Identification of Vehicle Plate Number Using Convolutional Neural Networks

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Abstract

Transportation currently has very large and essential role in the needs of the community, namely vehicles. Some problems that often arise related to license plates, such as the length of parking management. Research on this number plate identification system can help with several issues in parking management. The machine learning method related to license plate images is Convolutional Neural Networks. Therefore, the use of the Convolutional Neural Network in this study so that the accuracy of the number plate image is better, then we need a system that in this research process uses the number plate image as input. Many pre-process such as grayscale, segmentation, and plate finder are performed, then this number plate image is identified using Convolutional Neural Networks. This study will build a computational model in which identification uses Convolutional Neural Networks. The results of this study, found the license plate number in the vehicle image using a plate finder. The results of introducing number plate characters using CNN resulted in an accuracy of 96.87% for training data and 93.71% test data using the SGD optimistic model.

Keywords
Plate image, Convolutional Neural Networks, Segmentation and Image

1. Introduction
Transportation currently has a huge and essential role in the needs of the community, namely vehicles this factor increase vehicle users in the city. Every car in Indonesia has characteristics as mentioned in Government Regulation No. 44 of 1993 concerning motor vehicles. The features mentioned include the basic color or background of the vehicle's license plate in black and white writing; there is a tax number on the bottom of the vehicle's license plate.

The increase in the level of the population of vehicle users in the community can lead to many problems that occur, namely traffic violations, vehicle theft, and also the security system. The importance of these problems in identifying vehicle license plates can be implemented to overcome the problem of effective vehicle control. Some previous research used number plates in detecting characters contained in license plate (Prabhakar, Anupama, and Resmi 2014), and o detection vehicles lost (Hung and Hsieh 2010).

With the increasing technological development in the current era of globalization has provided many benefits and conveniences for the community. One of them is Artificial Intelligence and Deep Learning. Deep Learning has become one of the hot topics in the world of Machine

Learning because of its significant capabilities in modeling various complex data such as image, video, and signal. Convolutional Neural Network (CNN) is one of the Deep Learning methods to recognize images, times series data, signal patterns. Several studies used CNN widely, for instance, ingredient detection (Fadhilah et al. 2019), looking at halal food using CNN. Image retrieval does not only cover the number plate but with the area as with the vehicle, which will later be identified on the license plate (Kim, Jeon, and Koo 2017), object recognition with Backpropagation type training with accuracy above 90% (Kheradpisheh et al. 2018).

In this research process, there are several methods in the preprocessing used, namely grayscale, threshold, plate finder, and segmentation. Some research on preprocessing in number plate identification as in previous studies using renewal in otsu segmentation with the addition of Gaussian functions (Hidayah, Akhlis, and Sugiharti 2017), then in previous studies using two approaches in character segmentation to improve the accuracy of character segmentation (Wang et al. 2010). Whereas in this study, using character segmentation on the number plate.

In this study questioned the number plate format and scale in which obtained the test results obtained from normalized cross is 67.98% and the phase phase is 63.46% (Sharma 2018). Next, other studies detected license plates in Argentina, which resulted in recognition accuracy of more than 90% overall (Gazcón, Chesñevar, and Castro 2012). Whereas in this study, using a plate finder algorithm to search for vehicle license plate locations. Previous studies used the R-CNN Faster to character recognition of number plates that have been segregated (Brillantes et al. 2019), then this study detects text using R-CNN which uses LocNet localization (Zhong, Sun, and Huo 2019). Number plate identification in the study using sliding-windows darknet-YOLO reached an accuracy of around 98.22% in number plate detection (Hendry and Chen 2019). Then the study introduced the number plate using the modified Grabcut algorithm to localize the license plate which has an accuracy of 99.8% of the 500 vehicle license plate images (Salau, Yesufu, and Ogundare 2019). This study used CNN to the identification of the characters in the license plate.

This research will build a computational model that can identify the image of the vehicle number plate. In this computational model, there are several features or classes in which the number plate image results will be identified using the CNN method.

2. Research Method

The process of identifying vehicle number plates can be seen in Figure 1.

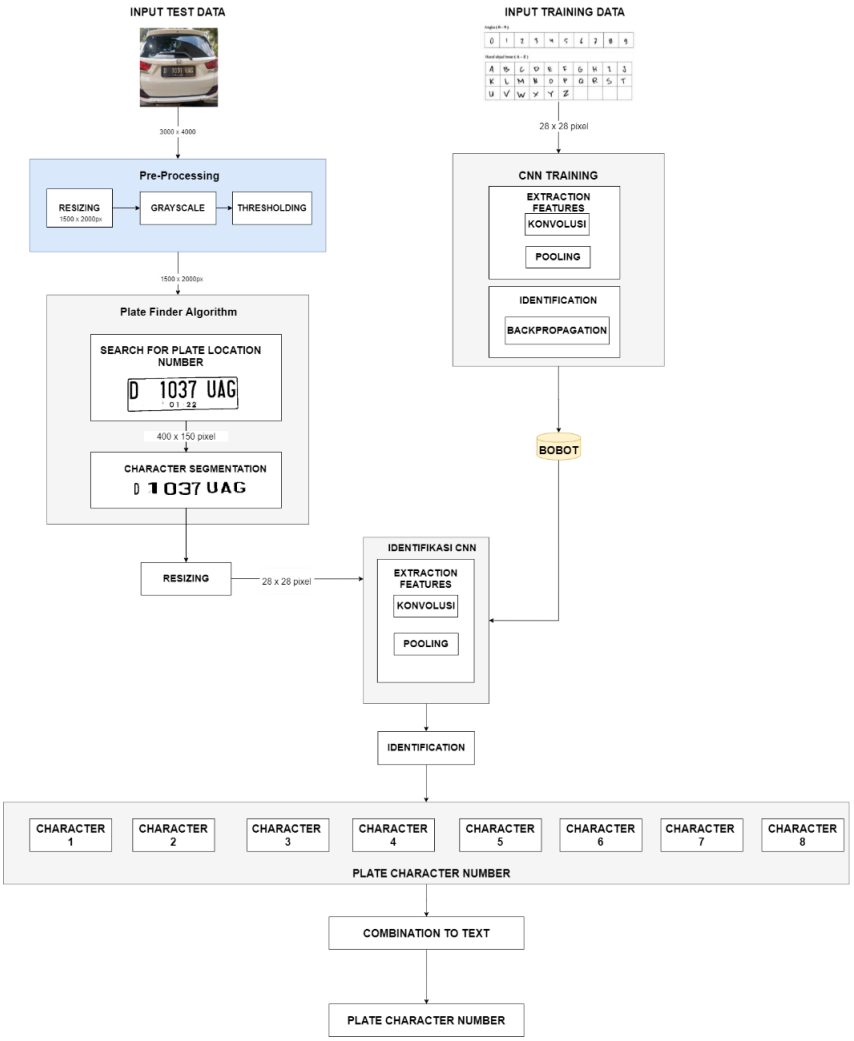


Figure 1. Vehicle Number Plate Identification Model.

Based on Figure 1, the process of identifying vehicle license plates begins with the acquisition of vehicle license plate data used for training data. The data is processed through preprocessing, namely resizing, grayscale, thresholding, plate finder algorithm, and character segmentation. After preprocessing, the data will be identified using CNN for training and testing.

2.1 Dataset

In this study, they were using 200 license plate data obtained in the vehicle parking lot. All sample data was collected using an Android phone camera with an 18-megapixel camera size with standard frame settings. The data used in this study consisted of training data and test data. The data used is in the form of vehicle license plates with dimensions of 3000x4000 pixels for test data. For training data or training using image data with specifications consisting of letters (A-Z) and numbers (0-9) with a size of 28x28 pixels with a black and white scale. The data format used is JPG.

2.2 Pre-Processing

Pre-processing is the initial stage of the data input process which is where the data will go through several processes. These pre-processing stages include resizing, a grayscale, threshold

2.2.1 Resizing

Resizing is used to reduce the dimensions of the number plate image data from initially measuring 3000 x 4000 pixels to a uniform size of 1500 x 2000 pixels. This size reduction is made to reduce computing time so that it is not too big.

2.2.2 Grayscale

Grayscale is used to convert images that were initially RGB in color to grayscale. RGB images have three color depths, namely red, green and blue. The grayscale process starts with the input of the image through the process in equation (1).

$$grayscale = 0.299\,R + 0.587\,G + 0.114\,B \tag{1}$$

The results of this process the image will be a gray color as in Figure 2.

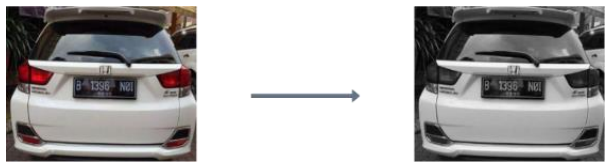


Figure 2. Grayscale Process

2.2.3 Threshold

Threshold or often called image binarization is used to change the gray image obtained from the grayscale process into a black and white image, as in Figure.3. Some researchers often use the threshold method by using the otsu threshold or thresholding for the number plate identification process or in images (Vijay and Patil 2016). The thresholding process can be done using equation (2). The value of zero represents black and the value of one represents white.

$$g(x,y) = \begin{cases} 0, & f(x,y) < 128 \\ 1, & f(x,y) \geq 128 \end{cases} \tag{2}$$

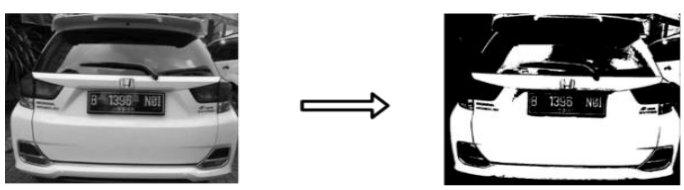


Figure 3. Threshold Process

Based on Figure 3, the thresholding process are pixels whose intensity results below 128 will be changed to black (value 0 = black) while pixels whose intensity above 128 will be changed to white (value 1 = white). In this process the image that has gone through the grayscale process is converted to black and white.

2.3 Plate Finder

The plate finder algorithm is an algorithm for locating vehicle license plate locations in image data. Some methods regarding number plate search in images are Run-Length Mearing Algorithm (RLSA), Length Transform (LT), and Connected Component Analysis (CCA). Some previous studies using the ANPR method as a number plate search (Patel, Shah, and Patel 2013).

In this study, using CCA or Connected Component Analysis as a number plate search algorithm, which in this algorithm will detect numbers or letters. The search stage is, looking for candidate numbers/digits in the image by counting each pixel. All possible objects in the form of letters or numbers will be searched at the location stage using equations (3) and (4)

$$Tinggi = k[i] = 1VP(x,y) = \ 0, tinggi \geq 45 \ldots\ldots\ldots \quad (3)$$

$$Lebar = k[i] = 1VP(x,y) = \ 0{,}100 \ \leq tinggi \geq 350 \ldots\ldots\ldots \quad (4)$$

After resizing, grayscale and threshold, a number plate search is done on the image of the threshold results. After the plate number is discovered, cropping or cutting will be done at the location of the number plate that has been found with a predetermined size.

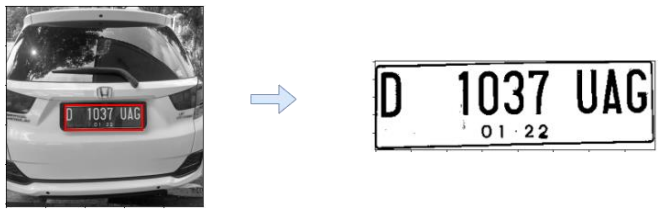


Figure 4. Plate Finder Process

2.4 Character Segmentation

Character segmentation is done by using images that have gone through preprocessing and plate finder stages. In this process, the segmentation of each character object on the number plate will represent the character (Panchal, Patel, and Panchal 2016). The character image obtained will be input for identification using CNN. This identification is carried out on specific letter and number features.

Figure 5. Character Segmentation

Based on Figure 5, the segmentation results produce an image measuring 28x28 pixels, which have character information that will be used as input.

2.5 Convolutional Neural Network

Convolutional Neural Networks to get the weight value for each class that is used as a reference in the testing process. Identification is done by using images that have gone through the process of character segregation. Then feature extraction using convolution, activation function, and max pooling. The input image is a binary image with a size of 28x28 pixels. While the classification process is carried out at the fully-connected layer (Dyrmann, Karstoft, and Midtiby 2016) using the Multilayer Perceptron (MLP) architecture.

2.5.1 Feture Extraction Layer

This feature extraction layer functions to change the image input to become vector features. This layer consists of Convolutional and Pooling.

2.5.1.1 Convolutional

Convolution is the operation phase of multiplication and the addition of two images using a kernel. Convolution is used to convert images into depths that can produce variations in features. The stride used in this study is one so that the kernel will shift every one pixel with which will be added to the input. The convolution process can be carried out using equation (5).

$$FM_{(i_l,j_l)}^{(l,m_l)} = f\left(\sum_{r_l=0}^{k_h}\sum_{c_l=0}^{k_w} C_{(r_l,c_l)}^{(l,m_l)} * FM_{((r_l+i_{l-1}),(c_l+j_{l-1}))}^{(l-1)}\right) \quad (5)$$

The output in this convolution process produces a feature map. After obtaining a feature map, if there is still a negative value, then ReLU Activation is carried out so that it can change the negative value to 0 so that the values on the feature map are positive. ReLU Activation is shown by (6).

$$f(x) = \max(0, x) \tag{6}$$

2.5.1.2 Poolong

Pooling is the process of downsampling or reducing the size of the image to be smaller than the result of activation to a smaller dimension. Max pooling is done to reduce the feature map to a smaller spatial size but does not lose the features that will be identified. In this study using 2x2 pixels of the stride value which is 2 pixels as in Figure 6.

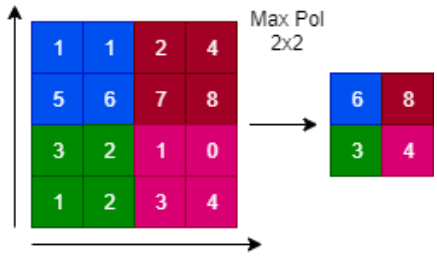


Figure 6. Operation Max Pooling

2.5.2 Classification Layer

In the Classification, the layering process consists of several configurations were the most commonly used is MLP. Feature map obtained from feature extraction is then converted to a flatten vector as the input of the classification layer.

2.5.2.1 Softmax

The Softmax function is used to calculate the probability of each target class for all possible target classes and will help to determine the target class for a given input. Softmax functions can be done using equation (7).

$$softmax(y_k) = \frac{e^{x^T w_k}}{\sum_{i=1}^{m} e^{x^T w_i}} \tag{7}$$

2.5.2.2 Loss Function

Loss Function is used to measure the difference between how many deviations occur between the results of the classification and class of data. This study uses the Cross-Entropy function shown in (8).

$$Cross\ Entropy = -\sum_{i=1}^{m} p_i \log \hat{p}i \tag{8}$$

2.5.2.3 Optimization Model

An optimization model used in machine learning to improve weight. In this study, using Stochastic Gradient Descent (SGD) and Adaptive Learning Rate (AdaDelta). This optimization method is intended to enhance weight and minimize errors. The difference between SGD and AdaDelta is that SGD trains the network using a random network sample to correct the weights. This weighting improvement is done in stages which can cause stalled repairs to the minimum local iteration. AdaDelta is a development of SGD which has techniques for adapting weight improvement so that it runs dynamically.

3. Result and Discussion

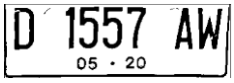
Number plate data is used as many as 200 data to be processed, consisting of number plate data. The data already obtained will be conducted for training and testing of the CNN model. Which is where the data will be divided into training data and test data. Testing the optimization model using the Anaconda 3 platform with GPU configuration.

3.1 Plate Finder

In the process of finding the location of this number plate using a plate finder algorithm, namely CCA, find the location of this number plate through several stages in the image such as resizing, grayscale, and threshold, then after the process begins searching for the number plate location by determining the maximum width, height, and

minimum width, height to get the desired size. Then search, once found it will find the location of the number plate by using a bounding box. The number plate search results can be seen in Table 1.

Table 1. RESULT OF PLATE FINDER PROCESS

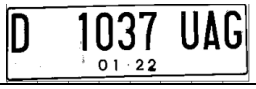
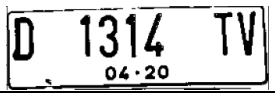
No	Image	Plate Finder Process Vehicle Plate
1.		
2.		
3.		
4.		
5.		

Based on Table 1, a search for the number plates' location can be done, but there are still unclear images because the test data used is too bright, so when the pre-process turns black. In this plate finder, the results of character segmentation will be entered at the identification stage. In this number plate search, there are still many shortcomings of finding the region in the image where there are still many errors such as lights or others.

3.2 Character Segmentation

The segmentation process is performed on each number plate obtained from the plate finder process. Where each character on the number plate will be segmented. The results of character segmentation on the license plates can be seen in Table 2.

Table 2. RESULT OF CHARACTER SEGMENTATION

NO.	Vehicle Plate	Segmentation
1.		
2.		

3.		
4.		

Based on Table 2, the results of this segmentation are black, wherein the plate finder process the number plate image is black because the light on the number plate is too bright so that the preprocessing stage becomes partially black.

3.3 CNN Identification

CNN identification is carried out on the result data from preprocessing, which consists of letters and numbers measuring 28x28 pixels. Identification using a device with Intel Core i7 9300H specifications, NVIDIA Geforce GTX 1050TI, 8GB RAM.

The optimization parameters or models used in this test are SGD and AdaDelta For the SGD learning rate of 0.01, momentum 0.9. With 100 epochs. The parameter optimization test results can be seen in Table 3.

Table 3. RESULT TESTING ESTIMATION MODEL

No	Optimization Model	Training Data		Test Data	
		accuracy	Loss	accuracy	Loss
1	SGD	96.87%	0.10	93.71%	0.372
2	AdaDelta	99.35%	0.03	97.48%	0.355

Based on Table 3, the AdaDelta optimization model has a better accuracy and loss value, namely an accuracy of 99.35% and a loss value of 0.03 compared to SGD, which has an accuracy of 96.87% and a loss value of 0.10. The graph of the accuracy using SGD and AdaDelta can be seen in Figure 7.

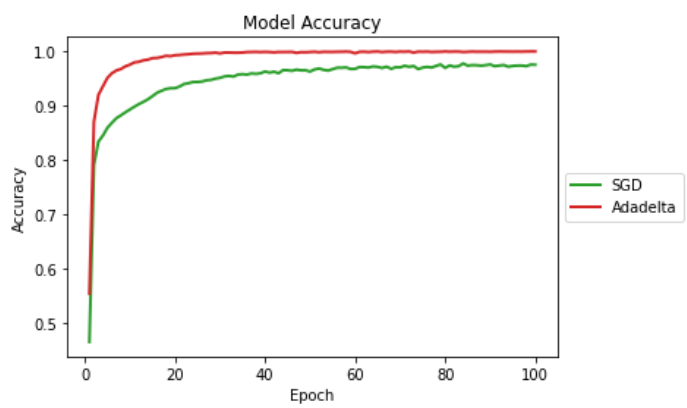


Figure 7. Model Accuracy

Based on Figure 7, it can be seen that the AdaDelta optimization model has a better value compared to the SGD optimization model in terms of accuracy. For the model of training data loss and test data can be seen in Figure 8 and Figure 9.

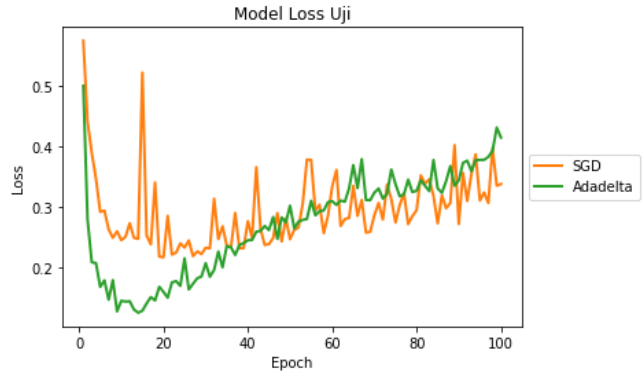


Figure 8. Model Loss Test

A graph in Figure. 9 shows that the AdaDelta model tends to be good at the beginning of the epoch but when it reaches 100 epoch the value of loss increases while in the SGD model the loss is unstable. Which is where the AdaDelta model has an optimal loss reduction compared to the SGD model.

Experiments carried out are changes in the learning rate of the SGD model with a learning rate of 0.001, 0.002, and 0.010 to determine whether the accuracy value can be increased or not. can be seen in Table 3.

Table 4. RESULT ACCURACY LEARNING RATE

No	Learning Rate	Training Data		Test Data	
		accuracy	Loss	accuracy	Loss
1	0.001	99.69%	0.354	96.42%	0.379
2	0.005	98.52%	0.063	95.25%	0.355
3	0.010	98.82%	0.040	95.56%	0.329
4	0.050	99.75%	0.007	96.45%	0.285
5	0.100	99.46%	0.017	95.91%	0315

Based on table 4. The results of experiments using different learning rates on the SGD computational model produce accuracy above 95%, which is very satisfying. Accuracy values using different learning rates can mean accuracy in training data or test data.

4. Conclusion

In this study, the identification of vehicle license plate images using Convolutional Neural Network to determine the accuracy of character recognition on each object number plate. This study searched for vehicle plate number locations using a plate finder algorithm where the data conditions also affect the search for plate number locations on vehicles where different number plate locations, light conditions when data retrieval where it affects when searching for plate locations number.

This research uses two optimization models that affect the computational model, with the aim of character recognition. The computational model used is SGD and AdaDelta. The accuracy results given in the optimization model that has better accuracy are the AdaDelta model which gives an accuracy of 99.35% and a loss of 0.03. This study presents a model for the identification of number plate image systems using Convolutional Neural Networks. In the plate finder process, the data retrieval that has been prepared must be correct. Some data used during the plate finder process cannot be detected or the distance of data collection also influences so that it cannot be detected correctly. In this research, the AdaDelta

optimization model with learning 0.01 and maximum epoch 100, produces a better accuracy value with an accuracy of 99.35% for the test data..

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