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NUMERAL SALVER UNCOVERING AND RECOGNITION USING NEURAL NETWORK

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ABSTRACT

Salver by Numbers Acknowledgment is critical to helping the government manage automobiles effectively as the global population of private vehicles rises dramatically. However, because they are unable to recognise the number plate, slightly altered number plate formats or distinct types of number plates might present problems for currently operating NPR systems. Furthermore, the NPR system reacts quickly to changes in its surroundings. In order to appropriately tackle these problems, this study presents a novel deep learning-based NPR system. a strong NPR system that combines the three pre-processing algorithms of defogging, low-light improvement, and super-resolution. And one of the study accomplishments of this work is that the number plate is successfully recognized in a variety of situations by employing these methods. Then, by applying contours using boundary following and filtering the contours according to geographical localization and character dimensions, the number plate is effectively segmented. Character recognition is then accomplished using the EfficientNet method following de-skewing and region of interest filtering. The suggested deep learning model makes use of the ImageAI library to improve training. We use pictures of Indian license plates to assess the model's effectiveness. Character recognition achieves an accuracy of 98.78%, while number plate detection achieves an accuracy of 99.2%. In comparison to earlier approaches, the suggested strategy achieves the extensive performance. The Python platform is used for the implementation.

Keywords: *Numeral Salver, Recognition, Uncovering, Neural Network.*

1. INTRODUCTION

NPR is a proficient and inventive descriptive research method in computer vision applications [1]. Due to the high number of cars on the road, the majority of the current systems—including manual and traffic police monitoring—fail to properly control and monitor vehicles. An intelligent system can address this problem quickly and efficiently [2]. Real-time number plate identification from moving cars is used to support traffic law enforcement and traffic monitoring systems [3]. In addition, the NPD sector is developing incredibly slowly, and from a logical standpoint, its implementation is hard [4].

Although the known models analyse the number plate location successfully, they have several limitations, including a high processing time, sensitivity to light, and inflexibility when it comes to being deployed on other platforms [13]. In the prior study, character segmentation was achieved by the use of relaxation labelling, application morphology, and related components [14] [15]. Additionally, the best character analysis techniques, including the Baye's classification,

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Support Vector Machine (SVM), Fuzzy C-Means (FCM), Markov chain model, K-Nearest Neighbour (KNN) classifier, Artificial Neural Networks (ANN), and Support Vector Machine (SVM), are used to accomplish the character segmentation [16] [17]. Multiple models carry out the segmentation of individual characters [18]. There are two kinds of character assessments that were developed: the numerical and the English. [19] [20].

This research uses EfficientNet to construct an intelligent system that can successfully recognise vehicle number plates. The identification system consists of five key processes: segmentation, picture pre-processing, NPD from the collected image, producing high-resolution images by a learning-based super-resolution technique, and character recognition. Since segmentation is used to acquire the total number plate evaluation, it is the most significant work. The segmentation determines each area of the number plate, including the kind, city, and vehicle number. The super-resolution approach is used to segment the blurry number plates in order to get a clear image from the blurry image. The bounding box approach is used to obtain excellent segmentation performance. By putting forward the EfficientNet-B4, the characteristics of the number plate are retrieved and the vehicle number is identified.

This study's structure is as follows: In section 2, the state of the art is summarized by citing a few relevant papers. In section 3, the suggested NPR algorithms are discussed in depth. Results of the implementation are presented in Section 4, along with a comparison with the most recent works. Section 5 presents the conclusion and next steps.

2. REVIEW OF RELATED WORKS

The automated identification of vehicles through the recognition and detection of licence plate numbers has been the subject of several studies and research projects in the past. Multiple strategies and algorithms are used by researchers to take into account the peculiarities of each nation's plate. Multiple research articles are consulted to get the precise information about NPR systems. Some of them have a thorough explanation given below.

Jamtsho et al. are developing the new real-time object detector [23]. This study created a YOLO (You Only Look Once) system for number plate recognition in motorcycle riders who do not use helmets. The single CNN of a rider without a helmet is used to identify the number plate from the input footage..

Izidio et al. [24] have created a unique and efficient NPR system for the purpose of identifying and detecting number plates. The CNN model is employed in this study's detection procedure. The Tiny YOLOv3 is used to identify license plates in the collected picture. Next, the convolutional network is used to identify the characters. Real license plate photos are utilised to fine-tune the network once it has been trained using synthetic ones.

Damak et al. [26] have suggested a computer vision technique for character segmentation (CS) and number plate position identification. also produced the novel optical character recognition (OCR) deep learning method. The CNN algorithm is analysed to determine the number after the location and characters of the number plate.

Yousif et al. [27] proposed an innovative method for recognizing license plates based on the state-of-the-art image processing techniques. Through the use of evolutionary algorithms (GA), this study produced an enhanced neutrosophic set (NS). Morphological and edge detection processes are two image processing techniques that are used to locate the license plate. By optimizing the (NS) functions utilising the GA evaluation, the most significant characteristics are extracted. Additionally, the k-means clustering technique is used to separate the characters from the number plate. The connected components labelling analysis (CCLA) efficiently extracts each character. This approach is used to identify the related pixel areas and arrange eligible pixels into components..

3. PROPOSED METHODOLOGY

In this study, a unique deep learning-based system is proposed to recognise the characters on the licence plate. Training of the deep learning model depends on massive volumes of data to get improved recognition results. Additionally, collecting and verifying actual licence plate photos by hand takes time and effort. Therefore, in order to generate huge number plate pictures for this experiment, a Python script was employed. The three main phases of the proposed methodology are as follows, image pre-processing, NPD, and NPR are shown in Figure 1. For defogging, the image is processed before the NPR

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phase using a dark channel prior algorithm for reducing the impact of outdoor atmospheric events. A better visual effect is achieved by using the CLAHE, and also the contrast and brightness of the image are enhanced and image details are restored by using this method. The low-quality images are managed by a reasonable method called the deep learning-based image super-resolution technique. When finalizing pictures, the bounding box method is applied. In image segmentation, thresholding is used to transform a grayscale image into a binary image. Number plate detection involves creating contours, filtering and grouping contours, and deleting overlapping characters and contours. Using a neural network, an expert system is developed that can consistently identify number plate letters in a distinct font.

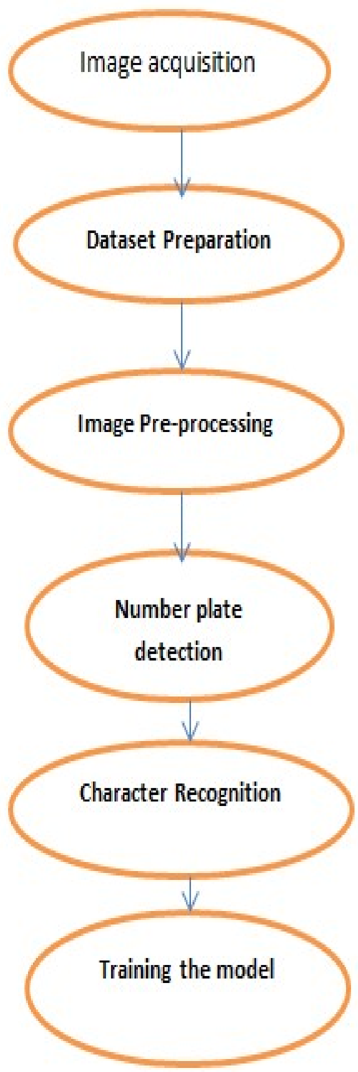

Figure 1. Schematic Diagram Of Our Proposed Methodology

Steps are
3.1 Image Acquisition
3.2 Dataset Preparation

3.3. Image Preprocessing

This system consists of two main components: one detects moving vehicle number plates, and the other recognizes the characters on the number plate. In the first stage, the number plate region is extracted from the picture of the car. The NPR procedure is given in three parts. (1) The super-resolution approach is used in the number plate region to transform a low-resolution image into a high-resolution image. After that, the RGB picture is transformed into a grayscale one. (2) The bounding box approach is used to segment characters. (3) The recognized letters and digits are sent into EfficientNet-B4 to extract features. This network model provides 4096 characteristics to identify each character.

3.3.1. Dehazing and Defogging
3.3.2 Low-Light Enhancement
3.3.3. Super-Resolution Technique
3.3.4 Bounding box segmentation

3.4 Number plate detection

The bounding box approach is used to produce the binarized picture following pre-processing with values of 0 or 255. The binarized picture is used as input for the detection and identification phases.

3.4.1 Applying contours

The process of creating contours, sometimes referred to as border following, involves contour tracing. A contour is a set of points that have the same intensity and form the border. In OpenCV, contour detection is akin to recognizing a white item against a black backdrop; hence, an inversion operation was required during the thresholding stage.

3.4.2. Contour filtering and grouping

When analyzing tiny regions, contours are especially useful for identifying sharp edges and noise outliers. A set of boundary boxes was initially assigned to each contour. Then, for each contour, the minimal contour area, the maximum and minimum possible aspect ratios, and the maximum and minimum contour height and breadth were taken into account. Effective number plate detection is achieved by filtering out outlines that aren't relevant. In the second stage of filtering, each contour is compared to every other contour according to a set of criteria, such as delta height, delta breadth, delta change in their region, delta

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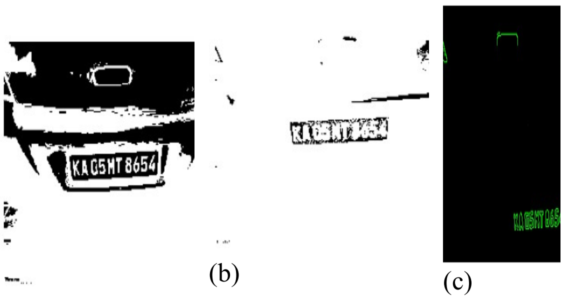
angle difference, and distance between contours. For a collection of contours to be regarded as a single set, they must all be met. There might be two or more.. The results of filtering and grouping are displayed in Figures 2(b) and (c). Applying contours to a binarized image yields the results shown in Figure 2(a).



(a) (b) (c)

Figure. 2. (A) Applying Contours; (B) Filtering Contours; (C) Grouping Contours

3.4.3. Remove overlapping characters/contours

The number "zero" represents a situation in which two or more outlines completely overlap. If the outside contour is obtained during the contouring process, the inner contour may completely contain it. This phenomenon serves as a means of distinguishing the two outlines as distinct characters throughout the recognition process.

This method eliminates the overlapping characters.

3.5. Character Recognition

3.5.1. Characters transformation and Prediction

The number plate's characters are improved, and after each contour's overlapping characters are eliminated, an image measuring 20 by 30 is produced. This is done in order to keep the image's dimensions consistent with the input format used by the learning model. After the model receives the scaled picture, the character is approximated. This procedure generates a string of characters for every contour. The retrieved segmented characters are utilised as an input for character recognition. Figure 3 displays the segmentation of characters.

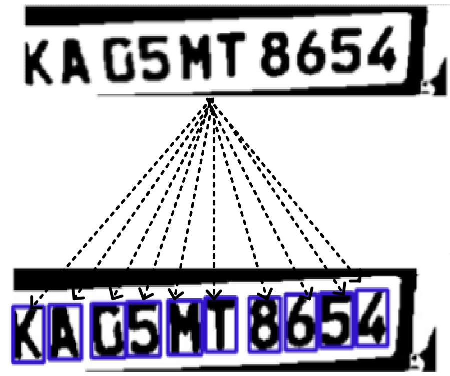


Figure 3. Character Segmentation

3.5.2. Training the model

EfficientNet, the most current iteration of CNN models, has the following main improvement. The data augmentation approach is used to increase the generalization capacity of the model, and an adaptive method is included during the data preparation step to update the dataset's relevant anchor box values. By employing the enhanced EfficientNet structure, more comprehensive contour fusion information is acquired and the calculation range is decreased. This network uses a variety of feature maps of different sizes. The size of the candidate box varies for each feature map. This is employed to assess a small object's capability. When dealing with numerous size objects, the EfficientNet method is utilised to quickly recognise NPR.

The suggested network model for sequence recognition first receives the full picture before extracting the deep features and compiling the local features. The transfer learning procedure makes use of the EfficientNetB4. By include the global_average_pooling2d layer in the network, overfitting is minimized and the number of parameters is decreased. The dropout layers and the three inner dense layers have been added to the network along with RELU activation functions. A 30% dropout rate is chosen at random to lessen the overfitting. One output dense layer has been modified with a softmax activation function in order to create the suggested Recognition system.

It includes three output units for multiclass classification and two output units for binary classification. Table 1 lists the layer's specifics and their distribution in the suggested model, including the total number of parameters (weights), the number of parameters (weights) in each layer, the

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output shape of each layer, and their order. There are 17,913,755 parameters in the whole network. ms, which the EfficientNet Models scale

A very efficient and straightforward model for the recognition procedures is NeuralNet Models. EfficientNet models generally surpass current CNNs, such as MobileNetV2, Google Net, ImageNet, and AlexNet, in terms of accuracy and efficiency. Efficient-Net might serve as a new basis for computer vision tasks in the future. Such study using EfficientNet for NPR transfer learning has not yet been conducted. Models in EfficientNet range from B0 to B7. A set of distinct parameters, ranging from 5.3M to 66M, correspond to each model. The suggested system uses the efficentNetB4 model, which contains 19M parameters since it is suitable for the NPR resources and objectives.

Table.1 The NPR Model's Layer Types And Parameters.

Layer (type)	Output shape	Parameter #
EfficientNetB4 (Model)	7 ×7× 1792	17,673,816
global_average_pooling2d	1792	0
dense (Dense)	128	229,504
dropout (Dropout)	128	0
dense_1 (Dense)	64	8256
dropout_1 (Dropout)	64	0
dense_2 (Dense)	32	2080
dropout_2 (Dropout)	32	0
dense_3 (Dense)	32	99
Non-trainable Parameters: 125,200		
Trainable Parameters: 17,788,555		
Total Parameters: 17,913,755		

The suggested model can distinguish between characters in various typefaces with ease. Furthermore, it's critical to keep in mind that a proper balance needs to be struck when combining many typefaces. If there are too many typefaces, some of the models may get overfit, which would result in poor generalization and incorrect detection. The EfficientNet model is used to address this overfitting. The model that resembles the common Number Plate fonts is trained using several fonts. This ensures that the input to the model is consistent. Figure 4(a) shows the typefaces, and Figure 4(b) provides an example of the extracted pictures for the character "P".

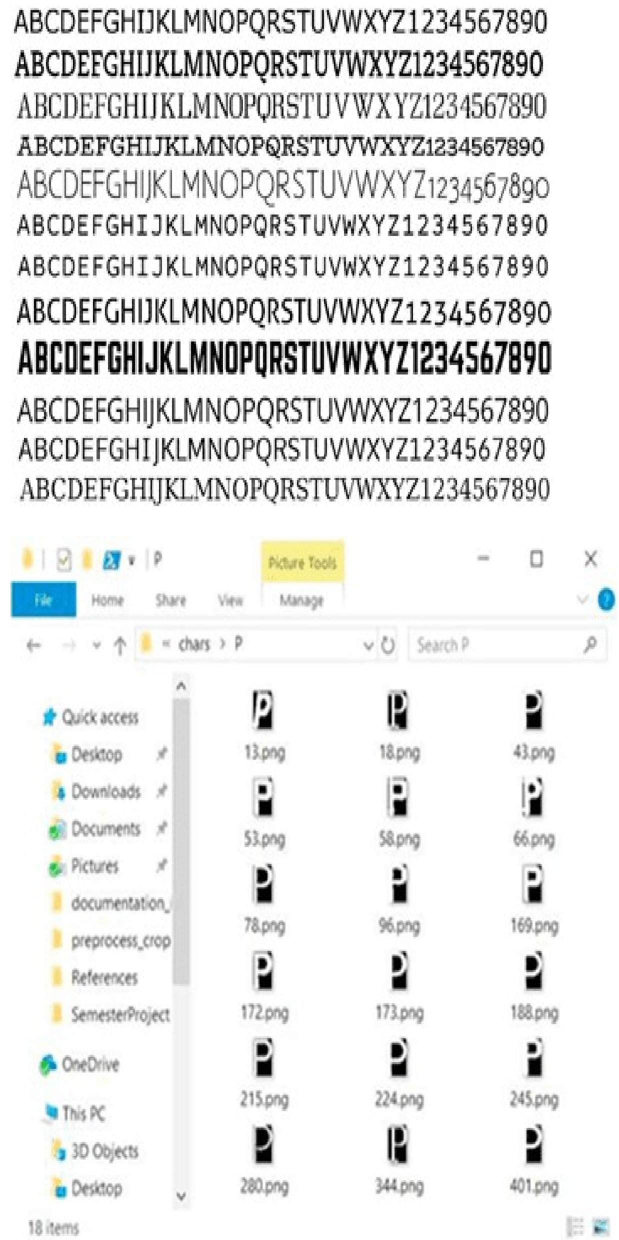

Figure. 4. (A) Training Fonts; (B) Images That Were Extracted For The Letter "P"

4. EXPERIMENTAL RESULTS

The i5 processor-equipped Windows 10 PC is used to conduct the experiment simulations. The Python OpenCV library is used to implement the image processing tools. The Kaggle pictures are utilised for simulation. The technology has been tested with images. All of the previously specified scenarios—such as angularly skewed plates, distant or up close plates, and stylistic writing plates—were taken into consideration as test cases for the system. Taking pictures in a

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range of environmental settings is part of the testing process. As seen in Figure 5, the GUI serves as a platform to enhance the system's sustainability and offer a user-friendly interface.

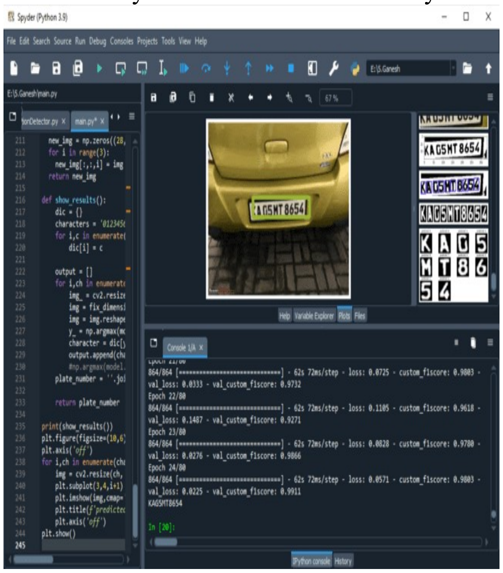

Figure 5. NPR System GUI

4.1. Image Preprocessing

By using three picture preparation techniques at first, the final recognition accuracy is raised. This section emphasizes not only the speed and visual impact of various image processing approaches, but also the performance of the picture preprocessing effect. Three picture preparation techniques enhance the image quality, as seen in Figure 6.

Figure 6. Three Different Image Preprocessing Techniques' Visual Effects Include Low-Light Enhancement, Defogging, And Super-Resolution.

Defogging may be used to remove dust and fog from an image by using the dark channel before approach. The contrast and visibility of the picture are effectively increased using the CLAHE algorithm-based low-light enhancement technique. Important information and an improved visual impression are provided by the reconstructed image following super-resolution. Processing times for individual images are rather short in the stages of fog removal and low light enhancement. Even at super-resolution, processing times are considerably slow because to the complex network design. The findings of the recognition indicate that the character was frequently mistakenly recognized as another character prior to image processing.

Because character segmentation is insufficient in cases of fuzzy pictures, the recognition performance for the complete number plate yields better results than the recognition performance based on individual characters. Nevertheless, most characters may be properly recognised after image processing, regardless of whether full identification of the character or number plate is required. The recognition performance for the entire number plate produces better results than the recognition performance based on individual characters since character segmentation is insufficient in circumstances of blurry photographs. However, following image processing, the majority of characters may be correctly identified, regardless of whether complete character or number plate recognition is necessary.

4.2 Number Plate Detection

Figure 7 (a) shows test case images with various backgrounds. The results of the NPD and NPR for each test case are displayed in Figure 7 (b). From the provided Indian number plate images, the number plates are successfully detected by the system, and it effectively recognizes the characters from the plates.

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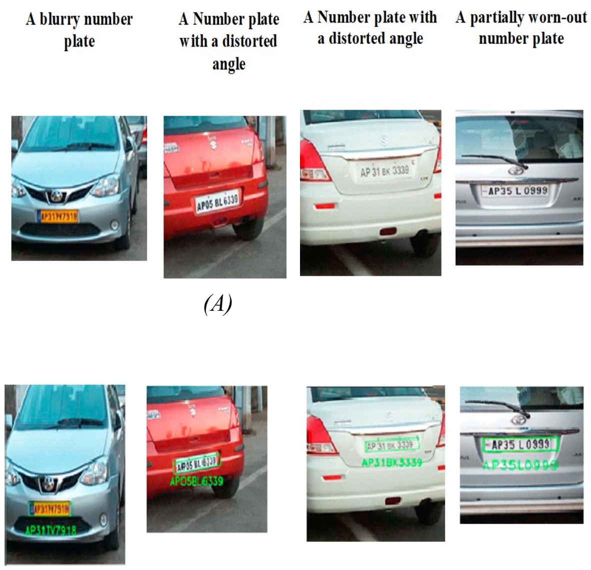

(A)

(B)

A) Images Of A Test Case For The Angled And Distorted Number Plate. B) The Results Of Detection And Recognition Of The Number Plate Across All Test Cases.

Figure 7. The Experimental Results Of The Number Plate Images

4.3 Numeral Salver Recognition

In order to train the model for character identification, 67 distinct character types—including numerals, region names, and Hangul—were included. During the training phase, the initial momentum and learning rate are set to 0.9 and 0.001, respectively. Using the stochastic gradient descent (SGD) method, the model was optimized. The batch size is 128 and the overall epoch was set to 15. The training and validation performance is displayed in Figure 8. Training and validation accuracy both increased, peaking at 99.1% during the 12th epoch. The training and validation loss is gradually reduced until it approaches zero.

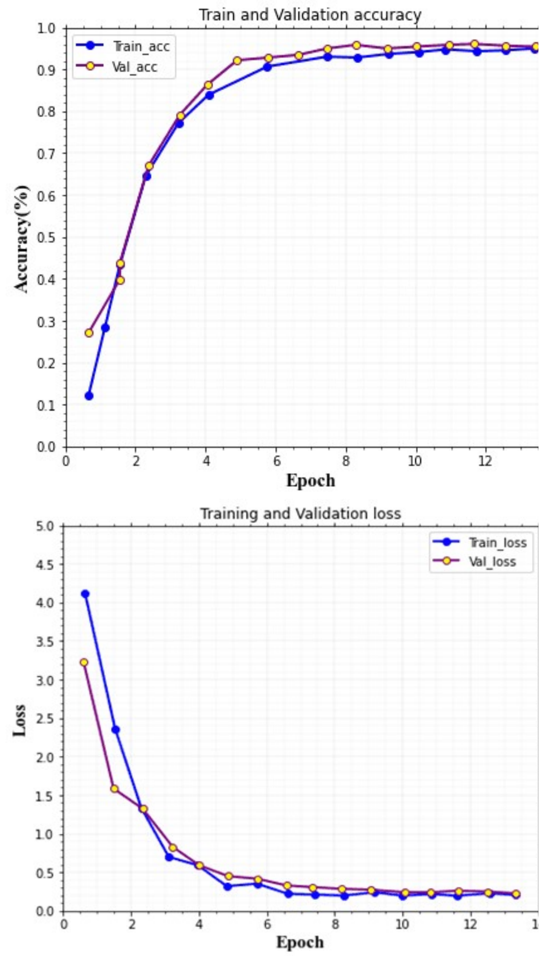

Figure 8. The Performance Results Of The Character Recognition Module's Training And Validation (Accuracy And Loss).

The technology correctly detects 99.2% of the number plates. Furthermore, 98.78% of the characters on the plates can be properly recognized. This section analyses and contrasts the performance of the proposed NPR system with existing cutting-edge NPR systems. The accuracy of NPR is defined as the proportion of correctly predicted number plates throughout the whole test set. Table 2 illustrates how the suggested Neural Net performs better in recognition when compared to the findings on YOLO and YOLOV3. Nonetheless, the ResNet-10 system outperforms the YOLO detection technique in terms of performance. This is due to the fact that the system's number plate detection involves two procedures, namely the identification of the vehicle and the number plate. The license plate detection is affected when the LP region of different images in the dataset is not fully collected during the vehicle detection process.

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Table 2. Performance Comparison Of Proposed And Existing Methods

Methods	Component	Accuracy (%)
YOLO	NPD	92
	NPR	93.7
YOLOv3	NPD	95.6
	NPR	96.82
Neural Network	NPD	97.2
	NPR	98.78

In comparison to current existing methodologies, the suggested EfficientNet-B4 method successfully performs the NPD and NPR. Using the same dataset, the suggested EfficientNet approach in this study achieves a processing speed of 0.069s. Figure 9 presents a visual comparison of the number plate detection and identification accuracy with different models.

5. CONCLUSION

This study examines NPD and NPR in relation to Indian number plates, often known as number plates. One of the major contributions of this study is the consideration of challenging conditions, such as partially worn-out or non-standard number plates, noisy pictures, skewed, blurry, and variable lighting. During the picture preprocessing stage, three techniques are used to improve the quality of the input image. Next, contours are used for number plate segmentation utilising boundary following. Contours are then filtered using the spatial localization and character dimensions. Character recognition is then accomplished by the EfficientNet following de-skewing and region of interest filtering. With pictures, the suggested EfficientNet-B4 works well for large amounts of data. The suggested approach reduces the overfitting issue and improves the image's capacity for generalisation. The suggested approach successfully detects 99.2% of the number plates and recognises over 98.78% of the characters. In comparison to the state-of-the-art techniques such as YOLO, CNN, YOLOv3, and ResNet-101, the performance results of the suggested method obtain higher detection and identification accuracy. In further study, this project aims to deploy a CNN that combines detection and recognition into a single framework.

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