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Multiclass Classification on Nominal Value of Rupiah Banknotes Based on Image Processing

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Abstract

This study aimed to classify the nominal value of Rupiah banknotes using image processing and classification methods. The research design was conducted by collecting a dataset of Rupiah banknotes consisting of 30 classes, each with 100 images. This research uses image preprocessing by using Canny Segmentation to create the edges of objects and clarify image details. The Hu Moments method, which describes the pixel distribution and shape of objects, was used to extract special features from images. Furthermore, classification modeling was carried out with Decision Tree and Random Forest to classify banknotes based on extracted characteristics. Model evaluation was carried out by measuring accuracy, precision, recall and f1-score performance and using cross-validation with k-fold = 5. The results showed that the Random Forest method was able to classify Rupiah banknotes well. In performance evaluation, the Random Forest method achieved an accuracy of 0.93 and good precision, recall, and f1-score scores for several banknote classes. The Decision Tree method also achieved good results, with an accuracy of 0.86. The results of the classification evaluation showed that the Random Forest method was better than the Decision Tree in classifying the banknotes.

Keywords: Rupiah Banknotes, Canny Segmentation, Hu Moments, Cross-Validation, Decision Tree, Random Forest

Introduction

Money is an economic tool used as a means of payment or medium of exchange in certain contexts. Rupiah is the official currency of Indonesia printed by Bank Indonesia, Central Bank of Indonesia, in all regions of Indonesia. From time to time, the nominal value of Rupiah in Indonesia is very diverse and looks very different in size, color, or pattern [1]–[3]. Based on **Figure 1**, currently there are several money circulating from different emission years, there are 2016, 2020, and 2022 emission years.

Figure 1. Rupiah Banknote Specimens from 3 Different Emission Years

Indonesians use Rupiah banknotes for business every day. All Rupiah notes have a unique nominal, which is useful for determining the value of goods and services traded. In fact, there are currently digital payments using electronic money, which makes some Indonesians unable to directly switch to digital money [4]–[6]. Therefore, some other people still make transactions using cash payment to meet their living needs and facilitate the transaction process.

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When making cash transactions, errors often occur due to similar conditions of banknotes. This condition can occur with anyone when making cash transactions, and this will inevitably result in losses for either party. This disadvantage led to the idea of building a system that could detect the nominal value of paper currency quickly and accurately, by using a computer or system to recognize the paper currency [7], [8].

Today, technological advances are growing rapidly, so that the transaction process is not only carried out between humans and humans, but also is carried out between humans and machines. In Indonesia there are several machines that use Rupiah banknotes transactions, such as vending machines. The transaction process between humans and vending machines must be supported by the ability of the machine as the seller to read and identify every nominal value of Rupiah currency as good as humans [3]. As for Cash Recycle Machine or cash deposit machine, has been provided by banks in Indonesia. Cash Recycle Machine helps Indonesians deposit their cash. This machine is very effective in increasing efficiency, so that some banks in Indonesia can save time and operating costs in cash deposit services [2], [10]. However, the fact is that vending machines in Indonesia are still not effective in reading the nominal value of Rupiah banknotes, so the vending machines are still ineffective used by the public. Not only that, Cash Recycle Machine provided by several banks in Indonesia, still limits the nominal value of Rupiah banknotes to deposit.

With information technology, humans can carry out daily activities more easily. Automation processes can complete frequent and meticulous work in a short time [11]–[13]. One of the problems with computer vision is the classification of objects in images because computers can model the ability of humans to understand image information, as well as recognize objects like humans [14], [15]. In this case, testing for the optimization of the nominal value of the Rupiah is an example. The testing process is needed to optimize the identification accuracy of the nominal value of Rupiah banknotes [11]. The image processing method is very suitable in the classification of the nominal value of banknotes. Data collection, image processing, feature extraction, classification, and performance evaluation are some of the steps that make up image classification [16].

Some researchers have conducted study on how to identify or classify nominal value of the Rupiah banknotes. Some employed the Local Binary Pattern (LBP) feature extraction method and the Naive Bayes classification method with an average accuracy of 100% and cv = 5. However, additional image data is required, including images from each side of the image, and various types of Rupiah banknotes [1]. Some use the KNN method as a banknote image detector with RGB color with an accuracy of 93.7%, sixteen test data indicated that fifteen banknote objects were detected correctly, and one object was incorrectly detected [2]. Some use the JST backpropagation recognition system to detect the nominal banknote with a 100% of taught data testing results, while the results of data testing that have not been taught were 78.8%, while the precision results were 96.67% to detect the nominal value Rp20000, 73.3% to detect the nominal value Rp50000, and 66.67% to detect the nominal value Rp100000 [4]. Some identify paper currencies using ROI-based methods and Canny detection, but it requires performance evaluation models that use quantitative measurements [8].

The current study uses a balanced multiclass dataset totaling 30 classes, where this dataset uses all nominal value of Rupiah banknotes based on 3 different emission years (2016, 2020, and 2022), most of which are already spread and used in Indonesia. In this study, it focuses on the nominal value classification of Rupiah banknotes using Canny segmentation as the initial process for image processing, Hu moments as feature extraction that produces features in numerical form, and Decision Tree and Random Forest as classification testing and performance evaluation. So that from the results of the performance evaluation, modeling was obtained to classify the nominal value of Rupiah banknotes.

This study compares the Decision Tree and Random Forest algorithms to predict the success of the classification method [33] of nominal Rupiah banknotes. Random Forest includes algorithms that are able to perform better classification, can cope with large amounts of training data, and effective methods for estimating data that include missing data [13]. Most datasets used for classification using the Decision Tree method have many variables. To reduce the number of non-essential variables or features in the data, the Decision Tree method also breaks the dataset into smaller subsets, which makes the learning process easier [18].

Method

This study has created a model to classify the image of Rupiah banknotes using Decision Tree and Random Forest. The goal was to examine how the two algorithms work to produce the best performance evaluation [19]. **Figure 2** shows the flow of methodology used in this study.

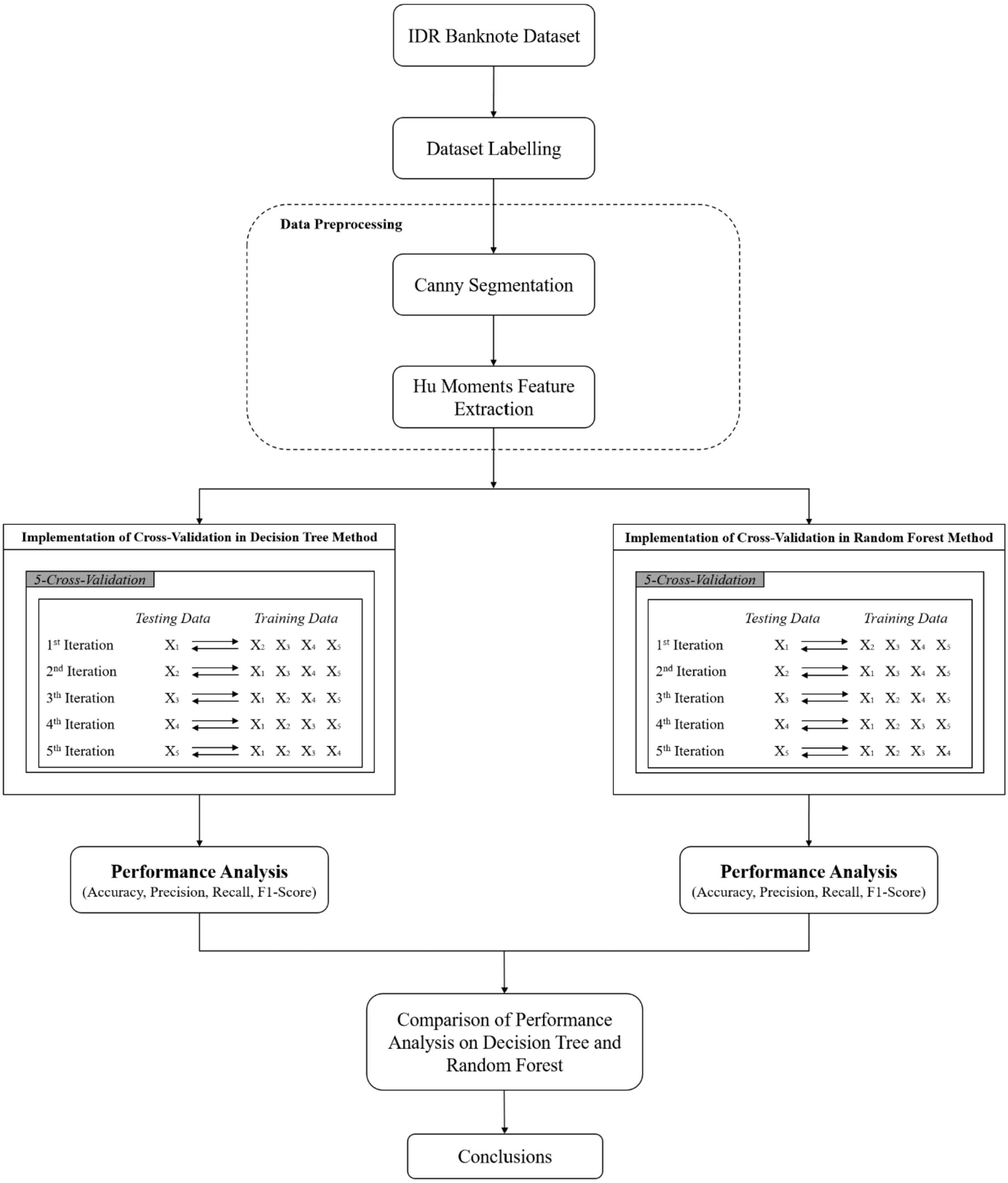

Figure 2. Flow in Multiclass Classification

A. Dataset Processing

The Rupiah banknotes dataset was collected using webcam cameras and https://teachablemachine.withgoogle.com/train/image websites. The dataset consisted of 30 classes that each contain a hundred representative images. Images of Rupiah banknotes were collected based on nominal, year of issuance (2016, 2020, and 2022), as well as the front and back sides of the notes, with an image resolution of 224×224 pixels.

Table 1. Dataset Information

Dataset	Number of Cases	Number of Attributes	Number of Classes	Attribute Characteristics	Missing Values
Rupiah Banknotes	3000	7	30	Numeric	No

Target of Dataset

te2016_001B	te2016_010B	te2016_100B	te2022_002B	te2022_020B
te2016_001D	te2016_010D	te2016_100D	te2022_002D	te2022_020D
te2016_002B	te2016_020B	te2020_075B	te2022_005B	te2022_050B
te2016_002D	te2016_020D	te2020_075D	te2022_005D	te2022_050D
te2016_005B	te2016_050B	te2022_001B	te2022_010B	te2022_100B
te2016_005D	te2016_050D	te2022_001D	te2022_010D	te2022_100D

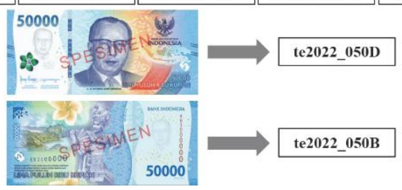

Figure. 3. Target the Dataset

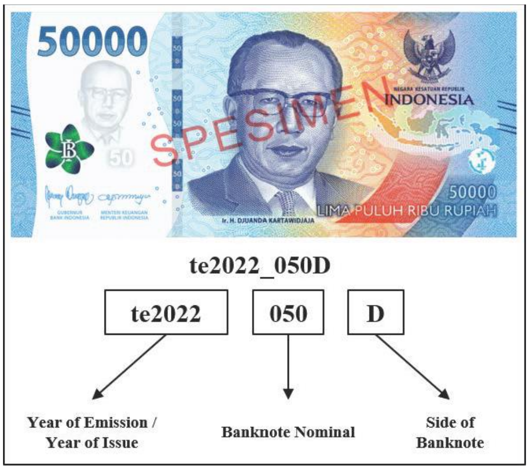

Figure. 4. Dataset Labelling

Based on **Figure 3** There are 30 targets, and each target had different initials, for example te2022_050D show a picture of the front of the IDR 50000 banknote, and te2022_050B show a picture of the back of the IDR 50000 banknote. On the **Figure 4** is the labelling concept on the Rupiah banknote dataset. In labelling te2022 was the 2022 emission year (issuance of Rupiah banknotes in 2016), then the term 050D was a nominal IDR 50000 on the front side, which was initialized with the letter D, and if initialized with the letter B indicates that the back side.

Table 2 shows a description of the dataset division. In the emission year column, there are three emission years, namely 2016, 2020, and 2022. In the 2016 and 2022 emission years, where researchers used all nominal Rupiah banknotes, namely IDR 1000, IDR 2000, IDR 5000, IDR 10000, IDR 20000, IDR 50000, and IDR 100000, and the 2020 emission year used only IDR 75000, and each nominal Rupiah banknote, researchers used all sides, namely the front and back sides of the Rupiah.

Table 2. Description of Dataset Sharing

Emission Year	Nominal	Side
2016	IDR 1000	Front and Back
	IDR 2000	
	IDR 5000	
	IDR 10000	
	IDR 20000	
	IDR 50000	

Emission Year	Nominal	Side
	IDR 100000	
2020	IDR 75000	
2022	IDR 1000	
	IDR 2000	
	IDR 5000	
	IDR 10000	
	IDR 20000	
	IDR 50000	
	IDR 100000	

B. Image Segmentation

The processing and analysis of images from a visual perspective is known as image processing [20]. Basically, there are two main functions of image processing. The two main bases of image processing are the first for analysis, storage, and transfer of data, and the second is for better interpretation of images by humans [21]. Edge detection identifies the boundary lines of objects in the image and can find changes in different intensities in the image plane [22]. The image always has important information on the edges, since the edges separate objects from each other. The purpose of detecting edges is to extract information such as shape, position, size, sharpness, and enrichment from the image [23]. John F. Canny introduced Canny's algorithm in 1986 to detect the edges of an object. The algorithm is also used to remove noise in an image and is applied to Gaussian filters [23]−[25]. Noise should be reduced to reduce the chance of faulty edge detection. To remove unwanted information and noise from the image, Gaussian filtering is used. In this study, using the size of the Gaussian filtering kernel, namely the kernel (3.3), which shows 3 × 3 pixels of the surrounding of the taken area. Equation 1 can be used to formulate the Gaussian function G(x,y) [20]:

$$G(x,y) = \frac{1}{2\pi\sigma^2} exp\left[\frac{x^2+y^2}{2\sigma^2}\right] \tag{1}$$

Where is the standard division (size) of the Gaussian filter used to adjust the smoothing level, so it is very important for the process of Canny detection in the image [24]. After applying Gaussian filtering, proceed using the Canny algorithm using a lower threshold value of 40 and using an upper threshold value of 80.

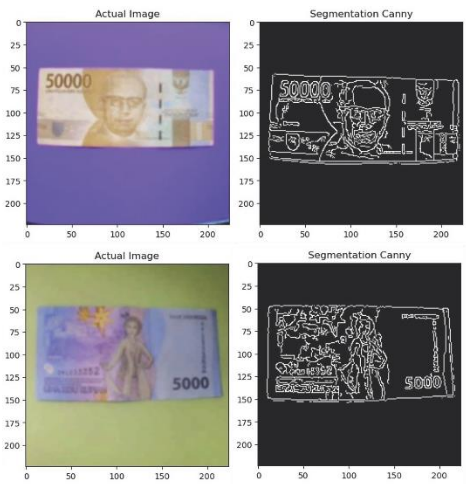

Figure. 5. Sample Visualization Dataset Using Gaussian Blur and Canny Segmentation

C. Feature Extraction

Feature extraction transforms pixel data into representations of shapes, motion, colors, and textures. An important stage in the construction of any classification of these patterns is to obtain information about the characteristics of each class so that it can be used for later stages [26]. Feature Extraction in computer vision and machine learning refers to a key set of data being measured and building on anticipated features so as not to be redundant and informative. Image recognition involves the process of extracting features. The recognition rate is directly affected by the reliability of the feature vector [27]. ML K. Hu put forward Hu's moment of invariant theory in 1962 [28]. The feature extraction method in Hu moments is used to produce seven features that can identify objects. The object taken can be a location, area, direction, and others [29]. Moment objectives with translational invariant, rotation, scaling, and scale are built on the theory of region moment invariant, which can describe the shape of the space region. Extract the shape aspect of the image, namely [30]:

$$M_1 = \eta_{20} + \eta_{02} \tag{2}$$

$$M_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \tag{3}$$

$$M_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \tag{4}$$

$$M_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \tag{5}$$

$$\begin{aligned} M_5 = {} & (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] \\ & +(3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \end{aligned} \tag{6}$$

$$M_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{12}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \tag{7}$$

$$\begin{aligned} M_7 = {} & (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] \\ & +(3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \end{aligned} \tag{8}$$

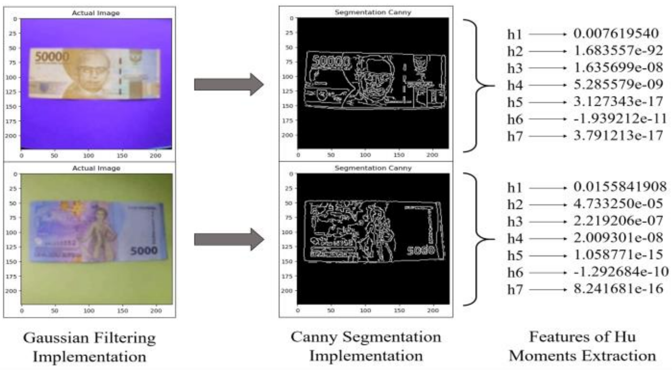

Figure 6. Feature Extraction Process

In this study, the Rupiah banknote image dataset was processed in the Hu Moments extraction feature step after passing the image segmentation stage using Gaussian Filtering and Canny segmentation. Hu Moments feature extraction yields 7 features in numerical form. These features will later be used to carry out the nominal classification process of Rupiah banknotes

D. Application of classification methods

One of the most common problems in machine learning is classification, which has been widely studied in various fields. Classification problems are usually divided into binary and multi-class problems based on the number of classes involved in the classification process [31]. This study applied a multiclass classification, because this research used 30 classes. For classification tasks, the Decision Tree algorithm is usually used. Decision Tree classifies data into a limited number of classes based on the value of the variable entered [32]–[33]. The classification algorithm used is Random Forest. It includes algorithms that can perform better classification. The algorithm can cope with large amounts of training data, and effective methods for estimating data that include missing data [17]. In the classifier parameters of the Decision Tree and Random Forest algorithms, the researchers used (random_state=42), which activates the random number generator used in the algorithm.

Datasets was shared with 20% test data and 80% training data. To find out how accurate the model was at the time of training, model evaluation was carried out on the training data using k-fold cross-validation with k=5. Test data was used for validation of models that have been created. The results of evaluation and validation of this model were used to analyze algorithm performance [34]. K-fold cross-validation was used to ensure that the data sharing of each part was fair and equitable, with k indicating the number of parts. The data in k-fold cross-validation was divided into two, namely training data and test data alternately. The data are tested and trained according to the number of its parts (k) [1].

E. Performance Measurement

To form a forecast model, a portion of data that has been categorically known was put into the learning phase. Next, some of the data that has been entered was tested with an already formed model [25]. Accuracy, precision, recall, and f1-score tests were used to measure the performance of a method. In addition, robustness of performance can be measured by applying cross-validation to performance tests [35], [36]. The current study used accuracy, precision, recall, and F1-score metrics to evaluate the performance of classifiers. The relevant formula for this research metric is shown in equations (9) through (12). Based on the following equation, TP, TN, FP, and FN represent the measures of True Positive, True Negative, False Positive, and False Negative, respectively. Picture. 5 provides more details about the following equations and related concepts [37].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

$$Precision = \frac{TP}{TP + FP} \tag{10}$$

$$Recall = \frac{TP}{TP + FN} \tag{11}$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{12}$$

Results and Discussion

A. Performance Evaluation Results

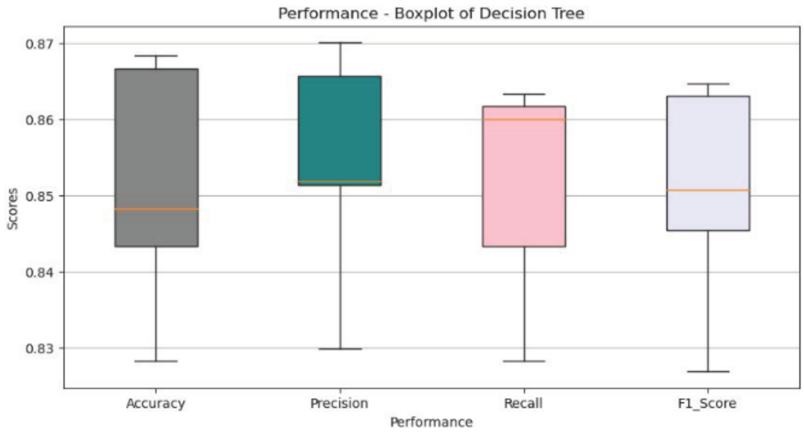

Figure. 7. Comparison of Each Cross-Validation in the Decision Tree Method

In **Figure 7**, performance results were obtained in the Decision Tree method, where the highest accuracy results in the 5th cross-validation were 0.87. The highest precision result in the 4th cross-validation was 0.8757746. The highest recall result in the 4th cross-validation was 0.87. The highest F1-score result in the 4th cross-validation was 0.87029246.

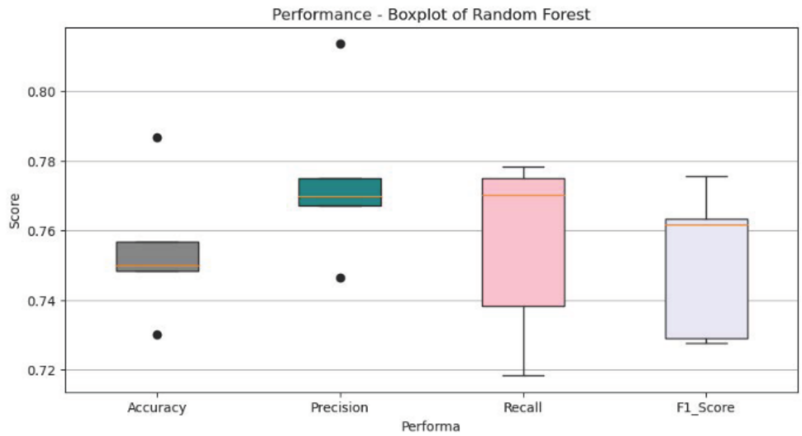

Figure. 8. Comparison of Each Cross-Validation in the Random Forest Method

In **Figure 8**, performance results were obtained in the Random Forest method, where the highest accuracy result in the 5th cross-validation was 0.94. The highest precision result in the 5th cross-validation was 0.9416643, the highest recall result in the 5th cross-validation was 094. The highest F1-score result in the 5th cross-validation was 0.93933971.

B. Classification Evaluation Results

Table 3. Dataset Performance

Σ Installment-Installment	Decision Tree Classifier	Random Forest Classifier
Balanced Accuracy	0.86	0.93
Accuracy	0.86	0.93
Precision Weighted	0.86	0.92
Recall Weighted	0.85	0.92
F1-Score Weighted	0.85	0.92

Table 4. Nominal Value of Rupiah Classification Using Decision Tree

Class	Precision	Recall	F1-Score	Support
te2016_001B	0.76	0.71	0.74	100
te2016_001D	0.82	0.75	0.79	100
te2016_002B	0.86	0.78	0.82	100
te2016_002D	0.80	0.85	0.83	100
te2016_005B	0.88	0.81	0.84	100
te2016_005D	0.81	0.81	0.81	100
te2016_010B	0.89	0.90	0.90	100
te2016_010D	0.96	0.98	0.97	100
te2016_020B	0.79	0.82	0.80	100
te2016_020D	0.90	0.86	0.88	100
te2016_050B	0.77	0.79	0.78	100
te2016_050D	0.82	0.81	0.81	100
te2016_100B	0.64	0.75	0.69	100
te2016_100D	1.00	0.99	0.99	100
te2020_075B	0.93	0.87	0.90	100
te2020_075D	0.94	0.90	0.92	100
te2022_001B	0.96	0.96	0.96	100
te2022_001D	0.87	0.85	0.86	100
te2022_002B	0.89	0.96	0.92	100
te2022_002D	0.99	0.98	0.98	100
te2022_005B	0.95	0.92	0.93	100
te2022_005D	0.96	0.92	0.94	100
te2022_010B	0.91	0.89	0.90	100
te2022_010D	0.83	0.90	0.87	100
te2022_020B	0.82	0.88	0.85	100
te2022_020D	0.93	0.95	0.94	100
te2022_050B	0.77	0.82	0.79	100
te2022_050D	0.87	0.93	0.90	100
te2022_100B	0.74	0.69	0.72	100
te2022_100D	0.75	0.73	0.74	100

Class	Precision	Recall	F1-Score	Support
accuracy	-	-	0.86	3000
macro avg	0.86	0.86	0.86	3000
weighted avg				3000

The evaluation results in **Table 4** show that the overall accuracy in all classes was 0.86. The highest pecision was 1.00 at the nominal IDR 100000 frontside (emission year 2016), while the lowest precision was 0.64 at the nominal IDR 100000 backside (emission year 2016). The highest recall was 0.99 at the frontside 100000 IDR (2016 emission year), while the lowest recall was 0.71 at a nominal IDR 1000 backside (emission year 2016). The highest F1-score was 0.99 at the nominal IDR 100000 frontside (emission year 2016), while the lowest F1-score was 0.69 at the nominal IDR 100000 backside (emission year 2016).

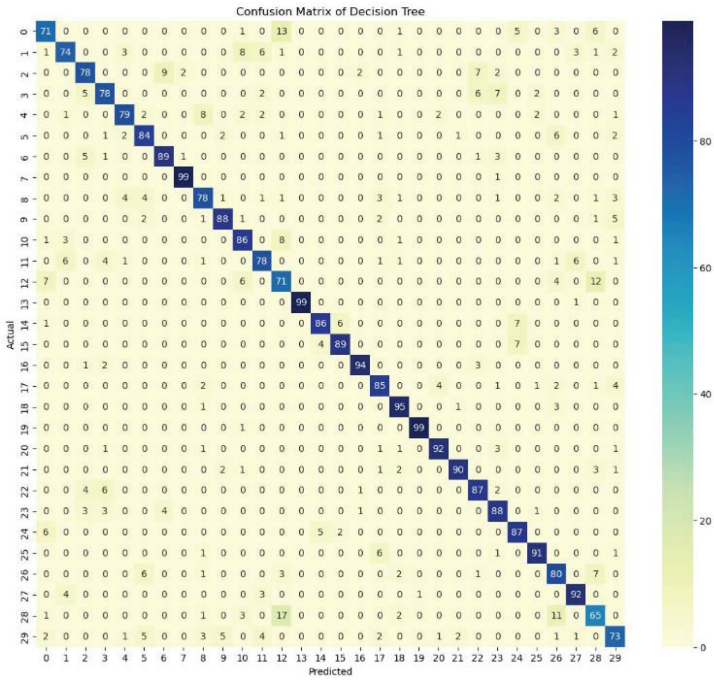

Figure. 9. Confusion Matrix in Decision Tree Method

Table 5. Nominal Value of Rupiah Classification Using Random Forest

Class	Precision	Recall	F1-Score	Support
te2016_001B	0.93	0.80	0.86	100
te2016_001D	0.88	0.84	0.86	100
te2016_002B	0.90	0.88	0.89	100
te2016_002D	0.95	0.91	0.93	100
te2016_005B	0.91	0.89	0.90	100
te2016_005D	0.94	0.88	0.91	100
te2016_010B	0.91	0.93	0.92	100
te2016_010D	0.98	1.00	0.99	100
te2016_020B	0.89	0.91	0.90	100
te2016_020D	0.90	0.95	0.92	100
te2016_050B	0.89	0.93	0.91	100
te2016_050D	0.91	0.90	0.90	100
te2016_100B	0.81	0.83	0.82	100
te2016_100D	1.00	0.99	0.99	100
te2020_075B	0.98	0.92	0.95	100

Class	Precision	Recall	F1-Score	Support
te2020_075D	0.94	0.96	0.95	100
te2022_001B	0.97	0.98	0.98	100
te2022_001D	0.99	0.97	0.98	100
te2022_002B	0.95	1.00	0.98	100
te2022_002D	0.97	0.98	0.98	100
te2022_005B	0.99	0.99	0.99	100
te2022_005D	0.96	1.00	0.98	100
te2022_010B	0.94	0.97	0.96	100
te2022_010D	0.95	0.93	0.94	100
te2022_020B	0.91	0.97	0.94	100
te2022_020D	0.95	0.98	0.97	100
te2022_050B	0.87	0.94	0.90	100
te2022_050D	0.88	0.92	0.90	100
te2022_100B	0.85	0.81	0.83	100
te2022_100D	0.93	0.86	0.90	100
accuracy	-	-	0.93	3000
macro avg	0.93	0.93	0.93	3000
weighted avg	0.93	0.93	0.93	3000

The evaluation results in **Table 5** show that the overall accuracy in all classes was 0.93. The highest pecision was 1.00 at the nominal of IDR 100000 frontside (emission year 2016), while the lowest precision was 0.87 at IDR 50000 backside (emission year 2022). The highest recall was 1.00 at the nominal of IDR 10000 frontside (emission year 2016), nominal of IDR 2000 backside (emission year 2022), and nominal of IDR 5000 frontside (emission year 2022), while the lowest recall was 0.80 at 1000 IDR backside (2016 emission year). The highest F1-Score was 0.99 at the nominal of IDR 10000 frontside and IDR 100000 frontside (emission year 2016), and at the nominal of IDR 5000 backside (emission year 2022), while the lowest F1-score was 0.82 at IDR 100000 backside (2016 emission year).

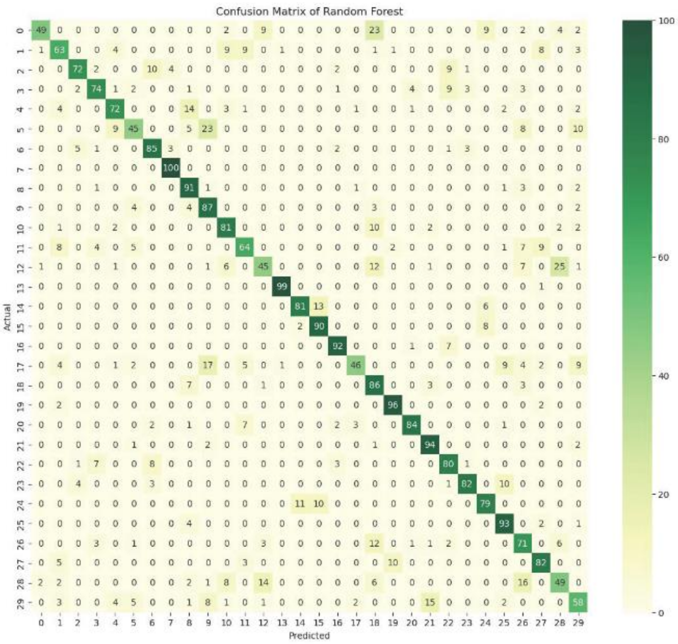

Figure. 10. Confusion Matrix in Decision Tree Method

Conclusion

This research shows that using image segmentation methods (Canny detection), feature extraction methods (Hu Moments), and classification methods (Decision Tree and Random Forest) can be used to classify various nominal value of Rupiah banknotes. Based on the present research, good performance results were obtained in the Random

Forest method with an accuracy of 0.93, while the Decision Tree method produced an accuracy of 0.86. By using the Decision Tree and Random Forest methods, the nominal value of Rupiah banknotes can be classified based on the collected dataset. In future research, the use of other methods or parameter optimization can be used to improve model performance. This research can be used to improve the security and efficiency of banknote processing in Indonesia by using an automated banknote recognition system.

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