Accredited Ranking SINTA 2
Decree of the Director General of Higher Education, Research, and Technology, No. 158/E/KPT/2021
Validity period from Volume 5 Number 2 of 2021 to Volume 10 Number 1 of 2026

Published online on: **http://jurnal.iaii.or.id**

JURNAL RESTI
(Rekayasa Sistem dan Teknologi Informasi)
Vol. 6 No. 2 (2022) 259 - 268 ISSN Media Electronic: 2580-0760

Classification of Rupiah to Help Blind with The Convolutional Neural Network Method

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Abstract

Currency is an item humans require as a medium of exchange in transactions, including for those with vision impairments. It can be challenging for certain blind people to identify currencies. This research aimed to help blind people identify nominal currency when in the transaction. Deep Learning with the CNN algorithm and preprocessing with a sequential model were the methods used in this research. This algorithm is modeled as neurons in the human brain that communicate and learn patterns. Data collecting, preprocessing, testing, and evaluation are the stages in this research. 681 datasets are used, consisting of IDR 50.000, IDR 75.000, and IDR 100.000. Model testing was carried out with different iterations of 5, 10, 15, and 20 epochs. Different epoch values will affect the time it takes the model to learn, but the longer of learning process will result more accurate models. The highest result obtained from all epoch tests is 100%. The class prediction results for the 69 test data show that they can be predicted based on the actual class, indicating that the model is adequate. The results of this classification might be used to construct a smartphone app that would assist visually challenged people in recognizing the nominals.

Keywords: *Blind, Currency, Deep Learning, CNN, Epoch*

1. Introduction

Money is a medium of exchange for transactions that can be in the form of pieces of metal or a sheet of paper and have different nominal values. Money becomes an item that is needed by humans, not least for people with disabilities such as the visually impaired who have limitations in seeing. The number of visually impaired people in Indonesia is the fourth greatest type of disabilities, according to data from the Ministry of Social Affairs of the Republic of Indonesia's Information System Management of Persons with Disabilities [1]. Meanwhile, according to the Persatuan Tunanetra Indonesia (Pertuni) based on estimates by the Indonesian Ministry of Health, the number of blind people reaches 1% of the total population of Indonesia [2].

The blind code feature applied to the paper rupiah currency, according to Bank Indonesia, can make it easier for the visually impaired to recognize the nominal value of money [3], [4]. But the existence of this feature seems to be still not widely known or understood by people with disabilities. This is proven by the continued frequency of examples of fraud peIDRetrated by unscrupulous individuals who take advantage of blind people's inability to identify money [5], [6]. Based on these problems, it is necessary to have a system that can help people with visual impairment to detect the nominal value of the currency at the time of making transactions.

Some research related to the above problems have been done using computer vision techniques. Computer vision is the field of artificial intelligence to train computers using deep learning so that computers are able to recognize and classify an object, especially in the form of images or pictures. Research using computer vision techniques can also be applied to classify and recognize the image of money, evidenced by some literacy related research that has been done. In the research Umar et al, using Local Binary Pattern (LBP) method for feature extraction and K-Means

Accepted: 04-02-2022 | Received in revised: 25-04-2022 | Published: 29-04-2022

Clustering for image classification of rupiah money is able to produce an average accuracy of 96.67% [7]. While in Miladiah et al, research, if the classification method is changed to K-Nearest Neighbor, the average accuracy produced is 95% [8]. Another method used by Sekarani et al, to detect banknotes is the support Vector Machine (SVM) supported with K-Fold Cross Validation to divide test data and training data that is able to detect money with 95% accuracy [9]. Pratama et al, research using RGB and K-Nearest Neighbor feature extraction method was able to detect the nominal value of money with an accuracy of 93.7% [10]. When using Accelerated Up Robust Feature (SURF) feature extraction method combined with feature matching identification method with Fast Library for Approximate Nearest Neighbors (FLANN) in Priadana and Murdiyanto research, the system can detect with 100% accuracy [11]. Another study by Birowo using the EigenFace method is able to recognize the image of money with an accuracy of 95.3% [12]. A study to recognize currencies using deep CNN 3 layer by Naresh Kumar et al, resulted in an accuracy of 96% [13]. While another study by Kamble et al, using the same algorithm only get an accuracy of 85.6% [14]. Ahmed et al, used Principal Component Analysis (PCA), LBP, Euclidean Distance, and a combination of these three methods obtained the best accuracy is when PCA combined with LBP at 100% [15]. Then research to recognize Rupee money by Dhapare et al, using C4.5 Decision Tree get accuracy of 93.94% [16]. Another method applied by Upadhyaya et al, is logistic regression which produces accuracy up to 99% [17]. Research by Dhar et al, to recognize the currency of Bangladesh (Taka) combining two features of extraction of LBP and SURF was able to produce an accuracy of 92.6% [18]. Jadhav et al, using deep learning algorithms with CNN to identify currencies from several countries showed that the method is capable of identifying counterfeit money [19]. Sarfraz et al, using SVM supported Scanning Electron Microscopy (SEM) and X-Ray Diffraction (XRD) were able to identify the authenticity of the Pakistani currency with almost 100% accuracy [20]. Kulkarni et al, comparing several algorithms such as SIFT, ORB, SURF, KAZE, BRISK, and FAST to identify the authenticity of money showed that the best algorithm is ORB with 92% accuracy [21]. From some research that has been done before shows that computer vision is able to solve problems related to paper money. However, most of these studies still use machine learning methods. While the newer method of deep learning is still not widely used. In addition to methods, most research datasets still use foreign currency.

This research aims to classify the nominal value of rupiah currency that can help people with visual impairment when making transactions. The Dataset used as the object of this study consists of rupiah banknotes for the year of emission 2016 worth IDR 50,000 and IDR 100,000 and "Uang Peringatan Kemerdekaan" (UPK) 75 which is worth IDR 75,000. The consideration for using the rupiah in the 2016 emission year is because it has not been widely used as an object of research, especially the IDR 75.000 money that was only issued in 2020. With banknotes of IDR 75,000 and IDR 100,000 have visual characteristics that are quite similar. From the three currency classes, front and rear-view images were taken using the Realme C17 mobile phone camera. The number of image data taken as many as 681 images which are then divided into data train, data validation, and data test. Because the dataset used consists of 3 classes, the class mode used is categorical. While the method to be used to identify the nominal value of money is a Deep Learning method with Sequential Convolutional Neural Network (CNN) algorithm.

Similar research has been done by Kurniawati et al, using Neural Network as a pattern of color recognition and learning [22]. While in this research using the architecture or method Convolutional Neural Network (CNN) which is actually part of the Neural Network (NN) itself. The fundamental difference that can be seen between the two is in the previous research applying embedded system in the recognition system that uses NN into a device equipped with TCS3200 sensors and several other components. While in this study will create a classification system that is expected to be developed into an application for use on smartphones.

2. Research Methods

The method to be used to classify the nominal value of money is Deep Learning method with Sequential Convolutional Neural Network (CNN) algorithm. This study was conducted in several stages as seen in Figure 1. The study began with the collection of image data for IDR 50,000, IDR 75,000, and IDR 100,000 which were divided into training data, validation data, and test data automatically. Then pass preprocessing with augmentation. The next stage is to build a model that will be trained in the training stage, and tested in the testing stage. The last step is to evaluate the model that has been made using confusion matrix.

2.1. Collecting Data

In Figure 2 shows the process of collecting data that will be used in this study, namely rupiah banknotes for the year of emission 2016 with a nominal of IDR 50,000, IDR 100,000 and uang peringatan kemerdekaan (UPK) 75 year of 2020 which is worth IDR 75,000. The condition of the money used is money that has been used to transact but is still in good condition or clean of stains and streaks, but specifically for UPK 75 using

DOI: https://doi.org/10.29207/resti.v6i2.3852

money that is still new. This data capture using the Realme C17 phone camera with the help of a tripod with a distance of 25 cm. The number of images or images of banknotes as many as 681 images, with details as follows, each banknote is grouped into 3 classes with shooting from the front side and the back side, the 50 thousand class group consists of 226 images, the 75 thousand class group consists of 235 images, and the 100 thousand class group consists of 220 images.

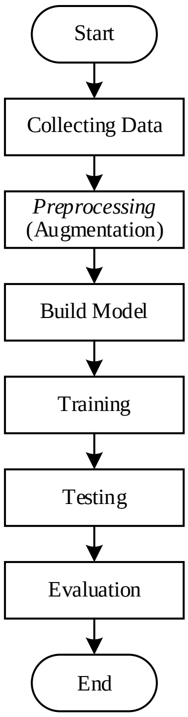


Figure 1. Research Stage

Figure 2. Data Retrieval Process

2.1.1. Splitting Dataset

In this study the dataset is divided automatically into 3 parts, namely:

Training Set

A Training set is a set of data used to train or build a model. From the 681 images taken, as many as 544 images were included as part of the training set.

Validation Set

Validation set is a set of data used to optimize the model being trained. From the 681 images taken, as many as 69 images are included as part of the validation set.

Testing Set

Testing set is a set of data that is used to test the ability of the model after the training process is completed. From the 681 images taken, as many as 68 images are included as part of the testing set.

2.2. Preprocessing

Preprocessing conducted in this study is data augmentation, which is a technique to manipulate a data without losing the core of the data. If the data used is in the form of an image or picture, it can be done in several ways such as rotate, flip, crop, and several other ways to manipulate the data. In this study the augmentation process is rotate and flip as shown in Figure 5.

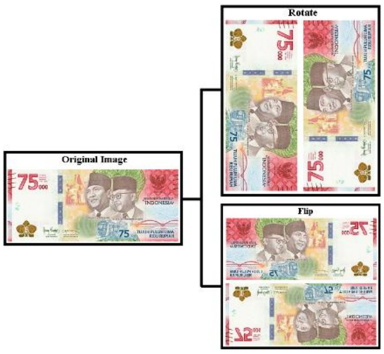


Figure 3. Data augmentation with Rotate and Flip

2.3. Build Model

To create a classification system, a deep learning model with CNN is needed that is composed of several layers. This Model will be trained in the training process and used in the process of predicting the nominal value of money.

2.3.1. Deep Learning

Deep Learning is a branch of machine learning that develops in the field of artificial neural network (ANN). ANN had a goal to simulate biological neural networks, but it was still too simple [23]. The algorithm adapts the workings of the human brain. Deep Learning is designed so that machines can recognize visual images (computer vision), recognize sounds (speech recognition), machines can communicate with humans (natural language processing), and several other capabilities [24]. In this study, the required ability is the

DOI: https://doi.org/10.29207/resti.v6i2.3852

ability of the system to recognize visual images with the best accuracy.

2.3.2. Convolutional Neural Network (CNN)

CNN is a development of Multi Layer Perceptron (MLP) and one of the most widely used neural network architectures in the field of image processing [25]. This architecture was developed by a Japanese researcher, Kunihiko Fukushima in 1980 under the name NeoCognitron [26]. The discovery is unique in pattern recognition, that is, it is not affected by changes in position. This research uses CNN sequential architecture consisting of several layers, namely input, convolutional, pooling, flatten, dense, fully connected, and output. Sequential is generally a linear composition of Keras layers. This Model is easy, lightweight as well as can represent almost everything available in the neural network. Sequential displays model classes to create models that are tailored to the needs of its users. Users can use the concept of sub-classes to create complex models individually.

2.3.3. Currency Rupiah Classification Model

The model architecture created for the currency rupiah nominal classification system can be seen in figure 4. The Model is composed of several layers such as convolutional, pooling, flattened, dense, and fully connected layers. The difference between Neural Network and CNN can be seen by the convolution processes and subsampling processes in the CNN architecture.

2.3.3.1. Convolution

Convolution is a process that uses filters for input. In the study of the input used in the form of images the filter used is the size of height, width, and thickness. The value given to this filter is random, where the value is a parameter that affects the learning process. In this study, there are three times processes on the convolution layer with different parameter values, namely 32, 64, and 128 which can be seen in Figure 4.

2.3.3.2. Subsampling

Subsampling is the process of reducing the size of an image data. In image processing, this process aims to increase the positional invariance of the feature. In most CNN, the subsampling method used is max pooling which can be seen in Figure 5. The Max pooling/pooling layer divides the output of the convolution layer into several small grids and then takes the maximum value from each grid to compose the reduced image matrix [27].

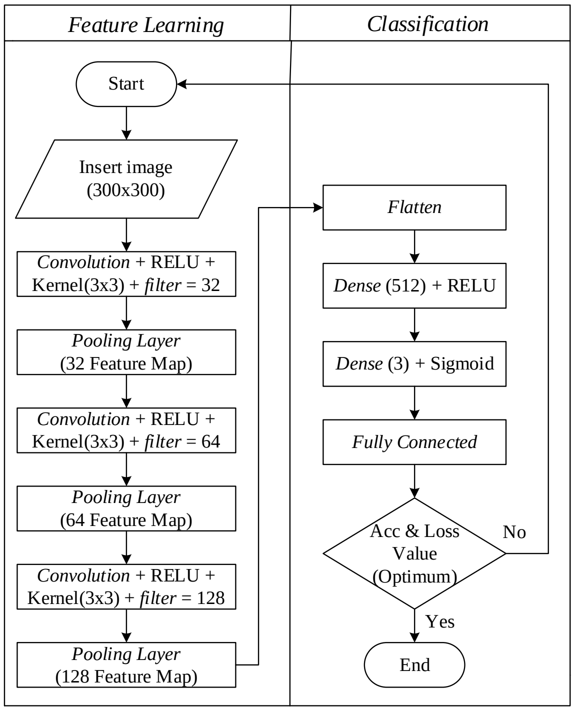


Figure 4. Sequential CNN Architecture

2.4. Training

The Training Process is a stage where the model built will be trained to learn information from the image data in the training set. The training process also uses validation sets to optimize the model being trained to achieve maximum results.

2.5. Testing

This process will be tested on the ability of the model built and has been trained in classifying the nominal value of the currency rupiah. There are 2 ways of testing can be done, namely testing the data as a whole in one folder and testing the data one by one.

2.6. Evaluation

Evaluation is the measurement of performance or model ability based on the training process that has been done. To find out how the performance of the model that has been made can use the help of a confusion matrix.

2.6.1. Confusion Matrix

To obtain the accuracy of the process of classifying money, this study uses the Confusion Matrix. The Confusion Matrix is a table with different combinations of predicted values and actual values commonly used to measure performance in machine learning classification processes [28]. Four terms represent the results of the classification process in the confusion matrix, namely True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) like a table 1.

Table 1. Confusion Matrix

Class	Actual (Positive)	Actual (Negative)
Predicted (True)	TP (True Positive)	TN (True Negative)
Predicted (False)	FP (False Positive)	FN (False Negative)

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \times 100\% \quad (1)$$

$$\text{Precision} = \frac{\text{TP}}{\text{FP+TP}} \times 100\% \quad (2)$$

$$\text{Recall} = \frac{\text{TP}}{\text{FN+TP}} \times 100\% \quad (3)$$

The results of the confusion matrix can be used to calculate the value of accuracy, precision, and recall. Accuracy is the degree of accuracy of a model in classifying objects, which can be calculated using Formula (1). Precision is the conformity between the expected data with the predicted results of the model, which can be calculated by Formula (2). Recall is the ability of the model to rediscover information once received, it can be calculated using the formula (3).

3. Results and Discussion

The results of this study showed that the Sequential Convolutional Neural Network (CNN) algorithm can read the nominal currency rupiah based on the results of data testing through the image classification stage to determine the value of accuracy obtained. This model tested using a Jupyter Notebook with a dataset of 681 images. The dataset consists of several nominal, they are IDR 50,000, IDR 75,000, and IDR 100,000, which divided into training data, validation data, and testing data. The IDR 75,000 is special edition money that many rejected in the sale and purchase transactions by traders in various regions in Indonesia because it is considered not a legitimate medium of exchange. So, the reason for the selection of IDR 75,000 money to be one of the datasets is to inform the public that although the money is issued specifically, it is still declared as a legal tender or medium of exchange by Bank Indonesia. So, expect no more rejection of the money.

In the training phase, each weight and bias of each neuron will be updated continuously until the output is generated as expected. In each iteration (epoch) will be an evaluation process that is used to determine when to stop the training process (stopping point), so that the better the system in learning the training data, the better the system in predicting the testing data. This test is done to get the best accuracy value with the loss value getting smaller and higher accuracy value.

3.1. Training Model

This model tested in different epoch values, they were 5, 10, 15 and 20 epochs. The results of training process were as follows:

1. Models with an Epoch value of 5

This model will see the results of visualization during training, where all training loss or accuracy and validation loss or validation accuracy will be represented in table 2, figure 5, and figure 6.

Table 2. The Results of Accuracy Test with Epoch Value 5

Epoch	Loss	Accuracy	Validation Loss	Validation Accuracy
1/5	1.9640	0.6000	1.1024	0.6000
2/5	0.1563	0.9667	0.0294	1.0000
3/5	0.0186	1.0000	0.0112	1.0000
4/5	0.0091	1.0000	0.0071	1.0000
5/5	0.0065	1.0000	0.0066	1.0000

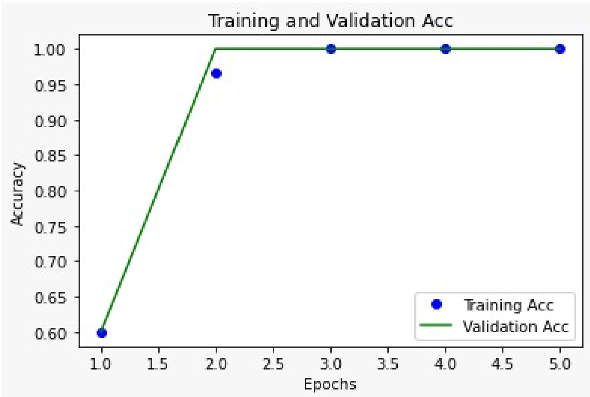


Figure 5. Training and Validation Accuracy on Epoch 5

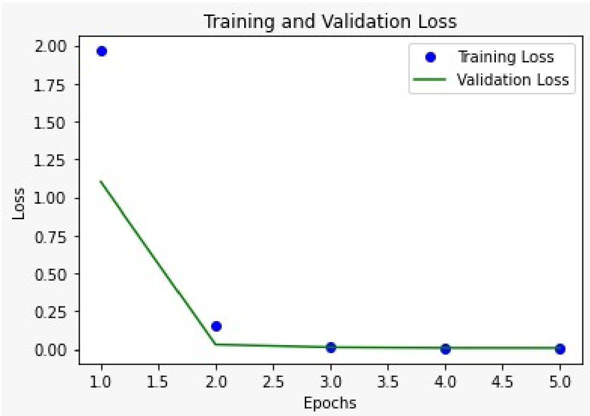


Figure 6. Training and Validation Loss on Epoch 5

In figure 5 and figure 6 it is seen that the X-axis shows epoch and Y-axis shows accuracy with accuracy and loss values that are close to stable, where the accuracy of the data train reaches 100% and the accuracy of the validation data also reaches 100% in the 3th to 5th epochs, with the lowest accuracy value of 60%. While

DOI: https://doi.org/10.29207/resti.v6i2.3852

the value of loss decreased with increasing epoch. But in the 3 until 5 epochs, the difference in loss value is not too large. So, the graph shows that the model is trained for good fitting.

2. Models with an Epoch value of 10

This model will see the results of visualization during training, where all training loss or accuracy and validation loss or validation accuracy will be represented in table 3, figure 7, and figure 8.

Table 3. The Results of Accuracy Test with Epoch Value 10

Epoch	Loss	Accuracy	Validation Loss	Validation Accuracy
1/10	1.0958	0.7333	0.2114	1.0000
2/10	0.3872	0.8983	0.0691	1.0000
3/10	0.0615	0.9833	0.0200	1.0000
4/10	0.0128	1.0000	0.0097	1.0000
5/10	0.0085	1.0000	0.0081	1.0000
6/10	0.0064	1.0000	0.0059	1.0000
7/10	0.0058	1.0000	0.0056	1.0000
8/10	0.0054	1.0000	0.0054	1.0000
9/10	0.0053	1.0000	0.0053	1.0000
10/10	0.0052	1.0000	0.0052	1.0000

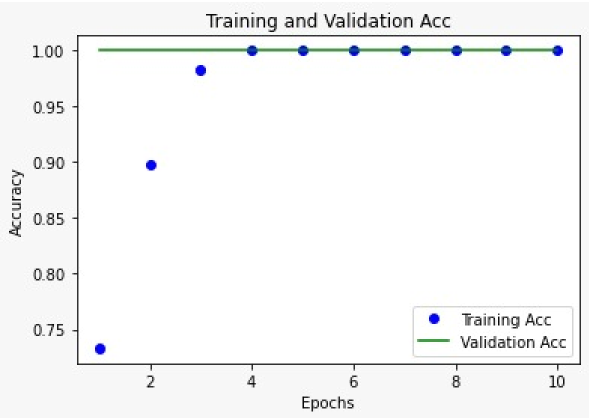


Figure 7. Training and Validation Accuracy on Epoch 10

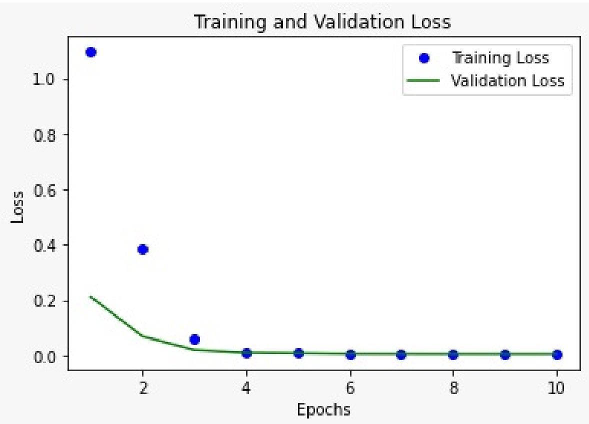


Figure 8. Training and Validation Loss on Epoch 10

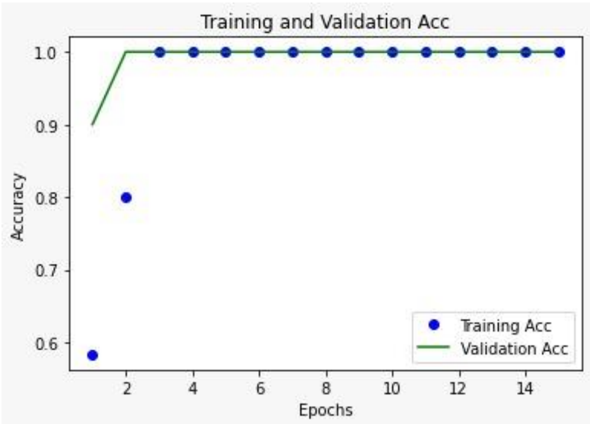
Figure 7 and figure 8 shows the value of accuracy and loss are stable, where the value of data train accuracy reaches 100% and the value of the accuracy of the validation data also reaches 100% in the 4th to 10th epochs, with the lowest accuracy value of 70%. Thus, the graph model shows the occurrence of underfitting but with more stable graph results compared to the Model 5 epoch.

3. Models with an Epoch value of 15

This model will see the results of visualization during training, where all training loss or accuracy and validation loss or validation accuracy will be represented in table 4, figure 9, and figure 10.

Table 4. The Results of Accuracy Test with Epoch Value 15

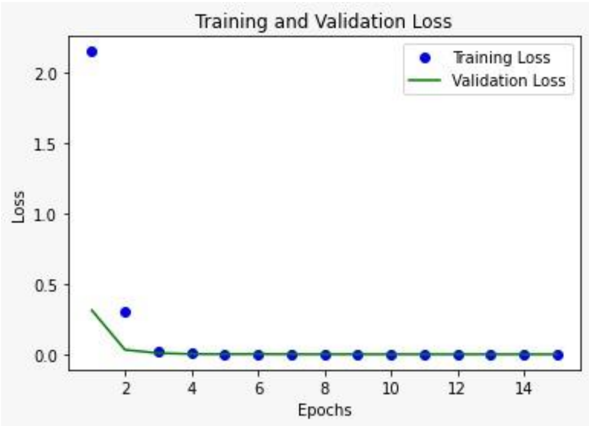
Epoch	Loss	Accuracy	Validation Loss	Validation Accuracy
1/15	2.1511	0.5833	0.3168	0.9000
2/15	0.3071	0.8000	0.0369	1.0000
3/15	0.0203	1.0000	0.0135	1.0000
4/15	0.0098	1.0000	0.0070	1.0000
5/15	0.0065	1.0000	0.0061	1.0000
6/15	0.0059	1.0000	0.0070	1.0000
7/15	0.0060	1.0000	0.0055	1.0000
8/15	0.0055	1.0000	0.0055	1.0000
9/15	0.0054	1.0000	0.0054	1.0000
10/15	0.0054	1.0000	0.0053	1.0000
11/15	0.0053	1.0000	0.0053	1.0000
12/15	0.0052	1.0000	0.0052	1.0000
13/15	0.0052	1.0000	0.0051	1.0000
14/15	0.0051	1.0000	0.0050	1.0000
15/15	0.0050	1.0000	0.0049	1.0000



Gambar 9. Training and Validation of Accuracy on Epoch 15

Figure 9 and Figure 10 shows the value of accuracy and loss are stable, where the value of data train accuracy reaches 100% and the value of the accuracy of the validation data also reaches 100% in the 3th to 15th epochs, with the lowest accuracy value close to 60%. Thus, the graph model shows the occurrence of underfitting but with more stable graph results compared to the Model 10 epoch.

DOI: https://doi.org/10.29207/resti.v6i2.3852



Gambar 10. Training and Validation of Loss on Epoch 15

4. Models with an Epoch value of 20

This model will see the results of visualization during training, where all training loss or accuracy and validation loss or validation accuracy will be represented in table 5, figure 11, and figure 12.

Table 5. The Results of Accuracy Test with Epoch Value 20

Epoch	Loss	Accuracy	Validation Loss	Validation Accuracy
1/20	1.5641	0.5085	0.3056	1.0000
2/20	0.1544	1.0000	0.0326	1.0000
3/20	0.0233	1.0000	0.0119	1.0000
4/20	0.0091	1.0000	0.0070	1.0000
5/20	0.0067	1.0000	0.0060	1.0000
6/20	0.0057	1.0000	0.0056	1.0000
7/20	0.0560	0.9833	4.6473	0.3000
8/20	0.3922	0.9333	0.0069	1.0000
9/20	0.0070	1.0000	0.0060	1.0000
10/20	0.0065	1.0000	0.0059	1.0000
11/20	0.0059	1.0000	0.0056	1.0000
12/20	0.0055	1.0000	0.0054	1.0000
13/20	0.0054	1.0000	0.0053	1.0000
14/20	0.0053	1.0000	0.0052	1.0000
15/20	0.0052	1.0000	0.0052	1.0000
16/20	0.3774	1.0000	0.0066	1.0000
17/20	0.0060	1.0000	0.0055	1.0000
18/20	0.0064	1.0000	0.0053	1.0000
19/20	0.0053	1.0000	0.0052	1.0000
20/20	0.0052	1.0000	0.0052	1.0000

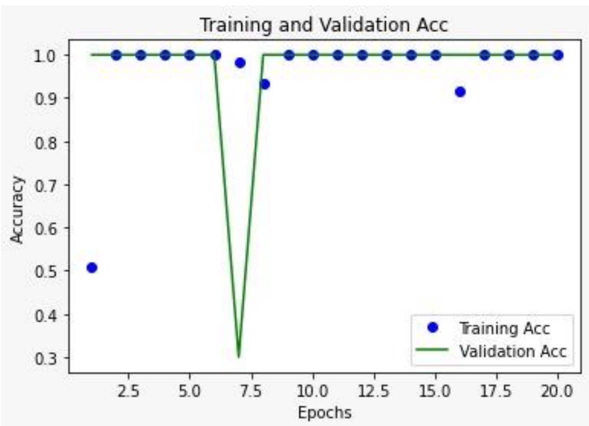


Figure 11. Training and Validation of Accuracy on Epoch 20

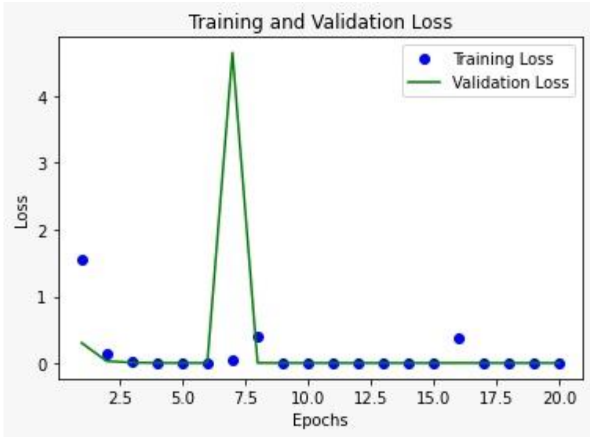


Figure 12. Training and Validation of Loss on Epoch 20

Figures 11 and 12 show that the value of accuracy and loss are less stable, with the value of data train accuracy reaching 100% and the value of validation data accuracy also reaching 100% in the 2nd to 6th epochs, but the value of accuracy has decreased slightly in the 7th and 8th epochs, with the lowest accuracy value close to 50%. Because the model has increased and decreased, the model graph represents the occurrence of overfitting, although the loss value tends to remain stable at some points.

Based on the training and validation of the four models obtained results that show the value of data train accuracy of 100% and data validation results in the lowest accuracy value of 50%. In models with epoch values 5, 10 and 15 produce stable graphs with underfitting models while in models with epoch values 20 produce less stable graphs and overfitting occurs in the model. This happens because the system is not good enough in learning the training data with 20 iterations, but the system can predict the testing data very well. The Program is said to be good when the accuracy value is higher while the loss value is lower, this can be proven in the results of the table that shows every epoch increase the accuracy value reaches 100% while the loss value is only 0.5%.

3.2. Model Testing

In the classification process for data train, each category of banknotes using 244 image data for training, while for data testing there are 25 images of money IDR 50,000, 22 images for nominal money IDR 75,000 and 22 images for nominal money IDR 100,000. Data testing is used to test whether the nominal money. Testing Data is used to test whether the nominal money tested in accordance with the real predicted class and determine whether the program runs correctly as expected with the results of testing that has been done. Based on Table 2 to Table 5 above, it can be seen that the system managed to classify all the images of banknotes of IDR 50,000, IDR 75,000, and IDR

100,000 as evidenced by the predicted class value of 1 or close to 1 shown in the figure below.

```
In [8]: class_dictionary = train_generator.class_indices
        class_dictionary

Out[8]: {'100_ribu': 0, '50_ribu': 1, '75_ribu': 2}
```

Gambar 13. Class dictionary of the data


```
Predicted class is: [[0.1103473  0.9996568  0.00114542]]
```

Figure 14. The Results of Testing Image Money 50 Ribu


```
Predicted class is: [[0.03905272 0.02986962 0.95450795]]
```

Figure 15. The Results of Testing Image Money 75 Ribu


```
Predicted class is: [[0.97282493 0.07841939 0.04304168]]
```

Figure 16. The Results of Testing Image Money 100 Ribu

The result of class division of the trained dataset is shown in Figure 13. The data was classified: IDR 100,000 in Class 0, IDR 50,000 in Class 1, and IDR 75,000 in Class 2. Figure 14 shows the results of testing for the IDR 50,000 currency parameters, which show that the system successfully classifies the image of the currency with the results of the anticipated class, and that is value 1, in the second column (Class 1). The results of testing for the parameters of the currency IDR 75,000 are displayed in Figure 15, where the results indicate that the system properly classifies the currency images with the results of the predicted class, which is value 1, in the third column (Class 2). Figure 16 shows the results of testing for the IDR 100,000 currency parameters, which show that the system successfully classifies the image of the currency with the results of the predicted class, which is value 1, in the first column (Class 0).

3.3. Evaluation of the Model

The CNN model's performance for the nominal classification of rupiah must be evaluated in order to see how well it predicts the test data.

Table 6. Test Results

		Actual Class	
Predicted Class	IDR 50.000 (25 Data)	IDR 75.000 (22 Data)	IDR 100.000 (22 Data)
IDR 50.000	100%	-	-
IDR 75.000	-	100%	-
IDR 100.000	-	-	100%

Based on the results of the predicted class, the system managed to predict in accordance with each nominal image of money both from the front side and the back side. In the confusion matrix results in Table 6, the three nominal classes of money generate image detection of money that corresponds to the actual class by using the CNN algorithm. The following is the result of accuracy value calculation, precision, and recall of the system created.

$$\text{Accuracy} = \frac{69+0}{69+0+0+0} \times 100\% = 100\%$$

$$\text{Precision} = \frac{69}{0+69} \times 100\% = 100\%$$

$$\text{Recall} = \frac{69}{0+69} \times 100\% = 100\%$$

The results of the training and testing process are quite good, with the value of accuracy, precision, and recall reaching a value of 100 percent.

4. Conclusion

The value of the rupiah currency was successfully identified using the Deep Learning Methodology and the Sequential CNN algorithm. The accuracy rate of 100 percent is obtained from 3 currency classes with a total quantity of data of 681, where 80 percent of the data is used as training data and 20 percent as validation data. The model's ability to correctly forecast the testing data is demonstrated by the outcomes of the predicted class of 69 testing data evaluated. The system is then indicated to be successful in forecasting based on each nominal image of money on the front or rear.

Furthermore, the number of epochs in the learning system influences the degree of accuracy obtained as well as the length of time it takes to analyze data. The more data the system learns, the better it anticipates the testing data and the longer it takes to process the data. The algorithms, methods, and tools chosen have a significant impact on the accuracy obtained.

The results of the classification and identification method, which can read the nominal value of rupiah currency, can be developed to assist people with visual impairments in conducting transactions. The development that can be done is to create a smartphone application that produces a sound notification when the nominal money is successfully recognized. Furthermore, the findings of this study can be used to the process of combining many collections of money, because in some transactions, more than one item of money is used.

Acknowledgment

Thanks to Kemendikbudristek RI and Huawei who have organized the MSIB Batch 1 program so that this research can be carried out. This research is part of the final project on the topic of Artificial Intelligence. Thanks also to all the mentors who have guided and involved in this research.

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DOI: https://doi.org/10.29207/resti.v6i2.3852