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Nominal Detection of Rupiah Banknotes with Audio Output Using MobileNetV2 Transfer Learning Method

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Abstract

Banknotes are widely used all over the world. Banknotes are a means of payment used by the public, including the visually impaired. The visually impaired still depend on others to recognize the nominal rupiah banknotes. One of the efforts that can help the visually impaired is creating a machine-learning model that can recognize the nominal rupiah banknotes. This research aims to assist the visually impaired in independently identifying the nominal rupiah banknotes. In this study, the MobileNetV2 pre-trained model was used to learn how to make a model that can detect the nominal amount of rupiah banknotes. The dataset consisted of 1,400 images of rupiah banknotes, divided into 80% for training data and 20% for testing data. The evaluation carried out on the model using the confusion matrix resulted in a model accuracy value of 99.2%.

Keywords: *Blind, Banknotes, Pre-trained Model, MobileNetV2, Tensorflow*

1. Introduction

Banknotes are a form of currency widely used around the world. They are often used to make payments for goods and services during buying and selling activities. As a means of making payments, paper money has become a tool used by people worldwide, including the visually impaired. However, with their limitations, there is a possibility of a situation where banknotes are exchanged and mistaken, and the worst thing is that some people maliciously take advantage of the situation [1] .

In society, the general term "visually impaired" refers to a person who experiences impairments or impairments in the functioning of the sense of vision [2]. The visual limitations of blind people are an obstacle to communicating with the surrounding environment. This is because they can only rely on their sense of touch and hearing to understand information [3]. One of the vital aspects of daily life is the ability to recognize and distinguish the nominal amount of paper money, which is very important for transacting and managing finances independently. However, visually impaired people often face difficulties in doing this. Vision limitations force them to recognize banknotes using their sense of touch [4].

Visually impaired people are still often faced with a one-sided view and are considered incapable of living independently. Therefore, the role of institutions and active participation of the community is needed to provide guidance and assistance to them. At this time, one of the ways the visually impaired can identify the nominal of banknotes is by sorting banknotes from the largest nominal to the smallest. In addition, they also make folds of money with different patterns, such as folding IDR 100,000 bills into two parts or folding IDR 50,000 bills to form triangles [5].

An official institution, namely Bank Indonesia, has tried to overcome this problem. Bank Indonesia released the latest design of the 2016 banknotes, which includes a blind code on the face of the banknote [6]. Although currently, the rupiah banknote has been equipped with a blind code feature, which is in the form of an embossed line on the side of the banknote [7], this is less effective because most of the money in circulation in the community is shabby so that the blind code is difficult to touch and recognize [8]. This can result in vulnerability to fraud and errors in financial transactions.

One of the efforts that can assist visually impaired individuals in identifying the nominal of Indonesian Rupiah banknotes is the development of a mobile application capable of recognizing banknote values and providing audio-based output. An effective method that can be utilized for this purpose is the application of Artificial Intelligence (AI).

Artificial Intelligence (AI) is a branch of computer science that studies how machines (computers) can be developed to behave and think in ways that resemble human intelligence [9]. One of the most widely used approaches within AI is machine learning, which has been applied extensively for various purposes, particularly in object identification tasks.

In the modern era, the capabilities of deep learning have demonstrated remarkable performance, largely driven by advances in computational power, the availability of large-scale datasets, and improved training techniques for deep neural networks [10]. One of the commonly used algorithms in deep learning is the Convolutional Neural Network (CNN). Past research has demonstrated the effectiveness of CNN in classifying batik motifs, revealing an model accuracy of 89% [11]. To leverage the potential of CNNs while simultaneously reducing computational burden and accelerating model development, the transfer learning method can be employed [12]. Transfer learning is an approach that utilizes a previously trained (pre-trained) model as a starting point for learning a new or related task [13].

Previous research has demonstrated the successful use of the pre-trained MobileNetV2 model for object detection tasks. Evan et al. [14], utilized MobileNetV2 to detect traffic lights and generate real-time audio output using the TensorFlow framework. Their results showed an object detection accuracy of 97.98%, while the generated audio output achieved 100% accuracy.

In addition, another study successfully identified the nominal of Indonesian Rupiah banknotes using the pre-trained VGG-16 model [15]. This research, conducted by Andi Muhammad et al., employed a dataset of 630 images across seven classes, with each class containing 90 images. The VGG-16 model achieved an accuracy of 83% in identifying the banknote nominal.

Related work was also carried out by Ario Prima et al. [16]. This study utilized a dataset of 7,035 images of Indonesian Rupiah banknotes issued in 2022, with the training process conducted for a total of 56,900 steps. The results demonstrated that the SSD MobileNetV3 model performed well in detecting banknote nominal, achieving an average model accuracy of 91.28%.

By applying the transfer learning approach, we intend to utilize the pre-trained MobileNetV2 model as the foundational architecture for developing a model capable of detecting the nominal of Indonesian Rupiah banknotes and producing audio output. The distinction of the proposed study lies in the choice of the pre-trained model, namely MobileNetV2. This model was selected due to its lightweight and efficient performance, making it suitable for deployment on mobile devices [17].

The banknotes used in this study consist of the 2022 emission series of Indonesian Rupiah in nominal of IDR 1,000, IDR 2,000, IDR 5,000, IDR 10,000, IDR 20,000, IDR 50,000, and IDR 100,000. The primary objective examined in this research is the detection of banknote nominal, the authenticity of the banknotes is not included as part of the evaluation. This study aims to produce a trained model using the transfer learning method, capable of performing real-time nominal detection of Rupiah banknotes. The resulting machine learning model is then implemented into an Android application to validate and test its performance. The audio output feature is developed using the Text-to-Speech (TTS) capabilities provided by Android Studio.

2. Methodology

The research methodology used by we in the study consists of several stages, as seen in Figure 1.

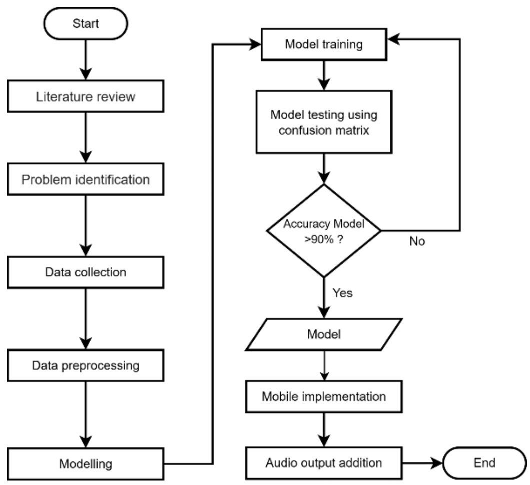


Figure 1. Research methodology.

2.1 Literature Review and Problem Identification

Literature studies were conducted as an initial step to gather theoretical foundations and relevant information related to the research topic. This stage aimed to identify research gaps and strengthen the scientific basis of the study by reviewing previous works. The literature reviewed focused on studies related to banknote denomination detection using various methods, which served as references in designing the proposed system and determining suitable approaches for this research.

Based on the insights obtained from the literature review, the next stage involved direct observation to understand real-world conditions. Observations were carried out to examine buying and selling transaction processes within the community, particularly those involving people with special needs, such as visually impaired individuals. In addition, the study observed the primary transaction tools used, namely paper banknotes. These observations were conducted at the Bangkinang State Special School (SLBN) to obtain contextual and practical data relevant to the research objectives.

To further deepen the understanding gained from observations, interviews were conducted with relevant stakeholders. Mrs. Yerna Ayub, a teacher at SLB Bangkinang, was interviewed on February 20, 2024. Through direct discussions with experienced teachers who work closely with visually impaired students, valuable insights were obtained regarding the daily challenges faced by visually impaired individuals, particularly in conducting financial transactions independently.

The results of the observation and interview stages revealed a significant problem encountered by visually impaired individuals in performing buying and selling transactions. Their visual limitations pose substantial barriers to interacting with the surrounding environment, especially when identifying banknote denominations. As a result, visually impaired individuals rely heavily on their senses of touch and hearing to interpret information, which is often insufficient for accurately recognizing paper money. These findings underline the importance of developing an assistive technological solution to support financial independence for visually impaired people.

2.2 Data Collection and Labelling

Data was collected directly by taking photos of Rupiah banknotes using a Redmi Note 11 Pro 5G[1] (48 MP) smartphone camera that produced a photo file with a JPG extension. The dataset used in this study is image data on rupiah banknotes of IDR 1,000, IDR 2,000, IDR 5,000, IDR 10,000, IDR 20,000, IDR 50,000, IDR 100,000 issued in 2022. All images were taken at a 90-degree angle, with a mix of both front and back sides of banknote. In addition, several images were captured with a rotation of approximately 30 degrees to increase dataset variability. The photo-taking process was conducted under natural lighting conditions, using a plain white background, at an approximate distance of 30 cm from the banknote. The banknotes used varied in condition, ranging from new to slightly worn. The collected images were then organized into training and testing sets using an 80:20 split, resulting in 1,120 training images and 280 testing images.

Figure 2. Dataset examples.

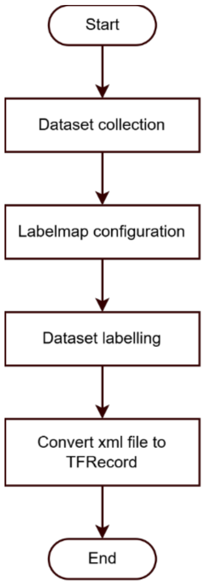


Figure 3. Flowchart preprocessing data.

Following the data collection stage, the next process involved labeling the acquired images to prepare them for model training, as illustrated in Figure 3. Flowchart preprocessing data. Labeling was performed using the LabelImg[2] software, which is integrated with Python, by assigning

[1] https://www.mi.co.id/id/product/redmi-note-11-pro-5g/

[2] https://github.com/HumanSignal/labelImg

annotations to each image in the dataset. Through this process, each labeled image generated an annotation file in XML format, which was then stored in the corresponding training and testing directories. After all images had been successfully labeled, a labelmap was created to define each class name and assign it to a corresponding integer-based class ID. Furthermore, before the dataset could be utilized in the model training phase, the labeled data were converted into the TFRecord format. TFRecord is a data serialization format used by TensorFlow to efficiently store and process large-scale datasets during training and evaluation.

2.3 Model Building and Evaluation

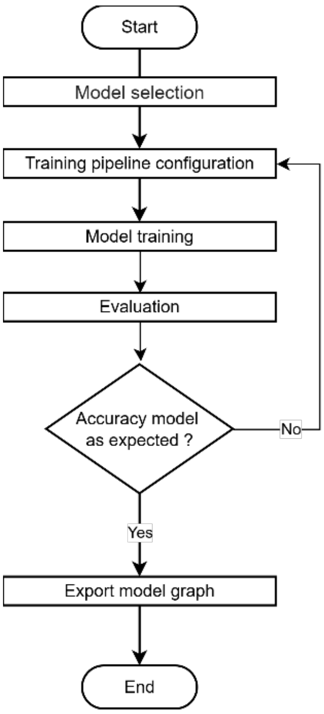


Figure 4. Flowchart model training

At this stage, we builds a model using the MobileNetV2 pre-trained model as the basis for learning transfer learning. Figure 4 shows the architecture of MobileNetV2. The model needs to be prepared through the configuration of the training pipeline, which defines the parameters of the model that will be used in the training process. The configuration file is provided in the Tensorflow Zoo models folder and obtained from the Tensorflow Object Detection API[3], a pipeline.config file. In this study, the pipeline. the hyperparameters of the model were configured according to Table 1. After the training process is completed, the performance of the MobileNetV2 model is evaluated and its accuracy is compared with the accuracy of VGG-16 and MobileNetV3 models reported in previous related studies. This comparison is carried out to understand how well the MobileNetV2 model performs compared to other deep learning models used in similar research.

Following the pipeline configuration, the next step is model training, as illustrated in Figure 5. The training process is carried out using Jupyter Notebook. The model is trained for 100,000 steps with a batch size of 4. The training process takes approximately 1 hour and 46 minutes and is conducted using a Legion Five Pro laptop equipped with an Intel Core i7-12700H processor and an NVIDIA RTX 3070Ti GPU. After the training is completed, the training results are monitored using TensorBoard, which provides visualizations of Classification Loss, Regularization Loss, Localization Loss, and Total Loss curves to evaluate the convergence of the model.

Table 1. Hyperparameters.

Parameter	Value
Model Name	MobileNet V2
Class	7
Batch Size	4
Step/Iteration	100000
Input resolution	320 × 320 px
Feature extractor	ssd_mobilenet_v2_fpn_keras
Optimizer	Momentum optimizer
Learning Rate	0,8
Metrics	COCO detection metrics
Pipeline File	ssd_mobilenet_v2_fpnlite_320x320_coco17_tpu-8.config
fine_tune_checkpoint_type	"detection"
fine_tune_checkpoint	"Tensorflow/workspace/pre-trained-models/ssd_mobilenet_v2_fpnlite_320x320_coco17_tpu-8/checkpoint/ckpt-0"
label_map_path	"Tensorflow/workspace/annotations/label_map.pbtxt"
input_path (train)	"Tensorflow/workspace/annotations/train.record"
input_path (eval)	"Tensorflow/workspace/annotations/test.record"

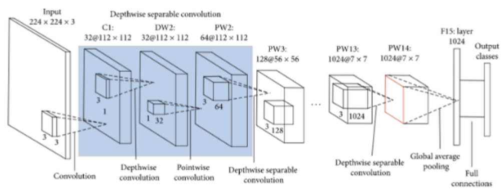


Figure 5. MobileNetV2 architecture.

[3] https://tensorflow-object-detection-api-tutorial.readthedocs.io/en/latest/

Subsequently, the trained model is evaluated using previously collected test data that has not been included in the training process. The test data consists of image samples, ensuring an unbiased evaluation of the model's performance. Model performance is measured using a confusion matrix, which analyzes the comparison between the model's predicted results and the actual labels of the test data.

3. Results and Discussion

After the model is trained with training data, the model training results are viewed through the tensorboard. The tensorboard displays Classification Loss, Regularization Loss, Localization Loss, and Total Loss curves. The model is trained for 100,000 steps/iteration with a total batch size of 4.

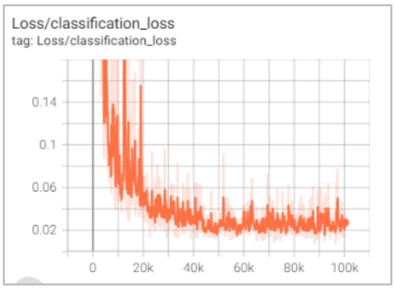


Figure 6. Classification loss.

As illustrated in Figure 6, the classification loss curve declined sharply to below 0.06 in the first 20,000 steps. This shows that the model quickly distinguishes between different classes in the training data. After about 30,000 steps, the curve began to stabilize with a classification loss value close to constant around 0.04. This signifies that the model has reached a steady level of learning and has only experienced slight improvement step by step. At the100,000th step, the classification loss is at 0.03714. This indicates that the model has reached convergence, where the loss value is no longer significantly reduced, and the model has achieved optimal performance with the parameters used.

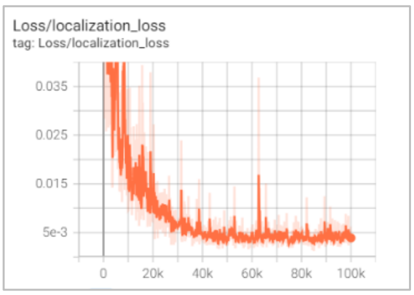


Figure 7. Localization loss.

As illustrated in Figure 7, The localization loss curve decreased sharply to below 0.015 in the first 10,000 steps. This shows that the model is quickly learning to localize objects in the image, indicating that the model understands how to position the bounding box around the banknote. After about 60,000 steps, the curve began to show stabilization with a localization loss value close to constant around 0.0045. This signifies that the model has reached a steady level of learning and has only experienced slight improvement step by step. At step 100,000, the localization loss curve starts to flatten at 0.0035546. This indicates that the model has reached convergence, where the localization loss value is no longer significantly reduced, and the model has achieved optimal performance with the parameter.

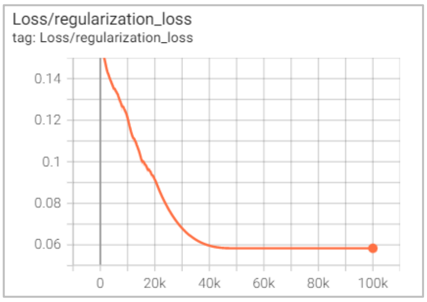


Figure 8. Regularization loss.

Figure 8 shows that the regularization loss curve decreases steadily during training. This is a positive indication that the model is learning and reducing overfitting. Reduced regularization loss indicates that the model is getting more regular over time. At the 40,000 steps, it can be seen that the regularization loss value reaches around 0.0596 and starts to flatten. This shows that the model is starting to converge, where the loss decline is prolonged. The model gets a final value of regularization loss of 0.05836. This indicates that the model has learned quite a bit from the data, and further improvements will be minor.

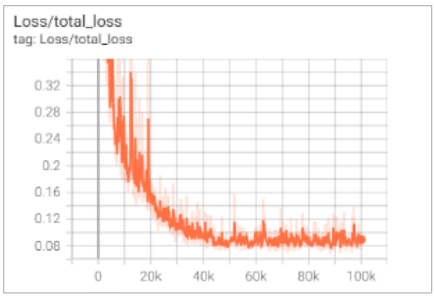


Figure 9. Total loss.

Figure 9 displays the total loss curve. The loss value is a metric that shows how well the model predicts the given data. The lower the loss value, the better the model's performance. At the beginning of the training, the total loss value is relatively high (above 0.4). This shows that the model needs to be trained better, and its predictions are far from correct. As the number of training steps increases, the total loss value decreases rapidly, indicating that the model learns from the data and improves its ability to detect the nominal value of the banknote. After about 60,000 training steps, the decline in the total loss value began to slow down. At the100,000th step, the total loss curve starts to flatten and gets a value of 0.09906. This indicates that the model has reached convergence, where additional training no longer significantly improves model performance.

Once the model has been trained using the dataset, the next step is to test the model's performance. At this stage, the model is used to predict the image labels in the test data. The test was carried out using 280 test data. The resulting predictions are then compared with the original labels from the test data to create a confusion matrix. This confusion matrix provides an overview of the number of correct and incorrect predictions for each class and helps identify patterns of errors created by the model. From the confusion matrix, evaluation metrics such as model accuracy are obtained. The results of the model evaluation using the confusion matrix can be seen in Figure 10.

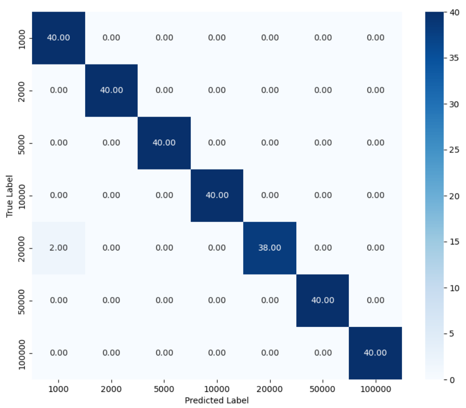


Figure 10. Confusion matrix.

$$Model\ Accuracy = \frac{TP+TN}{TP+TN+FP+FN} = \frac{40+40+40+40+38+40+40}{280} = 99{,}2\%$$

The accuracy of the model is 99.2% based on the results of tests carried out using a confusion matrix. The confusion matrix test was carried out using 280 images of testing data. Table 1 presents a comparison of the model accuracy obtained in this study with the accuracy of models from previous studies with similar topics, as discussed in the introduction section.

Table 2. Comparison of the model accuracy achieved in this study with previous research in the literature [15][16].

Model	Accuracy
MobileNetV2	99,2%
VGG-16	83%
MobileNetV3	91,28%

Based on the comparison results presented in Table 2, the MobileNetV2 model demonstrates the strongest performance among the baseline models referenced from previous studies used as literature.. With model accuracy of 99.2%, MobileNetV2 demonstrated a significant improvement compared to previous studies where the VGG-16 model only achieved 83% model accuracy, and the MobileNetV3 model which achieved 91.28% model accuracy.%. These differences indicate that the MobileNetV2 architecture possesses superior capabilities.

The trained model is exported to .tflite format so that the model can be used for Android application implementation. The Android implementation is used as a test medium for models created to determine the model's performance on the Android platform. Figure 11 shows the results of the model implementation on the Android platform. The addition of audio output to the Android implementation is done using the text-to-speech (TTS) in Android Studio. Text-to-Speech (TTS) in Android Studio is a feature that allows developers to integrate the ability to convert text to speech directly within Android apps.

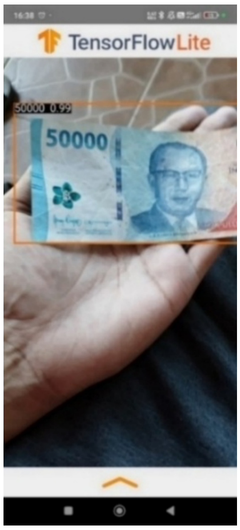


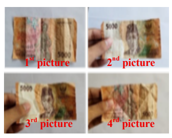
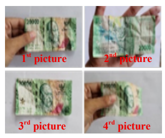
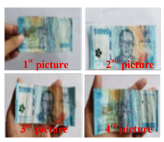
Figure 11. Android implementation

As presented in Table 3, audio output was tested using 28 data testing images, including four images for the IDR 1,000 class, four images for the IDR 2,000 class, four images for the IDR

5,000 class, four images for the IDR 10,000 class, four images for the IDR 20,000 class, four images for the IDR 50,000 class, four images for the IDR 100,000 class. These 28 images constitute 10% of the total testing data of 280 images. After testing the 28 images, it was found that the accuracy of the audio output was 100%. The audio successfully appears according to the object detected by the model.

$$Audio\ accuracy = \frac{Total\ of\ correct\ audio\ outputs}{Total\ of\ testing\ data\ used} = \frac{28}{28} = 100\%$$

Table 3. Output audio testing.

Image	Input Image	Output Audio	T/F
	1st Picture	1000	T
	2nd Picture	1000	T
	3rd Picture	1000	T
	4th Picture	1000	T
	1st Picture	2000	T
	2nd Picture	2000	T
	3rd Picture	2000	T
	4th Picture	2000	T
	1st Picture	5000	T
	2nd Picture	5000	T
	3rd Picture	5000	T
	4th Picture	5000	T
	1st Picture	10000	T
	2nd Picture	10000	T
	3rd Picture	10000	T
	4th Picture	10000	T
	1st Picture	20000	T
	2nd Picture	20000	T
	3rd Picture	20000	T
	4th Picture	20000	T
	1st Picture	50000	T
	2nd Picture	50000	T
	3rd Picture	50000	T
	4th Picture	50000	T
	1st Picture	100000	T
	2nd Picture	100000	T
	3rd Picture	100000	T
	4th Picture	100000	T

Testing by the visually impaired was carried out to evaluate the effectiveness of the application in detecting and identifying the nominal amount of money with audio output. The test was carried out involving five visually impaired people. Each visually impaired person was given seven banknotes, namely IDR 1,000, IDR 2,000, IDR 5,000, IDR 10,000, IDR 20,000, IDR 50,000, and IDR 100,000. The testing begins with a brief briefing on how to use the app. Next, participants are instructed to place banknotes in front of smartphones, and the application will detect the nominal amount of the banknotes and output audio based on the given object. As shown in Table 4, which presents the testing of mobile implementation by the blind, the results indicate that the application is able to detect the nominal of banknotes with a high level of accuracy for most of the banknotes tested. From the test of 5 visually impaired people (7 nominal banknotes for 5 participants), the application detected 35 times correctly, so it obtained an accuracy of 100%.

$$Accuracy\ Testing\ by\ the\ Blind = = \frac{Total\ of\ correct\ outputs}{Total\ of\ Tests} = \frac{35}{35} = 100\%$$

Table 4. Testing of mobile implementation by the blind.

Respondent's Number	Testing Predictions	Sound Output	T/F
1	1000	1000	T
	2000	2000	T
	5000	5000	T
	10000	10000	T
	20000	20000	T
	50000	50000	T
	100000	100000	T
2	1000	1000	T
	2000	2000	T
	5000	5000	T
	10000	10000	T
	20000	20000	T
	50000	50000	T
	100000	100000	T
3	1000	1000	T
	2000	2000	T
	5000	5000	T
	10000	10000	T
	20000	20000	T
	50000	50000	T
	100000	100000	T
4	1000	1000	T
	2000	2000	T
	5000	5000	T
	10000	10000	T
	20000	20000	T
	50000	50000	T
	100000	100000	T
5	1000	1000	T
	2000	2000	T
	5000	5000	T
	10000	10000	T
	20000	20000	T
	50000	50000	T
	100000	100000	T

4. Conclusion

Using the MobileNetV2 pre-trained model in conducting transfer learning to detect the nominal rupiah banknote results in excellent model performance. The evaluation carried out on the model using the confusion matrix resulted in a model accuracy value of 99.2%. Overall, the model has managed to detect the nominal banknotes well. The model has been successfully implemented into an Android application with audio output using Text-To-Speech (TTS). The test carried out on the audio output obtained an accuracy of 100%, while the application test carried out by the visually impaired obtained an accuracy of 100%. When used by the visually impaired, the mobile application successfully detects the nominal rupiah banknote.

Acknowledgement

We would like to express our sincere appreciation to Mrs. Yerna Ayub, a teacher at SLB Bangkinang, for her willingness to participate in the interview. Through direct discussions with an experienced educator of visually impaired children, we gained important insights into the daily challenges faced by visually impaired individuals, particularly in conducting financial transactions. Her contributions significantly enriched the practical perspective and relevance of this research.

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