A Preliminary Study of Vehicle License Plate Detection and Identification

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Abstract. In this study, the authors would like to proposed vehicle license plate detection and identification using machine learning approaches. The goal of this study is to pave the way for more in-depth research on vehicle license plate detection and identification using machine learning approaches. A license plate is the vehicle's unique identity that serves as proof of the legitimacy of the vehicle's operation. It is typically in the form of a plate or other material with specific specifications issued by the police. This plate is installed on each vehicle and contains the area code, registration number, and validity period. This study begins with a review of several related publications, with a focus on license plate detection and identification for each method. The investigation is furthered by identifying and comprehending the benefits of each method. Finally, the authors attempt to propose a vehicle license plate detection and identification model based on the advantages of each method previously discussed. The proposed model is simulated using Python programming. The simple simulation results show a 99 percent accuracy rate. Based on the simulation results, it shown that the contribution of this study is that the Faster RCNN-based model is proven to be used for vehicle license plate detection and identification with a fair accuracy. This model, however, is still conceptual and needs to be improved. It will be fully tested and discussed in future work.

Keywords: Plate Detection, Number-plate Recognition, Faster R-CNN.

1 Introduction

The detection and identification of vehicle license plates are critical in smart transportation systems. It has a wide range of potential applications, from speed monitoring, traffic monitoring, parking management to security systems, so it has attracted a lot of attention in recent years. This is understandable because, as the number of vehicles increases, so does the number of crimes committed against vehicle owners, such as theft, or robbery. There are several studies with various methods related to vehicle license plates detection and identification. Most existing methods are only effective under specific conditions or with sophisticated image capture systems. In an uncontrolled environment, recognizing vehicle license plates accurately remains a difficult task. The tasks of plate detection and identification, on the other hand, are always

linked. The methods used in these two phases should complement one another. The detection accuracy can be used to improve identification accuracy, and the outcome can be used to eliminate errors in vehicle number plate identification.
As an input medium, the vehicle license plate detection mechanism can utilize closed circuit television cameras (CCTV) that are already installed along the highways. There are high-tech CCTV cameras with ultra HD systems with the best capture results. For component protection, this high-tech CCTV is protected by a special metal that is resistant to extreme weather, such as hot temperatures or corrosion due to rain. This can be the best solution, to get a clear vehicle license plate on the highway.
Through this short paper, the author would like to discuss several studies related to vehicle license plate detection and identification. The discussion focuses on license plate detection, character segmentation, and character recognition for each method. The study is furthered by identifying and comprehending the benefits of each method. Finally, the authors attempt to propose vehicle license plate detection and identification method based on the advantages of each method that are already discussed.

2 Related Works

In general, the topic of vehicle license plate detection and identification has been discussed for a long time and is still evolving. Kakani et al. [1] propose automatic number-plate recognition (ANPR) method based on optical character recognition (OCR) that improves performance with trained neural network features. Localization of license plates, character segmentation, and character recognition are the three layers of methods that have been implemented. 300 license plates from India and other countries were tested. The accuracy score for plate localization is 96.7 percent, and character recognition is 92.2 percent, according to the test results. The overall accuracy of plate detection is 94.45 percent. Furthermore, Nayak et al. [2] applied the ANPR methodology to make it easier to detect stolen vehicle number plates. The ANPR methodology is applied using edge finding and Window Filtering methods. The progress of this study shows that ANPR with the Edge Finding method and the Window Filtering method obtained quite good results.

Yogheedha et al. [3] also used the ANPR technique with the template matching method in their research. The results of this study show a 92 percent accuracy rate, with the ability to correctly detect 13 plates out of a total of 14 vehicle license plates tested. This ANPR method was proposed to support Universiti Malaysia Perlis' smart parking system. Sharma [4] investigated the performance of a vehicle number plate recognition system using an ANPR method based on template matching. Several layers of algorithms are used, including morphological operations, edge recognition, smoothing and filtering, plate localization, and character segmentation. According to Selmi et al. [5], a complicated hardware specification is required to obtain a high-quality plate image. Different treatments should be implemented for high-speed vehicles and vice versa. The author employs a variety of image pre-processing and convolution neural network approaches to divide images into two categories: vehicle plate and non-plate. In this study, the author used two datasets, Caltech and AOLP, each with 126 images and 2,049 vehicle license plates. According to the evaluation results, the approach proposed by the author achieves an accuracy score of 94.8 percent when tested using the Caltech dataset.

The output of a CCTV camera is typically in the form of videos (moving objects) or images. This video or image is fed into detection and identification algorithms. The following discussion will center on research into detection and identification methods. The object on the vehicle plate image is isolated into a square shape using the detection method. Color-based detection, texture-based detection, edge-based detection, and character-based detection are the four types of detection methods [6]-[8].

Color-based detection methods are based on the observation that the color of the license plate is typically different from the color of the background. Chang et al. [9] proposed a method for detecting Taiwan license plates in RGB images using the difference between the foreground and background. They created a color detector mechanism that detects the edges of red-white, black-white, and green-white objects. Another study looked at the pixels of object color to develop a plate detection method [10]. A strip search was used to isolate vehicle license plates using the color-geometric template. To detect inclined or deformed license plates, color-based detection methods can be used. However, in natural scene conditions, this method is very sensitive to various lighting effects and cannot distinguish other objects in the image that are similar in size and color to the license plates.

Texture-based detection methods attempted to detect license plates based on pixel intensity distributions in plate localizations. Giannoukos et al. [11] proposed a Sliding Concentric Window (SCW) technique for identifying license plates in images based on the texture of local irregularities. To increase detection speed, Operator Context Scanning (OCS) was used. Yu et al. [12] used a wavelet transform to extract the plate image's horizontal and vertical details. The projection data was then processed using Empirical Mode Decomposition (EMD) to locate the desired wave crest, which indicates the position of texture in a license plate image. Texture-based detection methods outperform color-based detection methods but have a higher computational complexity. Vehicle license plates are typically rectangular in shape with a specific aspect ratio, and they have a higher edge density than the rest of the image, so this edge shape is widely used to detect license plates. Yuan et al. [13] proposed a novel line density filter approach for connecting high edge density regions and removing low edge density regions in each row and column of a license plate image. Another study [14] developed an edge-based method for plate detection. Edge clustering was performed using Expectation-Maximization (EM), which extracts regions with a high density of edges and shapes similar to plates as candidate license plates. Edge-based detection methods are quick to compute, but there is a problem if the input is a complex image with many irregular edges.

A character-based detection method contains more detailed information than color, texture, or edge detection method. Initially, Li et al. [15] used the Maximally Stable Extreme Region (MSER) to extract candidate characters from license plate images. Continue with the Conditional Random Field (CRF) method to develop the relationship between license plate characters. Finally, license plates were located using the sum-product message sent over CRF. License plate detection was approached as a visual matching problem by Zhou et al. [7]. For each character, the Principal Visual Word (PVW) was used to obtain geometric properties such as orientation, characteristic scale, and relative position. This property is used to extract license plates. To detect localized character regions, Llorca et al. [16] combined the Maximally Stable Extreme Regions (MSER) and the Stroke Width Transform (SWT). Finally, the Hough transform was used to localize the regions with characters on license plates. Character-based detection methods are more relevant and can be improved further, most notably by implementing deep learning techniques.

Other studies on license plate identification usually broke down the characters in the plate first and then identify each selected character using Optical Character Recognition (OCR) methods. Maximally Stable Extreme Regions (MSER) was used for character segmentation by Hsu et al. [14]. For feature extraction, a Local Binary Pattern (LBP) was used. The authors then used Linear Discriminant Analysis (LDA) to classify the characters. In other research, Hou et al. [17] proposed an SWT-based method for segmenting characters on license plates. Characters on reverse license plates can also be identified using this method. MSER was used by Gou et al. [18] to break characters in license plates and determine character location on license plates. The characters on the plate were identified using Restricted Boltzmann Machines (RBM) in the following stage.

To be honest, character segmentation is a difficult job, because influenced by illumination, shadow, or blur in the license plate image. It has an immediate impact on license plate recognition. It immediately affects plate recognition. Even with a great method, the character cannot be correctly identified if the segmentation is incorrect. Deep learning enhancements allow for direct identification of the entire license plate without character segmentation. This reduces overall time complexity. Moon et al. [19] use Hidden Markov Models (HMMs) in conjunction with the Viterbi algorithm for label sequence determination to perform character segmentation. Another study, Goodfellow et al. [20], used a large distributed method with a deep layered neural network to propose a probabilistic model for reading arbitrary multi-digit numbers without character segmentation. According to Li and Shen [21], sequence labeling is a major issue in license plate identification. Convolutional Neural Networks (CNNs) were selected to be used in a sliding window fashion to extract a sequence of feature vectors from the license plate localize box.

3 Proposed Method

The authors proposed a license plate detection and identification model by studying and comprehending the benefits and limitations of several related methods that have been discussed. For detection and identification, this conceptual model employed character-based enhancement. We call it 'enhancement' because deep learning algorithms are used to improve the performance of this character-based detection [22,23,24]. The detection and identification of license plates is accomplished using a single deep learning method, a deep neural network. This was chosen in order to more-effective in the detection and identification process [25,26,27]. Fig. 1 depicts detailed explanations of the proposed model:

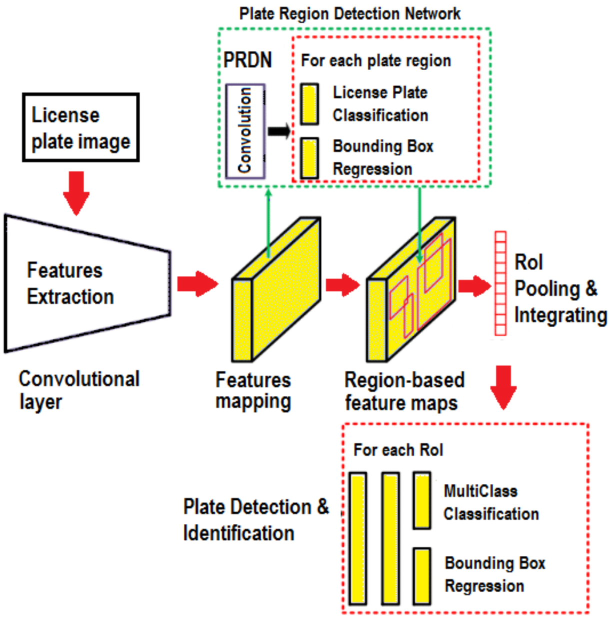

Fig. 1. Conceptual Model.

We used Faster Region Convolutional Neural Network (Faster R-CNN) as a backbone in this conceptual model for license plate detection and identification. The main part of the Faster R-CNN model is convolutional layers. The main purpose of the convolutional layer is to detect local anomalies of a feature from the previous layer and map the results. In each convolution layer, there are several m_1 filters. The number of filters used in one convolution screen is equal to the size of the feature map volume from the previous layer. Each filter can detect a specific feature at each locations on the vehicle plate based on the feature mapping. The output of $Y_{(l)}{}^{i}$ from the first layer $m_{(l)}{}^{1}$ is a feature map of size $m_{(l)}{}^{3} \times m_{(l)}{}^{3}$. For the *i-th* feature map, more popularly known as $Y_{(l)}{}^{i}$, the score can be calculated using the equation 1:

$$Y_i^{(l)} = B_i^{(l)} + \sum_{j=1}^{m_1^{(l-1)}} K_{i,j}^{(l)} * Y_j^{(l-1)} \tag{1}$$

where $K_{i,j}^{(l)}$ is a filter of size $2h_1^{(l)} + 1 \text{ x } 2h_2^{(l)} + 1$ which brings together the j^{th} feature map in layer (l−1) with the feature map in layer and $B_i^{(l)}$ shows the bias matrix. The path of the convolution layer that meets the following layer produces the classified vehicle plate image information as shown. All pixels are then assembled into edges, all edges are assembled into motifs, all motifs are assembled into parts, all parts are assembled into objects, and all objects are assembled into scenes [28,29,30]. Fig. 2 depicts a detailed explanation of the Faster R-CNN convolution layers.

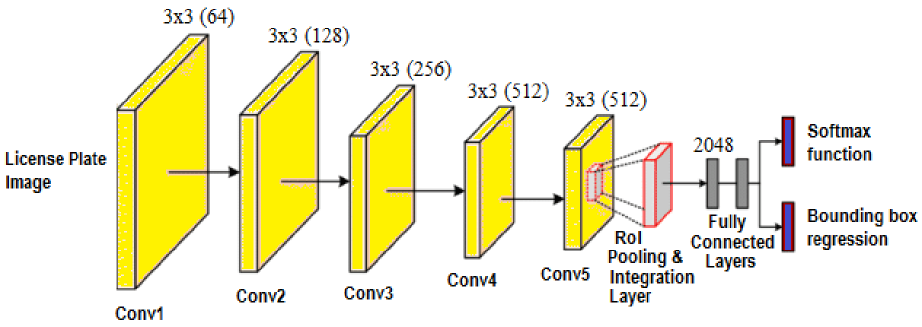

Fig. 2. The Faster R-CNN Convolution Layers.

The region proposal network (RPN) begins with the input of a vehicle plate image entered into the core of the convolutional neural network. First, the vehicle plate image is resized so that it has a minimum side size of 600px and the longest side a maximum of 1000px. The output of the core network with a size of h x w has a smaller size than the vehicle plate image (input). The size of this output is very dependent on the core network used. The two most commonly used core network types are ZF-Net or VGG. In the convolution layer, starts with a layer size of 3 x 3 (64 units) and ends with a size of 3 x 3 (512 units).

The proposed model consists of a number of convolutional layers to extract discriminative features for license plates. Plate region detection network (PRDN) is a modification of the Region proposal Network (RPN) approach proposed by Ren et al. [31]. This Region Proposal Network (RPN) was developed for object detection applications that rely on the region proposal method to predict object locations. They used a single network for RPN, which generates region operation proposals, and Fast R-CNN, which categorizes regions. For license plate detection and identification, a plate region detection network tailored specifically for car license plates, a Region of Interest (RoI) pooling and integrating layer, deep learning classifier, and bounding box regression are used [32,33]. Faster R-CNN shares a full-image convolutional layer with fast R-CNN for feature mapping, resulting in low complexity and cost-free region proposals. Faster R-CNN uses the high-quality region proposal performed by PRDN after it has been trained end-to-end for region detection. A PRDN is a fully connected network that detects plate bounds as well as scores at the same time.

This procedure speeds up plate detection and identification. A PRDN takes any size plate image as input and outputs a set of rectangular image plates, each with a plate score. Begin with m x m reference boxes for each sliding window, which is initialized by PRDN to have different aspect ratios and scales at each convolution feature map location. Each sliding window is converted into a lower-dimensional vector, which is then fed into two pairs of fully connected layers, a multiclass classification layer, and a bounding box regression layer [34].

4 Results

The Faster RCNN-based model has been simulated in Python programming using less than 100 license plate images. The simple simulation results show a 99 percent accuracy rate. Table 1 shows the results of testing the recognition of letters and numbers contained in license plate images.

Table 1. Testing for Letters and Numbers.

Letters/Numbers	Precission	Recall	f1-score
B	0.99	1.00	1.00
D	1.00	0.99	1.00
G	1.00	0.99	0.99
0	0.99	0.99	0.99
1	1.00	0.99	0.99
4	0.99	1.00	1.00
5	1.00	1.00	1.00
6	1.00	1.00	1.00
8	1.00	0.99	1.00
9	1.00	1.00	1.00
H	1.00	1.00	1.00
J	1.00	1.00	1.00
L	0.99	0.99	0.99
T	1.00	1.00	1.00
W	0.99	1.00	1.00

Classification using Faster R-CNN succeeded in predicting almost 100 percent (average score of 99 percent) letters or numbers correctly (precision and recall scores). Faster R-CNN produces an average comparison of precision and recall of letters or numbers that have been identified by 99 percent (f1-score). When compared to other deep learning algorithms, detection using Faster R-CNN has a better accuracy score and test time. Details of the results of the comparison are shown in Table 2.

Table 2. Accuracy and Test-time Comparison

Model	Accurary	Miss	Test time (s)
R-CNN	78%	22%	49,2
Faster R-CNN	99%	1%	2,30
SPP-Net	92%	8%	4,40

Table 2 shows a brief comparison between the proposed identification method and other related deep learning methods. The author deliberately chooses the deep learning method with many similarities as a comparison so that the comparison results are relevant and based on the same theory. Based on the comparison, it can be seen that the use of Faster R-CNN proved to have better accuracy (99 percent) than R-

CNN and SPP-Net (78 percent and 92 percent). When viewed from the test time (s), the comparison results put Faster R-CNN in the fastest position, which is only 2.3 seconds, while R-CNN and SPP-Net are 49.2 seconds and 4.4 seconds. The results of this comparison show that the selection of Faster R-CNN as the core for the vehicle plate detection and identification method is the right and relevant choice. However, the author realizes that it is still very early to state that the proposed method is better overall than other detection methods, the real conditions in the field greatly affect the outcome. Testing involving various factors is needed so that when implemented it can accommodate all unexpected conditions in the field.

5 Discussion

If Table 2 shows the results of the comparison of the accuracy of the Faster R-CNN-based method that the author proposes to several other methods, then Table 3 shows a comparison of the results of the identification of our proposed method against the identification method proposed by several other authors.

Table 3. Accuracy Comparison to Other Related Studies

Authors	Method	Accuracy
Kakani et al. [1]	Feed-forward ANN based OCR algorithm	94.45%
Yogheedha et al. [3]	ANPR Technique	92.00%
Selmi et al. [5]	CNN Approaches	94.80%
Sanmorino et al. (This study)	Faster R-CNN	99.00%

Table 3 shows Kakani et al. [1] proposed an identification method using Feed-forward ANN based OCR algorithm succeeded in getting an accuracy score of 94.45 percent. Another author, namely Yogheedha et al. [3] managed to get a score of 92.00 percent. While Selmi et al. [5] uses Convolution Neural Networks approaches as the core for the proposed method to identify vehicle plates, obtaining an accuracy score of 94.80 percent. It can be understood based on this comparison, the accuracy score obtained by the author in this study is at a fairly good level (99.00 percent). The author does not say that our proposed method is the best because the identification process is also influenced by various factors so it requires more comprehensive testing in the future.

The author realizes that the results of this test are not final, in the sense that the accuracy score obtained can still decrease. The limited number of datasets used in the test is one of the obstacles in this study. However, this does not mean that the results of this test will be in vain, because from the beginning the author considered that what had been done in this study was still preliminary, according to the title that we carried on the first page. For a more comprehensive comparison against other related methods, a factor to consider is the similarity of the variables used in the test. In our view, there will always be differences in the use of variables, but the conditions should not exceed the generally agreed-upon threshold. So for the similarity of the variables used, the closer to 100 percent the better, if it cannot be met then more than or equal to 90 percent is still acceptable. This figure is still acceptable because there are various factors in the field, such as difficulties in obtaining data or at least references to a variable.

6 Conclusion

There have been numerous studies and discussions about vehicle license plate detection and identification. The advantages and limitations of each method are known as a result of the discussion and comparison. By understanding the benefits of the methods discussed, the author proposes a vehicle license plate detection and identification model. This proposed model used a Faster R-CNN approach with modifications to the Region Proposal Network (RPN). This proposed model appears to be relevant in terms of reducing test time while also being more accurate. It is evident from the test results that obtained a score of 99 percent for accuracy. Better than other related CNN methods. The test time(s) for the proposed method is also better than that of R-CNN and SPP-Net. The proposed method only takes 2.3 seconds. In the future, the author will increase the amount of image data as an input convolutional layer and involve several external factors in the field (real conditions), so that the accuracy that has been obtained can be maintained.

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