Character level vehicle license detection using multi layered feed forward back propagation neural network

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ABSTRACT

Real-world traffic situations, including smart traffic monitoring, automated parking systems, and car services are increasingly using vehicle license detection systems (VLDS). Vehicle license plate identification is still a challenge with current approaches, particularly in more complicated settings. The use of machine learning and deep learning algorithms, which display improved classification accuracy and resilience, has been a significant recent breakthrough. Deep learning-based license plate identification using neural networks is proposed in this article. The number plate is detected using a multi layered feed forward back propagation neural network (MLFFBPNN). In this method, there are 3 layers namely input, hidden, and output layers has been utilized. Each layer has been related with interconnection weights. In feed forward of information, initially a set of randomly chosen weights are feed to the input data and an output has been determined. Back propagation training algorithm is utilized to train the network. Then character level identification is performed. The suggested proposed method is compared to the region-based convolutional neural network (RCNN) method in terms of accuracy and computational efficiency. The proposed method produced the character level recognition accuracy of 89%. It is improved by 4% when compared with the RCNN recognition method.

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1. INTRODUCTION

The use of vehicles in our daily lives is increasing dramatically, and as the number of vehicles grows, more and more of them are breaking traffic laws. Robberies of automobiles, entry into restricted areas, and an unusually high number of accidents all contribute to an increase in the number of crimes. Throughout the globe, a vehicle registration number will be critical in identifying any vehicle and ensuring that it is properly identified. It primarily serves to strengthen the overall safety and security of the system. In addition to being employed at entrance points to different workplaces, societies, and other establishments, the vehicle license plate (LP) recognition system may also be used for vehicle authentication [1], [2]. This technique has the potential to be completely automated. The access technique for visitors, personnel, or understudy visiting the region includes a security labor force that validates the facts by reviewing the identifiable proof archive. This is true for the majority of the vehicle entry ports. Due to the fact that this is a manual process, there is a significant likelihood that human errors may occur throughout the affirmation and enrolment procedures. Employees assigned to the specified location may find the work of manually recording and compiling material to be time-consuming and difficult to do successfully.

The majority of car license plate recognition systems are designed on traffic images or video analysis, in which case computer vision methods are often used to recognizelicense plates. The use of machine learning and deep learning algorithms, which display improved classification accuracy and resilience, has been a significant recent breakthrough. Several car-related applications, including vehicle identification, vehicle categorization, vehicle plate recognition, and road condition monitoring, have benefited from the development of deep learning and computer vision approaches [3]. Deep learning approaches, as opposed to computer vision methods, offer certain benefits in terms of generalization capacity and resistance to uncertainties, noise, and occlusion in images, but at the expense of a larger computing burden and a greater need for sample set size. In order to take advantage of these newly developed techniques, several methods have been proposed, including the dirty number plate detection system based on you only look once (YOLO) [4], [5] the license number plate recognition system based on convolutional neural network (CNN) [6], recurrent neural network (RNN) [7], and support vector machines (SVM) [8].

Tayara *et al.* [9] suggests thatfew drawbacks exist, however, when it comes to using deep learning algorithms for identifying vehicles and their license plates. Complex environments surrounding the car, including buildings, trees, people, and other things, cause deep neural networks to get confused and hence impair the accuracy of detection. In addition, the human aspect, the vehicle's speed, and the driver's conduct are taken into consideration. All of the factors listed above make achieving precise and efficient detection more challenging. This paper presents an automated authentication technique that would eliminate the need for human verification and decrease the amount of labor required of security personnel. The rest of the paper is organized as follows: the remaining part of section 1 gives the related works, section 2 explains the proposed method, section 3 presents the experiments and analysis, and section 4 concludes the paper.

A vehicle's license plate serves as an identification number. So, in an intelligent driving system, the automated detection and identification of license plates is one of the most significant responsibilities. In order to recognizelicense plates, a variety of techniques have been explored. Kumar *et al.* [10] suggested that the histogram method, which was only tested by cars from five nations, was used to determine the range of a license plate using the back vehicle lights. YOLO was suggested for automated license plate identification [4], which had a recognition accuracy of 78%. Silva and Jung [11] presented a method to simultaneously identify and recognize all characters in a cropped image. YOLO's first eleven layers and four additional convolutional layers are combined to enhance non-linearity. Later YOLOv2 model is developed in [12], while in [13], the spatial pyramid pooling was added to YOLOv3. They have good identification rates in different datasets, but its LP recognition depth makes it impossible to match the real-time needs of vehicle license detection system (VLDS) applications, notwithstanding their success. A bi-directional long short-term memory (LSTM) network was used in [14] to find the characters on the LP. A 1-D attention module was investigated to extract important information from the character areas in order to improve the accuracy of LP identification. Zhang *et al.* [15] used a 2-D attention mechanism to improve their recognition model, which relies on the feature extraction capabilities of an Xception-based 30-layer CNN.

Wang *et al.* [16] was presenteda weight-sharing classifier that can detect all occurrences of a character in any place. Small cross-dataset studies have been conducted in recent years to test the generalizability of the suggested approaches, since recognition rates using the classic split methodology have grown dramatically in recent years. The images from chinese city parking dataset (CCPD) dataset is used to train their recognition models for Chinese LPs. Silvano *et al.* [17] developed a system that combines Mercosur LPs with real-world images with different LP layouts. The findings of a model trained only on synthetic images were encouraging, but it is impossible to evaluate these results correctly since the test images were not made accessible to the scientific community.

LP of motorbikes frequently contain two rows of characters, which are difficult for sequential/recurrent-based algorithms, and since they are smaller in size and sometimes slanted, they have been removed from several studies. In order to give LPs with one or two rows of characters the same weight in the evaluation of VLDS systems, there is a high need for a public dataset for end-to-end VLDS with the same number of images of vehicles and motorbikes. However, real-world applications still have a problem with the accuracy of the rate. In addition, most of these technologies demand a substantial amount of computing power since they require the system to search through vast and high-resolution images or videos that were taken from the road.

Deep learning is a machine learning approach based on neural networks [18]-[21]. Various deep learning network structures, including as AlexNet, over feat, GoogLeNet, and ResNet, have been depleted. Because of its tremendous performance in image processing, region-based convolutional neural network (RCNN) is the most used deep learning model. The RCNN is built up of neurons with weights and bias that may be adjusted. Images may be used as input data, and the layers of the RCNN contain three dimensions (width, height, and depth). RCNNs are commonly utilised in the detection of vehicles and vehicle number plates. In order to improve the recognition accuracy, in this study a multi layered feed forward neural network will be used to recognise automobile license plates with high accuracy and speed.

2. PROPOSED METHOD

Regular monitoring of cars in a hectic traffic environment necessitates a complicated system. Detecting cars with adequate accuracy is crucial to the overall system functioning. Figure 1 shows the overall workflow of the proposed system. In this paper, character level number plate recognition is accomplished using the multi layered feed forward back propagation neural network (MLFFBPNN). The moving vehicles are identified in the vehicle level detection. The plate level detection detects the number plate area once the vehicle has been located. Instead of seeing the whole image, this level concentrates on the license plate zone. This significantly minimises the computation complexity. Following that, MLFFBPNN is used to perform character level recognition.

Figure 1. Workflow of the proposed system

The character level number pate recognition using MLFFBPNN has been described in Figure 2. In this method, there are 3 layers namely input, hidden, and output layers has been utilized. Each layer has been related with interconnection weights. In feed forward of information, initially a set of randomly chosen weights are feed to the input data and an output has been determined. Back propagation training algorithm is utilized to train the network. During back propagation, the propagation error has been determined, then the new weights are calculated and the weights are attuned for the minimization of error. This process has been repeated until the weights are calibrated to exactly predict an output [22].

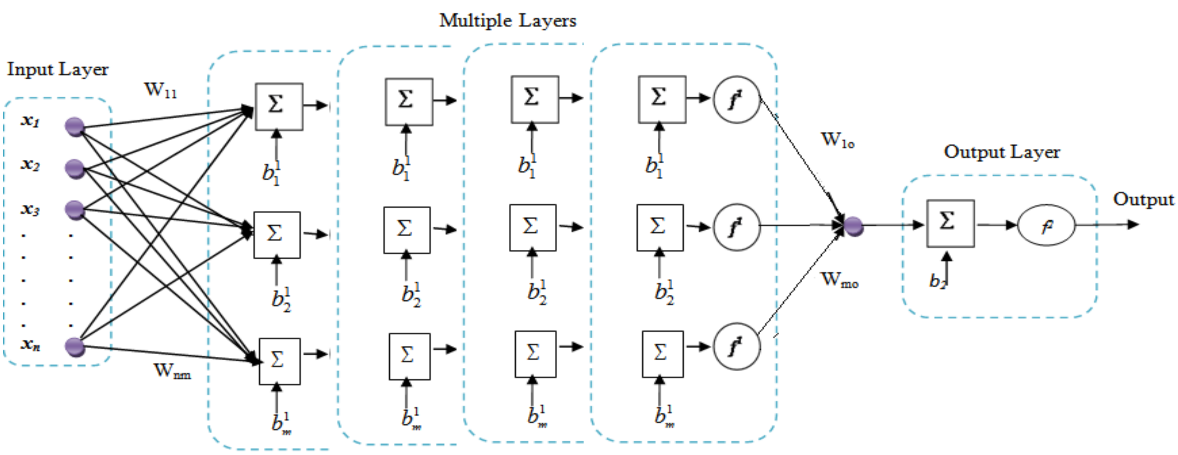


Figure 2. MLFFBP neural network

2.1. Number of neurons in the hidden layer

Rule-of-thumb method been utilized to determine the number of neurons in the hidden layer. Let Ni be the number of input neurons, Nh be the number of hidden neurons and No be the number of output neurons [23], [24]. 10 input neurons and 15 hidden neurons have been used in this network. Gray level co-occurrence matrix (GLCM) properties have been used as an input feature.

2.2. Back propagation training algorithm

Backpropagation is a widely used algorithm for training feedforward neural networks. The steps involved in algorithm are as follows:

a. *Initialization of weights*-small random values are selected as initial weights.
b. *Feed forward*- all the input features are transmitted to the hidden layer through input layer. The sigmoid function has been determined in both the hidden layer and the output layer. The required consequences are obtained from the output layer.
c. *Back propagation of errors*-the associated error has been determined by comparing the activation y_o' and the target value y_o. Then the new weights are computed for error minimization.
d. *Updation of the weights.*

2.3. Estimation of change in weight

The total error can be represented as,

$$\varepsilon = \frac{1}{2}\sum (y_o - y_o')^2$$

The relationship among the weight and the error can be written as,

$$W^* \propto -\frac{\partial \varepsilon}{\partial W}$$

$$W_{mo}^* \propto -\frac{\partial \varepsilon}{\partial W_{mo}} \tag{1}$$

It can be rewritten as,

$$W_{mo}^* = -\alpha \frac{\partial \varepsilon}{\partial y_o'} \frac{\partial y_o'}{\partial W_{neto}} \frac{\partial W_{neto}}{\partial W_{mo}} \tag{2}$$

Consider the terms separately and simplify,

$$\frac{\partial \varepsilon}{\partial y_o'} = \frac{\partial\left(\frac{1}{2}(y_o - y_o')^2\right)}{\partial y_o'} = -(y_o - y_o') \tag{3}$$

$$\frac{\partial y_o'}{\partial W_{neto}} = \frac{\partial\left(1+e^{-W_{neto}}\right)^{-1}}{\partial W_{neto}} = \frac{e^{-W_{neto}}}{\left(1+e^{-W_{neto}}\right)^2} = y_o'(1 - y_o') \tag{4}$$

$$\frac{\partial W_{neto}}{\partial W_{mo}} = \frac{\partial W_{mo} y_m'}{\partial W_{mo}} = y_m' \tag{5}$$

The weight change at hidden layer to output layer is,

$$W_{mo}^* = \alpha(y_o - y_o')y_o'(1 - y_o')y_m' = \alpha\delta_o y_m' \tag{6}$$

Where, $\delta_o = \alpha(y_o - y_o')y_o'(1 - y_o')$. To find the Weight change for an input layer to hidden layer,

$$\begin{aligned} W_{nm}^* \quad &\propto -\left[\sum \frac{\partial E}{\partial y}\frac{\partial y}{\partial W_{neto}}\frac{\partial W_{neto}}{\partial y_m'}\right]\frac{\partial y_m'}{\partial W_{netm}}\frac{\partial W_{netm}}{\partial W_{nm}} = \\ &\alpha\left[\sum (y - y')y'(1 - y_o')W_{mo}\right]y_m'(1 - y_m')y_n' = \alpha\left[\sum \delta_o W_{mo}\right]y_m'(1 - y_m')y_n' \\ &= \alpha\delta_m y_n' \end{aligned}$$

3. METHOD

3.1. Dataset

The Universaldade Federal do parana-automated license plate readers (UFPR-ALPR) dataset contains 4,500 fully annotated images taken from 150 cars in real-world circumstances in which both the vehicle and the camera (located inside another vehicle) are moving. The images were taken using three separate cameras and are in the portable network graphics (PNG) format, with a resolution of 1,920 by 1,080 pixels. The dataset is divided into three parts: 40% for training, 40% for testing, and 20% for validation. Figure 3 shows some of the UFPR-ALPR dataset's sample images [25].

Figure 3. Test images of UFPR-ALPR dataset

3.2. RodoSol-ALPR

The Rodovia do Sol (RodoSol)-ALPR dataset contains 20,000 images collected by pay toll cameras operated by the RodoSol concessionaire, which runs 67.5 kilometres of highway (ES-060) in the Brazilian state of Esprito Santo. Images of various sorts of vehicles (e.g., automobiles, motorbikes, buses, and trucks) were taken at different times of day and night, from different lanes, on clear and rainy days, and the distance between the vehicle and the camera fluctuates somewhat. All of the images have a 1,280 720 pixel resolution. Figure 4 shows some of the UFPR-ALPR dataset's sample images.

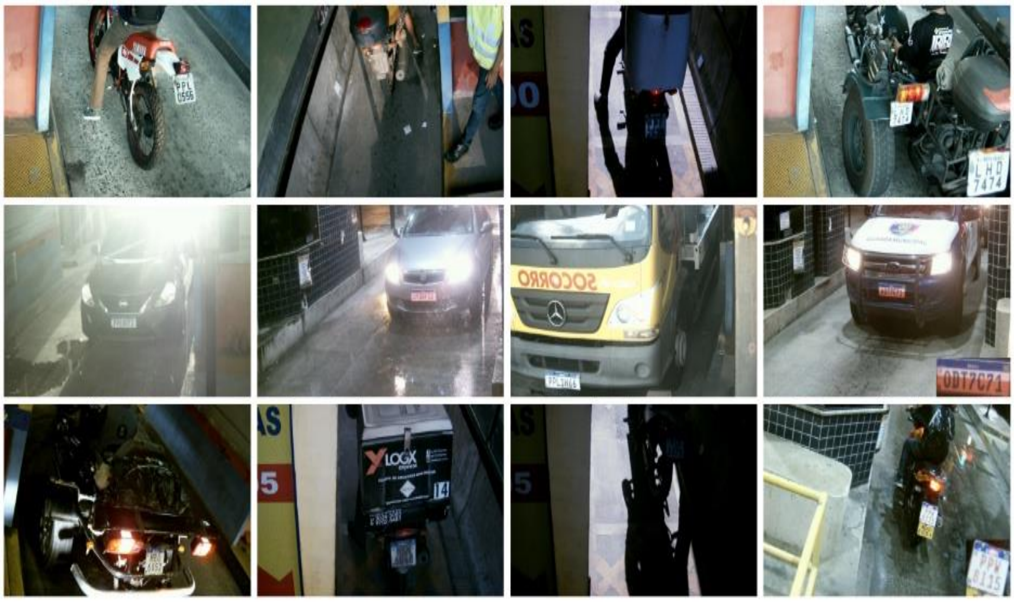


Figure 4. Test images of RodoSol-ALPR dataset

3.3. Simulation results of character level recognition

The RodoSol-ALPR and the UFPR-ALPR dataset is used to train the MFFBPNN. The vehicle level and plate level recognition of images are given in Figure 5. In this work, we have considered 500 epochs. The best performance is obtained with the mean squared error of 0.16529, this has been given in Figure 6. Figure 7 shows training, validation and testing performance.

Figure 5. Vehicle level and plate level recognition

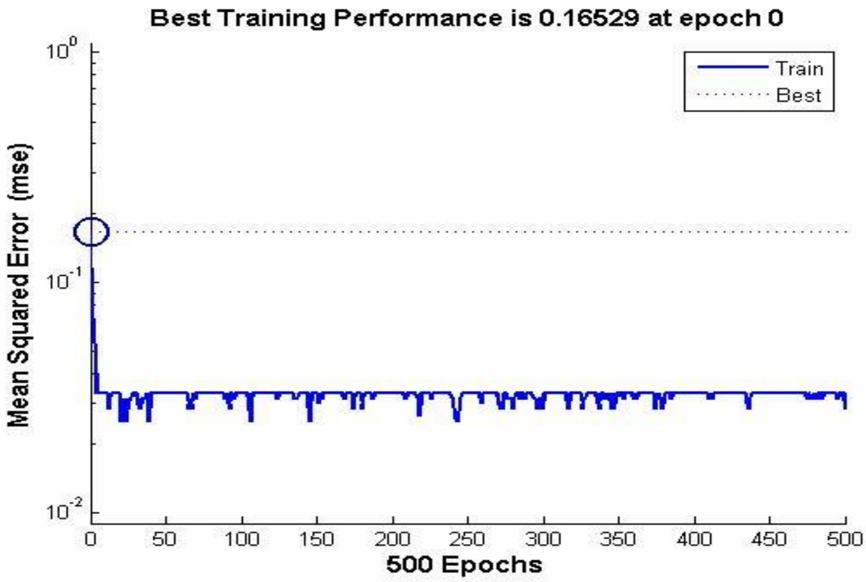


Figure 6. Mean squared error

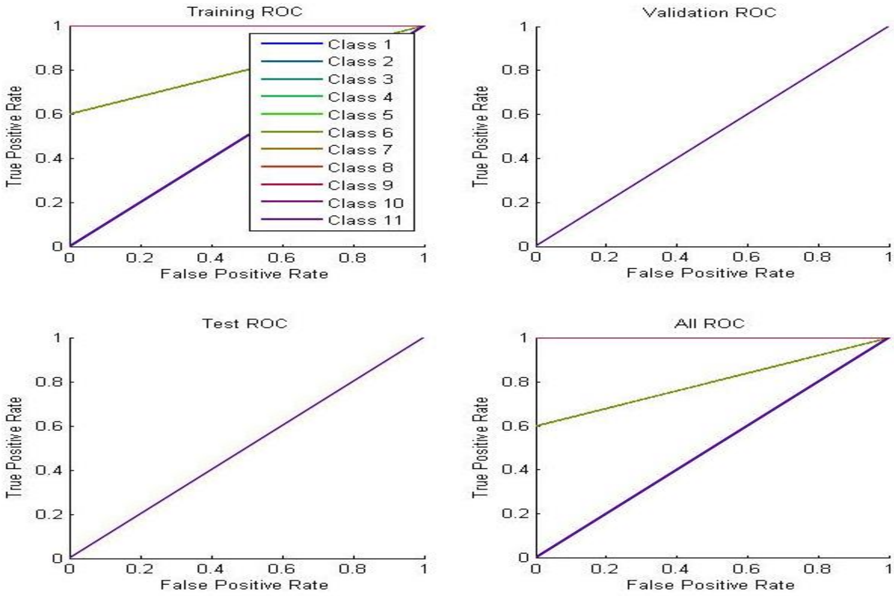


Figure 7. Training, validation and testing performance

4. RESULTS AND DISCUSSION

In the 12-layer MLFFBPNN (with two convolution layers) and the original (3 convolution layer) networks, the weight of the first convolution layer is adjusted once training is completed. The weights of the networks reveal that both networks have a good grasp of the dataset's visuals. Therefore, the structural adjustment does not have a substantial impact on the ability to extract features. In the next experiment, the middle layers are further reduced to a single convolution layer (9-layer RCNN). The image characteristics were not captured by the weights of the single convolution network. Two convolution layers have been removed, reducing the learning ability. The accuracy of the 12-layer and 15-layer MLFFBPNNs during training iterations is almost identical. Learning capacity is unaffected by a decrease in the number of layers. The 9-layer MLFFBPNN, on the other hand, has a much lower accuracy rate of 32.3%. Figure 8 (a) to (c) shows the results of the suggested technique, as presented in the Appendix.

Table 1 gives the accuracy of the four MFFBPNNs after the intermediate layers were trained. The accuracy is calculated by dividing each letter’s recognition sample by the overall sample value and multiplying by 100. The comparison of recognition accuracy of MLFFBPNN and RCNN is given in Table 2. Although the classification capacity is reduced when a convolution layer is removed from the MLFFBPNN in vehicle and plate levels have similar accuracy. This is because the plate detection issue is simpler than the vehicle identification problem, and hence a smaller MLFFBPNN can achieve the same accuracy. This also implies that the all-in-one MLFFBPNN may be tweaked without significantly affecting its accuracy. Because characters have fewer characteristics, their degree of accuracy is lower than that of plates or vehicles. As a result, the character-classification issue becomes a multiclass issue. Finally, extra training sets should be considered for the character's final layers. Experiments showed that the suggested technique worked by reducing MLFFBPNN and improving overall system performance. The comparative analysis of recognition accuracy of MLFFBPNN and the RCNN is given in Figure 9. From the analysis, it is clearly show that the proposed method gives better accuracy in character level recognition.

$$Accuracy(\%) = \left(\frac{Recognition\ Sample}{Total\ Sample}\right) * 100$$

Table 1. Comparative analysis of accuracy and computation time

Method	Layers	Training Time (min)	Accuracy
RCNN	15	49	56.7
	12	44	52.5
	9	32	10
MLFFBPNN	**15**	**32**	**62.4**
	12	30	61.9
	9	27	32.3
	3	21	17.2

Table 2. Comparison of recognition accuracy

Methods	Vehicle level	Plate level	Character level
MLFFBPNN	98	98	89
RCNN	98.5	97	85

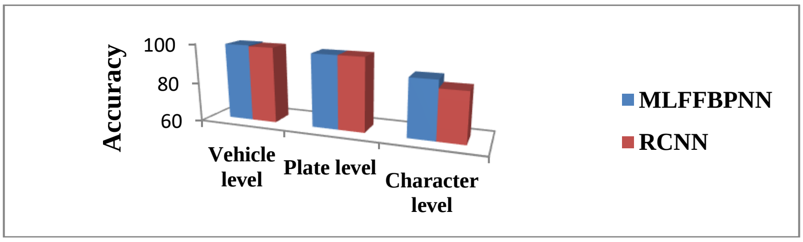
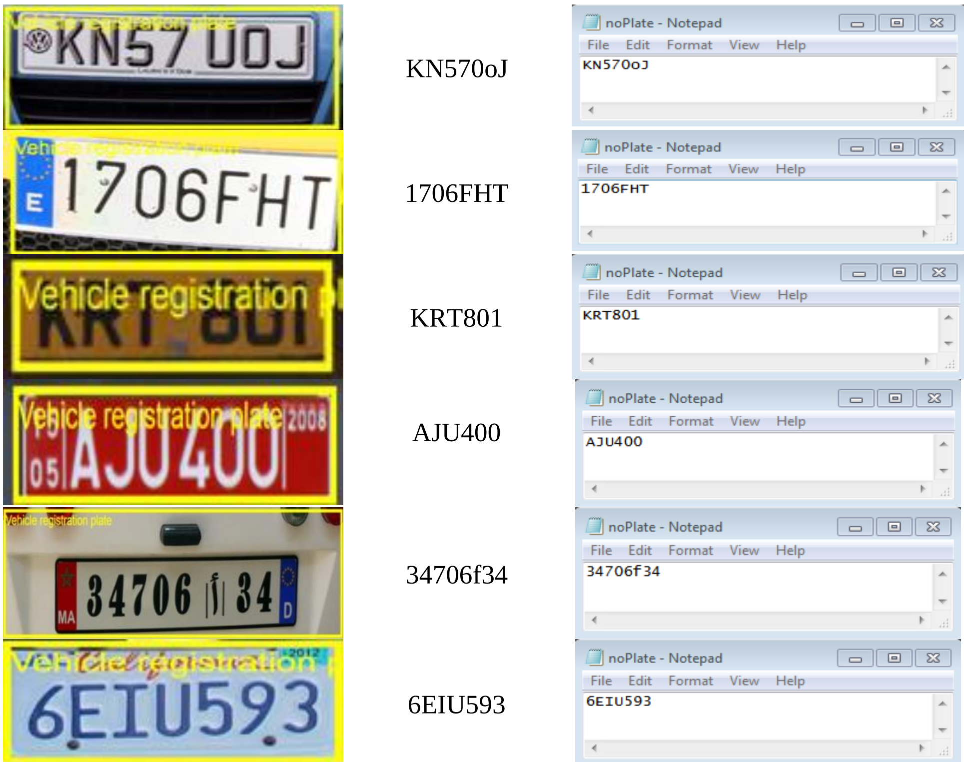


Figure 9. Recognition accuracy of MLFFBPNN and RCNN

5. CONCLUSION

In this paper, deep learning based MLFFBPNN has been presented for vehicle license plate detection and recognition. Here, three levels of recognition have been performed such as vehicle level, plate level, and character eve recognition. The proposed work is executed with the different number of layers. Here, we observed that, when the number of layers increased, the training time and the accuracy also get increased. We get the better performance with 15 layers. The performance of MLFFBPNN is compared with the RCNN network. The recognition accuracy of the proposed method is 89% and it is improved by 4% when compared with RCNN. In future, we planned to design a separate network for each level based on particular properties in the respective subtask and enhance MLFFBPNN's character level to enhance plate recognition.

APPENDIX



(a) (b) (c)

Figure 8. Character level LP recognition (a) plate level detection, (b) manual detection, and (c) character level detection

(a) (b) (c)

Figure 8. Character level LP recognition (a) plate level detection, (b) manual detection, and (c) character level detection (continue)

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