A Proposed Batik Automatic Classification System Based on Ensemble Deep Learning and GLCM Feature Extraction Method

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***Abstract*—Classification of batik images is a challenge in the field of digital image processing, considering the complexity of patterns, colors, and textures of various batik motifs. This study proposes an ensemble method that combines texture feature extraction using Gray Level Co-occurrence Matrix (GLCM) with the Residual Neural Network (ResNet) classification model to improve accuracy in batik image classification. Texture features such as contrast, dissimilarity, entropy, homogeneity, mean, and standard deviation are extracted using GLCM and combined with ResNet to produce a more robust classification model. The experimental results show that the proposed method achieves high performance, namely above 90% for each evaluation metric used, such as accuracy, precision, recall and F-1 Score. The best performance in classifying batik images is obtained by the Standard Deviation feature with accuracy, precision, recall, and F1-score of 95%, 93%, 93%, and 93%, respectively. Furthermore, the application of the ensemble method based on the hard voting approach has proven effective in increasing the accuracy of batik image classification by utilizing a combination of texture features and deep learning models. The proposed method makes a significant contribution to the efforts to preserve batik culture through digitalization and can be implemented for various purposes such as an image-based batik search system.**

Keywords*—Batik; GLCM; ResNet; ensemble method; hard voting

I. Introduction

Batik is an Indonesian cultural heritage that has high artistic and historical value [1], [2], [3], [4]. Each batik motif contains a certain philosophical meaning and can reflect the cultural identity of the producing region. Along with the development of digital technology, digitization and classification of batik images have become important needs, both for cultural preservation and commercialization. However, batik image classification has its own challenges, considering the diversity of complex motifs, colors, and textures [5], [6]. Batik image classification faces challenges in the field of pattern recognition and digital image processing due to the diverse and complex batik motifs [7]. Although there have been various methods applied to classify batik images, such as the use of conventional machine learning-based methods (eg, SVM, KNN) and deep learning (eg, CNN), there are still several limitations that have not been fully overcome.

Many studies only rely on artificial neural networks or deep learning methods for batik image classification without considering specific local texture features, such as those that can be obtained with the GLCM method. This can cause additional problems due to the loss of important information related to patterns and textures that are characteristic of batik motifs. In addition, most previous studies tend to focus on the use of a single technique, either classical feature extraction or deep learning, without combining the advantages of both methods in one ensemble model. This suggests an opportunity to explore a hybrid approach that can improve classification accuracy by leveraging the strengths of GLCM-based texture feature extraction and the generalization capabilities of ResNet.

In this study, it is proposed a batik automatic classification system that combines a texture feature extraction approach using Gray Level Co-occurrence Matrix (GLCM) and an artificial neural network-based classification method, namely Residual Neural Network (ResNet). This ensemble method aims to improve classification accuracy by utilizing the advantages of both approaches. GLCM is known to be effective in describing texture characteristics [8], [9], [10], [11], while ResNet offers advantages in the ability to learn complex feature representations from images through deep network architectures [12], [13]. This research is expected to make a significant contribution to the field of pattern recognition, especially for batik image classification. Furthermore, the presence of this research is expected to provide alternative solutions that are more accurate and efficient in identifying batik images.

By developing an automatic classification system, the digitization and cataloging of Batik patterns can be streamlined, contributing to cultural preservation in the digital age. This also supports educational and archival efforts, making Batik accessible to global audiences. Furthermore, an automated classification system could help streamline various processes, from quality control to market segmentation, and assist in inventory management. For instance, it can aid designers, retailers, and manufacturers in quickly identifying and categorizing different Batik types, improving the overall supply chain and customer service experience.

II. Literature Review

A. GLCM Feature Extraction

Feature extraction is the first and foremost step in image processing, also known as computer vision. This stage involves transforming an image into a set of features that are easier for a computer to understand and relevant for further analysis, such as classification or segmentation [14]. Among the various techniques for feature extraction, Gray-Level Co-Occurrence Matrix (GLCM) which is introduced by Haralick et al. in 1973, is widely used, especially in texture analysis [15], [16]. GLCM is a statistical method that considers the spatial relationship between pixels to analyze texture [17], [18]. GLCM has become a popular choice for feature extraction due to its many advantages. GLCM is able to capture complex texture information in an image by measuring the spatial relationship between pixels [19]. This method allows for more detailed texture analysis compared to simple statistical methods such as mean or variance. It is particularly useful for detecting subtle and complex patterns in images, such as small differences in tissue texture in medical images or variations in surface texture in quality inspection. In addition, GLCM is effective in detecting subtle differences in texture that may not be visible with other analysis techniques [19]. In representing an image, GLCM can produce several features to quantify the texture of an image such as Contrast, Correlation, ASM, homogeneity and so on.

Due to its advantages, GLCM is considered very suitable for image processing in batik because of its ability to analyze textures in depth and capture complex texture patterns. Batik is a traditional fabric that has unique patterns and textures with complex and repetitive motif variations, so it requires effective techniques to recognize, classify, or even detect these patterns. For example, GLCM is able to measure the spatial relationship between pixels in a way that captures the texture properties found in batik images, such as how often a particular pattern appears or how the color intensity changes along the pattern. In addition, GLCM can detect subtle variations in texture with features such as contrast, homogeneity, and energy, which helps identify small patterns and texture differences in batik designs. To date, there have been many studies that applied the GLCM feature extraction algorithm to the task of batik image classification. The summary of the research is shown in Table I.

Based on Table I, it can be seen that GLCM has played a major role in building a batik image classification system. Furthermore, from the literature study that has been conducted, it can be concluded that the majority of these studies apply the k-NN algorithm as their choice. Very few studies have tried to apply Deep Learning-based image classification which is considered one of the best methods in image classification. This is one of the research gaps found and attempted to be solved in this study. A detailed discussion related to this issue will be presented in the following research gap and research contribution sections.

B. Ensemble Method

Ensemble methods have gained significant attention in recent years for the task of image classification due to their ability to improve model accuracy and performance. Ensemble methods are approaches that combine multiple machine learning models to produce a more robust and accurate model [32], [33]. The main goal of ensemble methods is to reduce the prediction error generated by a single model by combining the results of multiple models. Some popular ensemble techniques include Bagging, Boosting, Stacking and Voting [34], [35], [36].

TABLE I. RELATED RESEARCH OF GLCM IMPLEMENTATION FOR BATIK CLASSIFICATION

Authors	Method	Result
[20]	k-NN	Acc = 75%
[21]	k-NN	Acc = 97.96
[22]	Neural Network	Acc = 84%
[23]	SVM	Acc = 78.3%
	k-NN	Acc = 92.3%
[24]	Canberra Distance	Acc = 41.67%
[25]	MLP	Acc = 88.89%
[26]	LVQ	Acc = 98.98%
[27]	Backpropagation Neural Network	Acc = 94%
[28]	Linear Discriminant Analysis	Acc = 96.5%
[29]	Backpropagation Neural Network	Acc = 80%
[30]	k-NN	Acc = 73.33%
[31]	k-NN	Acc = 97%

Bagging (Bootstrap Aggregating) is one of the commonly used ensemble techniques for image classification. This technique works by training several different models on a subset of the training data taken randomly with replacement. Random Forest, one of the Bagging-based algorithms, has been widely used for image classification. Boosting is an ensemble technique that attempts to improve model performance by training the model in stages, where each new model focuses on data that was incorrectly predicted by the previous model. One of the popular Boosting algorithms is AdaBoost (Adaptive Boosting). Stacking is an ensemble technique that combines several learning models to produce a final prediction through a meta-learner model. This technique usually involves heterogeneous models, such as a combination of neural network models and decision tree models. Voting is a relatively simple ensemble technique where several base models are trained independently, and the final prediction is made by voting on the predictions from each model. There are two types of voting-based ensemble methods, Hard Voting and Soft Voting. In Majority Voting (Hard Voting), the final prediction is the prediction that appears most often (the most votes) from all the base models. In contrast to the Weighted Voting (Soft Voting) type, in this type each model is given a weight based on its performance. The final prediction is made based on the weight of each model.

This study chooses the Voting-based ensemble method technique in order to produce a reliable and robust batik image classification system. This is because the voting method has been recognized as a very simple and efficient method [37], [38]. It does not require a lot of complex parameter settings or selection. This makes voting an attractive choice when the main goal is to improve prediction accuracy without adding much complexity. In addition, this Voting method has been proven to be able to overcome the weaknesses of the Single Model which in many cases has certain weaknesses or biases. By using voting, it can reduce the impact of these weaknesses because the final decision is made based on the consensus of several models. This is very useful when there is uncertainty about which model is most appropriate for a particular dataset. On the other hand, the voting method tends to be more stable and reliable when faced with new or previously unseen data. Because the final result is based on the consensus of several models, this method can adapt better to data that may not follow the training data pattern. However, the implementation of the ensemble method is still rare to produce a batik image classification system. This can be seen in the following Table II.

TABLE II. RELATED RESEARCH OF ENSEMBLE METHOD IMPLEMENTATION FOR BATIK CLASSIFICATION

Authors	Method	Result
[39]	Histogram Feature Extraction with k-NN classifier	Prec = 86.67%
[40]	Ensemble CNN	Acc = 100%
[41]	GLCM + LBP Feature Extration with k-NN classifier	Acc = 93.9%

Based on the study literature summarized in Table II, it can be concluded that the implementation of the ensemble method to produce a robust batik image classification system is still very rare. Especially related to the implementation of the ensemble method combined to GLCM feature extraction and Deep Learning-based classification. Three out of five studies related to the application of the Ensemble Method for batik image classification, it was found that two studies applied the k-NN algorithm as the choice of classification algorithm. Only one study applied a CNN-based Deep Learning algorithm. This problem is another research gap that is tried to be addressed in this study which will be summarized in the following section.

C. Research Gap and Contribution

Regarding the discussion of related research that has been explained in the previous section, it can be concluded that although there have been various methods applied to classify batik images, there are still some limitations that have not been fully resolved. The highlighted meeting problem is the scarcity of research that tries to combine the reliability of GLCM-based feature extraction with Deep Learning classification algorithms. The majority of studies that apply GLCM feature extraction are combined with classical machine learning algorithms such as k-NN instead of utilizing the reliability of the Deep Learning algorithm. The second research gap is the Lack of Ensemble Approaches that Combine Feature Extraction Techniques and Deep Learning. Most previous studies tend to focus on the use of a single technique, be it classical feature extraction or deep learning, without combining the advantages of both methods in one ensemble model. This shows an opportunity to explore a hybrid approach that can improve classification accuracy by utilizing the strengths of GLCM-based texture feature extraction and the generalization capabilities of ResNet. A summary of the research gaps found along with the research contributions proposed by this study is illustrated in Fig. 1.

Based on the illustration related to the research gap illustrated in Fig. 1, it can be concluded that this study proposes two contributions that can bridge those research gap. The first contribution is related to the effort to combine the GLCM feature extraction algorithm which has advantages in recognizing batik textures into a Deep Learning-based classification algorithm. The second contribution attempted by this study is the application of ensemble methods for batik image classification. This study introduces an ensemble method that combines GLCM-based feature extraction techniques and classification using ResNet. By combining these two algorithms, it is hoped that the proposed method can overcome the limitations in capturing complex texture information and fine patterns that are characteristic of batik. Furthermore, through these two contributions, it is hoped that the goal of developing a reliable and robust batik image classification system will be achieved.

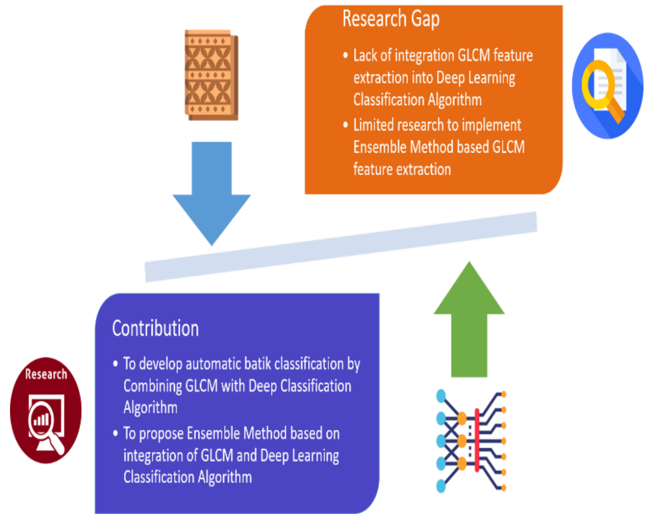

Fig. 1. Research gap and proposed contribution.

III. MATERIAL AND METHOD

A. Dataset Material

The dataset used in this research is a combination of datasets sourced from public datasets such as batik classification Resnet [4] and deep learning batik classification [6]. Furthermore, the dataset used consists of five classes of batik motifs such as lereng, parang, nitik, kawung and ceplok batik, which are illustrated in Fig. 2.

The batik dataset that has been collected consists of 5 classes of 4,284 images and is then separated into three types of data, such as training, testing, and validation data. To assemble data for training, testing, and validation, the dataset was separated by applying a ratio of 70:20:10. The final data for training, testing, and validation can be seen in Table III.

The next step is image preparation from raw data to ready-to-use data, known as the image pre-processing stage. At this image pre-processing stage, two activities are carried out, namely size adjustment and image dataset augmentation. In the image adjustment activity, customization is carried out so that all batik images have a uniform size of 150 x 150 pixels. After that, data augmentation is carried out on the rescaled image using the horizontal rotation method. The overall results of the data collection and pre-processing stages are described in Fig. 3.

Fig. 2. Batik dataset.

TABLE III. DATASET

Batik Class	Data	Training	Testing	Validation
Lereng	405	284	81	41
Parang	1,197	838	239	120
Ceplok	1,053	737	211	105
Kawung	747	523	149	75
Nitik	882	617	176	88
TOTAL	**4,284**	**2,999**	**857**	**428**

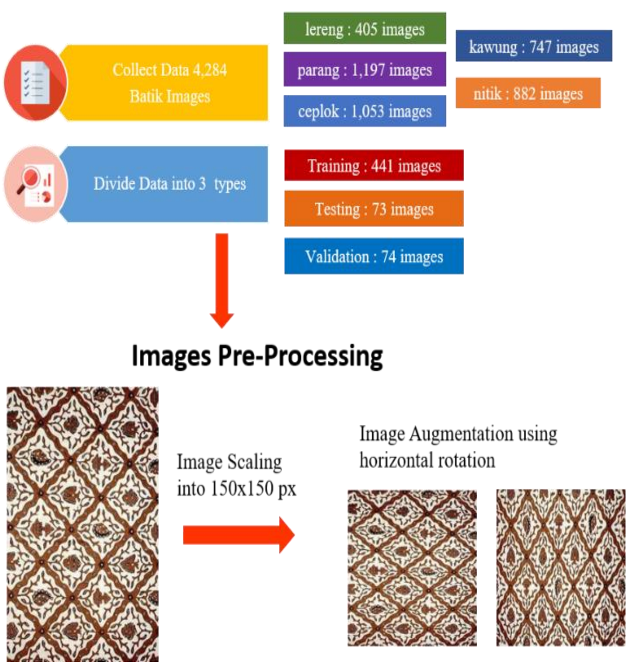

Fig. 3. Image pre-processing stage.

B. Proposed Method

As explained previously, the main contribution of this research is the development of an automatic classification system for batik images by applying the ensemble learning algorithm. Ensemble learning is a method in machine learning that works by combining several machine learning models to produce a more robust and accurate model. The basic concept of ensemble learning is that by combining predictions from several different models, we can reduce errors and improve prediction performance. The concept of ensemble learning applied in this research is based on hard voting. Hard voting is done by calculating the prediction results where the final prediction is determined based on the majority of votes. The overall flow of the proposed ensemble learning for batik image classification is depicted in Fig. 4.

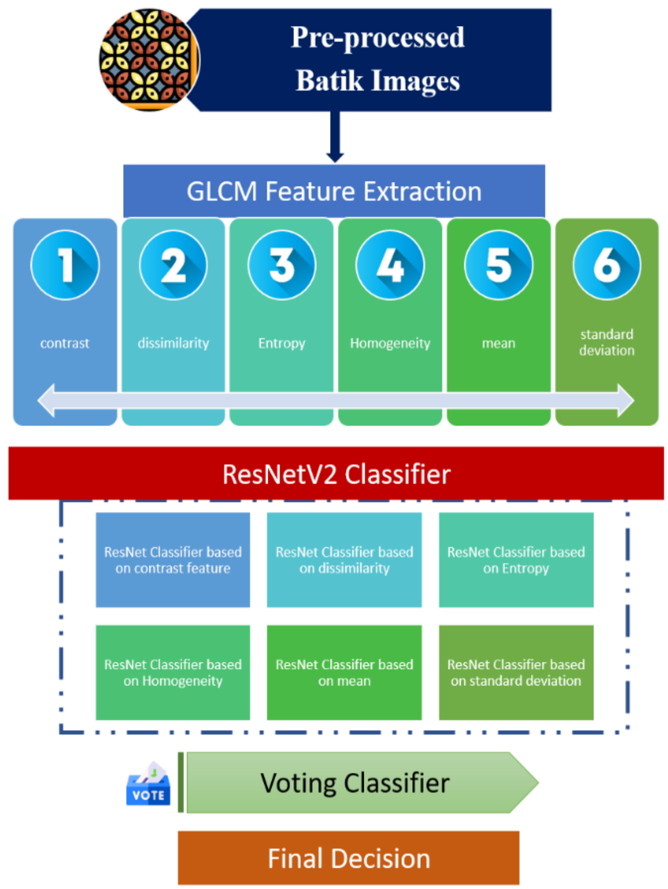

Fig. 4. Flowchart of proposed ensemble deep learning based on GLCM feature extraction.

As seen in Fig. 4, the proposed ensemble deep learning method consists of two main components, namely the GLCM algorithm as a feature extraction layer and the ResNet18 architecture. GLCM (Gray Level Co-occurrence Matrix) is a method often used in image analysis for texture feature extraction. GLCM calculates how often a pair of pixels with a certain intensity value appears in an image at a certain distance and angle. The use of GLCM (Gray Level Co-occurrence Matrix) as a feature extraction algorithm has several advantages that make it a popular choice in image texture analysis. Even when compared to the very popular convolution method, GLCM has advantages such as the ability to describe texture, various texture features, simple implementation, computational affordability, lower data requirements and so on.

To perform feature extraction using GLCM (Gray Level Co-occurrence Matrix), the first step is to convert the color image to grayscale, because GLCM is applied to grayscale images. After the image is converted, the GLCM parameters are determined, such as the distance between pixels and the angle (0 °, 45 °, 90 °, 135 °). The GLCM matrix is generated by calculating the frequency of occurrence of pixel pairs with certain intensity values at predetermined distances and angles. Once the GLCM matrix is obtained, texture feature extraction is performed by calculating the contrast, dissimilarity, homogeneity, mean, and entropy values of the GLCM matrix. Moreover, this study uses 4 angles at once with a distance between pixels of 1. So that the total features generated for each image are 24 features (4 features for each texture).

After feature extraction with GLCM is completed, the next stage is the application of the CNN algorithm to determine the class of each image by utilizing the Pretrained Residual Network (ResNet) architecture. The ResNet architecture was developed with the aim to overcome the issue of degradation in very deep neural networks. As the depth of the network increases, model performance tends to deteriorate and has difficulty in training due to the vanishing gradient problem. ResNet introduces a residual block that allows information to pass through several layers through "shortcut connections" or "skip connections". ResNet comes in several variants, which differ in the number of layers and network depth. This study applies ResNet18 which is considered suitable for tasks with low data complexity. The block diagram of the ResNet18 architecture is conceived in Fig. 5.

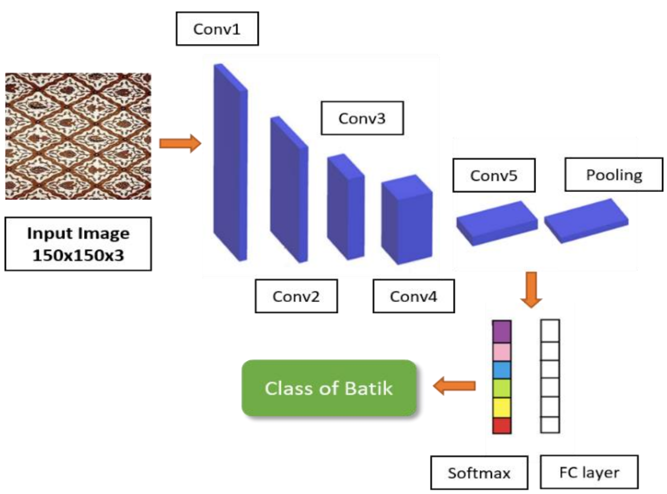

Fig. 5. Block diagram of ResNet18 architecture.

In addition, the ResNet18 architecture is chosen in this study compared to other architectures because of its smaller parameter size. This makes model loading, model weighting, and training much faster. ResNet-18 serves as the base network, and the introduction of the Inception module enhances it. This module combines complex kernels of various sizes to facilitate feature extraction at different image scales, thereby improving recognition accuracy.

The process of identifying the class of batik images will produce six classification results according to the number of textures used. Therefore, an ensemble learning method based on hard voting is then carried out to determine the final class of the batik image. As previously explained, the application of hard voting by combining several different models (ensemble learning) is expected to reduce the risk of overfitting that may occur in a single model. This is because errors made by one model can be offset by other models.

C. Metric Performance

Once the batik image classification model based on ensemble learning was successfully created, the research continued to the performance evaluation stage of the created model by utilizing the confusion matrix. This matrix is very useful for showing the number of correct and incorrect predictions, which are divided into True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN). This helps in calculating other metrics and provides deeper insight into the types of errors made by the model. After the Confusion Matrix is successfully identified, the next step is to calculate the level of accuracy, precision, recall and F-1 Score. The illustration of the confusion matrix can be seen in Fig. 6.

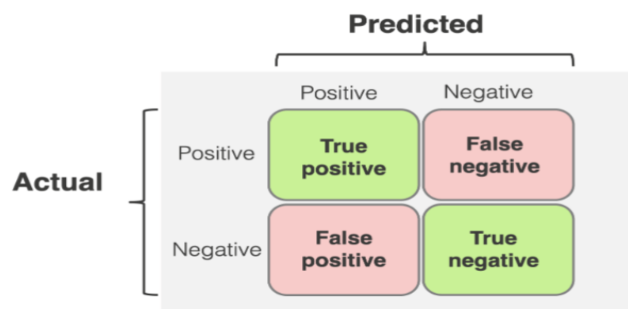

Fig. 6. Confusion matrix scheme.

Each of these metrics has its own advantages and disadvantages. So by using these various metrics, a more comprehensive picture of the ensemble learning model for batik classification will be obtained.

IV. RESULT AND DISCUSSION

As explained, this research applied the concept of ensemble deep learning extraction integrated with CNN algorithm as a feature layer to get the best performance in batik image classification. In this section, a confusion matrix-based performance evaluation will be carried out followed by measuring accuracy, precision, recall and F-1 score. The confusion matrix results for each GLCM feature are shown in Fig. 7 to Fig. 12.

Based on the results depicted by the confusion matrix in Fig. 7 to Fig. 12, it was found that the average GLCM feature has a balanced performance in recognizing batik images. This is indicated by the accuracy of batik class identification between the predicted results and the actual values. Furthermore, there is no significant difference between each GLCM feature used in the classification of batik images. Therefore, it can be concluded that each GLCM feature has a fairly balanced performance in batik classification. Furthermore, by utilizing the results obtained in the confusion matrix, a performance evaluation based on accuracy, precision, recall and F-1 score was carried out using the following formula.

$$accuracy = \frac{(\mathrm{TP+TN})}{(\mathrm{TP+TN+FP+FN})} \tag{1}$$

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \tag{2}$$

$$Recall \quad = \frac{TP}{TP+FN} \tag{3}$$

$$F1\,Score \quad = \frac{2*(Precision*Recall)}{(Precision+Recall)} \tag{4}$$

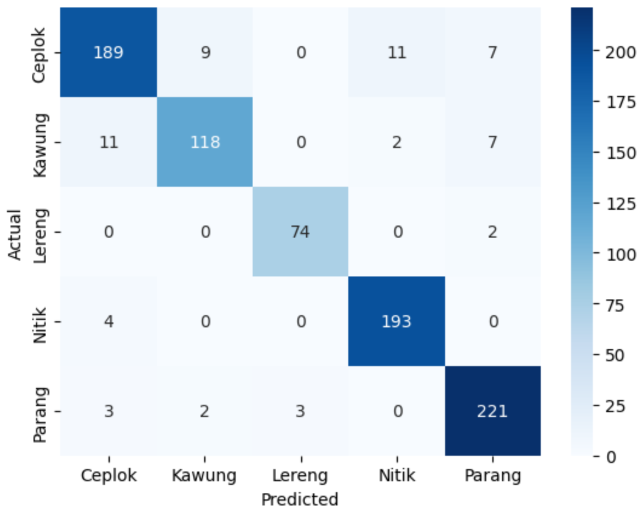

Fig. 7. Confusion matrix based on contrast features.

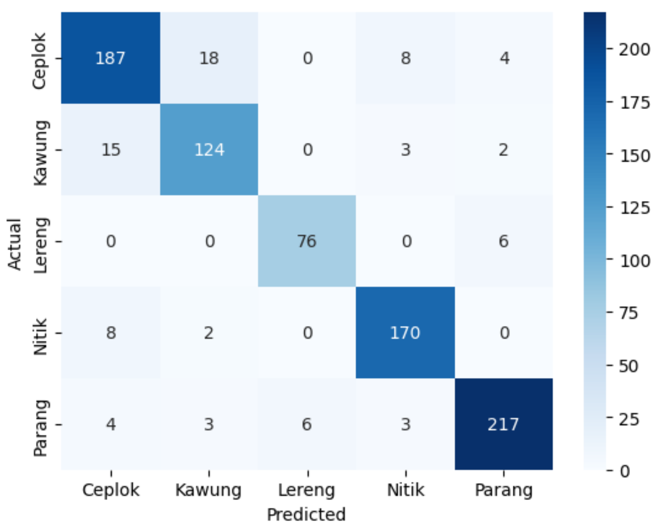

Fig. 8. Confusion matrix based on dissimilarity features.

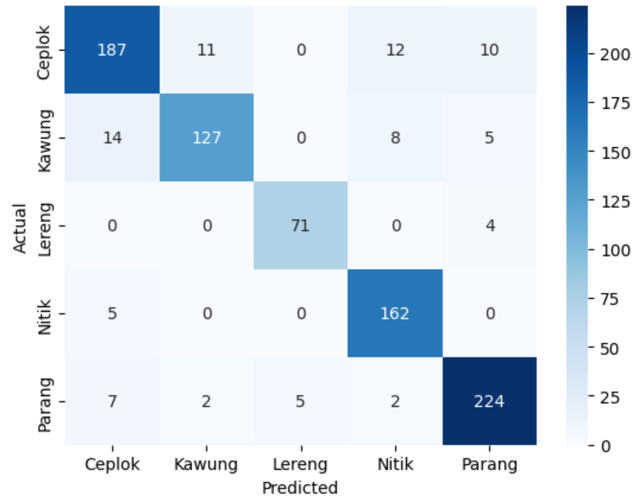

Fig. 9. Confusion matrix based on entropy features.

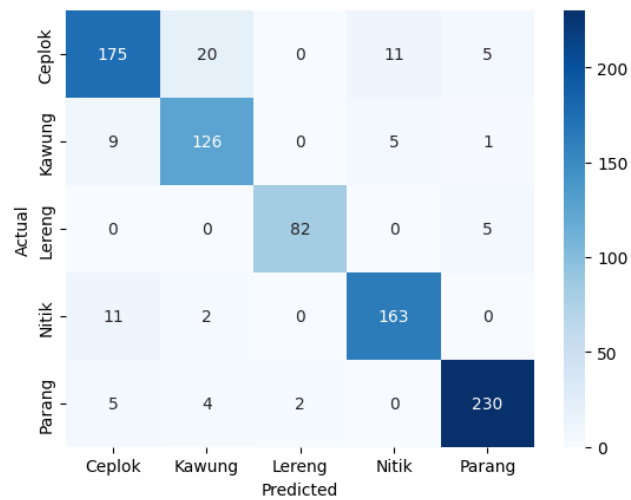

Fig. 10. Confusion matrix based on homogeneity features.

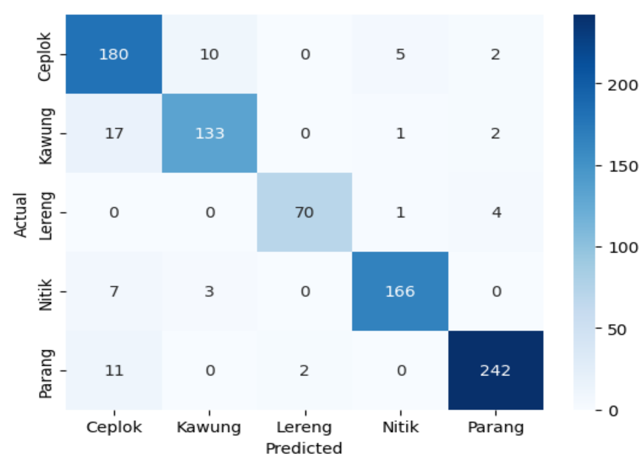

Fig. 11. Confusion matrix based on mean features.

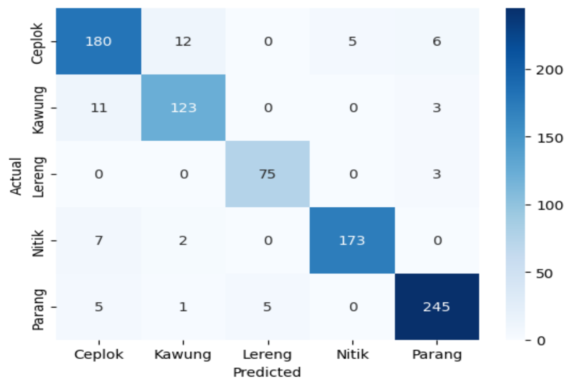

Fig. 12. Confusion matrix based on standard deviation features.

The overall performance evaluation of this research can be seen in Table IV.

TABLE IV. CLASSIFICATION PERFORMANCE FOR EACH GLCM FEATURE

	Acc (%)	Prec (%)	Rec (%)	F1 (%)
Contrast	0.93	0.93	0.90	0.91
Dissimilarity	0.90	0.90	0.90	0.90
Entropy	0.90	0.90	0.90	0.90
Homogeinity	0.95	0.91	0.91	0.90
Mean	0.95	0.92	0.91	0.91
Standard Deviation	0.95	0.93	0.93	0.93

It can be concluded from the performance evaluation results listed in Table II that Standard Deviation is the feature with the best performance because it has the highest value for all metrics (Accuracy, Precision, Recall, and F1-Score) with a value of 93%. Meanwhile, Homogeneity and Mean also show high performance, with the highest accuracy (95%) but have slight differences in precision, recall, and F1-score values. Entropy and Dissimilarity show consistent performance but are lower than other features. In order to improve the classification results, an ensemble method based on hard voting is used. This method is expected to complement each other's shortcomings in the performance of each feature extraction. To test how effective the application of the ensemble method is, a classification of batik images is carried out on the test data. Based on the test, it was found that the application of the ensemble method can improve the performance of the batik image classification system. As an example in a test scenario, by applying the ensemble method based on hard voting, the classification error of the batik class can be avoided. The scenario for testing the effectiveness of the application of the ensemble method is illustrated in Fig. 13.

Based on one of the test results, the prediction results obtained that four out of six features successfully predicted the class of batik images. The other two features failed to identify the class properly. The final result based on majority voting successfully selected the Kawung class which is the right class for the batik image. Therefore, by applying the ensemble method, the performance of the batik classification system can be improved because the final prediction based on the majority decision tends to be more stable and accurate, especially if the data varies. In addition, this ensemble method also has advantages because it can overcome the weaknesses of individual models such as the homogeneity extraction-based classification model which tends to have lower performance in terms of F1 score but has advantages in terms of accuracy. Hence, it can be concluded that by combining predictions from several classification models, the possibility of errors that can occur if only relying on one model can be reduced. This is because the weaknesses of one classification model can be compensated by another model. Although the study has successfully proven that the implementation of the ensemble method based on the GLCM feature extraction algorithm and the ResNet architecture is able to produce a robust system for producing a batik image classification system, there are many more things that need to be improved in further research. Recommendations for further research will be discussed in the following conclusion section.

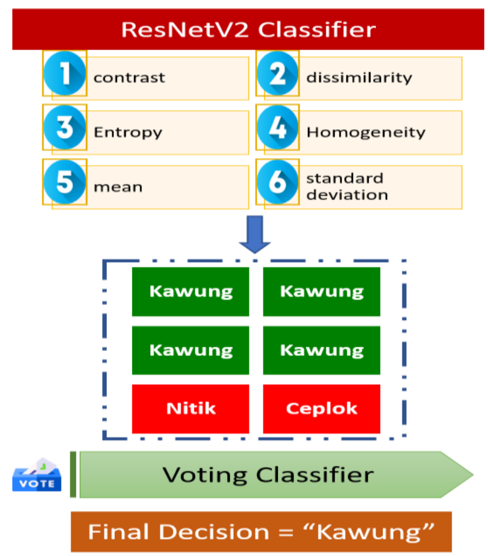

Fig. 13. Testing scenario for ensemble methods implementation.

V. CONCLUSION

The study exploited image extraction algorithms to obtain texture images that can be used in batik image classification tasks. The image extraction algorithm used is GLCM which is known to be reliable in describing the texture of images effectively. Furthermore, the application of GLCM produces 6 features including Contrast, Dissimilarity, Entropy, Homogeneity, Mean, and Standard Deviation. Based on the results of applying these features to classify batik images, several interesting findings were obtained. The Standard Deviation feature showed the best performance with accuracy, precision, recall, and F1-score of 95%, 93%, 93%, and 93%, respectively. This shows that this feature is very good at capturing important characteristics of batik motifs. The Mean and Homogeneity features also showed very good performance, with an accuracy of 95% and other metric values slightly lower than the Standard Deviation feature. On the other hand, the Contrast feature showed quite high accuracy (93%), but had a lower recall value (90%), indicating good performance but not as good as the top three features. The last finding related to the Dissimilarity and Entropy Features, these two features were recorded to have similar performance with accuracy, precision, recall, and F1-score values of 90%, indicating that these features are less effective than other features.

In addition, to improve the performance of batik image classification, the application of the Ensemble method based on majority voting (hard voting) is proposed. By combining the results of several models trained using different features through the Majority Voting method, the performance of batik image classification can be improved. This method utilizes the advantages of each feature, thereby increasing the accuracy and stability of the model as a whole. The Ensemble method with Majority Voting shows that although some individual models may have lower performance, combining predictions through majority voting produces a more reliable and accurate model. By utilizing the diversity of information captured by various texture features, the ensemble method helps reduce prediction errors and improves the generalization ability of the model.

This study shows that the use of ensemble method with Majority Voting is an effective approach for batik image classification. The combination of texture features Standard Deviation, Mean, and Homogeneity gives the most optimal results, but the ensemble of various features as a whole increases the accuracy and reliability of the model. These results emphasize the importance of using ensemble methods to handle complex image classification problems and support practical applications such as automatic motif recognition for batik products. As a continuation of the research, it is interesting to conduct experiments by applying various other ensemble methods such as bagging, boosting to find the ensemble method with the best performance. In addition, from the classification algorithm side, the application of other algorithms such as Random Forest, Xgboost, SVM and so on. Hence, it can be obtained automatic classification system which is truly reliable and robust in recognizing batik images.

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