Journal of Theoretical and Applied Information Technology
31st March 2024. Vol.102. No 6

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

# A NOVEL METHOD FOR INDIAN NUMBER PLATE DETECTION AND RECOGNITION USING EFFICIENT NET

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**ABSTRACT**

Number Plate Recognition (NPR) is essential in supporting the government in properly managing vehicles as the number of private vehicles increases significantly throughout the world. However, different number plate types or slight variations to the number plate format can disrupt existing NPR systems because they fail to detect the number plate. Additionally, the NPR system is very responsive to environmental factors. To properly address these issues, this research introduces an innovative deep learning-based NPR system. A robust NPR system that integrates three pre-processing algorithms including super-resolution, low-light enhancement, and defogging. And the number plate is effectively-recognized by using these algorithms in a range of environments, it is one of this paper's research achievements. Then the number plate is successfully segmented by applying contours through border following and filtering the contours based on spatial localization and character dimensions. Finally, the EfficientNet algorithm is used for character recognition after de-skewing and region of interest filtering. The ImageAI library is used by the proposed deep learning model to enhance training. Images of Indian number plates are utilized to evaluate the model's performance. The accuracy of 99. 2% is achieved for number plate detection and an accuracy of 98.78% is achieved for character recognition. The extensive performance is achieved by the proposed method compared to previous methods. The implementation is performed under the python platform.
**Keywords:** *Number Plate; Super-Resolution; Spatial Localization; Defogging: Segmentation: Character Recognition.*

## 1. INTRODUCTION

In computer vision applications, NPR is an effective and innovative descriptive research [1]. Most of the existing systems are failed to control and monitor vehicles effectively due to a large number of vehicles on the road including traffic police monitoring and manual monitoring. This difficulty can be easily and effectively solved by an intelligent system [2]. The performance of traffic law enforcement and monitoring traffic systems are done with the help of real-time number plate detection from moving vehicles [3]. Furthermore, the development of the NPD field is extremely slow and the implementation of this field is complex from a logical viewpoint [4].

The three major steps make up a significant automatic NPR system such as detection of the number plate, segmentation of the characters, and recognition of the number plate [5] [6]. The number plate location is determined by using the NPD system in a specific image. From the detected Number plate, each character is segmented by the process of character segmentation and the individual characters are classified by the character recognition process [7]. Since the character recognition process is directly impacted by the prior two processes, they are essential for proper Automatic NPR [8]. The succeeding phases fail if the number plate is not localized in the initial stage. This difficulty is solved by combining the character recognition and segmentation phases in the process of object recognition [9] [10]. Between the three stages, the inter-dependency is eliminated by the recent effective deep learning framework [11] [12].

The location of the number plate is effectively analyzed by the established models, but it has some drawbacks such as high processing time, sensitivity to illumination, and lack of flexibility to be implemented on varied platforms [13]. In the previous investigation, relaxation labeling, application morphology, and associated components are used to attain the character segmentation [14] [15]. And also the character segmentation is performed by using the optimum range of character analysis approaches such as K-Nearest Neighbor (KNN) classifier, Markov chain model, Support Vector Machine (SVM), Fuzzy C-Means (FCM), Artificial Neural Networks (ANN), and Baye's classification [16] [17]. The individual character segmentation is performed by several models [18]. The numerals and English are the two types of character evaluations that were developed [19] [20].

An intelligent system is developed by this research using EfficientNet for recognizing vehicle number plates effectively. There are five main processes in the recognition system such as image pre-processing, NPD from the image that was captured, high-resolution images can be produced using a learning-based super-resolution approach, segmentation, and each character's recognition. The more significant task is segmentation because the overall number plate evaluation is obtained by using this segmentation. Each region of the number plate is determined by the segmentation, such as vehicle number, type, and city. The blurred number plates are segmented by using the super-resolution technique, which is used to get a clear image from the blurred number plate image. The performance of perfect segmentation is achieved by applying the bounding box method. The number plate features are extracted and the vehicle number is recognized by proposing the EfficientNet-B4.

The main contributions of the research are

- This research, first performing the pre-processing phase, uses several image processing techniques, including the dark channel prior algorithm, contrast limited adaptive histogram equalization (CLAHE), and image super-resolution. The bounding box method is used to perform the image binarization.
- Then, borders are used to apply contours for number plate segmentation the spatial localization and character dimensions are used to filter contours.
- Finally, the character recognition is done by using the EfficientNet following de-skewing and region of interest filtering.
- The Indian number plate images (Kaggle) dataset is used for the classification of NPD and NPR, the experiments are performed on the Python platform. It's employed to compare and contrast the proposed and existing methods. According to the experimental results, the proposed EfficientNet outperforms the previous techniques.

The structure of this research is as follows: By identifying some related publications, an overview of the state of the art is provided in section 2. The proposed NPR algorithms are covered in detail in section 3. Section 4 reveals implementation results and a comparison to the state-of-the-art works. The conclusion and future work are presented in Section 5.

## 2. RELATED WORKS

Numerous investigations and research work have previously been completed on automatic vehicle detection using license plate number detection and recognition. Considering each nation's plate features, researchers employ multiple techniques and algorithms. The specific information on NPR systems is determined by consulting multiple research papers. A detailed explanation of some of them is provided below.

A new innovative deep learning-based NPR system is proposed by Pustokhina et al [21]. In this paper, the segmentation is performed by using optimal K-means (OKM) clustering and the recognition is performed by the CNN, termed as OKM-CNN model. There are three primary steps in the proposed OKM-CNN system such as NPD, segmentation, and NPR. The Connected Component Analysis (CCA) and Improved Bernsen Algorithm (IBA) models are used for the localization of the number plate and detection of the number plate in the first stage. The LP image is then segmented using the OKM clustering with Krill Herd (KH) algorithm. With the aid of the CNN model, the number plate characters are recognized finally.

Omar et al [22] developed a cascaded deep learning approach. In this research, NPD and NPR are performed effectively by using this proposed approach. The multiple preprocessing approaches are employed by the proposed method. For further processing, the input images are prepared by using adaptive image contrast enhancement and Gaussian filtering. Then the input image's three number plate regions are determined by a deep semantic segmentation network. The deep encoder-decoder network structure is then employed for

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

segmentation. Next, the two separate CNN models are used for the recognition of the number plate and the determination of the city.

The new real-time object detector is developed by Jamtsho et al [23]. This research developed a YOLO (You Only Look Once) for the detection of number plates in non-helmeted motorcyclists. From the input video, the number plate is detected by using the single CNN of a non-helmeted motorcyclist.

A novel effective NPR system is developed by Izidio et al [24] for detecting and recognizing the number plates. In this research, the CNN model is used for the detection process. In the captured image, the Tiny YOLOv3 is used for detecting the license plates. Then the characters are identified by using the convolutional network. The synthetic images are used to train the network and real license plate images are used to fine-tune the network.

A hierarchical CNN-based end-to-end NPR approach was evaluated by Silva et al [25]. The vehicle and the region of the number plate are identified by using the two passes on the same CNN. Next, the characters of the number plate are recognized by a second CNN. The character recognition of the number plate is achieved effectively by presenting the temporal coherence technique.

A computer vision algorithm is proposed by Damak et al [26] for identifying the location of the number plate and Character Segmentation (CS). And also generated the new deep learning technique for Optical Character Recognition (OCR). After the location and characters of the number plate, the CNN algorithm is examined to find the number.

According to the most recent image processing methods, Yousif et al. [27] suggested a novel approach for recognizing license plates. This research developed an improved neutrosophic set (NS) based on evolutionary algorithms (GA). The location of the number plate is determined by performing certain image processing approaches including morphological and edge detection operations. The most important features are extracted by using the evaluation of GA to optimize the (NS) functions. Moreover, the number plate characters are segmented by using the k-means clustering algorithm. Each character is effectively extracted by using the connected components labeling analysis (CCLA). The connected pixel regions are identified and suitable pixels are grouped into components by using this analysis.

## 3. PROPOSED METHODOLOGY

The number plate characters are recognized by proposing a novel deep learning-based framework in this paper. Enhanced recognition results are achieved by the deep learning model's training depending on the support of enormous amounts of data. Furthermore, manually gathering and validating real number plate images requires multiple efforts. As a result, a Python script was used to create large number plate images for this investigation.

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 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. The bounding box approach is used to binarize images. Thresholding is used in image segmentation to convert a grayscale image into a binary image. The process of contour generation, filtering and grouping contours, and removing overlapping characters/contours are used to detect number plates. An expert system that can reliably recognize number plate characters in a different font is created using the EfficientNet.

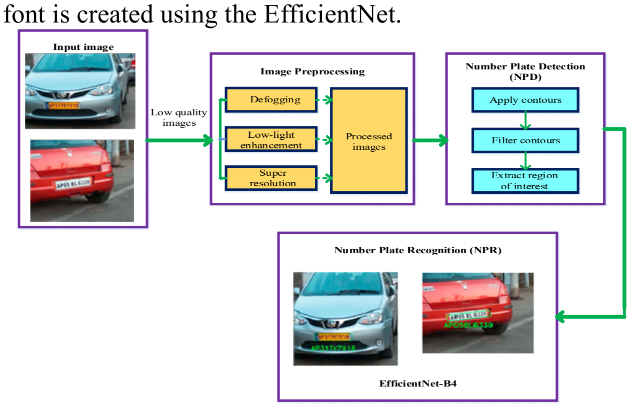



*Figure 1. Schematic Diagram Of Our Proposed Methodology*

### 3.1 Image Acquisition

The algorithm is implemented to work with the system, which helps it recognize number plates in all dynamic conditions. Any Automatic NPR system must have a camera as a major element. By using their IP address, this system is designed to give users access to all cameras. Images

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

can be acquired from CCTV footage of parking system cameras, border crossing cameras, stolen car tracking cameras, and traffic control cameras. Every frame of the converted videos is processed for vehicle detection on a frame-by-frame basis.

### 3.2 Dataset Preparation

The car dataset from Kaggle is utilized for training. There are 16,185 images in the dataset, divided into 196 classifications. It is divided into testing and training. 8144 images are used for training and 8041 images are used for testing in the dataset. Creating two folders with the labels train and validation is the first step. The two subfolders are presented in train and validation, such as images and annotations. All of the train and test images will be in the image folder, and the XML file is located in the annotations folder. A set of rules is defined by the XML (Extensible Markup Language) file for encoding documents in a manner that is usable by both machines and people.

### 3.3. Image Preprocessing

There are two major parts to this system, detecting moving vehicle number plates is one part while the other is for recognizing the number plate characters. The number plate region is extracted from the vehicle's image in the first step. Three aspects are presented in the process of NPR. (1) In the number plate region, a low-resolution image is converted into a high-resolution image by using the super-resolution method. Then the RGB is then converted into a grayscale image. (2) Character segmentation is done using the bounding box method. (3) EfficientNet-B4 is used to extract features from the recognized numbers and letters. Each character can be recognized using 4096 features provided by this network model.

### 3.3.1. Dehazing and Defogging

The scattering impact of atmospheric particles with atmospheric processes, including haze and fog, significantly reduces the quality of the images. Before the NPR phase, these outdoor atmospheric effect is reduced by applying the defogging technique named dark channel prior algorithm for processing the image. The local area's darkest value is filtered to create the dark channel image in the defogging process.

### 3.3.2 Low-Light Enhancement

A CLAHE method is used to solve the difficulties of images with blurry, low contrast, and low brightness, and also the image details are restored and a higher visual effect is achieved by this method. The CLAHE algorithm is expressed in the formula below. The threshold value for Cliplimit must be established in advance of the algorithm's execution. The original pixel distribution is represented by $Q_{Original}$ and the algorithm's pixel distribution is represented by $Q_{CLAHE}$ respectively. The sum is the total of all histogram pixel values that are greater than Cliplimit. In an image, the number of pixels is represented by $N$.

$$P_{CLAHE} = \begin{cases} Q_{Ori} + \left(\text{Cliplimit} - \frac{Sum}{N}\right), & \text{if } Q_{Original} > \left(\text{Cliplimit} - \frac{Sum}{N}\right) \\ \text{Cliplimit}, & others \end{cases} , \quad (1)$$

For each gray level, the number of pixels is counted by the histogram where each pixel on an image represents a different grey scale. On the low gray level side, the histogram's elements are focused in the darker image. Contrast limiting is the main difference between typical Adaptive Histogram Equalization (AHE) and CLAHE. For each small area in the CLAHE, contrast limiting is required. AHE's over-amplification noise problem is solved by using the CLAHE algorithm.

### 3.3.3. Super-Resolution Technique

The image resolution that is captured is limited by the surveillance camera's performance and the hardware's design. From the blurry plate region, the number plate's character cannot be read. The limitation is successfully solved in this research using a spatial super-resolution approach. The high-resolution images are created using super-resolution techniques from a combination of successful low-resolution images. The super-resolution method's main concept is non-redundant data is combined from many low-resolution frames into one high-resolution frame.

From multiscale low-resolution, the spatial resolution approach is used to obtain the high-resolution image. The high-resolution number plate image is obtained by using this method. By converting the image samples, the system uses the down sampling method like local statistics, alignment vector, and local gradient. Then the high-resolution RGB image and down sampling image are created by the kernel. Next, the gray-scale image is converted from the high-resolution image by Equation (2).

$$I = Wr * R + Wg * G + Wb * B \quad (2)$$

The RGB color image's linear in luminance monochromatic color values (red, green, and blue, respectively) are represented by the R, G, and B. Wr, Wg, and Wb are the colors red, green, and

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

black's respective coefficients (fixed weights), with respective values of 0.299, 0.587, and 0.114. All three weights' summation equals 1.

The super-resolution methods are an excellent solution for blurry images. There are numerous methods for super-resolution. The spatial super-resolution approach outperforms the others in terms of results. The high-resolution scene sub pixels are moved across many low-resolution frames using down sampling. The camera's image processing limitations are solved by building the super-resolution to match low-resolution observations and sub-pixels are combined into high-resolution image grids. The original image is divided into several low-resolution images using this method. In the plate region, the quality of the image is considerably enhanced with the optimum contrast and brightness balance by using this super-resolution algorithm.

**3.3.4 Bounding box segmentation**

The most important aspect of this work is segmentation since exact segmentation is necessary for the correct recognition of each character. Recognition won't be effective if segmentation is done incorrectly. Each character's specific region is segmented using the bounding box method. Each character's boundaries are determined effectively using this method. It has a rectangular box around the area that is labeled. The lower left and top left corners of the rectangle are then determined using the y and x coordinates, and each character's label is provided by this. Equation (3) describes the bounding box approach. The target location is described by this bounding box algorithm.

$$K(x) = \sum_{a \in \beta} P^a \times x_a + \sum_{\{a,b\} \in \in} Q^{ab} \times |x_a - x_b|,$$

where $a \in \beta$ is a set of pixels in the image β. Assuming values of 0 and 1 for the background and foreground, $x_a$ is represented as an individual-pixel label. $Q^{ab}$, $P^a$, and $\in$ define pairwise potentials, unary potentials, and adjacent pixel pairs.

Characters are identified as foreground objects by using the algorithm after choosing a frame, with a target bounding box. The normalization ROI and target bounding box represent the region of the target image with the aspect ratio. The target image's feature vector was then extracted. The image segmentation is performed by matching the training data to its features. Until the segmentation of all the regions is performed, the process is continued.

**3.4 Number plate detection**

The binarized image is obtained by the bounding box method after the process of pre-processing with values of either 0 or 255. The stages of detection and recognition phases use the binarized image as input.

**3.4.1 Applying contours**

The contour tracing is used for generating the contours sometimes known as border following. The boundary is defined by a contour, which is a series of points with the same intensity. Detecting contours in OpenCV is similar to identifying a white object against a black background, hence inversion operation had to be used with the stage of thresholding.

**3.4.2. Contour filtering and grouping**

Contours are used for regarding small areas, particularly for noise outliers and sharp edges. Each contour was initially given a set of bounding boxes. Next, maximum and minimum feasible aspect ratios, maximum and minimum contour height and width, and the minimum contour area were considered for each contour. A number plate is detected effectively with the help of a filtering process for the irrelevant contours. Each contour is compared to every other contour based on certain factors in the second step of filtering including delta height, delta width, delta change in their region, their difference in delta angle, and distance between contours. All of these requirements must be satisfied for a set of contours to be considered as one. There may be two or more of these groupings formed. 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*

Journal of Theoretical and Applied Information Technology
31st March 2024. Vol.102. No 6

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

#### 3.4.3. Remove overlapping characters/contours

The number "zero" is an example of a case where two or more contours entirely overlap one another. The inner contour may entirely enclose the outer contour if it is acquired during the contouring process. This phenomenon is used for allowing both contours to be identified during the recognition process as different characters. The overlapping characters are removed by using this process.

### 3.5. Character Recognition

#### 3.5.1. Characters transformation and Prediction

The characters on the number plate are enhanced to create a 20 × 30 image after removing the overlapping characters for each contour. To maintain compliance with the learning model's input format, this process is carried out, then the image is resized. The character is estimated once the scaled image is delivered to the model. A string of characters is generated by this process is performed for each contour. Character recognition is used as an input with the segmented characters that were extracted. The character segmentation is shown in Figure 3.

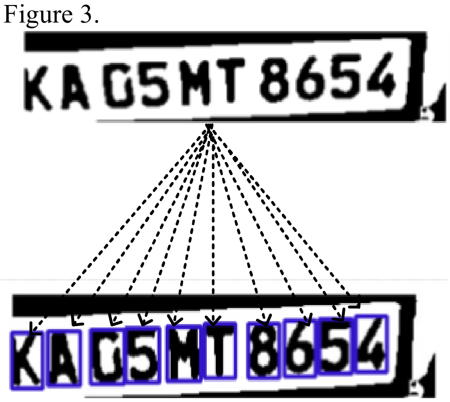


*Figure 3. Character Segmentation*

#### 3.5.2. Training the model

The most recent improved version of CNN models is EfficientNet, which has the following primary enhancement. The model's generalization ability is improved by using the data augmentation method and the dataset's appropriate anchor box values are updated by adding an adaptive method during the data preparation stage. More extensive contour fusion information is obtained and the computation range is reduced by using the improved EfficientNet structure. Different feature maps with various scales are used by this network. For each feature map, the candidate box has a different size. This is used for recognizing the ability of small objects. The EfficientNet algorithm is used for fast recognition of NPR with multiple scale objects.

First, the entire image is given to the model, then extracting the deep features and gathering the local features, are performed by the proposed network model for the sequence recognition. For the transfer learning process, the EfficientNetB4 is used. The parameters are reduced and overfitting is minimized by adding the global_average_pooling2d layer t the network. With RELU activation functions, and have been added the dropout layers and three inner dense layers to the network. The overfitting is reduced by randomly selecting a total of 30% dropout rate. To develop the proposed Recognition system, a softmax activation function has been introduced to one output dense layer. For multiclass classification, it has three output units, while for binary classification, it has two output units. The layer's details and their distribution in the proposed model are given in Table.1, such as the overall number of parameters (weights), the number of parameters (weights) in each layer, each layer's output shape, and their sequence. 17,913,755 parameters are present in the entire network. The CNN models have already been trained. For transfer learning, it can be used in multi-class image classification problems, which are scaled by the EfficientNet Models.

EfficientNet Models is a highly effective and simple model for the recognition processes. Over existing CNNs like MobileNetV2, GoogleNet, ImageNet, and AlexNet, EfficientNet models typically outperform them in terms of accuracy and efficiency. Future computer vision tasks may use Efficient-Net as a new foundation. There hasn't been research like it yet that employs EfficientNet for transfer learning concerning NPR.

Models from B0 to B7 are included in EfficientNet. Each model is represented by unique parameters ranging from 5.3M to 66M. The efficentNetB4 model is used by the proposed system, which has 19M parameters since it is appropriate for the NPR objectives and resources.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

*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 proposed model effectively recognizes the characters with different fonts. Moreover, it's essential to remember that while combining several fonts, a suitable balance must be achieved. Some of the models may get overfit and produce poor generalization ability and inaccurate detection if there are too many fonts. This overfitting is solved by using the EfficientNet model. Different fonts are used to train the model that matches the typical Number Plate fonts. This is done to guarantee that the model's input is consistent. The fonts are displayed in Figure 4 (a) and the extracted images for the character "P" are shown as an example in Figure 4 (b).

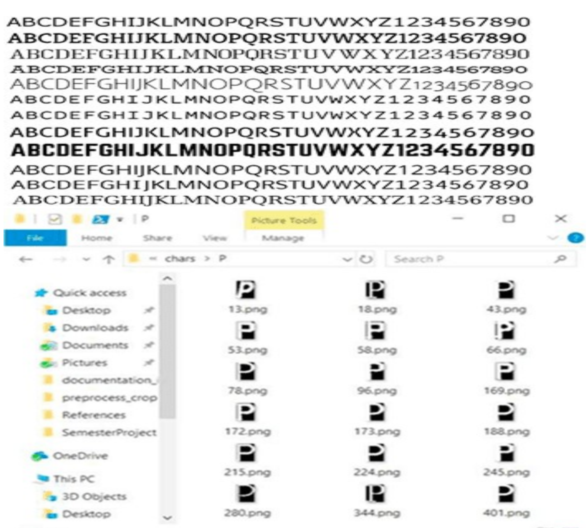



*Figure. 4. (A) Training Fonts; (B) Images That Were Extracted For The Letter "P"*

## 4. EXPERIMENTAL RESULTS

The experiment simulations are carried out on a Windows 10 computer and equipped with an i5 processor. The image processing tools are implemented using the Python OpenCV library. For simulation, the Kaggle images are used. Images have been used to test the system. All of the aforementioned scenarios, including plates with irregular illumination, plates that were angularly skewed, plates that were far away or close up, and stylized lettering plates were considered as test cases for the system. Testing involves taking images under various environmental conditions. As shown in Figure 5, the GUI is a platform to provide a user friendly interface and improve the sustainability of this system.

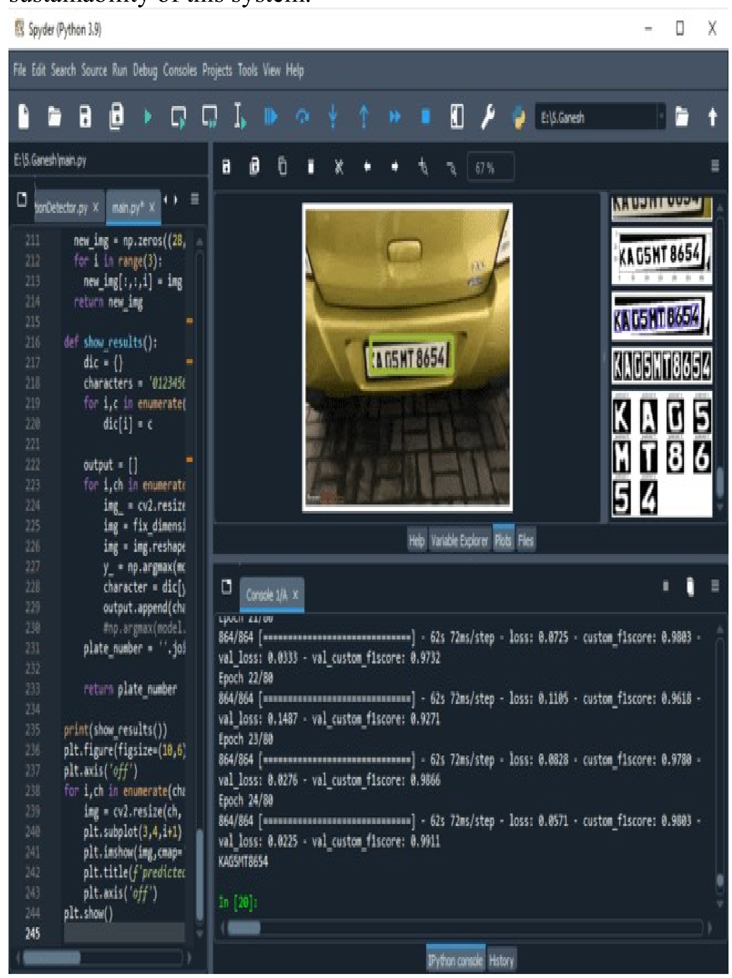



*Figure 5. NPR system GUI*

### 4.1. Image Preprocessing

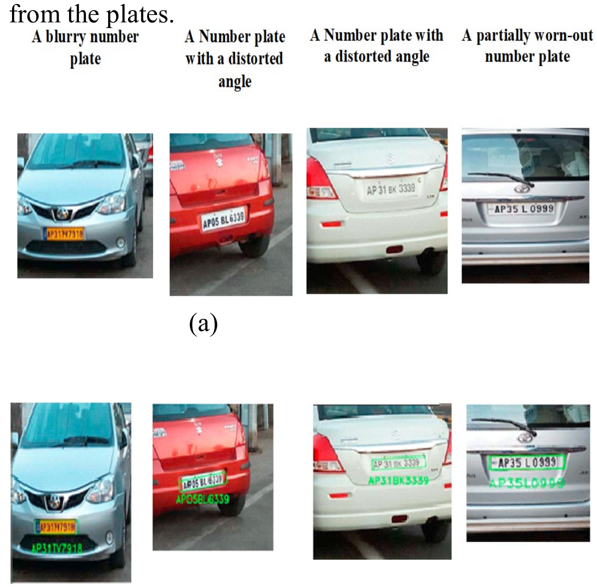
The final recognition accuracy is increased by applying three image preprocessing approaches initially. This section highlights the performance of the image preprocessing effect in addition to the speed and visual effect of these image processing techniques. The quality of the image is improved by three image preprocessing methods, as shown in Figure 6.


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

Dust and fog can be successfully removed from an image using defogging process through the dark channel prior algorithm. The image contrast and image visibility are increased effectively by using the CLAHE algorithm-based low-light enhancement technique. A better visual effect is achieved by the reconstructed image after super-resolution and also it gives significant information. In the process of weak light improvement and fog removal, the processing time is really short for a single image. While super-resolution, the processing time is considerably slow because of the complex network design. The results of the recognition reveal there were numerous instances in which the character was wrongly labeled as another character previously to image processing. The performance of recognition for the entire number plate achieves better results compared to the performance of recognition depending on individual characters because segmentation of the characters is inadequate in the situation of blurry images. However, after image processing, the majority of characters can be successfully detected, whether it depends on the complete recognition of the number plate or character.

### 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.




(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 Number Plate Recognition

Regarding character recognition, the model is trained by adding 67 different character types including region names, Hangul, and numbers. The basic momentum and learning rate in the process of training are set to 0.9 and 0.001, respectively. The model was optimized using the stochastic gradient descent (SGD) technique. The overall epoch was set at 15 and the batch size is 128. Figure. 8 shows the training and validation performance. The accuracy of training and validation is improved and reached its highest level of 99.1% at the 12th epoch. The loss of training and validation is progressively decreased and is close to zero at the end.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

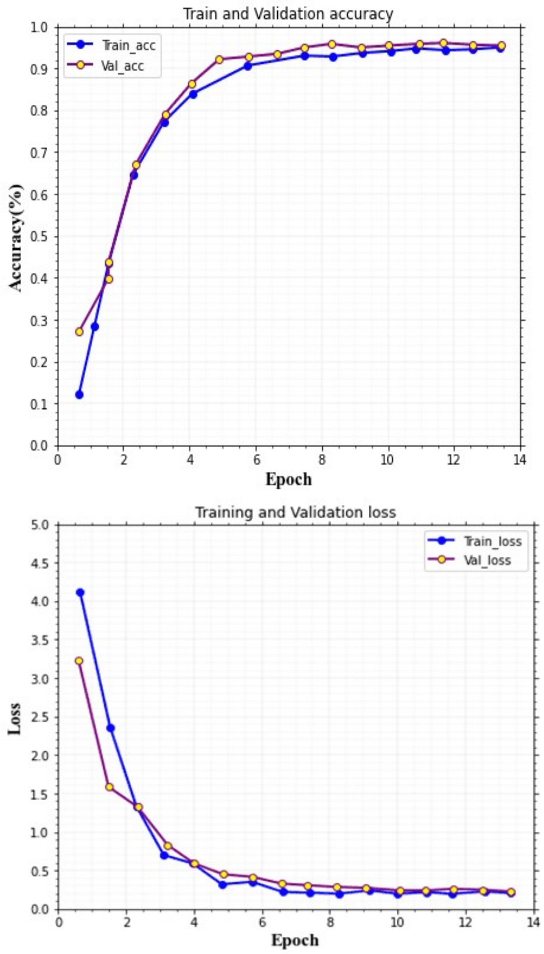



*Figure 8. The Performance Results Of The Character Recognition Module's Training And Validation (Accuracy And Loss).*

The 99.2% of the number plates are successfully detected by the system. And also 98.78% of the characters are effectively-recognized from plates. The proposed NPR system's performance is examined and compared with that of other state-of-the-art NPR systems in this section. The percentage of accurately predicted number plates over the entire test set is the accuracy of NPR. While comparing the result on YOLO, CNN, YOLOV3, and ResNet-10, the proposed EfficientNet achieves better recognition results as shown in Table 2. However, the ResNet-10 system performance is better than the performance of the YOLO detection method. This is thus because there are two processes involved in that system's number plate detection such as the detection of the vehicle and 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.

*Table 2. Performance Comparison Of Proposed And Existing Methods*

| **Methods** | **Component** | **Accuracy (%)** |
|---|---|---|
| YOLO | NPD | 97 |
| | NPR | 96.7 |
| CNN | NPD | 98.2 |
| | NPR | 97.8 |
| YOLOv3 | NPD | 98.6 |
| | NPR | 97.82 |
| ResNet-101 | NPD | 97.89 |
| | NPR | 97.6 |
| **Proposed (EfficientNet-B4)** | NPD | 99.2 |
| | NPR | 98.78 |

The NPD and NPR are effectively performed by the proposed EfficientNet-B4 method compared to recent existing techniques. In this research, the processing speed of 0.069s is attained by the proposed EfficientNet method based on the same dataset. The accuracy of the detection and recognition of the number plate is graphically compared with other models, as shown in Figure 9.

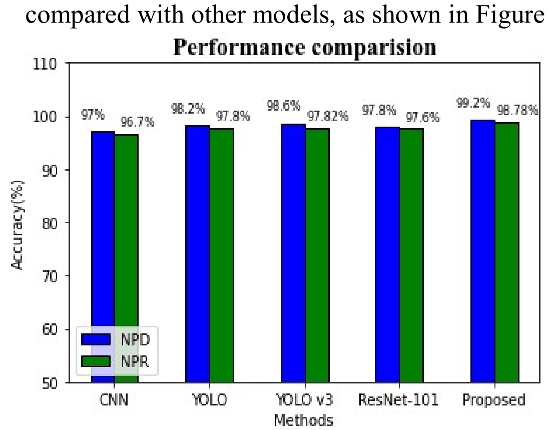



*Figure 9. Comparative Study On The Accuracy Of NPD And NPR For Different Existing Models*

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

## 5. CONCLUSION

Concerning Indian license plates or number plates, this paper discusses NPD and NPR. Consideration of difficult situations is one of this work's significant contributions such as partially worn out number plates, non-standard number plates, noisy images, skewed, blurred, and varying illumination. The input image quality is enhanced by using three methods in the image preprocessing phase. Next, by using border following, contours are applied for number plate segmentation. Then, the spatial localization and character dimensions are used to filter contours. Finally, the EfficientNet is used for character recognition after performing de-skewing and region of interest filtering. The proposed EfficientNet-B4 performs effectively with images for a huge amount of data. The overfitting problem is eliminated and the generalization ability of the image is increased by the proposed method. 99.2% of the number plates are effectively detected and over 98.78% of the characters are successfully recognized by the proposed method. The performance results of the proposed method achieve better detection and recognition accuracy when compared to the existing methods like YOLO, CNN, YOLOv3, and ResNet-101. This research intends to use a CNN that integrates detection and recognition into a single framework in future work

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