Character Level Segmentation and Recognition using CNN Followed Random Forest Classifier for NPR System

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***Abstract*—The number plate recognition system must be able to quickly and accurately identify the plate in both low and noisy lighting conditions, as well as within the specified time limit. This study proposes automated authentication, which would minimize security and individual workload while eliminating the requirement for human credential verification. The four processes that follow the acquisition of an image are pre-processing, number plate localization, character segmentation, and character identification. A human error during the affirmation and the enrolling process is a distinct possibility since this is a manual approach. Personnel at the selected location may find it difficult and time-consuming to register and compose information manually. Due to the printed edition design, it is impossible to communicate the information. Character segmentation breaks down the number plate region into individual characters, and character recognition detects the optical characters. Our approach was tested using genuine license plate images under various environmental circumstances and achieved overall recognition accuracy of 91.54% with a single license plate in an average duration of 2.63 seconds.**

Keywords—Character segmentation; convolutional neural networks; bilateral filter; character recognition; SVM classifier

I. Introduction

An automatic number plate recognition (ANPR) system identifies the vehicle's license plate without a person's involvement. Image acquisition and character retrieval are the two primary operations of ANPR systems. During this step, images of the vehicles are acquired. These approaches are used to process images of number plates and extract their characters. Surveillance cameras are often used in ANPR systems. Due to the fact that they are used for broad purposes, these cameras tend to capture larger-than-average images. The first step is to find the number plate area in the image and extract it. Afterward, the number plate's alphanumeric characters need to be deciphered from the backdrop. Then deep learning-based methods are used to identify the characters. The ANPR system comprises different phases as seen in Fig. 1: (1) image acquisition (2) number plate identification and extraction (3) character segmentation and (4) character recognition [1]. The first two phases identify and capture an image of the vehicle. Next, a number plate's possible locations in an image are identified. The identified area is used to isolate the characters in the third phase. Finally, the characters are identified in the last stage. This paper focuses on the character isolation phase. Therefore, this study does not include vehicle detection techniques. The contribution of this paper is to improve character recognition accuracy.

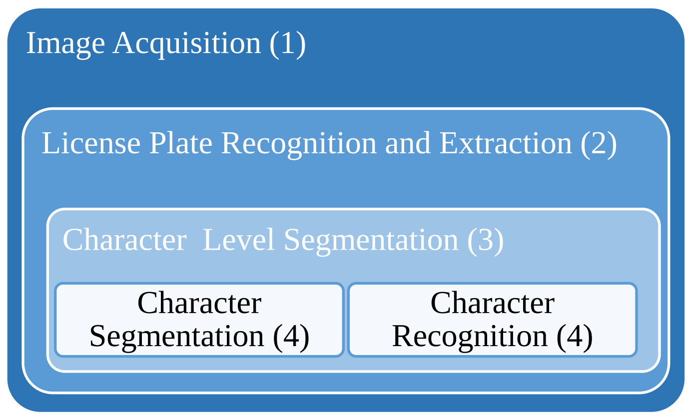

Fig. 1. Different Phases Involved in the ANPR System.

The paper is structured in the following manner. Section II gives an overview of the ANPR systems and techniques. Section III outlines the nature of the issue and the difficulties. The proposed methodology is narrated in Section IV. Section V details the results of the experiments and evaluations of the performance. Section VI concludes the paper.

II. Related Works

The convolutional neural network (CNN) has a state-of-the-art accuracy in HCR [2]. The performance of the recurrent neural network (RNN) is improved in [3]. In [4], presented a novel technique by combining the conventional RNN and deep CNN. HCR technology has been researched for a while and is used by the industry, but its poor accuracy hinders its usability and overall performance. The current character recognition systems aren't very reliable and require additional research to be used widely.

The YOLOv3 algorithm and background subtraction are suggested in [5] for the identification of vehicles and the localization of license plates. In [6], developed a system for optical character recognition to identify stolen vehicle license plates. CNN is used in [7] to develop an embedded system that can identify and recognize Brazilian license plates. Finally, the system uses a Tiny YOLOv3 architecture and a NN is trained on synthetic images and fine-tuned on actual license plate images to identify the license plate characters.

A. Character Segmentation

Using k-means clustering to discover linked pixel areas and combining appropriate pixels into components to efficiently extract each character, a method known as connected components labelling analysis (CCLA) was described in [8] for segmenting license plate (LP) characters. In [9], created a unique sharpness-based methodology for segmenting the characters in LP images. In the segmentation procedure, the model faced a gradient vector and a lack of accuracy. In [10] used a successful model for LP detection on a variety of lighting systems. Binarization and the superpixel paradigm were used in conjunction with this model to segment the characters in LP. LP recognition is expected to be implemented using edge detection and CNN [11] [12].

Prediction and identification of LP vehicles based on character features were utilized by [13] [14]. Segmenting characters from LP areas was initially the model's first step toward refinement. There were both vertical and horizontal projection elements in the approach for character segmentation. For images with challenging backgrounds, the features given may not work. In [15] developed a technique for character segmentation using a binarized input image without character shapes or presence among the characters improves the performance quite a little. It is thus exceedingly difficult to use a binarization model that distinguishes foreground and background data in images consisting of complicated backgrounds. Finally, it was discovered that a greater variety of ways had been explored in an effort to address the problems caused by the reduced light impacts on the environment. However, it does not include issues such as blur, touch, and challenging backdrops.

B. Character Recognition

Riesz fractional-centric detection and identification of LPs was proposed in [16]. This method is used to explain why LPs are difficult to find and identify. An enhancement in LP images may lead to an increase in recognition outcomes, which is not ideal for real-time environments, according to the experimental results. For low-quality images, [17] used an ensemble of Adaboost cascades for LP recognition. Classification models for LP analysis from images impacted by different variables are used in this model to identify that the texture assigned relies on the LBP job completed by the user. Consequently, this technique's primary job is to learn from and count examples of simulated situations. Text prediction has also been constrained in terms of value, although the established technique still allows for recognition. Due to the fact that the detection procedure does not acquire whole character forms, text detection is simpler than text recognition. In recent years, there is more development of numerous DL techniques for the identification of low-level features, such as LPs. In [18], suggesting a CNN-based approach to LP identification. LP analysis has been performed by using R-CNN. In [19], developed a deep localization and error detection technique for LP detection. In [20], used kernel-based Extreme Learning Machines (ELM) with significant attributes to develop Chinese vehicle LP identification. Once this was established for LP identification, the researchers looked at how CNN and ELM might be combined to improve performance. Deep learning (DL) modules that function effectively in the presence of a large number of predefined samples were found to have these characteristics. However, images impacted by a number of negative circumstances make it difficult to identify a predetermined instance that demonstrates plausible distinctions from LP recognition. Additionally, the DL approach is hampered by inadequacies like as parameter optimization for various databases and the ability to retain the dependability of DNN in the face of these issues [21]. The established criteria show that there is a discrepancy between the previous models and the more current demands. This discovery prompted the development of a new method for LP identification that did not rely on classification models and counted more labelled samples than the prior techniques. Based on the genetic algorithm and an improved neutrosophic set (NS), a new LP recognition model has been developed in [22].

III. Challenges in ANPR

A. A Lack of Standardized Number Plates

Various nations and areas within the same country have different number plates [23]. Number plates are not standardized. Several factors, such as plate sizes, plate backdrops, character sizes, and plate textures, all contribute to the variety of number plate forms [24]. Intelligent algorithms [25] are necessary for improved number plate recognition. It has been suggested that a number of strategies may be used to enhance the system. As a result, this study is a difficult one that is limited to a small area.

B. Erroneous Character Interpretations

The characters such as "O - 0, I - 1, B - 8, C - G, A - 4, D - 0, D - O, G - 6, and 2 –Z" are close enough that character recognizers may get them mixed up. All of these flaws should be addressed by character recognition algorithms [1, 10, 20]. In spite of the increased emphasis given to character recognition in ANPR systems, the ambiguous character problem remains a major issue. Furthermore, the issue of ambiguous characters has not been examined in depth.

In addition, segmenting the characters, which is the third stage in the ANPR process, is one of the most difficult. There are a variety of techniques used to categorize the characters of various license plates in the literature. Optical character recognition systems for letters and numbers may be employed separately to address the issue posed by ambiguous characters. This will improve the accuracy rate of the character identification phase since it will eliminate the ambiguous character issue.

In this paper, an image processing-based approach is described to address the issues outlined above. In the character recognition stage, we may employ various models specifically built for letters and numbers provided we accurately segregate the areas. The first step is to determine whether a character is a letter or number before we can do anything further. According to our knowledge, no research has looked at identifying the character's kind (letter, number).

IV. Methodology

Fig. 2 gives the workflow of the proposed license plate recognition, which will be explored in more detail below. This method includes different phases. The four processes that follow the acquisition of an image are pre-processing, number plate extraction, character segmentation, and character identification. Character level segmentation is performed using CNN and character recognition is done by using a Random forest classifier. The proposed method would expedite registration and provide additional advantages such as vehicle security and traffic control.

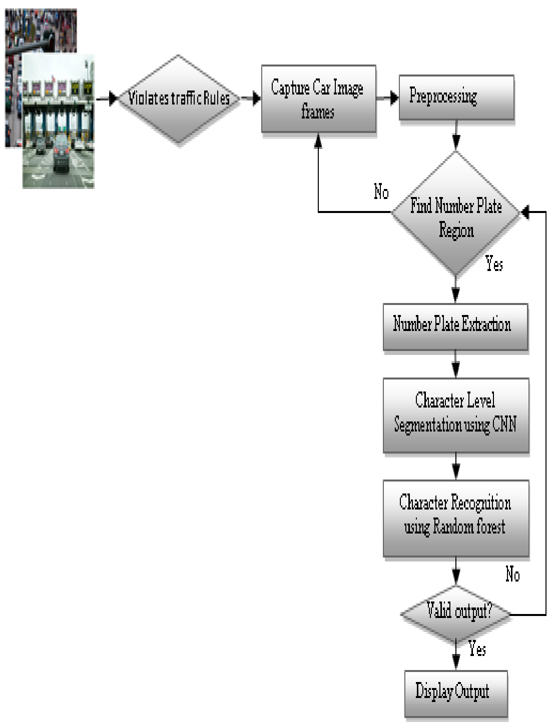

Fig. 2. Flow Diagram of the Proposed License Plate Recognition.

A. Pre-Processing

Input images face a myriad of issues, including interference, deformation, underexposure, and other. These effects may be minimized by doing image preprocessing on the input, which simplifies and speeds up the processing of images. In the pre-processing step, first, the input images are converted into grayscale images. The reason behind this is, standard number plates come in white and black, which are the only two colors available. As a result, it's not necessary to include all of the colors in the image.

1) Bilateral filtering: Noise reduction is made possible with the employment of a bilateral filter. To remove noise while maintaining the sharpness of characters, a kernel size of 3x3 is highly recommended. Filtering is the process of replacing each pixel value in an image with the average weighted sum of nearby pixels. The number of pixels in the weighted average is determined by the kernel size. Because larger kernels take longer to process and smaller kernels are useless at removing noise, a kernel size of three is the most efficient in this paper for decreasing noise.

2) Contrast enhancement: When the lighting is dim, boosting the contrast is a necessary step in number plate recognition. In order to better distinguish between the black text and the white background on the number plate, the contrast between the two colors must be increased. CLASH is used to increase contrast. Using this method, the image is broken up into smaller units known as tiles. Then histogram equalization is performed on each 8x8 tile separately. After contrast enhancement, the image can be converted into binary. When converting an image in to a binary image, the pixel values are reduced to two values [0 and 255].

3) Dilation of image: Dilating a number plate's characters makes them more prominent, which in turn makes their edges more prominent. When an object's area rises, so does the image's overall perimeter (edges). The number plate may be more precisely located if the character's borders are thicker, as edge-detection is used to do so. A number plate frame with no extra edges avoids the false edges from being picked up by the camera.

B. Localization of Number Plate

By recognizing the image's boundaries, edge detection can be utilized to determine the location of a number plate. The number plate region, which is actually the number plate characters themselves, has a lot of edges. This is because most of the number plates have black writing on a white background. As a result, the edges of the characters stand out against the background. Number plates tend to be densely packed with letters and numbers since it is where localized edges are found to be the most numerous. The number plate has the highest concentration of edges in the picture, despite the fact that the edges are visible across the image. Through the use of pre-processing, the contours of these objects become clearer. Because of this, the number plate is shown by a bounding rectangle. The picture is visited to count the number of edges it covers. The number plate is located in the portion of the image that has the most localized number of edges in the enclosing rectangle. Number plate locator software used an ingenious edge-detecting mechanism. Because it is more accurate, Canny edge-detection can pick up on both horizontal and vertical edges. When a car is in motion, the horizontally structured rear windshield usually sits immediately below the license plate just above it. Similarly, the bumper just under the license plate has a structure that is almost horizontal as well.

C. Character Segmentation using CNN_CL4 Network

The characters of the number plate are retrieved using a localized number plate as input. CNN has garnered a lot of attention as one of the most successful deep-learning models for picture segmentation. It's employed in a slew of new applications, including medical picture categorization, vehicle monitoring, self-driving vehicles, and face recognition, among others. Because of the self-optimization feature of artificial neurons, CNNs are able to learn just like brain neurons. Other algorithms cannot extract characteristics and segment images as accurately as it does because of this self-optimizing nature. The input data has to be processed minimally, yet it produces very accurate and exact outputs. HyperOn the basis of these qualities, CNN attempts to comprehend and distinguish between the images. Low-level information such as edges, gradient direction, or color may be captured by the first few layers of convolutional neural networks (CNNs). However, as the number of convolutional layers increases, it begins to extract characteristics at a higher level. Higher dimensions and convolution lead to exponentially increasing network parameters. As a result, CNN computations are slowed. This is because the number plate images have a lower pixel density than the images that are given to the input layers.

The CNN model for character-level segmentation is given in Fig. 3. Layers of the convolutional network are fed images from the input layer. Because it only contains four convolutional layers, the model is small and quick to run on a computer. Convolutional layer with 3 x 3 kernels and ReLU activation function in the first layer. 2D convolutional layer in the second layer. There are several deep learning algorithms that make heavy use of the ReLU activation function. In contrast to other activation functions, such as tanh, neurons are only partially stimulated when using ReLU. Except for zero, the continuous and differentiable function ReLU is a piecewise linear one. Additionally, it has a lower probability of a vanishing gradient than other methods because of its simplicity and empirical ease. Negative values can be simply returned as zero, which is shown in Fig. 4 by ReLU's basic concept of returning positive input values to output. A max-pooling layer and ReLU-activation function follow the first three 2D convolutional layers. To reduce the size of our input images, a sample-based discretization max-pooling is used. It helps to minimize the network's dimensionality by pooling the maximum value from each feature map patch. Over fitting may be avoided by removing non-essential factors and thereby reducing the overall number of parameters. To avoid overfitting the initial convolutional layer, a 2 x 2 max-pooling layer is added to all except the first layer. A 1D string is formed as a result of the fourth convolutional layer, which is then passed on to the final fully connected layer. The activation units in the next layer are linked to all neurons in the completely connected layer. The first layer's neurons are all linked to the activation unit of the second layer's neurons in a two-layer model. All inputs are then passed to the Soft max activation algorithm, which segments the characters on the number plate. Finally, the segmented characters are given to the SVM classifier to classify the numbers and the alphabet.

D. Character Recognition

The maximal margin classifier and random forest (RF) classifier have been utilized to categorize these segmented characters into respective digits and alphabets, and their performance has been evaluated.

1) Support Vector Machine: SVM is a maximal margin classifier. By constructing hyperplane, it categorizes the data. It works better for categorizing binary classes. It is also used for solving multiclass issues. Figure shows the maximum margin hyper plane of the support vector machine. There are two types of SVM classifications are there name one-vs-one (OvO) and one-vs-rest (OvR).

In this paper, a polynomial kernel of degree three is used. The magnitude of the allowable misclassification is determined by parameter ‘C.' Larger values of 'C' will choose a hyperplane with a narrower margin. Smaller values of 'C', on the other hand, compel the classifier to search for a bigger margin, even if the hyperplane misclassifies the points. In general, a high 'C' value is desired, although it may lead to over fitting [2]. The shape of the class dividing hyperplanes affected by the parameter γ. When γ is high, only points near the hyperplane are considered, while a lesser value of γ considers points far away from the hyperoverplane. In general, a low value of γ is preferable, since a higher number might result in overfitting. The low value of kernel width parameter is selected with greater value of optimal cost parameter. Table I lists all of the critical parameters [5].

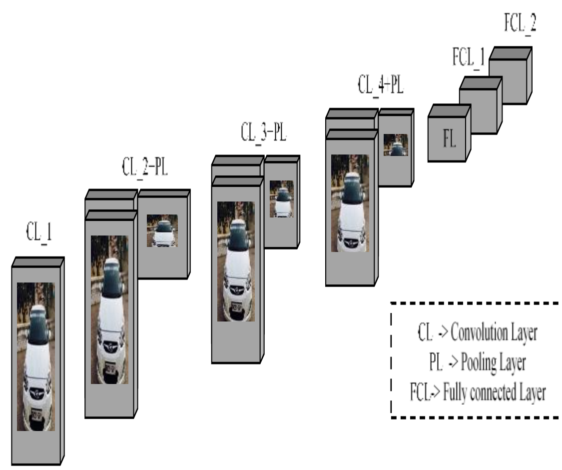

Fig. 3. CNN Model for Character Level Segmentation.

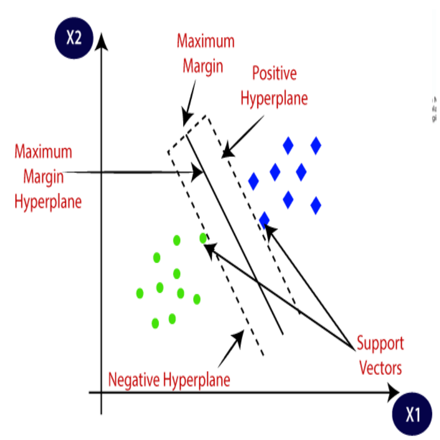

Fig. 4. Support Vector Machine.

TABLE I. PARAMETERS OF SUPPORT VECTOR MACHINE

Classifier	SVM
Approach Cost parameter (C) Kernel width parameter (γ) Degree of polynomial kernel	One-versus-all 1 Auto-deprecated 3

2) Random Forest (RF) Classifier: It is based on an ensemble of decision trees. Nodes make up a tree, and each node makes a decision based on a parameter. It has been trained using a bagging technique. Random forest employs a slightly different method to bagging, in which a subset of characteristics is chosen for node split, while bagging utilizes all features. As a consequence, an RF is a collection of trees that lowers the influence of noise in a single tree. As a consequence, bagging improves the overall outcome. Two key parameters must be set: Two variables are the number of features in each split (F_s) and the number of decision trees in the forest (N_t). Although the big value of parameter N_t is maybe superfluous, it has no negative impact on the model. It will almost certainly improve the accuracy of the forecasts, but it may slow down the model. The number of features to take into account while dividing a node is specified by the parameter F_s. It is always a subset of the whole amount of characteristics. The value for N_t was set to 100, and the value for F_s is set to the square root of the model's number of features.

V. RESULTS AND DISCUSSIONS

The characters from the number plate are extracted using character segmentation, which is subsequently used to train different classification models. All segmented characters for training have been reduced to 20 x 20 pixels. SVM and Random Forest classifiers are used in this study. The performance is also compared with other existing methodologies such as KNN, and Neural networks. The simulation results are given in Fig. 5. Initially, the number plate region is extracted from the car, and the extracted region is given in Fig. 5(a). Then the images are given to preprocessing stage where the input images are preprocessed, enhanced and finally converted to a binary image and it is shown in Fig. 5(b). The bounding box for character segmentation is given in Fig. 5(c). Finally, the recognized number plate is given in Fig. 5(d).The comparative analysis on the recognition accuracy of different methods are tabulated in Table II. The performance of four different classifiers such as Random Forest Classifier, SVM Classifier, KNN and Neural network has been analyzed. From the analysis, we can clearly say that, the random forest classifier gives better recognition accuracy of 91.54% whereas, the lowest recognition accuracy is given by the neural network classifier.

A. Comparative Analysis

The graphical representation on the comparative analysis of different classification methods are given in Fig. 6. The graphical analysis shows that the random forest classifier performs well when compared to other techniques.

(a) (b) (c) (d)

Fig. 5. (a) Original Image (b) Binary Image (c) Boundary Box for Character Segmentation (d) Recognized Number Plate Value.

TABLE II. COMPARATIVE ANALYSIS

Classifier	Recognition Accuracy
Random Forest Classifier	91.54
SVM Classifier	89.47
Neural Network	86.82
KNN	82.19

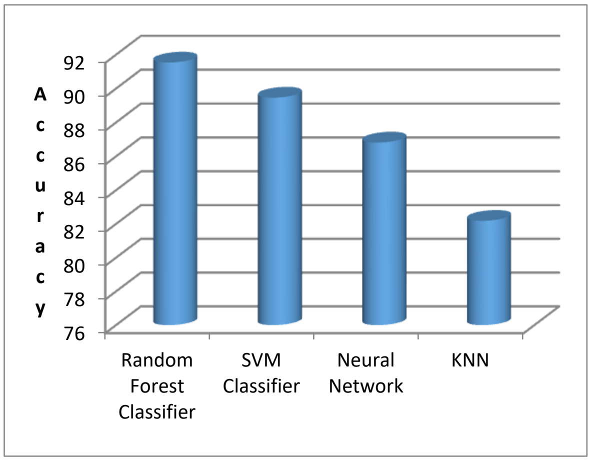

Fig. 6. The Graphical Representation of Comparative Analysis of Different Methods.

For a variety of reasons, RF outperforms SVM in this scenario. SVM is a binary classifier, but random forests are inherently multiclass classifiers. It is necessary to convert the multiclass issue to a multiple binary class problem for SVM to operate. Despite this, random forest beats SVM since it is a multiclass classifier. The second problem is that pictures, no matter how much preprocessing is done, will always be noisy. In this instance, the noise-resistant classifier is expected to perform better. There is evidence to support this notion since RF outperforms SVM. Consensus results from several trees are used to form RF's overall classification. As a consequence, even if some trees are trained using noisy input, the end outcome should still be as predicted. While SVM is notoriously slow to train, using RF you can train several models at the same time, which is something you can only accomplish with SVM. Neuronal networks can handle noise, thus they are accurate. There is no substitute for a random forest, which is an ensemble of decision trees based on a kind of bagging strategy, in terms of accuracy.

VI. CONCLUSION

The four stages: Preprocessing, number plate localization, character level segmentation, and character recognition are the processes discussed in this study. Converting the RGB image to grayscale, using the bilateral filter to reduce noise, improving the image's contrast, translating the image to a binary image, and finally distorting the image are all part of the preprocessing stage. Character segmentation begins by segmenting the characters from the number plate that have been accomplished using CNN after removing an unnecessary area of the number plate, The first step in character segmentation is to separate the characters from the number plate, which is done using CNN. Individual characters are recognized using character recognition utilizing random forest classifier and support vector classifier. The proposed method achieved an overall recognition accuracy of 91.54% with a single license plate in an average duration of 2.63 seconds. This method is also compared to state-of-the-art methods, demonstrating that the suggested method outperforms other existing methods.

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