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IDENTIFICATION OF BANKNOTES ON THE VISUALLY IMPAIRED PERSON THROUGH DEEP LEARNING

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ABSTRACT

The identification of banknotes is one of the main problems for the blind person. Money is a tool that is used in everyday life to carryout buying and selling transactions by all humans in every part of the world, so this makes money as a primary item for everyone, even for people with disabilities such as the visually impaired ones. The weakness of the visually impaired person in seeing and identifying money can cause into money confusion, mis-taken, or even deceived at the time of the transaction. Therefore, tools are needed to ease the visually impaired to identify the value of money. The purpose of this study is to propose one of the deep learning-based methods of convolutional neural networks (CNNs) that can be used to detect the value of Indonesian currency banknotes. Data sets used in the form of paper money images with an amount of 1000, 2000, 5000, 10000, 20000, 50000, 100000 thousand rupiah, which amounted to 100 images each, bringing the total images used as a dataset reaching 700 images. At the training stage, the CNN model that was built received 560 paper money image inputs (80% of the total dataset), while, 140 images used at the testing stage (20% of the total dataset). Once the trial completely conducted, it is obtained 94. 29% as the best accuracy in the 60th epoch with the kernel size in the first convolutional layer is 3x3 and the kernel size in the second convolutional layer is 2x2.

Keywords: *Deep Learning, Convolutional Neural Networks (CNN), Banknote, Visually Impaired Person.*

1. INTRODUCTION

According to WHO data, an estimated of 2.2 billion people have close or distant visual impairment. In at least 1 billion or nearly half of these cases, visual impairment can be prevented or has not been yet treated properly. The main causes of visual impairment and blindness are refraction disorders and cataracts. The majority of people with visual impairment and blindness are coming from those who are over the age of 50. However, vision loss can affect people of all ages [1]. In Indonesia, according to estimates of the Ministry of Health of the Republic of Indonesia, it is recorded that about 1.5% of the population of Indonesia or about 3,750,000 people are suffered from with visual impairment [2]. This condition then lead into several issues. One of the main problems for blind people comes as they experience the difficulty in seeing and identifying banknotes so that, it can cause confusion on using money, mis-picked, or even deceived at the time of transaction. Therefore, a tool is needed to ease the visually impaired in identifying the value of banknotes.

There are several ways to take a banknote image before the identification process is carried out such as using a scanner device or using a camera. Some existing portable banknote recognition devices include the Money Talker [3] devices made for the Australian dollar. Then there is note teller 2 [4] and K-NFB Mobile Reader [5], both of which can handle U.S. banknotes. Money Talker and Note Teller 2 are built on specific scanner-based hardware, while K-NFB Mobile Reader is implemented on smartphones. Systems that use scanner devices are rather difficult to carry, while, systems that utilize cameras can be applied to smartphones. In fact, smartphone has a camera feature that makes it available to the visually impaired. Therefore, a camera-based system will be easier and more suitable for usage of people with visual impairments.

In this paper, Indonesian currency with the banknotes value available are 1000, 2000, 5000, 10000, 20000, 50000, 100000 where the image of the banknote is photographed through a smartphone camera. Furthermore, it will be continued by the quick and precise process of identification and classification. Many previous studies that discussed algorithms for the process of classification in image (image recognition) are not even limited to currency images. Among them, Rahman, et al (2019) created a currency identification scheme for the visually impaired and used Bangladeshi currency as a test dataset and used the Oriented FAST and Rotated BRIEF (ORB) algorithms. The accuracy obtained reaching 89.4% for money against a white background and 78.4% for money with a complex background [6]. Subsequently, Ali and Manzoor created a currency classification system using the Pakistani currency. They used strategies based on the K-NN algorithm and achieved accuracy above 95%. [7]. In addition, many researchers also use classic methods on Computer Vision, ranging from histogram equalization [8], nearest neighbor interpolation [9], genetic algorithms [10] and fuzzy systems [11]. However, the primary issue with this method occur as its generalization capacity is relatively low towards new sample data nor its relatively low towards its accuracy. Then, there are also related methods based on Deep Learning using convolutional neural networks (CNN's) [12-14] which has outperformed classical machine learning techniques [15] and humans [16] in terms of classification. Therefore in this study CNN is selected as a method to identify Nominal Banknotes, particularly in this case of the Indonesian currency.

2. CONVOLUTIONAL NEURAL NETWORK

Convolutional network or also known as convolutional neural networks (CNNs) is the development of Multi Layer Perceptron (MLP) designed to process two-dimensional data [28]. CNN belongs to the Deep Neural Network type because of its high in depth network and widely applied to image data. However, In the case of image classification, MLP is less suitable to be used because it does not store spatial information from image data nor assumes each pixel is an independent feature, thus, it produces in poor results. CNN is also referred as a special type of neural network for processing data that has a net topology or grid-like topology. The naming of a convolutional neural network indicates that the network uses a mathematical operation called convolution, a linear operation. In other words, a convolutional network is a neural network that uses at least one convolution in its layers [17]. In addition to that, CNN is used to classify labeled data using supervised learning methods. This method works though the availability of both data trained and targeted variables, thus it is aimed at grouping the data into existing data.

CNN is often used to recognize objects over a scene and detect and segment objects. CNN learns directly from imagery data, thus, it can eliminate feature extraction by manual means. The initial research on which this discovery was based was initially conducted by Hubel and Wiesel who examined visual cortex research on cats' sense of sight. Visual cortex in animals is very powerful in the visual processing system ever. Thus, many studies were inspired by how it works and resulted in many new models, some of which are, Neocognition, HMAX, LeNet-5 and AlexNet.

CNN is also a nerve that is used to process data within a box structure. For example, it is in the form of two-dimensional image data. The name convolution is an operation of linear algebra that multiplies the matrix of the filter in the image to be

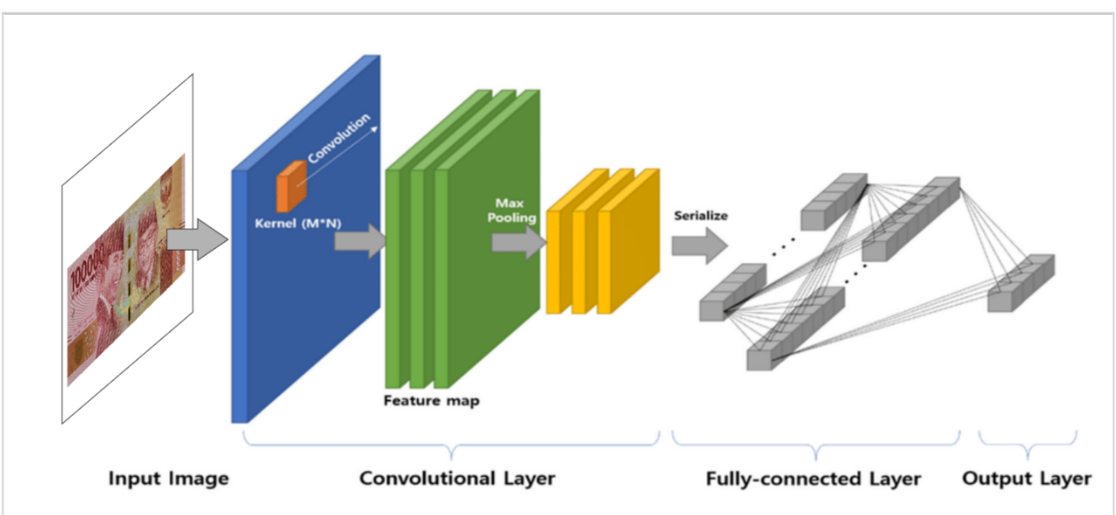

Figure 1 : CNN's Structure for Image classification

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processed. This process is called the convolution layer and belongs to one of the many layers that can be owned in a network. However, this convolution layer is the most important primary layer used. Another type of layer commonly used is called pooling layer, the layer that used to take a maximum value or average value of the pixel layer parts in the image. Figure 1 is presented the architecture of the net convolution.

Based on figure 1, it can be revealed that each entered *input* layer has a 3-dimensional arrangement of neurons, such as width, height and depth. Width and height are the size of layers, while interior is the number of layers. Each obtained amount is calculated from the results of the ration of the previous layer and the number of *filters* used. This network model has proven effectively in dealing with image classification issues. CNN is capable of having tens to hundreds of layers which each layer studies the detection of various images. Image processing is applied to each image trained at a different resolution and *the output* of each image data is processed and used as *input* to the next layer. Image processing can be begun as a simple feature, such as brightness and edge size or increase complexity on features uniquely to determine objects according to layer's thickness [18]. In general, there are two type of CNN layer, as follows:

- Feature Extraction Layer
  This layer is located at the beginning of the architecture. Neurons within this layer are connected to the local area of the previous layer [28]. Convolutional layer is the first type layer and pooling layer is the second layer. This layer receives the image input directly and then processes it until it produces an output in the form of vectors, the matter that processed in the next layer [28].
- Classification Layer
  This layer is composed of several layers and each layer is composed of neurons that are fully connected to other layers. This layer receives input from the output of the extraction layer of vector image features then transformed as Multi Neural Networks with the addition of several hidden layers [28].

2.1 Convolution Layer

The Convolutional Layer consists of three main operations called convolution operations, activation functions and pooling. Those layer operational would be explained as follows:

2.1.1 Convolution Operation

Convolution operations imposed on functions *x(t)* with weights (or often called kernels) *w(t)*, $x*w$, are mathematically defined in equation (1). In the equation, *s(t)* is the result function of convolution operations, *t* is the variable of the function, and *a* is constanta.

$$s(t) = (x * w)(t) = \sum_{a=\infty}^{\infty} x(a) * w(t-a) \tag{1}$$

In machine learning applications, input *x* is an array of many dimensions that contain data. While the weight *w* is a multi-dimensional array, the parameter that can be learned. Since inputs and weights must be stored prior to processing, input values and weights are considered zero in all components except stored components. So, the sum obtained is not an infinite sum but as recorded as the numbers of the element a or input arrays.

In digital image processing, convolution is moving a kernel K *sized m x n* on an image *I* that is *i x j* in size, and then taking the sum of the multiplication of the image and kernel values. The term convolution is almost the same as the term correlation. However, a slight difference comes as during the time of convolution, the kernel used first is reversed for 180. In machine learning applications, the two terms are considered the same, so when convolution is done, the kernel can be reversed at the first or not [19]. Formally, convolution in an image under the size *s x t* written in *I(s x t)*,with a kernel measuring m x *n* written in *K(m x n)*,can be expressed in equation(2) while, correlation is expressed with equation (3).

$$s[i,j] = (I * K)[i,j] = \sum_{m}\sum_{n} I[i-m, j-n]\, K[m,n] \tag{2}$$

$$s[i,j] = (I * K)[i,j] = \sum_{m}\sum_{n} I[i+m, j+n]\, K[m,n] \tag{3}$$

It can be explained as follows:
I represents the Input image, *K* is the applied kernel, *i* and *j* are the initial position of the image from which the filter will begin to operate, while *m* and *n* are the position of the filter element.

In both equations, the value (m,n) is centered in the middle of the kernel value (0.0). While the image coordinates (i,j) are valued (0.0) on the upper left side of the image. The size of the convolution-result image is reduced compared to the initial image and

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can be expressed by the equation (4). For example, if an image with a size *of 32x32* is subject to convolution with a kernel size of 3x3 then the final size becomes *(32-3+1) x (32-3+1) = 30 x 30.*

$$\text{Convolution result size} = \text{size before Convolution - filterSize} + 1 \qquad \textbf{(4)}$$

An illustration of the convolution process in the image, which is a two-dimensional array of I, under a weight of K (two dimensions) shown in figure 2 . In the image, it is measured *4x3* convoluted using a *2x2* kernel. The resulting image is *3x2 in* size. The first element in a convolution image is the sum of the multiplication of the kernel weight by the value of the image in question. In its application, additional zero padding can be added on the input image to maintain peripheral information.

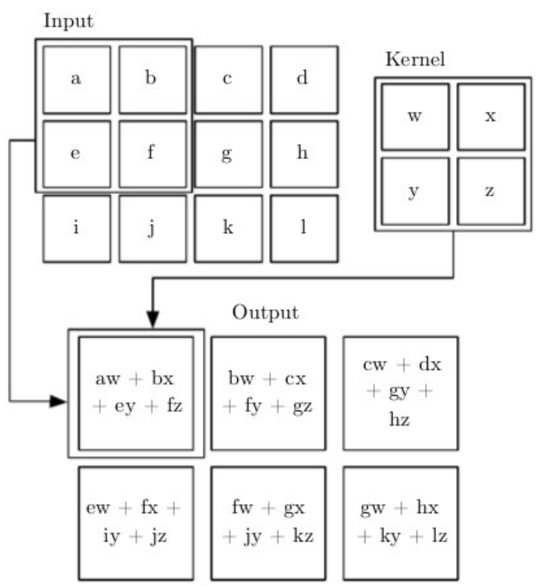

Figure 2 : Convolution process on input array

2.1.2 Activation Function

The second element of the convolutional layer is the activation function. In this process, the activation function used is taken from the tanh activation function where it will be activated on the results of convolution. this function works through converting the real values into values between -1 and 1 as in figure 3. , a very negative value is changed to a value of -1 while a very positive value is changed to a value of 1. While, 0 is the value center of this function. the equation for the tanh function can be seen as follows:

$$tanh(a) = \frac{e^{a} - e^{-a}}{e^{a} + e^{-a}} \qquad \textbf{(5)}$$

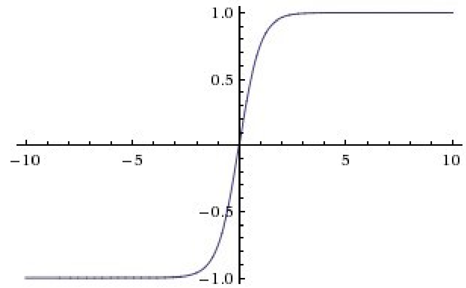

Figure 3 : Tanh Activation Function

Pooling or subsampling is a layer of functions for featuring maps as input and processing them with various statistical operations based on nearby pixel values. In the CNN model, the pooling layer is usually inserted regularly after several layers of convolution. Pooling layers that inserted between successive convolution layers in the composition of the CNN model architecture can progressively reduce the size of output volume on maps feature, thereby, reducing the number of parameters and to control overfitting. Therefore, choosing many types of pooling layers that in this case can benefit the performance of the model would be a crucial mater in making the CNN model. Pooling layers work in every feature maps arrangement and reduce their size. The most common form of pooling layer would be to use a *2x2* filter that is applied with a step of 2 and then operates on each slice and input. This shape will reduce the feature maps by up to 75% of the original size.

The layers on the pooling will run on each slice into the input volume alternately. In figure 4, the pooling layer uses one of the max-pooling operations which is the most common operation. The use of pooling layer on CNN aims to reduce the size of the image so that it can be easily replaced with a convolution layer with the same stride as the pooling layer in question.

2.2 Fully-Connected Layer

Fully-connected layer is the layer where all activation neurons from the previous layer are connected to neurons in the next layer as well as ordinary neural networks. Any activation from the previous layer needs to be converted into one-dimensional data before it can be connected to all neurons in the fully connected layer [29]. Fully-connected layers are commonly used in the Multilayer Perceptron method and are useful for processing data so that it can be classified [29]. The difference between a fully-connected layer and a regular convolution layer can be seen where the

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neurons in the convolution layer are only connected to a specific area of input, while a fully-connected layer has neurons that will be connected as a whole [28]. However, both layers still operate the dot product, thus it still perform similar function.

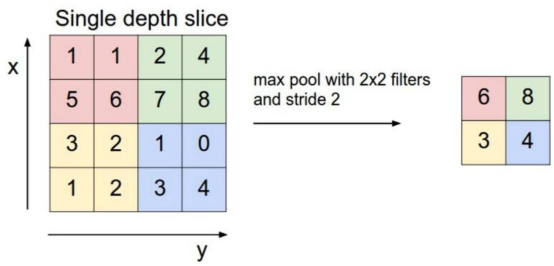

Figure 4 : Max-pooling process

2.3 Dropout Regularization

Dropout is a technique of regularization of artificial neural networks where some will be selected randomly and do not used while using training data. These neurons are also randomly discarded. This means that, the contribution of discarded neurons will be stopped while new tissues and weights are also not assigned to the neurons when performing backpropagation. This technique is very easy to apply to the CNN model so that it will give an impact on the performance of the model in training and reducing overfitting.

2.4 Softmax Classifier

Softmax classifier is another form of logistic regression algorithm that can be used to perform classifications of more than two classes. The standard of classification usually performed by algorithms of logistic regression is in terms of a task for binary class classification. Thus, Softmax has the following similarities :

$$F_j(z) - \frac{e^{z_j}}{\sum_k e^{z_k}} \quad (6)$$

In equation (6), for notation F_j shows the function result for each j element in the output of class vector. Argument z is a hypothesis given by the training model in order to be classified by the softmax function. Softmax also provides more intuitive results and has better probabilistic interpretation results compared to other classification algorithms. Softmax allows researchers to calculate probability values for all labels. The result of the existing label, will be taken a value vector that has a value of rill and converted into a vector with a value between zero and one. If the result is added up it will be worth one.

3. METHOD

The stages in this study as described in figure 5, starting from dataset collection then continued to Image Pre-processing, then CNN's training process, model testing and finally it is ended by calculating the accuracy.

3.1 Dataset Collection

The data set collection can be briefly described as follows: Firstly, collecting data on banknote image data with a value of 1000, 2000, 5000, 10000, 20000, 50000, 100000 where each of this bank notes is amounted to 100 images, thus, bringing the total image of 700 images that used as a dataset. The image data is taken outdoors with sufficient lighting using a smartphone camera with a resolution of ± 5 megapixels. At the training stage, the CNN model that was built received 560 paper money image inputs (80% of the total dataset), while at the testing stage, it is used 140 images (20% of the total dataset). The examples of banknotes used as datasets is displayed in figure 6.

3.2 Banknote Image Pre-processing

The second stage is callled preprocessing, where the image is prepared so that it can be processed at the CNN classification stage. At this stage, the image will be resized to 32x32 and the image color will be changed to grayscale. Afterwards, it is trasnform into a matrix form as input for the training process to test with CNN.

3.3 Training Process

The basic principle of this stage is to conduct training on CNN to get a model that is able to provide the best accuracy. The CNN training process begins by initializing parameters, namely the number of epochs, the number of convolution layers, the number of filters on each layer, the size of the kernel, and the number of neurons on the hidden layer. The CNN model training process is the same as the training process of other neural network models, called forward propagation and backward propagation as much as specified iterations. In this study, weight value renewal was conducted with adam optimizer and used 2 convolution layers. The number of convolution layers will determine the accuracy of the classification model. The convolution process is carried out on a 1-dimensional kernel. The convolution process in the second layer uses image input derived from the convolution process in the first layer.

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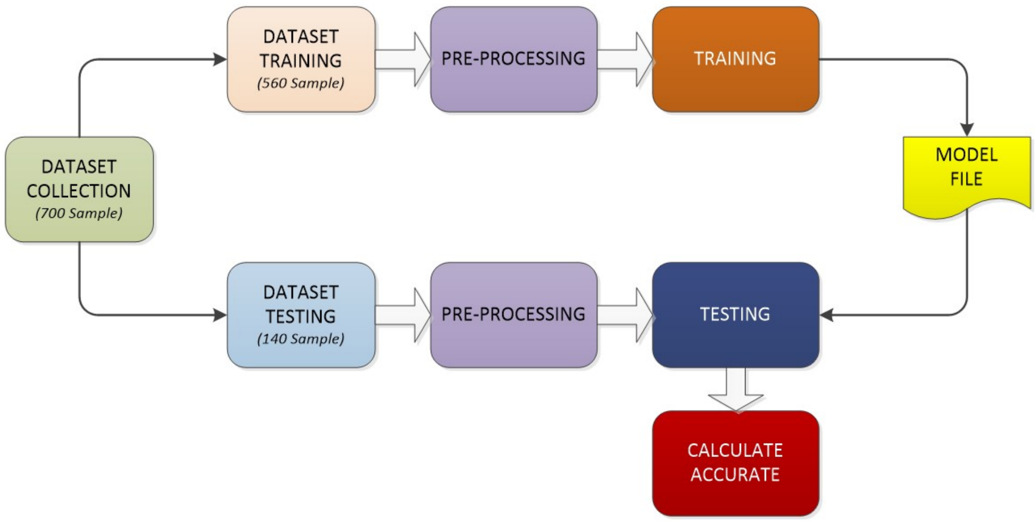

Figure 5 : Research Design

Figure 6 : Sample of Indonesian Banknotes

Furthermore, the pooling process is carried out with the aim of reducing the matrix. There are three types of pooling methods, namely, average pooling, max-pooling and sum-pooling. In average pooling, the taken value resulted from the average value, while in max-pooling, the taken value comes from the maximum value, and sum-pooling sums all the values. Therefore, this study applied the max-pooling method. The max-pooling is chosen to be applied as if the number of small matrix values in the pooling layer is higher than the number of matrix values with great value, then, the large value would be taken because it produce more image information, consequently, it will produce better accuracy. The output of the convolution process will be the input for the max-pooling process while the output of the max-pooling process is the largest value of the convolution result. The kernel size and stride in the pooling process for the first layer and the second layer are the same, which is *2x2*. This means that each step measuring *2x2* will be pooling and the step will shift two to the right or down. The activation function used in the pooling process is the Tanh function.
The next process is in a fully-connected layer. This layer is a hidden layer that is in the form of one dimension. The input on the fully-connected layer comes from the output at the previous convolution layer. Each matrix component of the convolution layer output is considered an input value for a fully-connected layer. The Tanh activation function then chose to be used in this process.

The final process at the CNN classification stage is the output layer, which is the last layer and consists of 7 neurons representing the 7 banknotes that the researcher want to classify. This layer is fully connected to the previous layer. This layer is a softmax layer so that if the activation value on each neuron is summed up, it will be worth 1. Softmax is the command used to classify objects in this study. The output of the CNN classification process is the result of the classification and accuracy value of the model.

This training process will be carried out repeatedly according to the specified number of epochs. The model produced by the training process will be saved to a file that will be used at the testing stage.

3.4 Testing Process and Calculate Accurate

At the testing stage using a dataset of 140 samples. There are 2 parameters that will be tested to get the best model on classification with CNN, namely kernel size and epoch number. For the first test, it was conducted by changing the combination of kernel sizes used in the convolution layer, namely:

1. Kernel Size in 1st convolution layer is 3x3, and Kernel Size in 2nd convolution layer is 3x3.
2. Kernel Size in 1st convolution layer is 3x3, and Kernel Size in 2nd convolution layer is 2x2.
3. Kernel Size in 1st convolution layer is 2x2, and Kernel Size in 2nd convolution layer is 2x2.

As for the second test, it was conducted by changing epochs ranging from 10 to 100. At the time of this test, the parameters that did not change were filters on the convolution layer of 20, the probability of dropouts of 0.1 and batch sizes of 100.
Then the last stage is to calculate the accuracy of the CNN classification for each scenario that has been set at the testing stage.

4. RESULT AND DISCUSSION

Based on the testing, the obtained result can be seen in table 1 and figure 7.
At table 1 and figure 7, it is shown that the best accuracy obtained in epoch 60 with kernel size on 1st convolution layer comes at 3x3, and kernel size on 2nd convolution layer comes at 2x2, which resulted 94.29%. From the 140 sample tested data, 132 samples were successfully identified within the banknotes value of 1000, 20000, and 100000 for 100% while 2 samples of banknotes in 2000, 10000 and 50000 were failed to be

Table 1 : Accuracy of CNN Classification

Kernel Size		Epoch									
CL1	**CL2**	**10**	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**	**100**
3x3	3x3	78.41	82.32	83.22	85.91	87.50	90.57	90.04	89.72	89.17	88.97
3x3	2x2	80.64	84.71	86.69	88.45	91.15	**94.29**	92.68	92.13	91.73	91.18
2x2	2x2	76.92	78.70	81.62	83.28	84.77	88.12	87.88	87.24	86.38	85.92

CL1 : 1st Convolution Layer; CL2 : 2nd Convolution Layer;

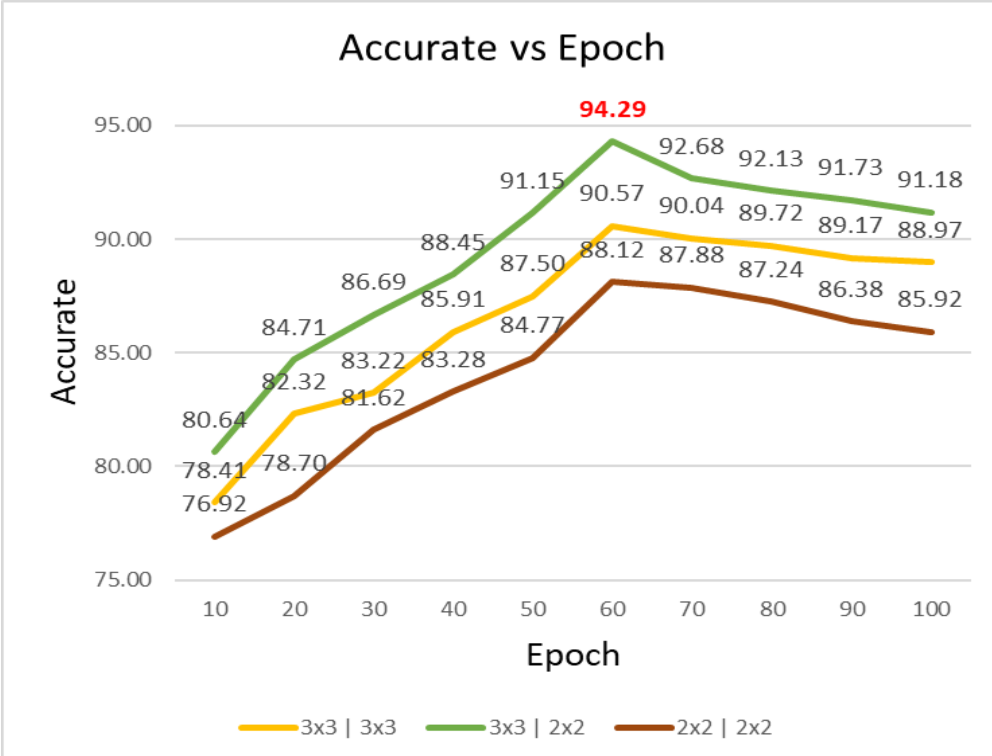

Figure 7 : Testing Result

recognized, then 3 samples of banknotes in 5000 were failed to be recognized. To sum, there are 8 samples of banknotes were failed to be recognized.

5. CONCLUSION

The introduction of Indonesian currency notes with a nominal of 1000, 2000, 5000, 10000, 20000, 50000, 100000 with CNN has a fairly good performance because its accuracy reached 94.29% in the 60th epoch with the kernel size on the first convolutional layer of 3x3 and the kernel size on the second convolutional layer 2x2. There are still many opportunities for further research where banknote image capture can be applied to bionic glasses that can be integrated with smartphones in order to help people with visual impairments.

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