposed a real-time detection of number plates using YOLO, for which they deployed the CNN layer. The accuracy of the model was 95.5%.

In [4], they DL method was proposed for vehicle detection using R-CNN and faster R-CNN, in which they tested and trained their model. The model has three steps: data acquisition, CNN design, and R-CNN. The mean average precision (map) values from faster R-CNN and R-CNN were approximately 0.73, 0.76, and 0.64, and 0.65, respectively. Another one had an overall accuracy of 94.98%. [5], proposed a deep learning model using an Image AI library for training. The model consists of four steps: video acquisition, detection of a vehicle, registration plate detection, and then registration plate character recognition. The model's accuracy was 96% for plate localization and 90% for character recognition was 90%. In [6], firstly, they made the image acquisition, after which they used pre-processing techniques like RGB to grayscale conversion, noise removal, and image banalization. For registration plate extraction, used Sobel's edge detection [7]. After that, the characters are segmented using the CNN layer for character recognition. The model had an overall accuracy of 95%. In [8] they proposed a highly accurate trained model for both registration plate detection and recognition [9]. The whole model was prepared by sharing a convolution layer with the above features. The proposed system had an accuracy of 94% for a jointly trained model. In [10], a framework for character detection using a differentiable binary process is presented. In [11], a framework requires text extraction from an input digital image in which the image has been processed and filtered thoroughly. They used the CV2 OpenCV library in Python for pre-processing and Tesseract for character recognition. Real-time plate detection was performed on a Bangla dataset [12]. For character recognition, the proposed model employed a CNN layer. The dataset used had a sample size of 5500, and the accuracy of successful recognition was 90.90% in a real-time study. In [13-14], YOLO is used for object detection. They trained and fine-tuned the CNN layer for each stage, then did the segmentation part. The SSIG dataset, which contained 2000 frames from 101 videos, was used. The system had an accuracy of 93.53% with 47 frames per second. In [15], 18] a kernel that was partially restricted was focused on with the help of direct blind deconvolution and denoising with CNN on a real-time blur image that was acquired from a traffic surveillance system used a neural network that was trained on artificial data. They used deep learning mode [19]-[28], which includes image acquisition, plate detection, segmentation, and character recognition. The data set was the Turkish vehicle license plate dataset, which consists of real-world images obtained from a security surveillance camera. Unlike other countries, India, with a population of 1 billion, has a unique need for ANPRs. ANPR's primary uses are highway monitoring, parking lot management, and neighborhood law enforcement safety. Existing literature says that in India, within every four minutes, one person dies, and surprisingly, most of them are because of over-speeding. ANPR monitors the average speed of vehicles, and vehicle owner information can identify vehicles violating the traffic rules. In this case, e-challans can be automatically generated for the penalized plate owner. This helps maintain law and order, which in turn minimizes traffic fatalities. ANPR provides the best solution for giving parking management. Vehicles with registered license plates are automatically allowed into the parking area, but unregistered vehicles will be charged at check-in and check-out. According to the study, approximately 200,000 cars are stolen annually in India. This number can be reduced by taking appropriate measures and using this model to track vehicles. This allows law enforcement agencies to determine when, where, and through which route the stolen vehicle is stolen, if vehicle is stolen. This allows us to bring justice to such a powerhouse quickly. The main objectives of the proposed system are as follows. (1) To understand ANPR and apply it to a license plate recognition system. (2) To improve the performance of the number plate detection system using OCR and DL approach. (3) The proposed system efficiently used for detection and recognition of vehicle number plate.

The study is organized as follows: Section I provide the literature review on problem formulation and various existing methodologies; Section II describes the proposed procedures. Following that, in Section III, the results are analyzed and discussed. Section IV explains the conclusion and future scope.

II. Proposed Method

Fig. 1 depicts the proposed framework of number plate detection in four essential parts: a dataset, license plate detection, segmentation, and OCR. Modern rural, urban, and national highway networks have proliferated in recent decades. This created the need to monitor and manage traffic on the road efficiently. The primary goal of this study is to train a model to recognize and identify license plates from their images correctly. Different countries have different characteristics of license plates, such as their number system, colors, sign language, style (font), and size of a license plate, so further research is needed.

Deep learning (DL) is a branch of Machine Learning (ML), and ML is a subset of Artificial Intelligence (AI) that mimics the way humans acquire certain kinds of knowledge. Deep learning is a critical component of data science, including statistics and predictive models. It benefits data scientists who must collect, analyze, and interpret large amounts of data. Deep Learning makes this process faster and easier. At its simplest, DL can be thought of as a way to automate predictive analytics. While traditional ML algorithms are linear, DL algorithms are built up in increasing complexity and abstraction layers. A shallow CNN quickly scans the test image and eliminates most sample windows. In the proposed approach, authors have used four layers to predict number plates. In the first layer, the number plate detection work is done; in the second and third layers, region extraction is calculated; and in the last layer, OCR is used. The automatic framework for number plate detection using OCR and deep learning architectures is shown in Fig. 2.

A. *Dataset*

The desired unit where deep learning problems fail is a need for a public dataset. As we know that, the wrong data sets can produce inaccurate or incorrect results. So, we need to ensure that there are no similarities between the content of a dataset other than its essential characteristics. Because India is a large country, hence need to consider all the contexts and ensure that the given dataset is well-balanced without favoring or disfavoring any entity, such as vehicle type or license plate layout. Firstly, the vehicle types present on the streets of a typical Indian city are cars, two-wheelers, buses, trucks, and pickups. So, every type of vehicle has its own format for displaying the registration plate. For example, most cars have one line of plates, but some people prefer a layout with two lines of plates. Registration plates belonging to Indians can be single-row or double-row and most two- and three-wheeler registration plates are two lines, but their layout differs. The font on both sides is also different, with some 3-wheeler auto rickshaw uses paint rather than printing the number plate. So here we found the basic first step in license plate recognition is to collect a database. In the proposed work dataset is downloaded from the Kaggle website, which includes license plates with significant variations in registration numbers collected by kaggle.com. Total of 4326 were trained on our model to identify the number plate and had used deep learning strategies as you can see in the Table I. It represents us the type of vehicle that were been trained as you can see the dataset is not biased as all type of vehicle are been taken into account.

B. *Preprocessing*

When images are acquired at this stage and passed to the algorithm for further testing and prediction, Image pre-processing is one of the crucial stages for any computer vision system. So, the main objective of this image pre-processing is to recognize the image and collect information regarding the image, which can be used in further processing [7]. Image pre-processing changes the operation performed on a non-figurative object. The primary goal is to improve image information to extract the necessary information from that image. Fig. 3 shows sample images from the custom dataset for experimental work.

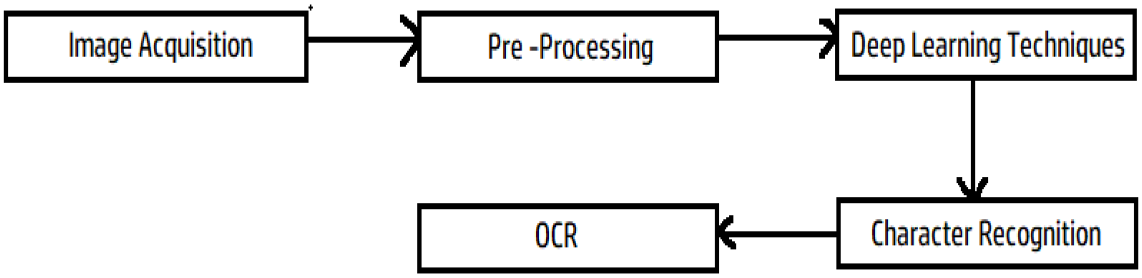

Fig. 1. The block diagram of proposed methodology.

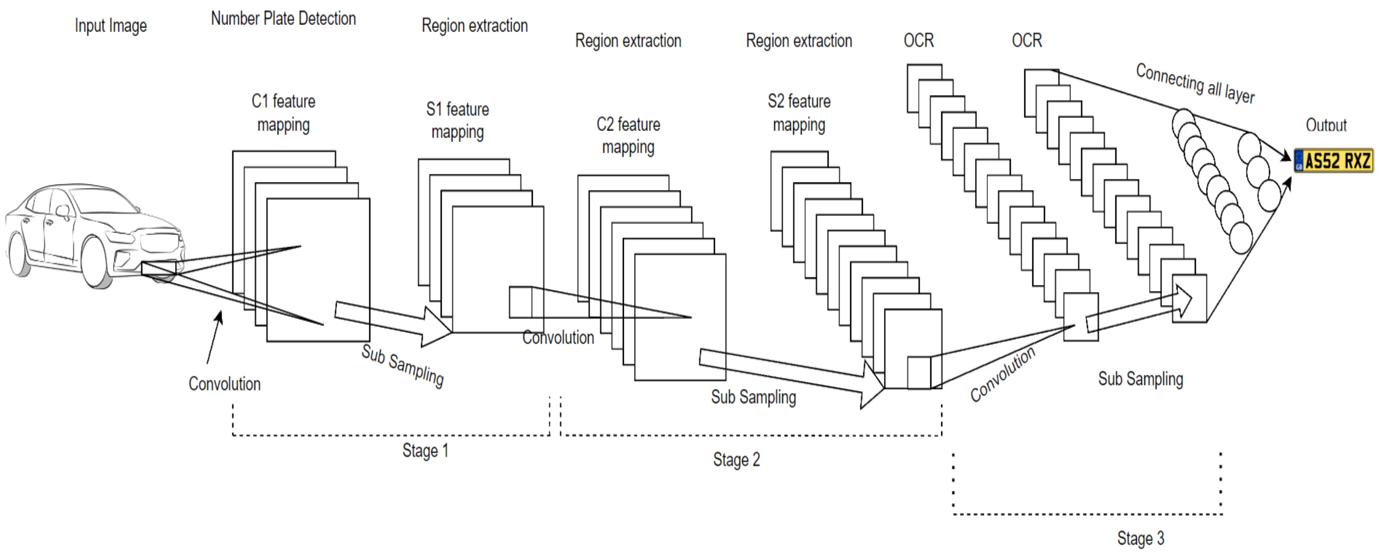

Fig. 2. An automatic framework for number plate detection using OCR and deep learning architecture.

C. Number Plat Detection

Most countries around the world have registration plates that are shaped like a rectangle. Moreover, the registration plate comes in different shapes and layouts in India. Sometimes it is seen that a two-wheeler uses a trapezoidal plate. In terms of size, the average size of the plate varies by vehicle, with the average size for cars being 500×120 mm and for motorcycles being 200×100 mm [11]. Three-wheeled vehicles such as an auto rickshaw have tiny plate painted mainly by a painter. Taking all the points into context, we put all the registration plates into a rectangular box. As shown in Fig. 2, the image of the car with the highlighted number plate is in the green-colored rectangular box. Fig. 4 shows the detection of registration plat.

The result uses a thresh holding algorithm on the number plate, and because of this thresh holding method, the plates are being segmented at a higher level. These thresholds help us recognize the character correctly.

D. Charactor Recognition

As discussed earlier, the main issue with character recognition is that there are many types and categories of the font used in the plate. So, the best way to train our desired model is to check for letters and digits to cover different typefaces, including those used in painted panels. Here, we used OCR for character recognition. The recognized and segmented character can be trained with our custom-built dataset for training and testing purposes.

A corresponding file was created for training and testing with a valid dataset of 4326 images. So, after all the model training, we figured out that our model is about 95% accurate at the detection range of the license plate and fails only when the license plate is a little smaller in size as compared to the standard plate size or when similar plates are present in the tested image.

Fig. 3. Sample images from the custom dataset for experimental work.

Now let's check how the OCR works. The attributes are extracted from the sample image. These features can be preferred as follows: (1) Distance to the wall (DTW): The calculation for such is based on active pixels. They are the highest intensity value possible, depending on the image format. For example, in an 8-bit grayscale format, the maximum level is 255; to calculate that, it is divided into 12 regions (4 rows x 3 columns). And the activated pixel is calculated concerning the horizontal and vertical areas within each region. (2) Cross-Time Feature (CTF): This feature includes the six widest white-to-black and black-to-white transitions across the character horizontally and vertically. The six widest shifts are computed for every row and column of character candidates. These intersections are sorted, and the first three rows and columns with the highest and lowest changes are saved along with their positions. (3) Active Region Ratio (ARR): The region is divided into four rows and three columns, respectively, and the area of active pixels is chosen as a critical feature for the block. (4) Height to Width Ratio (HWR): When talking about HWR, alphanumeric symbols for any language have been bifurcated into three types, namely, those with more extensive and equivalent height and width. Table I depicted describes the count of vehicle.

The positive score represents the character, and the negative score represents the non-character symbol within the plate. Optical character recognition has been around for the last 80 years. However, large technology companies initially were the primary developers of products that recognized optical [18] characters. Advances in machine learning and deep learning have enabled individual researchers to develop algorithms and techniques that can more accurately identify handwritten manuscripts. We also see more and more researchers using -convolutional neural networks (CNNs) to recognize handwritten and machine-printed characters. This is since CNN-based architectures are well suited for recognition tasks where the input is an image. CNN's were initially used for object detection tasks in images. ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is commonly used CNN-based architectures for visual recognition tasks.

Fig. 4. Detection of registration plate in rectangular boxes.

TABLE I. DESCRIBES THE COUNT OF VEHICLE

Type of vehicle	***Type of license plate***	***Font of license plate***
Two – Wheeler (300)	Printed (375)	Single line (273) Multiline (102)
	Painted (125)	Single line (89) Multiline (36)
Three – Wheeler (637)	Printed (157)	Single line (61) Multiline (96)
	Painted (480)	Single line (86) Multiline (394)
Car (2963)	Printed (2957)	Single line (2873) Multiline (84)
	Painted (6)	Single line (2) Multiline (4)
Truck & pickup (426)	Printed (82)	Single line (2) Multiline (80)
	Painted (344)	Single line (60) Multiline (284)

TABLE II. EXISTING METHOD FOR REGISTRATION PLATE DETECTION & RECOGNITION

Actual Registration plate	***Predicted Registration Plate***	***Mismatched Recognition***	***Accuracy***
P3RV P	P3RV P	0	900%
KL BOSS	KL 8OSS	1	84%
DL49 AK49	DL49 AK49	0	89%
DZI7 YXR	DZI7 YXR	0	85%
Mh 14 Gn 9239	Mh il Gn 9239	2	80%

III. RESULT AND DISCUSSION

The proposed system evaluates the car image from a given dataset. The most crucial factor in solving deep learning problems has an accurate dataset that is unbiased, because of which it produces inaccurate or skewed outcomes. It is necessary to ensure no similarities between the items in the dataset other than the characteristic of interest. After that, we came to the training part of the data set. We considered 4326 sample images and trained the model to detect the license plate. The results of OCR based approach are shown in Fig. 5. The captured registration plate is processed for letter segmentation. Separated characters are recognized using OCR (Optical Character Recognition). After which, the essences extracted from the registration plate are stored in an Excel spreadsheet. Table II shows the sample test cases on the real-time dataset.

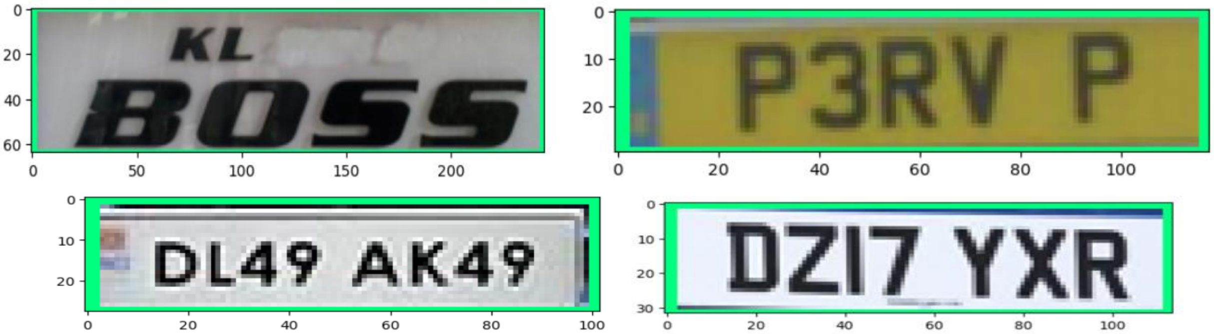

Fig. 5. Results of OCR approach to detect number plate.

TABLE III. COMPARISION WITH EXISTING METHDOS FOR NUMBER PLATE DETECTION AND RECOGNITION

Method/Ref.	***Accuracy (%)***	
	Detection	***Recognition***
YOLO, Response surface methodology (RSM) [5]	97 %	90 %
CNN, TensorFlow [16]	96.36%	93%
YOLO, CNN, Edge Detection [6]	94%	91%
RGB Scaling, CNN[9]	97%	94%
YOLO v3	91%	91%
Deep CNN [20]	98.1%	88.1%
Deep CNN, Fast RCNN [18]	99%	91%
RCNN, SVM, ANN [17]	94.4%	96%
RANSAC, SVM [16]	91.4%	91.4
RESNET, RCNN [3]	94.98%	92%
Proposed Method	**100%** (Vehicle Detection) 95% (License Plate Detection)	**96.23%**

The Table II clearly shows that a minimum of 80% accurate result can be obtained; in some cases, even 100% accurate prediction is achieved. Table III compares the proposed method's performance and existing literature. It can be concluding from the Table III that the proposed method performs far better than the existing method.

IV. CONCLUSION

This study shows that in the presence of anomalies, the performance of deep learning techniques is relatively better and beneficial in the process of ANPR as per India's conditions. Authors represented the entire end-to-end ANPR and noticed multiple lines of LP, non-uniform padding, plate shapes, fonts, and non-uniform font sizes. This presented a complete end-to-end pipeline for ANPR. For LPD, we proposed a model that works well in India and also introduced an alternate method for CR networks suitable for the Indian situation. Our LPD model achieved 96.23% accuracy with a detection threshold of 0.5, which only dropped because it has a 98% accuracy rate for small license plates on cars and buses and a total loss of less than 10% with a learning rate of 92%. The proposed network showed a high average accuracy of 94.9%, including multiline panels, and predicted 93.7% of the characters with a higher confidence level than 90%. ANPR can identify vehicle owners, vehicle model identification, traffic voltage and control, and vehicle location tracking. This model can be further extended as a multilingual ANPR to automatically identify the language of the characters based on the training data.

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