International Journal of Engineering Research and Technology.
ISSN 0974-3154 Volume 11, Number 10 (2018), pp. 1499-1510

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Research on Application of Conjoint Neural Networks in Vehicle License Plate Recognition

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ABSTRACT

Annually, the number of vehicles in each country is constantly increasing, creating challenges in traffic management. Vehicle license plate recognition plays an important role in developing social conditions to prevent vehicle theft, traffic law violations, vehicle retention. The vehicle license plate identification system basically consists of processing steps such as: detecting the license plates, segmenting the characters and identifying each character to be separated. In particular, the character segment is the most challenging part of the task, the accuracy of the results depends very much on the accuracy of the license plate in the segment. The problem of different lighting conditions, the distance and the angle of the picture, the license plates are dirty or old will reduce the accuracy of the character segment. Thus, to increase the accuracy of the author using conjoint neural networks with learning and processing methods used in identification with accuracy up to 95.7%.

Keywords: Artificial intelligence, vehicle license plate recognition, traffic monitoring.

I. INTRODUCTION

Traffic is making an important contribution to the growth of the world economy. In Vietnam and many Asian countries, the number of cars and motorcycles has grown rapidly over the past decades and has become a popular means of transport. Vietnam is a developing country with a population of 98 million while the total number of vehicles is about 59 million, which poses a major challenge to traffic management, security, traffic, etc. Each vehicle has its own unique license plate, so if you can correctly identify the license plate, it will help in traffic management, security checks, traffic charges, gatekeepers and parking management. This not only helps managers have the ability to cover all of their media, but also saves considerable work time [1,2]. In addition, this method will reduce the number of employees to assign them to other jobs.

In identifying vehicle license plates, the most important issue is character recognition, to increase processing speed and accuracy in identification, artificial intelligence has many advantages compared to other methods. Artificial neural networks, by learning, recalling and generalizing from training data, have become one of the main research directions of the field of artificial intelligence. In terms of theory, artificial neural networks are relatively independent of the nature of the physical processes to be classified, predicted [3,4]. In each of the above problems, there are common features in artificial neural networks: sample data collection, data preprocessing, network parameterization and training. Therefore, research to generalize mathematical problems and develop artificial neural network software can be used for many of the same class problems [5,6].

Conjoint neural networks (CNN), like other artificial neural networks, can achieve efficiency by accelerating by implementing parallel architectures. Parallel deployment accelerates CNN simulations, allowing for the use of more complex architectures in real time. It also significantly speeds up the training process [7].

In Vietnam, Automated monitoring systems in general and vehicle identification systems in particular have not been paid attention and it is also a relatively new field. Most of the management and handling of means of transport need human resources. From the above reasons, the researcher has developed a vehicle license plate identification system for vehicles. The research goes into partition license plates, separating the characters, recognizing characters, capturing sequential license plates after being identified, saved to the database for easy management and tracking.

II. IMAGE PROCESSING TECHNIQUES

The image processing system is a system that performs image input acquisition functions, performs image processing or image analysis, identifies outputs that meet specific requirements and applications.

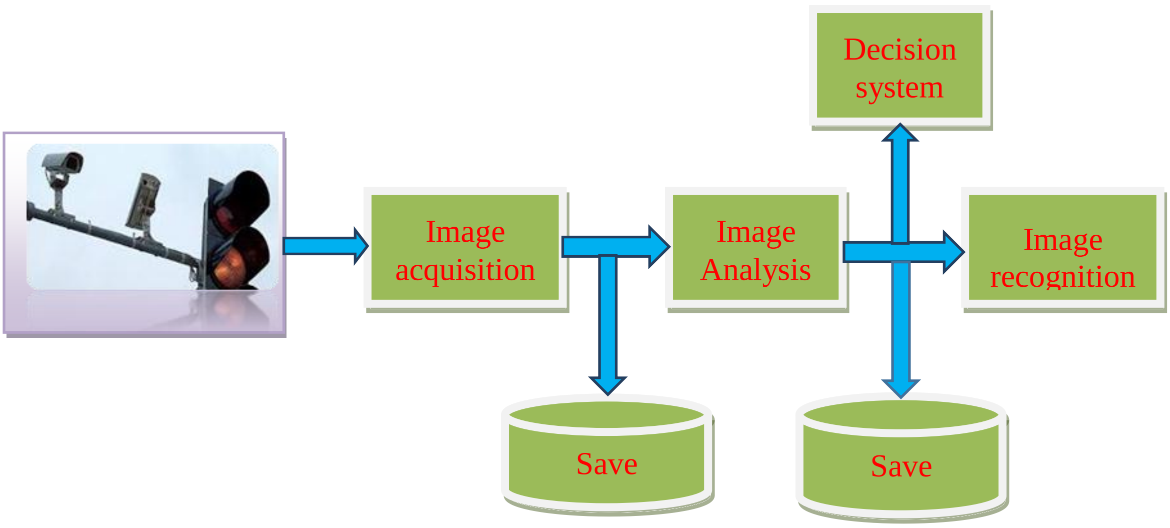


Fig. 1 General diagram of an image processing system

The general block diagram of this systems is shown in Figure 1. At first, the image was taken by a camera or digital camera and then connected to a PC. The images are in

RGB format and it is processed to exploit license plates. After that, you need to resize the image to keep the same aspect ratio.

- Image acquisition unit: perform image acquisition and digitization (stored in the required format).
- Image Analysis Unit: The system first performs image preprocessing with the purpose of enhancing, improving the quality of the image, highlighting the basic characteristics of the image, or making the image closest to its original state. Then, it is the process of analyzing the image and extracting the characteristic of the image such as the boundary, the folding point, the ending point, the cross point, etc.
- Block identification: based on the features acquired from the previous image analysis process to implement the identification process, making decisions for specific applications.

2. 1. Binary image

The original image used was a 256-level gray image. The use of 256-pixel images does not reduce the versatility of the application. Actually, 256 gray levels are still used, and many video recorders have the ability to manually convert color images into 256 gray levels. However, if a 256-level image is grayed out, the boundary detection is ineffective, since the constant change of gray levels makes it difficult to determine the boundary and finding the boundary continuum will be limited. So, we make a binary image conversion to make faster binding.

2.2. Noise reduction

Photo noise is caused by many factors including: time degradation, copying process. After being binary, the image will be filtered to reduce noise. Actually there are many types of noise, however, there are three main types of noise: noise, noise and pulse. They appear differently from the surrounding area. The nature of the noise is usually related to the high frequency and the theoretical basis of the filter is only for signals of some frequency through. With noise and noise, we use medium, low pass filters. With pulse noise, we use median pseudorange filter.

In average filtering, priority is given to directions to protect the boundary of the image from blurring when smoothing. Facial palms are used according to different circumstances. The above filter is a linear filter in the sense that the point in the center of the window is replaced by a combination of neighboring points tangent to the mask. Low pass filter is used to smooth the noise. Nonlinear filters are also used in image enhancement. In this technique a median filter, a mediocre filter, is used. With the pixel median filter to be replaced by the median of the image, the pseudorange filter, the pixels are replaced by the mean of the "median" values.

2.3. Photo discovery

Bound detection is part of image analysis, after image filtering (or image preprocessing). The steps of image analysis can be described in the Figure 2. Probe and image search is one of the characteristics of the selective block.

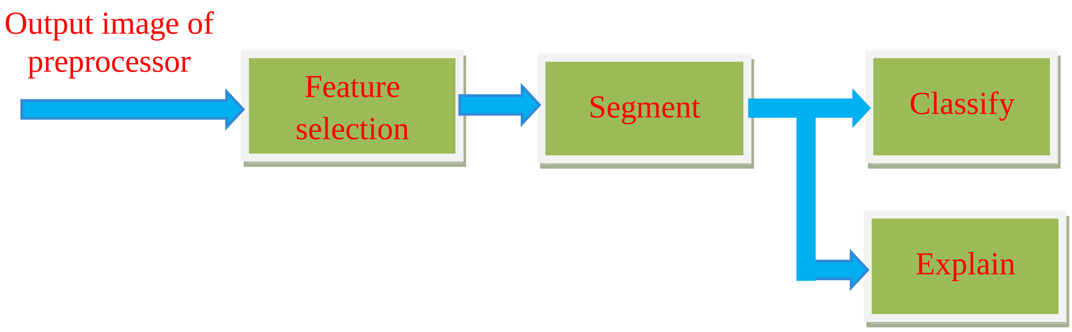


Fig. 2 Analysis and processing steps

Canny's picture ribbon splitter is based on a pair of top-level partial derivatives with noise cleaning. This item is reserved because this is a fairly common way of dividing the boundaries used by the derivatives. The method of the derivative is strongly influenced by noise. The method is highly effective when approximating the first derivative of Gauss.

$$\nabla f = \nabla(G \otimes I) = f_x + f_y$$

with f_x, f_y is the partial derivative of x and y of f.

so:

$$\nabla f = \nabla(G \otimes I)x + \nabla(G \otimes I)y = \nabla(G_x \otimes I) + \nabla(G_y \otimes I)$$

Taking the partial derivative of x and y of G results in:

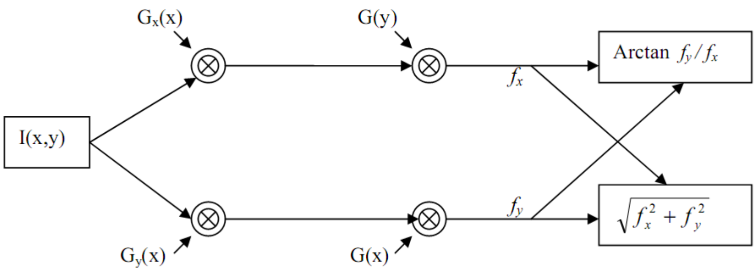


Fig. 3 Modeling of Canny method

Since the Gaussian filter is separable, it is possible to separately compute the convolutionals in x and y:

$$G_x(x,y) = G_x(x) \otimes G(y) \text{ và } G_y(x,y) = G_y(y) \otimes G(x)$$

From there we have:

$$f_x(x,y) = G_x(x) \otimes G(y) \otimes I \text{ và } f_y(x,y) = G_y(y) \otimes G(x) \otimes I$$

With the amplitude and direction calculated by the above formula, the algorithm is illustrated in Figure 3.

III. IDENTIFYING VEHICLE SEATS

At first, a plate license was taken. Now, this captured image is converted to a gray scale image. A gray scale conversion is performed to highlight the white area in the photo taken because the unwanted noise has to be removed by the average filter.

As noise is removed, the image intensities and background of the image become more apparent, whereby the method of balance and histogram contrast is applied in the license plate. The histogram balances were applied to observe the background white noise of the correct white background of the license plate number after the noise was removed. The contrast extension method applied on the image is detected to increase the background intensity of the white background pixel. The multi-level rounding system is applied to maintain equal space between the digits and the alphabet. Finally, the use of artificial intelligence on neural networks automatically detects images taken. Now for the training of neuronal neural networks, we have followed three steps: neural training, validation and testing.

3.1. Partition license plate

The system has the function of communicating with the camera through the supplied driver. The camera module automatically identifies the movement to take samples into the separation and identification plate system. Real-time processing system, fast processing and low system resources. Combined with some test cases to provide some ways to extract non-standard license plates. Or too much noise (glare, too bright).

The process is shown in Figure 4.

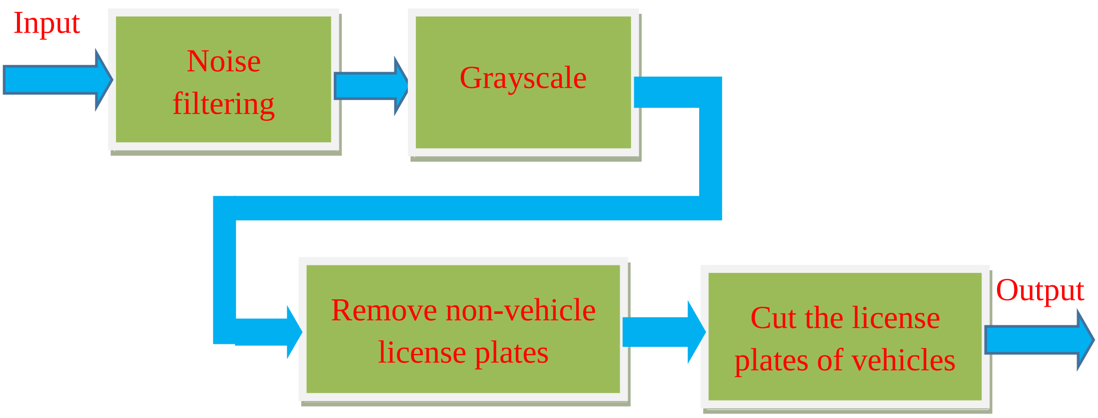


Fig. 4 Block diagram of the license plate partition module

3.2. Separation of license plates

After the license plates were standardized in size, we can rely on the morphological characteristics of each character, such as height, width, two-dimensional proportions, etc., to isolate characters from the license platespace.

The process is described in the following figure 5:

Fig. 5 Flowchart of the character separation process

3.3. Neural network convolution

Conjugated neural network (CNN) is the most common neural network used for image data. They are different from other neural networks: CNN is developed from the characteristics of the biological structure of the cerebral cortex, which combines simple and complex cells. These cells look for basic operations on the visual field. These areas are known as receptive fields. The neural network in a convolutional neural network connects directly to the area of the previous layer. The neural is unresponsive to regions outside the regions in the image. These regions can be stacked against each other, so that the neural of a CNN generates correlated spatial results, while in other neural networks, neurons do not share all connections and produce independent results. Each class after passing the trigger functions generates more abstract information for the next class. Each class after passing the trigger functions generates more abstract information for the next class. In the feedforward neural network, each neural input node for each neural output in the next layer. In the network, some neurons are connected to the external environment as outputs and inputs, as shown in Figure 6.

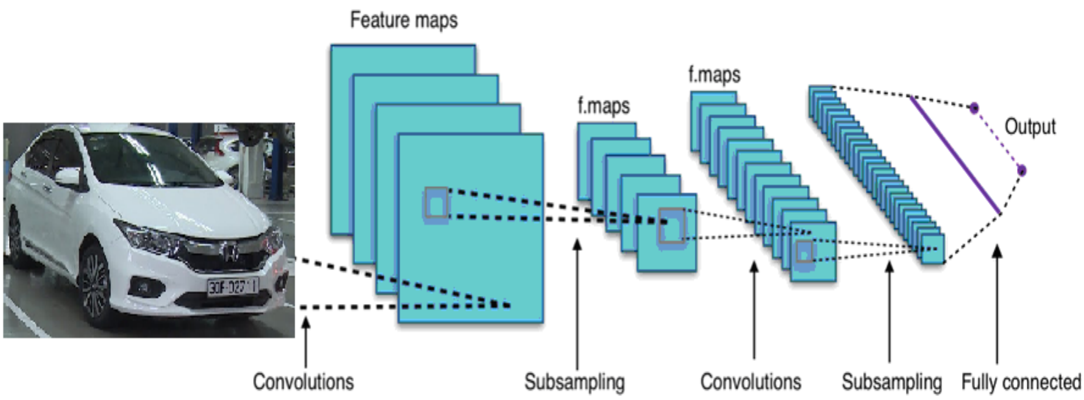


Fig. 6 Neural network diagram

Upon identification, a softmax layer and a valid classification layer follow the last fully connected class. To create these classes we use the softmaxLayer functions and the classificationLayer.

Output unit specified is softmax function:

$$y_r(x) = \frac{\exp(a_r(x))}{\sum_{j=1}^{k} \exp(a_j(x))}$$

Which: $0 \le y_r \le 1, \ \sum_{j=1}^{k} y_j = 1$

The softmax function is to activate the output unit after the last fully connected layer, which is used to classify the types in the classes studied:

$$P(C_r|x,\theta) = \frac{P(x,\theta|C_r).P(C_r)}{\sum_{j=1}^{k} P(x,\theta|C_j).P(C_j)} = \frac{\exp(a_r(x,\theta))}{\sum_{j=1}^{k} \exp(a_j(x,\theta))}$$

Which:

$$0 \le P(C_r|x,\theta) \le 1, \quad \sum_{j=1}^{k} P(C_j|x,\theta) = 1, \quad a_r = \ln(P(x,\theta|C_r).P(C_r))$$

$P(C_r|x,\theta)$ is the conditional probability of the sample for layer r

$P(C_r)$ is the conditional probability of layer r

The function softmax is known as the standard function and may be be determine the sigmoid logistic multi-class function.

The classification layer always follows the softmax layer. In a classification output class, trainNetwork retrieves values from the softmax function and assigns each input to one of the k classes in a reciprocal manner by using the entropy function for an encoding scheme.

$$E(\theta) = \sum_{i=1}^{n} \sum_{j=1}^{k} t_{ij} \ln y_j(x_i,\theta)$$

Which:

E(θ) is a crossentropy function

t_{ij} Indicates the ith form of the jth layer

θ is the parameter vector

$y_j(x_i,\theta)$ is the output of the i th sample. In this case, the value is derived from the softmax function. That is, it is the probability that the network associates the first input with layer j, $P(t_j = 1|x_i)$.

IV. RESULTS AND DISCUSSION

Research conducted on the database of 400 photographs, with image quality ranging from 640x480 to 1600x1200 pixels.

4.1. Gray level calculation

In the above step, the first horizontal chart is calculated. To find a horizontal chart we scan each column of the image. In each column, we scan in the order from the second row from top to bottom. Find the gray difference between the first and second pixels in the same column. If the difference exceeds a certain threshold (here it is 20), it will be added to the total value of the difference. The algorithm then moves down to calculate the difference between the third and the second pixel. So it moves until the end of a column and calculates the total amount of difference between neighboring pixels. Finally, an array containing the total column is generated, The result is shown in Figure 7. For the rows we calculate the same as above. To minimize the loss of important information after the above calculation, we smooth the chart. The result is shown in Figure 8.

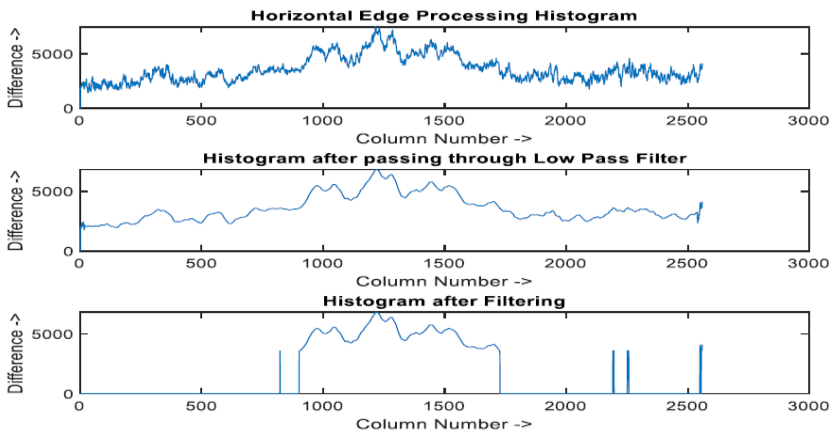


Fig. 7 Chart showing gray level difference in columns

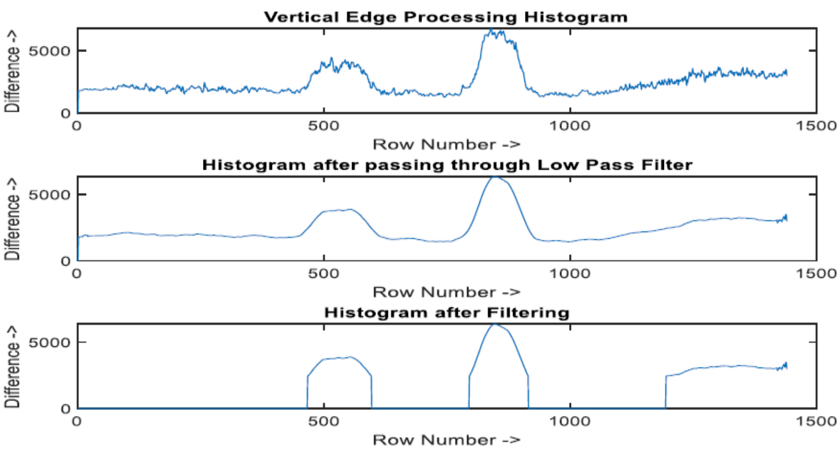


Fig. 8 Grayscale chart by row

Identify areas that may be license plates: We use a filter to delete unwanted areas from an image. In this case, undesirable regions are rows and columns with low histogram values (areas with a low gray difference value). The low graph value indicates that the image portion contains very few variations between neighboring pixels. Since an area with a license plate is an area that shares the same background and consists of alphanumeric characters in it, so the difference in adjacent pixels, especially at the edges of characters and license plates, will be very high. This leads to a high histogram value for such part of an image. An area with a high horizontal and vertical chart value will have a high rate of plate license. Therefore, areas with less value will be eliminated. Such areas are removed from an image by applying dynamic thresholds. In this algorithm, the dynamic range is equal to the mean of a graph. Both horizontal and vertical charts are transmitted through a dynamic range filter. The output of this process is a chart that shows high probability areas containing a license plate. The filtered graph is shown in Figure 9. After filtering out the license plate, we do the cutting license plate for convenience in the next step.

Fig. 9 Numbers obtained

4.2. Cut characters from vehicle license plates

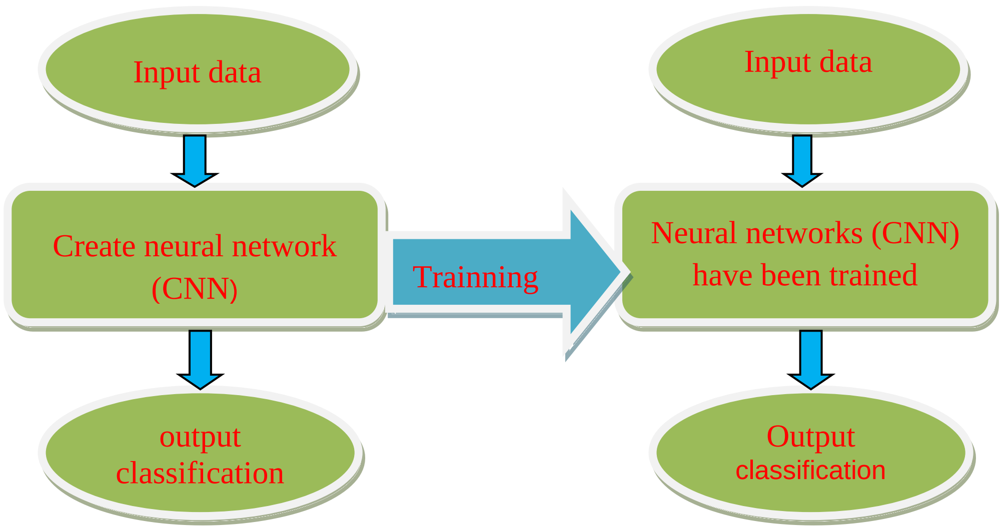
Character Stacking in vehicle license Identification consists of three basic steps: filtering input noise, removing non-character size areas, marking and trimming characters.

Character Cut: This step separates the characters (or samples) from the license plate. After separating the characters on the binary we compare it to the input image to cut out the character space, as shown in Figure 10.

Fig. 10 The letters in the vehicle license plate cut

Character recognition: The problem of character recognition on the vehicle license plate is a sorting problem. Similar to other classification problems, the problem here is the classification of alphanumeric characters in a car license plate. The method of operation of the problem consists of two basic steps:

- Create a neural network, and train it with the input data needed for character recognition.
- Use trained neural networks to predict the input character from the license plate for identification.



Data input: Using character images cut from the license plate by image processing to input data for training, as shown in Figure 11.

Fig. 11 Input data for neural networks

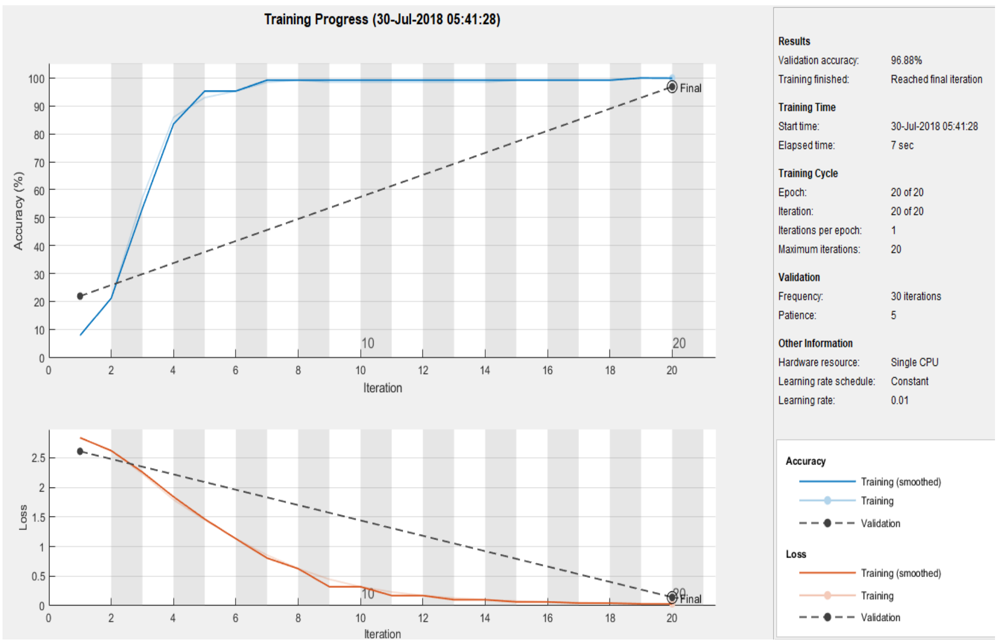


Fig. 12 Training with 20 epochs

In which: network training accuracy 96.88% of the input image, accuracy graph is the visibility of the training precision level, loss is the graph indicates the lack of training, as shown in Figure 12.

Predict the results after training, as shown in Figure 13.

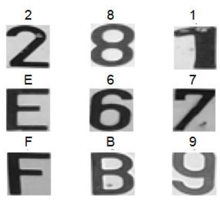


Fig. 13 Predict the input image and output the result

4.3. Statistics and Results of the Identification Module

After running the test, the vehicles license plate identification are shown in Figure 14 and Table1.

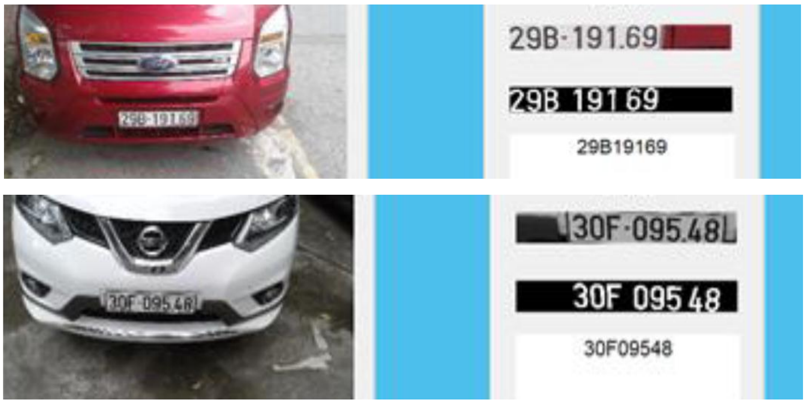


Fig. 14 Find the plate license of vehicles

Table 1. Statistical Character Identification Process Results

Number of photos	Quality	Accurate identification		Identification result of module	
170	Goog	163	95.9%	377/400	94.3%
130	Average	122	93,8%		
100	Poor	92	92%		

Thus, with the identity module, the recognition system achieved 94.3% with 400 input image characters, resulting in 375 images with accurate results, corresponding to 94.3%. When 140 manual pictures were included in the instructional part of the program, including 90 digital photos, 50 images were cut from standard license plates. Accurate identification results up to 95.7%.

Table 2. Statistical Results of Character Identification (Numbers - Letters)

Characters	Quantity	Accurate identification		Character recognition results	
		Quantity	%		
Number	90	86	95.6%	134/140	95.7%
Word	50	48	96.0%		

For images that are too loud, such as direct sunlight, or too dirty vehicle, the pre-processing stage is more likely to occur confusion in finding the license plate area, leading to the can not identify the license plate.

V. CONCLUSION

In this study, the author presents an efficient and convenient method for identifying license plates based on neural networks. Its performance is tested on 400 sample photo license plates extracted with different background, atmospheric conditions vary. The results showed that 95.7% of the images were correctly identified, indicating that the method of identifying plate licenses was highly accurate.

For some vehicle license plates that suffer from severe defects or poorly lit images, the results for identification are difficult and cause errors, which require research to improve performance. identification.

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