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Performance Analysis of CNN (Convolutional Neural Network) in Nominal Classification of Rupiah Emissions 2022

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Abstract- This study aims to analyze the performance of Convolutional Neural Network (CNN) algorithm in classifying the nominal of Rupiah banknotes issued in 2022. Three test models are developed, namely two CNN architectures with different optimizers (Adam and RMSprop), and one transfer learning model using VGG16. The dataset used consists of 1,848 banknote images of seven denominations: Rp1,000, Rp2,000, Rp5,000, Rp10,000, Rp20,000, Rp50,000, and Rp100,000. The data was collected using a smartphone camera and processed through augmentation, normalization, and classification stages. The model was evaluated using accuracy, precision, recall, and F1-score metrics. The results show that CNN with Adam's optimizer achieves a validation accuracy of 98.97%, while CNN with RMSprop reaches 99.59%. Meanwhile, the VGG16 model achieved perfect validation accuracy of 100%, with precision, recall, and F1-score values of 1.00 each. These results show that the transfer learning approach provides the best performance compared to conventional CNN models. This research supports the development of an accurate and efficient banknote recognition automation system for digital finance applications.

Kata Kunci: CNN; Transfer Learning; Image Classification; Rupiah Notes; Deep Learning

1. INTRODUCTION

The development of digital technology has had a major impact in various sectors, including in the financial sector. One of the technological implementations that is increasingly relevant and widely developed is an artificial intelligence-based image classification system, especially in the context of banknote recognition and classification. This system has wide potential in various practical applications, such as self-service cash registers, ATM machines, vending machines, to mobile-based financial applications that require a high level of accuracy in recognizing nominal money. Not only that, but such systems have also begun to be used in aids for people with disabilities, especially the visually impaired, to help them recognize the value of money independently [1]. Bank Indonesia's update of the rupiah banknote design through its 2022 issuance presents new challenges in the development of an automatic money recognition system. Significant visual changes, such as color gradation, element layout, and new, more complex security features, make conventional-based recognition methods such as pattern matching or color histogram analysis less effective.[2] This challenge is exacerbated when the system is deployed in real-world environments full of variations in lighting, shooting angles, or unstandardized backgrounds, such as the use of mobile phone cameras in various conditions.

Pattern recognition is one of the main fields in artificial intelligence that is widely applied in various domains including digital image processing. One popular approach to pattern recognition is the K-Nearest Neighbors (K-NN) algorithm, which works based on the proximity of distances between data features. Sitorus et al. [3] has applied the K-NN method to recognize patterns in the serial numbers of 5G devices. The results of the study show that K-NN is able to provide a fairly good classification accuracy on numerical data.

In addition, the selection of the right algorithm is highly dependent on the characteristics of the data used. In another study, Sitorus and colleagues compared the performance between Naïve Bayes and Support Vector Machine (SVM) in determining online shopping ratings based on user reviews [4]. The study emphasizes the importance of evaluating the performance of each algorithm in the context of different data. Similar principles were applied in this study, where Convolutional Neural Network (CNN) was used and evaluated in the context of the classification of rupee images, taking into account its advantages in recognizing complex visual patterns compared to conventional machine learning algorithms. Further trends in the utilization of machine learning algorithms in various data domains also demonstrate the flexibility of this method. Sitorus et al. conducted a sentiment analysis of Indonesian public opinion on electric motorcycles using the Orange Data Mining platform. Although the study focused on text data, the approach used describes how machine learning algorithms can be adapted to a wide variety of data types, including text and imagery[5].

As machine learning technology evolves, deep learning-based approaches, especially CNNs, are becoming a top choice in image classification due to their ability to extract features automatically and efficiently[6]. Meanwhile, another study conducted by Iqbal et al compared the CNN method with traditional machine learning approaches [7]. For example, the use of Naïve Bayes and C4.5 algorithms in the selection of MSME products, as well as credit risk analysis using the C4.5 decision tree algorithm [8]. The results of the study show that although classical classification algorithms can still be used, CNN performance is generally superior especially in the context of visual data because it does not require manual feature extraction processes. In the study conducted by Iqbal et al., CNN was used to detect and identify red snapper based on image data [9]. The study showed that CNN was able to recognize the visual features of objects effectively

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despite being in varied settings or conditions. These results reinforce the understanding that CNNs have great potential to be used in the case of other image-based object classifications, including the introduction of banknotes. Rewina et al. (2024) show that CNN is capable of being used not only to classify banknotes, but also coins, with promising results [10]. However, training CNN from scratch requires large amounts of data and significant computational time. Therefore, the transfer learning method is an efficient alternative solution. Pretrained models such as VGG16 or MobileNetV2 that have been trained on large datasets such as ImageNet can be reconfigured for the classification of Rupiah banknotes, thereby speeding up the training process and improving accuracy. Sadewa and Yamasari (2024) proved that VGG16 was able to achieve a validation accuracy of 94.3% in the nominal classification of Rupiah notes [11], while Agustin et al. (2024) showed that MobileNetV2 performance was able to achieve an accuracy of 97.9% [12].

In addition to CNN and transfer learning, object detection-based approaches such as YOLOv3 have also been applied in the classification of Rupiah banknotes. Hermawan et al. (2022) applied YOLOv3 to a dataset containing thousands of images of Rupiah banknotes, and succeeded in obtaining very high accuracy and recall results [13]. Meanwhile, Prima et al. (2022) used the MobileNetV3 SSD architecture to build a special money nominal recognition system for the visually impaired, and the system is able to detect money with an accuracy of between 80%–95% depending on lighting conditions [1].

On the other hand, several studies have also discussed the classification of good or bad money conditions, as done by Nandika et al. (2025) using CNN-based image processing [14]. These studies show that digital image-based money recognition is not only limited to nominal, but can also be extended to physical condition features and even the detection of the authenticity of money [15].

Although a lot of research has been conducted, most of them still focus on the application of one type of architecture and not many have compared several models in one controlled experiment, especially with the latest dataset that reflects the design of the 2022 emission money. In addition, many studies still rely on open datasets or synthesized datasets that do not yet fully reflect real-world challenges such as rotation, shadows, or low image quality.

This study aims to evaluate and compare the performance of three image classification models in the context of the 2022 emission Rupiah banknotes: two CNN models with different optimizers Adam and RMSprop, and one transfer learning-based model with VGG16 architecture. The three models were trained and tested on a dataset of 1,848 independently collected Rupiah banknote images, consisting of seven nominal classes (Rp1,000 to Rp100,000) taken under various lighting, orientation, and background conditions. This dataset is used consistently across all models so that the comparison results can be objectively evaluated. The model was evaluated using accuracy, precision, recall, and F1-score metrics.

By comparing these three different approaches, this study seeks to answer an important question in the development of a digital money classification system: which approach is the most optimal in terms of classification performance and predictive confidence stability. The findings of this study are expected to be a reference for the development of image-based money classification systems, both in commercial and social contexts such as technological support for the visually impaired. This research also opens up opportunities for further in-depth research on the influence of environmental conditions on classification performance, as well as the application of this system to embedded devices with limited computing power.

Overall, this research contributes to the development of a more efficient, accurate, and adaptive Rupiah banknote classification system that is more efficient, accurate, and adaptive to changes in the physical design of money, and is ready to be implemented in Indonesia's modern financial system, both at the hardware scale (embedded system) and mobile applications. With a strong foundation in the application of CNN architecture and transfer learning, as well as controlled experiments with real datasets.

2. RESEARCH METHODOLOGY

This research uses a quantitative experimental approach to evaluate and compare the performance of three deep learning-based image classification models in recognizing the nominal Rupiah banknotes issued in 2022. The models developed include two conventional Convolutional Neural Network (CNN) architectures with different optimizers, namely Adam and RMSprop, and one transfer learning model using the VGG16 architecture.

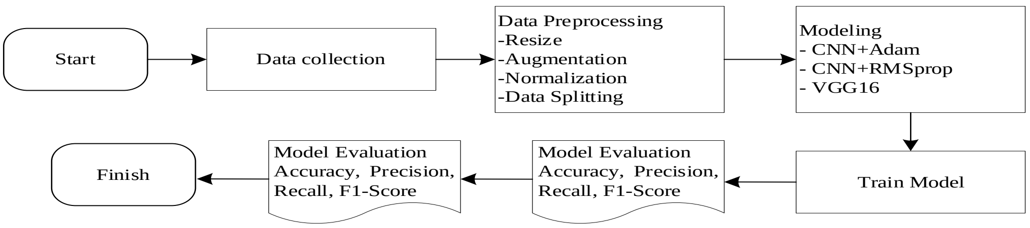

Figure 1. Research Flow

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2.1 Dataset Collection

The dataset consists of 1,848 images of genuine banknotes issued in 2022 that were collected manually using a smartphone camera with 12 MP resolution. Each image is categorized into one of seven nominal classes, namely Rp1,000, Rp2,000, Rp5,000, Rp10,000, Rp20,000, Rp50,000, and Rp100,000, each with 264 images.

2.2 Data Preprocessing

Before being used in the training process, all images undergo a preprocessing stage which includes:
a. Resize the image to a resolution of 512 × 512 pixels
b. Normalization of pixels to the range [0, 1]
c. Random data augmentation, including rotation, zoom, horizontal shift, vertical shift, and horizontal flip
d. Data division into 80% training data and 20% validation data

2.3 Modeling and Train Model

Two CNN Models were tested with differences in the Optimizer type and with 1 Transfer Learning, namely:
a. CNN + Adam Optimizer
b. CNN + RMSprop Optimizer
c. VGG16

Two CNN models were built using Keras and TensorFlow frameworks. The general structure of the model includes:
a. Convolution block Conv2D followed by Batch Normalization and activation function ReLU
b. MaxPooling2D for spatial dimension reduction
c. Global Average Pooling before fully connected layer
d. Dense layer with softmax activation function at the output layer for 7-class classification

The third model used ImageNet's pretrained VGG16 architecture, with the convolutional part frozen and only retrained the top few layers and the final classifier. Adjustments were made by adding Global Average Pooling, Dropout 0.5, and a Dense layer of 128 units with ReLU, and an output layer of 7 classes with softmax.

2.4 Model Evaluation

Model performance evaluation was conducted using four main metrics, namely accuracy, precision, recall, and F1-score. These four metrics were chosen because they provide a comprehensive overview of the model's performance in multi-class classification such as the 2022 Rupiah emission dataset.
a. Accuracy measures the proportion of correct predictions compared to the total number of predictions. It indicates how often the model correctly classifies the banknote images overall. Accuracy is particularly useful when the class distribution is balanced.
b. Precision measures the level of accuracy of the model in predicting a class. Precision is defined as the ratio between the number of positive correct predictions and the total number of positive predictions. In this context, precision indicates how often the model does not misrecognize a certain amount of money.
c. Recall measures the model's ability to find all instances of a class. A high recall value indicates that the model can detect almost all images of a nominal class, without missing much relevant data.
d. F1-score is a harmonization of precision and recall, and is particularly useful when a balance between the two is required.

As part of the evaluation, the predictions and confidence scores generated by each model on the test data were analyzed. This evaluation aims to measure the confidence level of the model in its classification predictions, so that it not only considers the correctness of the classification nominally, but also the confidence level of the model in its decision. Each model is tested on test image data with the same test scenario, and for each prediction, the confidence probability of the predicted class is also displayed. This approach is used to observe whether the model is only correct by chance or has high confidence in the chosen class.

3. RESULTS AND DISCUSSION

This study compares the performance of three image classification models in recognizing the nominal value of the 2022 Rupiah emission. The evaluation is based on training results, validation accuracy, as well as precision, recall, and F1-score metrics.

3.1 Model Training Results

a. CNN model with RMSprop optimization
   The CNN model trained using the RMSprop optimizer shows excellent training performance, as visualized in Figure 2. The left graph shows a steady increase in training and validation accuracy over 150 epochs. The validation accuracy fluctuates slightly in the early epochs, but gradually increases and approaches a perfect value (>99%) at the end of the training.

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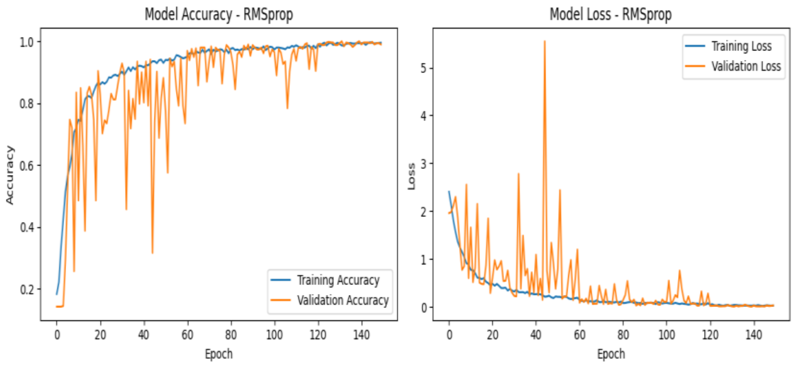

Figure 2. CNN with RMSprop Optimization

The right graph displays the training and validation loss. It can be observed that the validation loss shows a significant decrease and stabilizes after about the 60th epoch, although it had high fluctuations in the early stages. This indicates that the model starts to generalize well to the validation data as the training epochs increase. Based on the analysis of training and validation metrics, the lowest validation loss is 0.004586818 with validation accuracy 1 at epoch 139.

b. CNN with Adam optimization

The training process of CNN model using Adam optimizer for 150 epochs. The left graph shows the training and validation accuracy curves. The accuracy increases consistently at the beginning of training and reaches a value above 98% at the 50th epoch, then stabilizes until the end of training. Although there are small fluctuations in validation accuracy, the curves show a converging trend.

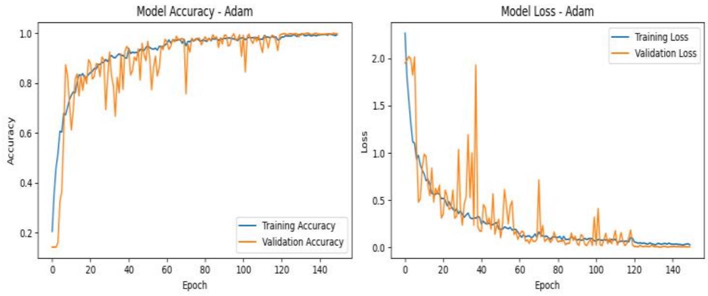

Figure 3. CNN with Adam Optimization

In the right graph, it can be seen that the training loss decreases steadily over time, while the validation loss shows quite high fluctuations at the beginning of training, before finally decreasing and stabilizing near the minimum value. This fluctuation is normal at the beginning of CNN training, especially when the model adjusts the initial weights. Based on the analysis of training and validation metrics, the lowest validation loss is 0.003538228 with validation accuracy 1 at epoch 133.

c. VGG16 Transfer Learning Method

The VGG16-based transfer learning model shows the most superior and stable performance compared to the previous two CNN models. As shown in Figure 4, the training and validation accuracy graphs show a sharp spike in the first 10 epochs and reach near-perfect values (>99%) in a short time. After that, both training and validation accuracies remain stable without any significant decline until the end of the 150th epoch.

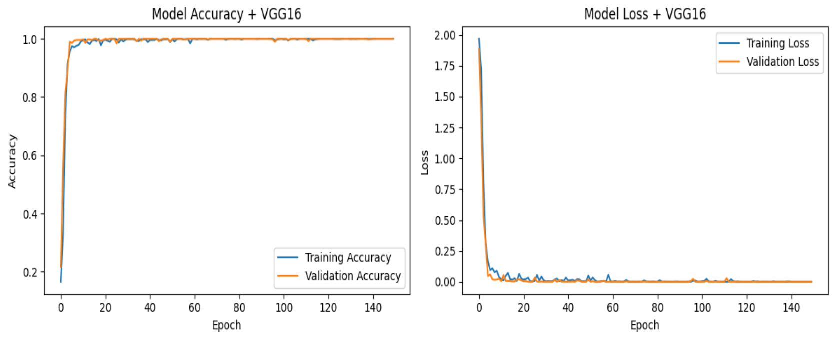

Figure 4. VGG16 Transfer Learning Method

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The loss graph also confirms the rapid convergence of the model. The training and validation losses decrease dramatically at the beginning of training and reach values close to zero, and remain stable. There are no symptoms of overfitting or underfitting, which indicates that the model is able to generalize very well despite the limited amount of data. This excellent performance is due to the fact that VGG16 already has pretrained weights from the large ImageNet dataset, so it only needs minor fine-tuning to perform classification on the new domain of 2022 Rupiah notes. This result proves the effectiveness of the transfer learning approach for complex and domain-specific image classification cases. Overall, the training results of the three models show that all architectures are able to learn the visual pattern of the 2022 Rupiah banknote image well, characterized by high validation accuracy and low loss. CNN models with RMSprop and Adam optimizers both show good classification capabilities, although each has different convergence characteristics. RMSprop tends to be slower to achieve stability, while Adam is faster but slightly more volatile at the beginning of training. Meanwhile, the VGG16 model with the transfer learning approach consistently gave the best results from all aspects of training. Fast convergence in the first few epochs, stability in accuracy and loss, and no indication of overfitting, indicate that this model has high generalization ability to new data. The superiority of VGG16 also reflects the efficient utilization of pretrained weights that have been developed from large datasets, thus strengthening the effectiveness of fine-tuning strategies in specific classification tasks such as Rupiah bills.

3.2 Model Prediction Results

The following is an image of the predicted model results

Figure 5. Model Prediction with RMSprop Optimization

Figure 6. Model prediction with Adam optimization

Figure 7. VGG16 Model Prediction

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Figures 5, 6, and 7 present the prediction results of the Rupiah banknote image by each model: CNN + RMSprop, CNN + Adam, and VGG16. Each row in the figure shows the prediction of the banknote amount and the confidence probability value of the model against the classification result. All models show excellent classification performance against a wide range of visual variations of the Rupiah note, ranging from different orientations, varying lighting, and non-uniform backgrounds. The following is an explanation of each model:

a. Figure 8 (CNN Model + RMSprop)
   The model was able to recognize all amounts with very high confidence, mostly reaching 100%, although there were slight variations in some images such as Rp5,000 or Rp10,000. However, the predictions remained label-accurate.
b. Figure 9 (CNN model + Adam)
   Almost all predictions are above 99.9%, with only a slight drop in some images. This indicates that the model has strong generalization, although it is not as stable as VGG16 in terms of confidence.
c. Figure 10 (VGG16 Model)
   The transfer learning model VGG16 showed very stable prediction results, with a probability value of 100% for all test images. This result corroborates previous results that VGG16 is not only accurate in prediction, but also very confident in its classification decisions, making it the best model in this experiment.

Figure 8. Probability by Image Number

Figure 8 shows the trend graph of the classification probability by image number on the test dataset. The probability in question is the confidence score of the model against the resulting predicted label. The three models are given different colors, namely, blue for the CNN model with RMSprop optimization, red for the CNN model with Adam optimization, and green for the VGG16 model.

In general, the VGG16 model shows the most stable performance, with a probability value that is consistent at 100% for all test images. This indicates that the model is very confident in its predictions without any significant fluctuations.

Meanwhile, the CNN + Adam and CNN + RMSprop models show small to moderate fluctuations in some images, especially after the 100th image. The confidence drop was below 95%, even approaching 93% at some points. Although the classification of the final result was still correct, these confidence values indicate that the model had doubts in some predictions.

This difference reinforces previous findings that the VGG16 model not only provides accurate classification results, but also does so with high and stable confidence. This capability is an important indicator in real-time classification systems, especially if the confidence score is used as a basis for further decisions, such as error detection or fallback systems.

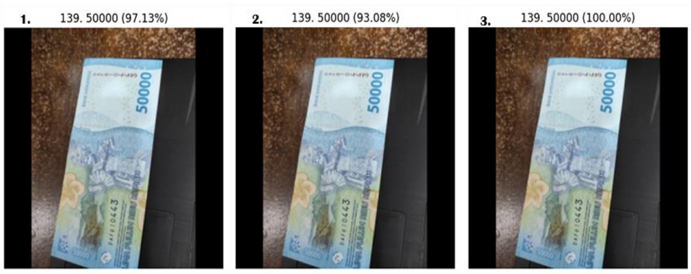

Figure 9: Model Probability against Banknote Image Number 139

Figure 9 presents a comparison of the prediction results for the 139th banknote image (IDR 50,000) by three different models, the purpose of this visualization is to observe how each model provides confidence on the same image.

a. Figure 1 CNN model with RMSprop optimization
   The model successfully classified the image as Rp50,000 with a confidence level of 97.13%. Although the classification is correct, the confidence score shows that there is a slight doubt in the prediction.
b. Figure 2 CNN model with Adam optimization
   This model produces correct predictions with a lower confidence of 93.08%. This decrease in confidence can be an indicator that the model is less confident in the classification, although the final result is still accurate.
c. Figure 3 VGG16 model

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Unlike the previous two models, VGG16 provides predictions with maximum confidence (100%), indicating a consistently high level of confidence. This is consistent with previous findings that VGG16 tends to provide more stable predictions.

3.3 Model Performance Evaluation

Table 1 shows the results of metric evaluation on three models: CNN with Adam optimizer, CNN with RMSprop, and VGG16 transfer learning. All three achieve very high precision, recall, and F1-score values, even touching the value of 1.00 (100%) across all nominal classes, including for classes that tend to have visual similarities, such as Rp5,000 and Rp10,000.

Table 1. Evaluation of Accuracy, Precision, Recall, F1-Score Metrics

Model	Nominal	Precision	Recall	F1-Score
CNN + Adam	1000	1	1	1
CNN + Adam	2000	1	1	1
CNN + Adam	5000	1	1	1
CNN + Adam	10000	1	1	1
CNN + Adam	20000	1	1	1
CNN + Adam	500000	1	1	1
CNN + Adam	100000	1	1	1
CNN + Adam	Accuracy	1	1	1
CNN + Adam	Macro Avg	1	1	1
CNN RMSprop +	1000	1	1	1
CNN RMSprop +	2000	1	1	1
CNN RMSprop +	5000	1	1	1
CNN RMSprop +	10000	1	1	1
CNN RMSprop +	20000	1	1	1
CNN RMSprop +	500000	1	1	1
CNN RMSprop +	100000	1	1	1
CNN RMSprop +	Accuracy	1	1	1
CNN RMSprop +	Macro Avg	1	1	1
VGG16	1000	1	1	1
VGG16	2000	1	1	1
VGG16	5000	1	1	1
VGG16	10000	1	1	1
VGG16	20000	1	1	1
VGG16	500000	1	1	1
VGG16	100000	1	1	1
VGG16	Accuracy	1	1	1
VGG16	Macro Avg	1	1	1

The table above reflects a very precise and consistent classification performance. Not only does the global accuracy rate approach or reach 100%, but also the per-class evaluation shows no significant false positives or false negatives. The macro average and weighted average values for each model are also at the maximum. This optimal performance was achieved thanks to several factors:

a. Systematic image preprocessing such as augmentation and normalization.
b. CNN architecture structure that effectively captures the visual pattern of money
c. The power of VGG16 transfer learning that utilizes pretrained weights from ImageNet.

In addition, the relatively controlled data collection conditions also contributed to the quality of the dataset. However, these excellent results still need to be tested on more diverse datasets to ensure the generalizability of the model.

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Table 2 shows the confusion matrix of the model's classification results for the 7 classes of Rupiah bills, namely Rp1,000, Rp2,000, Rp5,000, Rp10,000, Rp20,000, Rp50,000, and Rp100,000. Based on the visualization, all model predictions are on the main diagonal of the confusion matrix table, indicating that all images are correctly classified without any misclassification between classes. Each class had 20 samples in the test data, and all of them were correctly predicted by the model. There were no false positives or false negatives. This result reinforces the previous findings on the precision, recall, and F1-score metrics that reached a value of 1.00 in all classes.

Table 2. Confusion Matrix

Model	1000	2000	5000	10000	20000	50000	100000
CNN + Adam	20	0	0	0	0	0	0
CNN + Adam	0	20	0	0	0	0	0
CNN + Adam	0	0	20	0	0	0	0
CNN + Adam	0	0	0	20	0	0	0
CNN + Adam	0	0	0	0	20	0	0
CNN + Adam	0	0	0	0	0	20	0
CNN + Adam	0	0	0	0	0	0	20
CNN RMSprop +	20	0	0	0	0	0	0
CNN RMSprop +	0	20	0	0	0	0	0
CNN RMSprop +	0	0	20	0	0	0	0
CNN RMSprop +	0	0	0	20	0	0	0
CNN RMSprop +	0	0	0	0	20	0	0
CNN RMSprop +	0	0	0	0	0	20	0
CNN RMSprop +	0	0	0	0	0	0	20
VGG16	20	0	0	0	0	0	0
VGG16	0	20	0	0	0	0	0
VGG16	0	0	20	0	0	0	0
VGG16	0	0	0	20	0	0	0
VGG16	0	0	0	0	20	0	0
VGG16	0	0	0	0	0	20	0
VGG16	0	0	0	0	0	0	20

This excellent performance shows that the model is not only able to recognize the unique visual patterns of each banknote, but also has a very high generalization ability to the validation data. The VGG16 model, as the best model in this study, demonstrates the superiority of the transfer learning approach in complex banknote image recognition.

4 CONCLUSION

Model VGG16 has the best performance compared to the other two models. It produces a prediction probability of 100% on all test data, and shows a stable and fast loss convergence. The VGG16 architecture, which is the result of transfer learning, allows the model to utilize the weights from previous training on large-scale datasets, thereby better extracting banknote image features. The model also showed a consistently high confidence score on almost all test images, making VGG16 the most reliable key component of the classification system. The CNN model with Adam's optimization also performed quite well, with an average probability of 99.90%. Although the accuracy and loss results during validation were more volatile than VGG16, this model still provided stable predictions. Adam's optimizer is known to have a good convergence speed, but is prone to fluctuations if not accompanied by adjustments to the learning rate and other parameters. The CNN model with RMSprop optimization produces a high average probability of 99.90%, but experiences a slower and more fluctuating convergence loss. This shows that this model still needs improvement, such as hyperparameter tuning, use of regulation techniques, or enrichment of training data to improve generalization.
Overall, the VGG16 model is the best choice for the Rupiah currency nominal classification system, both in terms of accuracy and prediction stability. The CNN model with RMSprop still needs further development to achieve equivalent performance.

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