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Car Number Plate Recognition Scheme Using Morphology and Backpropagation Neural Network

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ABSTRACT

Car Number Plate Recognition (CNPR) is a term for automatic recognition of vehicle license plates. It is compatible with future projected transportation systems and has acquired considerable notice for its broad implementation domain in traffic departments, law execution, and security systems. The main target of CNPR systems is to extract characters from vehicle license plate images precisely. However, the type of number plate, the font style, color, and font size of the plate, as well as the location of the number plate and environmental elements like brightness, and weather, are key challenges to detecting and identifying license plates. This paper discusses a novel CNPR scheme evolution that combines a segmentation method using mathematical morphology with a backpropagation neural network scheme as an accurate recognition solution to overcome these limitations. Furthermore, this paper contributes to segmenting the car number plate stage by using a 2D entropy function for the binarization image of the pre-processing method, which is proposed for their role in improving the overall performance of the CNPR scheme, in addition to image resizing and noise reduction. In addition, the effect of dataset size on the training and testing phases of the CNPR scheme is discussed. The proposed scheme displays the best accuracy score of 97.5% when utilising the entire dataset and 98.8% when using only half of the dataset.

1. INTRODUCTION

With CNPR technology, intelligent transport networks are already being developed without the need for human participation. There are additional security measures besides the roadside camera and parking lot barrier. CNPR has become a crucial methodology for traffic applications and security, such as vehicle surveillance, automated toll collection, road traffic monitoring, vehicular law enforcement, traffic volume calculation, vehicle activity analysis, tracking for safety, and criminal pursuits. This takes static or video images and extracts the exact number plate number of the vehicle [1]. When numerous approaches, like image processing, object identification, and pattern recognition, are integrated to satisfy this framework, it is known as automatic car plate recognition, vehicular number plate identification, and optical character recognition (OCR) for cars [1]. Modern CNPR cameras can read license plates in addition to providing other helpful data like counting, direction, groups of cars, and speed. The ability of CNPR technology to detect and interpret a huge number of moving cars has led to its incorporation into many facets of the current digital landscape. The main purpose of CNPR technology, which comes in a variety of packages, is to give a very precise system for reading a vehicle without human interaction [2].

Chen and Zong [3] summarized the process of number plate recognition steps as follows:

- The use of a camera to capture images of license plates from the intended scene. Several image processing-based recognition algorithms are used to further process either still images or photographic videos so that they can be converted into text entries using alphanumeric characters.
- Number plate extraction.
- Character segmentation and.
- Character recognition.

The number plate formats typically change from one country to the next, including distinct colors, languages, and fonts. Some license plates may have borders that are a

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different color from the background around them, while others may only have a single-color background, which can make it more difficult to find and identify the car plate. The rate of license plate identification will vary depending on ambient factors like illumination and image background type of license plate, color, and the font of the plate, location of the number plate that make it more challenging to detect and identify license plates [2]. Related works used static feature extraction, leading to less robustness [3]. As a result, this paper contributes to closing these gaps by presenting a novel strategy that overcomes the drawbacks listed above by providing enough decrease and enhancement execution improvement and working with car number plate recognition. On the other hand, this paper contributes to segmenting the car number plate stage by using a 2D entropy function for the binarization image and the maximum entropy as an adaptive threshold and deploying a backpropagation neural network for the recognition step [4].

In contrast, other researchers included CNPR methodologies in their studies. A review [5] states various methods for detecting objects in videos and images. like extraction and identification. There is further pre-processing. Edge detection suggests a feature extraction method that only keeps the most important characteristics. The PASCAL VOC 2007 dataset, which contains images from almost 20 different image classifications, is taken into account.

In research published by Yi and Chen [6], the conventional neural network (CNN) model was compared to RCNN and Faster RCNN. The number of bounding boxes created by RCNN is close to 1800–1900, which is quite high when compared to the CNN model, which only generates about 100 bounding boxes, demonstrating the authors' efficiency. The Region Proposal Network (RPN), a fully convolutional network, forecasts object limits and objectiveness scores at each place.

The authors of [7] also proposed a Faster R-CNN as a detector and applied cross-entropy loss to concentrate learning on challenging examples. This work used the COCO dataset.

The output space of bounding boxes is condensed into a collection of default boxes with various aspect ratios and scales for each feature map position in the research described by Liu et al.[8] that used a single shot multi-box detector (SSD)is simple to implement into a detection system and train. With a smaller input image, SSD demonstrates improved precision.

While in the study by Tekleyohannes et al. [9], object detection employed morphological techniques. Erosion and dilation are the fundamental processes. The structural component that makes these operations possible.

Additionally, the morphological operations were suggested by Charouh et al. [10] as a technique for modifying these morphological characteristics in real-time. The first-order, second-order, third-order, and fourth-order statistical properties of grayscale images are used to train machine learning models like K-Nearest Neighbors, Naive Bayes, and Artificial Neural Networks (ANN).

According to their processing speed, recall, precision, and map, Babayan et al. [11] compare how three artificial neural network architectures (YOLO, SSD, and R-CNN) perform in machine learning algorithms. A total of 6700 images have been marked up as objects for the system's training.

On the other hand, Alexander et al. [12] offer a sophisticated computer vision model to address the issue of identifying motorcyclists who disobey the law's requirements for wearing helmets. To address the abovementioned issue, it comprises a model that uses CNNs, image processing, and classifiers like local binary pattern (LBP).

Conversely, other studies have integrated CNPR into a mobile-based platform. Mutholib et al. [13] is one example. Whereby the device took a picture of a license plate. The number plate typically needs to be detected under a variety of circumstances, such as a variable background, illumination, and light condition, thus this approach is not appropriate for the real-world situation.

In the work described by Do et al. [14], the morphologically based technique was applied to the detection of license plates. Because the morphologically based method uses a less complex algorithm than previous ways, it is significantly more effective. It speeds up processing, according to the authors, making it perfect for mobile applications.

Furthermore, in work introduced by Shobayo et al. [15] smart plate number recognition system for speedy cars with web application traffic has been developed. A minimum amount of time was established during testing for the sensor to identify the object, and the microprocessor recorded this time. When the timer ran out, the camera was activated to record the plate number and store the image. The numbers on the acquired image are extracted by image processing. Through an IP address, the numbers on the captured image were viewed on a web page.

The remainder of the article is described as follows, Section 2 introduces the research method. The proposed CNPR scheme is explained in Section 3. Section 4 introduces the validation proposed CNPR scheme, and Section 5 provides the study conclusion.

2. MATERIALS AND METHODS

2.1 Pre-processing

The image had to be pre-processed to reduce noise without lowering the necessary data. Here are a few pre-processing actions, as follows.

2.1.1 Conversion into Grayscale

Each RGB (Red, Green, and Blue) pixel that is transformed to a single channel value during the grayscale conversion loses value. Numerous scholars suggested these processes [16]. To speed up processing, the size of the image was reduced as part of this conversion.

2.1.2 Grayscale to Binary Image Conversion

Some academics advise utilising the Thresholding approach to transform grayscale images into binary images. Thresholding was used to distinguish objects from their background. Thresholding is a simple and efficient method for segmenting images. Thresholding is a widely used approach in a variety of image processing tasks, including pattern identification and classification, due to its simplicity and convenience of usage. One of the main techniques for image thresholding is the entropy function method [16]. One of the most extensively used methods for image thresholding is the entropy-based approach [4]. Due to its strong theoretical foundation in physics and influential performance in practice, it is widely used in theoretical research and applications. The histogram of an image can be used to roughly calculate the entropy or average information of the image. The histogram displays the various probabilities for each gray level in the image [4].

2.1.3 Resizing the Image.

The goal was to reduce the size of the image to hasten the calculating process. Most researchers used this procedure [17].

2.2 Segmentation

The goal of character segmentation is to separate and filter the detected characters on the number plate. To determine the letters and numerals listed on the number plate, the characters that have been separated and filtered are then identified [18]. The morphological segmentation technique, among the several that have been put forth for image segmentation, is seen as promising because it depends on MM operations that are particularly alluring for handling object-oriented criteria like size and form [19].

A morphological operation compares each output pixel to its neighbours in the input image to determine its value. By choosing the neighborhood's dimensions and form, a morphological process that is responsive to specific shapes in the input image can be constructed. The morphological operation's goal is to extract structural information (such as size and shape) [20]. The two most fundamental morphological processes are dilation and erosion. In an image, erosion is the process of removing pixels from object borders, whereas dilation is the addition of pixels to those limits. How many pixels are added to or deleted from the objects in the image depends on the size and shape of the structuring element used to process the image [21]. To find potential character candidates, every contour area will be scanned. To determine if a candidate is a character or not, each candidate will be examined. A plate can have three to nine characters. According to the camera's distance, each researcher has a distinct size, indicating that the candidate for the character has a size of 21x15 pixels. Another researcher proposed a length-to-width ratio of 1 and had an outside area of 600–8000 pixels if the location of a contour is large. In contrast, any outlines that don't fit the bill won't be considered [17].

2.3 Recognition

Recognizing the segmented characters is the last step in car number plate systems. The magnification and camera-sensor distance may cause the segmented characters to vary in size and thickness. In addition, noise may break, skew, or affect the characters [19] neural networks one of most methods used to recognize steps in various applications [22]. The backpropagation neural network (BPNN) algorithm is one of the most popular recognition algorithms. BPNN is a supervised learning technique used to reduce output error. The BPNN sets up the essence of the CNPR scheme to be composed of: the input layer, one or more hidden layers, and the output layer Each layer has several neurons, as shown in Figure1. The training phase consists of the forward propagation of the input directly into the output and compares the result with the target value using one of a loss functions. by adjusting parameters such as learning rate, number of neurons, and number of epochs, the output will have high accuracy. Data is provided in the input section, and during the process, the weight value is provided by using output error to minimize the error's value and achieve the desired output target. Many researchers utilise the BPNN approach [19, 17, 23].

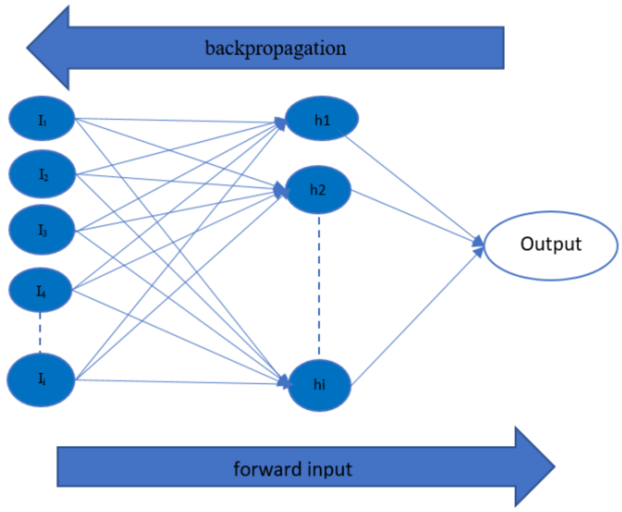

Fig. 1. BPNN structure

3. PROPOSED CNPR SCHEME

Pre-processing, binarization, segmentation, recognition, and evaluation are the five primary processes that make up the proposed CNPR scheme algorithm.

Input: Capture the image from the dataset

Step 1: Apply pre-processing on the captured image
- resize the captured image
- convert to gray level
- apply a median filter

Step 2: Apply the binarization (thresholding) method
- calculate the 2D- histogram
- determine the max-entropy
- convert to binary

Step 3: Apply segmentation and extraction number plate
- apply the morphological dilation method
- segment characters and numbers

Step 4: Recognize the characters and numbers of the plate
- apply back-propagation neural network
- save the result into a text file

Step 5: Evaluation of the scheme by using a confusion matrix

The proposed CNPR scheme is shown in Figure 2. The proposed CNPR is described in depth in the following subsections.

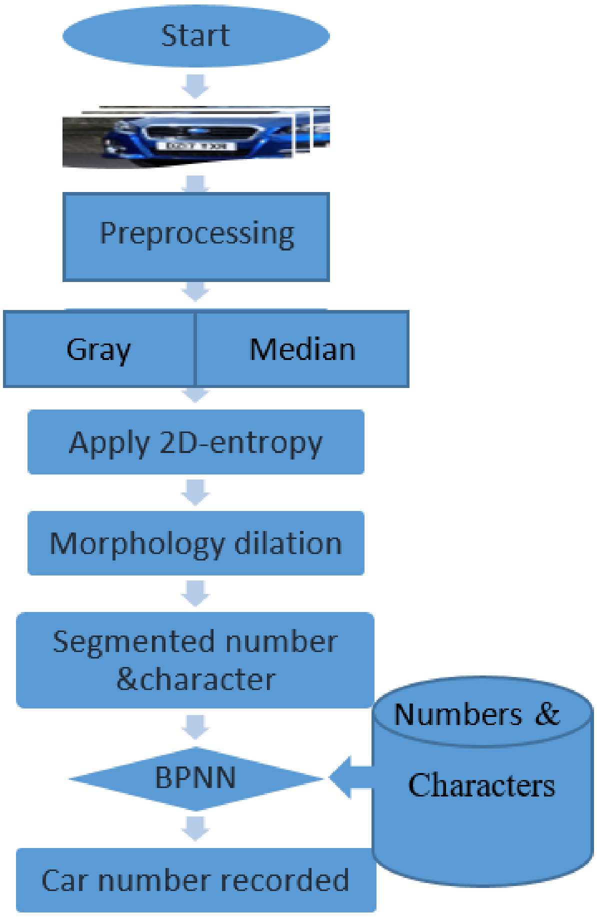

Fig. 2. Proposed CNPR Scheme

3.1 Car Number Plate Capture

A dataset of 433 photos with bounding box annotations of the vehicle license plates within the image may be found in a public dataset [24]. The annotation format is PASCAL VOC. The images have a variety of sizes; the country is Sweden. Figure 3 displays a sample of the dataset.

Fig. 3. Samples of Car Plate Number

3.2 Car Number Plate Pre-Processing

Starting with CNPR preprocessing, all phases of image processing and analysis are conducted. The dataset's acquired image essentially serves as the basis for our research. Following the image capture, the following steps were taken: first, resize the images to a constant size. Since the sizes of the images in the dataset vary, reduce the image's size to about 150*150. Then, convert to gray level. Images can occasionally be unclear, even in grayscale, since unwanted areas can damage them or noise can be removed. Finally, the median filter removes noise while maintaining the edge details of the CNP image [4].

The following formula determines the median filter:

$$m(x \times y) = med(f(x \times y)) \quad (1)$$

Where $f(x \times y)$ is the original image and $m(x \times y)$ is the image after the selected median filter. The proposed approach employs a 7×7 median filter. The 7×7 median filter is suggested because of how well it can eliminate noise while preserving the edge [4]. Pre-processing is summarized in Figure 4.

a. Resized image b. Gray image c. filtered image

Fig. 4. Pre-processing Steps

3.3. Car Number Plate Binarization

In this work, the gray CNP image's 2D histogram is produced after the noise is eliminated using a median filter by the previously mentioned techniques. In a grayscale image with 8 bits/pixel and a maximum value for intensity of 255. Gonzalez : [25] states that the formula for the histogram H (i) image is:

$$H(i) = N(i) \quad (2)$$

Where $N\ (i)$ is the number of pixels with intensity i, and $H\ (i)$ is the histogram of the gray level with intensity (i). Using Equation (2) yields a 2D histogram with a 255-element integer array. Once the histogram is known, the 2D histogram - entropy equation is computed as follows [26]:

$$(H) = -\sum_{i=0}^{l-1} pi\ log\ pi \quad (3)$$

where:p(i) $= \frac{n_i}{M \times N}$ is the probability in the histogram of gray levels: n_i a gray pixel level,1 $\geq\ pi \geq 0$

To determine which pixel has the most information, entropy Equation 3 is based on a 2D image histogram of CNP that is unique to each column and correlates to all pixels' information. Next, the image's adaptive threshold was set to the maximum entropy value. The threshold value will be compared to the total intensity of the histogram. If the intensity value is greater than the threshold value, the intensity will be 255; otherwise, it will be 0. The new binary image is constructed using the new histogram, which is in the range of 0 and 1. Binary images can be used to detect edges. An outside line can be computed using the edges. Figure 5 illustrates the binarisation step.

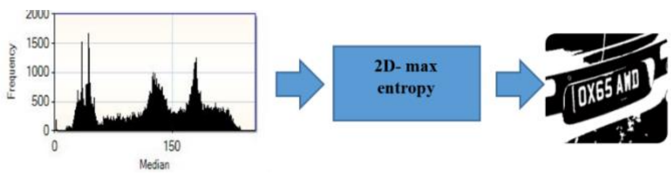

Fig. 5. Binarization Image Step

Once a binary CNP image has been obtained, it will be fed into the segmentation process.

3.4. Car Number Plate Segmentation

The dilation morphology is used to segment the plate number image. Applying the dilation process after receiving a binary image from the preceding phase, which was developed for binary images frequently makes use of a structuring element to probe and amplify the forms existing in an input image [27,28]. Due to the huge size of the images utilized in this research, the maximum matrix size for the structural element is 9 by 9. Dougherty [29] defines the dilatation A by B is as follows:

$$A \oplus B = \bigcup_{b \in B} A_b \tag{4}$$

Where A is translated into Ab by b.

To locate a large area on the image, the dilation method gradually enlarges the boundaries of the foreground pixel regions. The regions of the foreground pixels increase while the corresponding holes are minimized to impose the image's features. Figure 6 shows the effect of the dilation operation on the binary CNP picture.

Fig. 6. Effect of dilation on binary CNP images

3.5. Car Number Plate Recognition

A matching algorithm is required to complete the recognition step. The accurate BPNN algorithm was used in this work to enhance the recognition step. Binary images of numbers and characters that have been segmented are fed into neural network inputs. The final results will be saved into a text file. The BPNN structure consists of one input layer with one neuron, one hidden layer with six neurons and one output layer with one neuron which represent the target. BPNN performs matching between the characters and numbers that were collected during the segmentation stage and the characters and numbers template. The BPNN is created using the MATLAB program. The recognition procedure is depicted in Figure 7. Number of epochs needed are equal to 10 epochs.

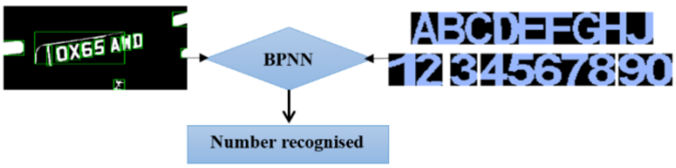

Fig.7 . CNPR Procedure

4. RESULTS AND DISCUSSION

The system has been constructed, which involves several tasks. The pre-processing procedure is used first, followed by binarization of the images. Employed the segmented approach next. The BPNN classifier is then used to recognize the segmented images. The accuracy rate and ROC curve measurements, which are based on the confusion matrix, are employed as the benchmark of evaluation in the recognition step to examine the performance of the suggested scheme. To implement the analysis, MATLAB programming is used.

Two experiments are run, the first utilising 215 images (half the dataset) and the second using all 433 images. Figure 8 and Table 1 illustrate how the accuracy rate of ratio recognition changes as the number of epochs increases. Figure 9 represent the ROC which demonstrates that performance increases along with the number of epochs. ROC curves obtained from the sensitivity and specificity resulting from fusion matrix calculation are shown in Table 2. Thus, the final implementation took into consideration 5 epochs. The best accuracy score is 97.5% when utilising the entire dataset and 98.8% when using only half of the dataset.

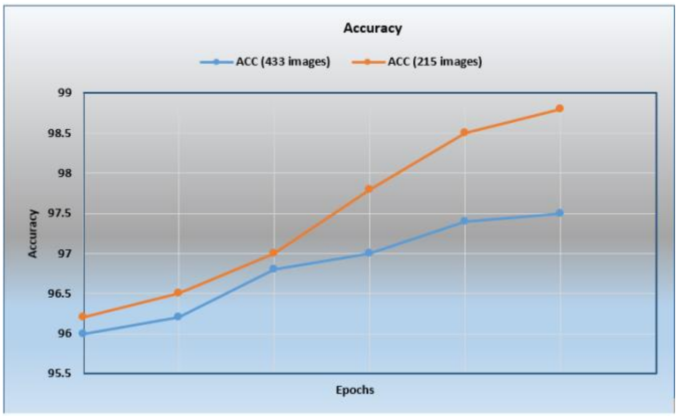

Fig. 8. Accuracy Rates of CNPR Scheme

Table 1. Accuracy Rate of CNPR

No. epochs	Accuracy (433)%	Accuracy (215)%
0	96	96.2
1	96.2	96.5
2	96.8	97
3	97	97.8
4	97.4	98.5
5	97.5	98.8

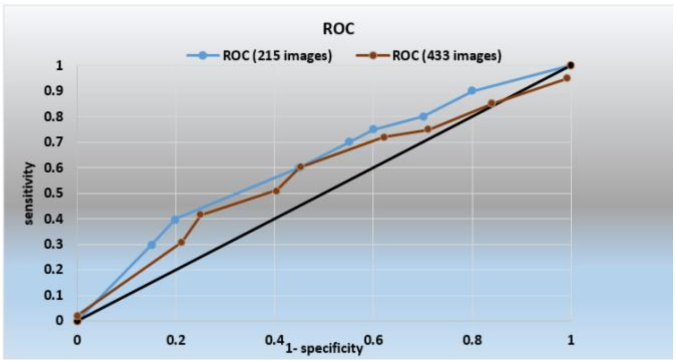

Fig. 9. ROC of CNPR Scheme

Table 2. Sensitivity and 1- specificity values

ROC (433 images)		ROC (215 images)	
Sensitivity	**1- Specificity**	**Sensitivity**	**1- Specificity**
0.020	0.001	0.305	0
0.310	0.212	0.412	0.150
0.415	0.250	0.620	0.220
0.512	0.405	0.712	0.451
0.602	0.451	0.750	0.550
0.720	0.621	0.813	0.614

0.750	0.711	0.912	0.705
0.851	0.840	0.990	0.804
0.950	0.991	0.995	0.991

Both figures (8 and 9) show that the suggested recognition method's performance evaluation findings are successful.

5. Conclusion

It might be difficult to identify car license plates from images. To overcome the abovementioned issues and challenges and increase accuracy, this work proposed a system that involves binarization based on 2D entropy and segmenting using a morphological dilation. On the other hand, BPNN for recognition is accurate and rapid since it only needs to be trained once and then used everywhere the software calls for it. The broader applications of CNPR are protection and monitoring, a citified arrangement such as jam flux analyses, general transport. This study demonstrates outstanding accuracy with 97.5% when utilising the entire dataset and 98.8% when using only half of the dataset. The future work will focus on using deep learning in the segmentation step.

Declaration Statement

We declare there are no ethical considerations in the dataset used.

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