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Improving the transfer learning for batik besurek textile motif classification

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ABSTRACT

This proposed research discussion is a new combination model for classifying batik besurek fabric from the implementation transfer learning with mixed contrast enhancement, activation function, and optimizer method. The size of the batik besurek fabric motif image as an input image is 250×250 with three channels consisting of red, green, and blue totaling five classes, namely *kaligrafi*, rafflesia, *burung kuau*, *relung paku* and *rembulan*. All images in the dataset will be divided into train data (1540 images), validate data (380 images), and test data (480 images) that are taken directly from the batik store in Bengkulu. The division method used is stratified random sampling to take all the data, shuffles it, and divides the data sets for each class. Based on the experiment results, ResNet50 obtained the best performance compared to MobileNetV2, InceptionV3, and VGG16, with a training accuracy of 99.60%, a validation accuracy of 97.44%, and a testing accuracy of 98.12%. In the improvement experiment phase, the ResNet50 model with Adam optimizer, rectified linear unit (ReLU) activation function and contrast limited adaptive histogram equalization (CLAHE) as the contrast enhancement method obtained the highest test accuracy (98.75%), showing that CLAHE was very effective in improving performance on batik besurek data.

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1. INTRODUCTION

Indonesian batik was inaugurated as a heritage of humanity and intangible culture and has been recognized by the United Nations Educational, Scientific, and Cultural Organization (UNESCO) as the intellectual right of the Indonesian nation on October 2, 2009. The definition of batik is an illustrated cloth that is explicitly made by writing or explaining the night on the cloth; after that, it is explicitly made by writing or explaining the night on the cloth, and the processing goes through a specific process [1], [2]. Indonesia is a country that consists of different self-evidence and has extraordinary social diversity; culture is the result of mind and energy in the form of creation, charity, and taste that has human tendencies [3], [4].

One of the batik handicraft industry producing areas with its characteristics is batik crafts found in Bengkulu City, which is famous for batik besurek. Batik besurek is a traditional craft that has long developed and is a legacy of the ancestors of the Bengkulu people for generations. This batik besurek contains the meaning of a letter or writing [5]–[7].

Besurek cloth was once only used in religious ritual ceremonies in the Bengkulu region; along with the times, the use and design of batik besurek motifs underwent modernization. Batik besurek motifs totaling five famous motifs, namely *kaligrafi*, rafflesia, *burung kuau*, *relung paku*, and *rembulan*. Batik besurek is also an art, so one besurek cloth motif can be created, of course, by artisans who understand the motif. Thus, one batik cloth motif will not only have one shape but will have many similar shapes [8]–[10].

Digital image processing is carried out on images to obtain certain desired results. Using digital image processing, we can classify several similar batik images [11]. This method can be one way to solve the problem of the introduction of batik besurek motifs [12]. Previous researchers have researched digital image processing to introduce batik fabric motifs by combining several digital image processing methods. Research conducted by Kusanti and Suprapto [13] is related to the analysis of seven classes of Surakarta batik, namely kawung motif, sido mukti motif, truntum motif, sawat motif, satrio manah motif, parang motif, and semen rante motif. The data used is 100 images divided into 70 training data and 30 test data. The results showed that the accuracy rate of Otsu and Canny was 93%.

Andrian *et al.* [14] conducted research related to the classification of Lampung batik motifs consisting of jung agung, siger kembang cengkeh, siger ratu agung, and sembagi. To recognize the Lampung batik motif, the gray level co-occurrence matrix (GLCM) feature was extracted, and k-nearest neighbor (k-NN) to obtain the best accuracy achieved at a level of 97.96%. Research conducted by Girsang and Muhathir [15] is the classification of batik motifs because it is challenging to identify batik motifs in Indonesia. So, it takes classification with precise accuracy to make it easier to recognize batik patterns easily. This study uses the histogram of the oriented gradient (HOG) as a characteristic extraction process to obtain the characteristics of batik motif density and multilayer perceptron as the classification method. The accuracy rate obtained in the study was 83.4% [15].

Research conducted by Riski *et al.* [16] is related to the introduction of Madura batik motifs. The class of Madurese batik motifs consists of satompok flower, manuk poter, broken beling, seaweed, and sekar jagat. The GLCM method is used to extract image features, and the backpropagation algorithm is used for classification. Using the GLCM method, the accuracy of the experiment reached 98% in the testing process.

Research conducted by Senarathna and Rajakaruna [17] uses local binary pattern (LBP) as a vector of texture features, Hu moment invariants (HIM) for the extraction of shape features, and GLCM for the extraction of texture features. The research dataset used in this study consisted of 300 images with 50 classes. The data augmentation method is applied to the primary dataset and generates 1200 new images with the same number of classes. Test scenarios compare the accuracy between the original and additional data at an 80:20 ratio for training and testing data. This study classifies batik images by applying deep learning using the ResNet method with an accuracy performance of 96%.

Research was conducted to introduce six batik motifs from various regions in Indonesia. The batik motifs studied include banji motifs, ceplok motifs, kawung motifs, mega mendung motifs, parang motifs, and sekar jagad motifs. The research dataset consisted of 994 images divided into six classes. The ratio of the division of the training dataset and the test dataset used is 8:2. The results of experiments on the test data showed that the algorithm produced excellent performance, which was demonstrated with 94% accuracy using the DenseNet architecture. In this study, the data augmentation method was applied to provide variations in training data and prevent overfitting [18]. Based on the research, most previous research using feature extraction methods such as HOG, LBP, scale-invariant feature transform (SIFT), moment invariants (MI), GLCM for improving classification performance. However, this research attempted to improve the classification model by examining several methods, including contrast enhancement, activation function, and optimizer.

The appropriate optimizer technique is instrumental in transfer learning because of its ability to adjust the learning rate adaptively, faster convergence, and better gradient management [19]–[21]. This research will also determine the appropriate activation function so that the transfer learning model can provide the necessary non-linearity, solve the problem of disappearing gradients, improve computing efficiency, and accelerate training convergence [22]–[24]. In addition, contrast enhancement in batik besurek data is also discussed because many cases of datasets in the field have poor contrast because the implementation will be later on images taken from indoors [25]–[27].

This study is divided into the transfer learning experiment phase and the transfer learning improvement experiment phase. This research can be a reference for the best combination model based on contrast enhancement, activation function and optimizer for classifying the batik textile motif. The experiment was carried out four times using different transfer learning models, namely MobileNetV2, ResNet50, InceptionV3 and VGG16. The architecture of each model follows the model architecture in the previous study which used the same model to classify the batik dataset.

2. METHOD

Batik besurek is a type of batik motif with a distinctive pattern with Arabic accents for animals and plants living in Bengkulu. This image classification uses a transfer learning model in this study that utilizes transfer learning models trained on large datasets such as ImageNet. The advantage of this transfer learning is that it allows the model to utilize the knowledge it has learned to recognize common visual features. In this study, the dataset used was batik besurek. This batik image is collected directly using mobile cameras from various locations, including batik besurek Sari Rasa Store on Soekarno Hatta Street, offering a variety of authentic motifs; Sanggar Batik Besurek Fabric Grya Tien Collection on Ciliwung Street, known for its traditional and modern patterns; Gallery of Batik Besurek Swarnabumei on Fatmawati Street, which showcases intricate besurek designs; La-Mentique Batik Besurek on S. Parman Street, specializing in contemporary styles; and Batik Atik Besurek on Soekarno Hatta Anggut Atas Street, featuring classic Bengkulu-inspired batik pieces.

The dataset that has been collected is batik besurek image with the extension *.jpg which consists of four classes. The dataset of images of batik motifs that have been collected is grouped by category or class. Datasets must be labeled correctly according to the existing categories of batik motifs, as depicted in Figure 1: Figure 1(a) *kaligrafi*, Figure 1(b) rafflesia, Figure 1(c) *burung kuau*, Figure 1(d) *relung paku*, and Figure 1(e) *rembulan*. In the preprocessing stage, the dataset is adjusted based on the image size to the size that suits the needs of the MobileNetV2, ResNet50, InceptionV3, and VGG16 models.

(a) (b) (c) (d) (e)

Figure 1. Data class of batik besurek motif (a) *kaligrafi*, (b) rafflesia, (c) *burung kuau*, (d) *relung paku*, and (e) *rembulan*

All images in the dataset will be divided into training data, and test data. The division method used is stratified random sampling implemented using the scikit-learn library. The stratified random sampling method takes the entire data, shuffles the data, and then divides the data into training and testing sets for each class. The ratio of sharing train data and validate-test data is 70:30. The experiment consists of two phases, namely the comparison phase of the transfer learning model and the phase of improving the transfer learning model. In the transfer learning model improvement phase, the experiment used a combination of optimizer (OP), activation function, retinex, contrast limited adaptive histogram equalization (CLAHE), and gamma correction (GC) methods. The experimental scenario as seen in Figure 2.

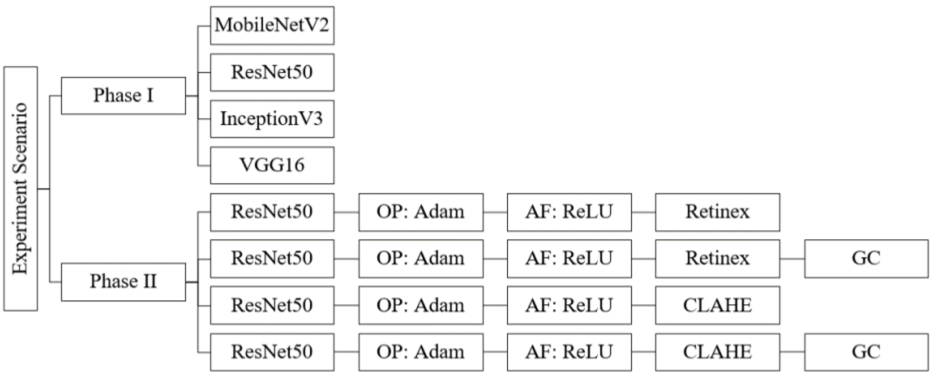

Figure 2. Experiment scenario

The neural network architecture used in this study is the ResNet50 architecture by using activation rectified linear unit (ReLU). The reason of ReLU implementation in the ResNet50 model addresses the vanishing gradient problem and enhances computational efficiency by producing zero outputs for negative values. Additionally, using ReLU after batch normalization and convolution allows for better learning of residual representations, improving the model's accuracy. In testing, the number of batches was set to 6 and the number of epochs or first generation was 50. If after 50 epochs there has not been convergence, training will be stopped and training results will be taken at the 50^{th} epoch. Training is called convergent if there is no change in the training accuracy value (plateau) or if the training accuracy value has reached 100%. The optimizer to be used is the Adam optimizer with learning rate parameters of 0.001. The architectural parameters that will be used in ResNet50 in phase 2 can be seen in Table 1.

Table 1. Parameter of model ResNet50

Parameter	Value
Number of layers	16
Batch size	6
Number of epochs	50
Optimizer Adam	(learning rate 0.001, beta_1=0.9, beta_2=0.999, epsilon=1e-07)
Activation function	ReLU

3. RESULTS AND DISCUSSION

The experiment in the first phase was carried out to compare the performance of the transfer learning algorithm at the training, validation and testing stages. The first experiment in phase one was carried out using the MobileNetV2 model. This model is chosen because MobileNetV2 is a lightweight architecture designed for mobile devices with good computing efficiency. In this MobileNetV2 model, several dense layers are added for classification on top of the feature output of MobileNetV2. Based on the experimental results, the training performance for the MobileNetV2 model shows a very high training accuracy of 98.14%, which shows that this model can learn the features from the training data very well. The performance for the MobileNetV2 model at the validation stage was slightly lower than that of the training at 94.60%, indicating the possibility of slight overfitting. However, this difference is manageable, suggesting that the model can generalize well. Performance analysis at the testing stage showed that the MobileNetV2 model obtained an accuracy of 96.46%, which means that MobileNetV2 also performed well on previously unseen data despite a decrease in training accuracy.

The second experiment in phase one was carried out using the ResNet50 model. This model has a residual architecture allows intense network training with skip connections. In the ResNet50 model, a classification layer is added to the features of ResNet50 and fine-tuned to the last few layers. Based on the experiment results, ResNet50 has the highest training accuracy of 99.60%, which shows that this model can learn training data. A validation accuracy of 97.44% shows that this model has excellent generalization ability, even with a slight decrease in training accuracy. The test accuracy of 98.12% is the highest among all models, indicating the best performance in the new batik besurek data.

The third experiment in phase one was carried out using the InceptionV3 model. This model has a variety of filter sizes in a single layer, allowing for the extraction of complex features. The InceptionV3 model has added a classification layer on top of the features of InceptionV3 and fine-tuned the batik besurek dataset. Based on the experiment results, InceptionV3 showed a lower training accuracy than other models, which was 96.35%. The validation accuracy reached 96.59% or almost equivalent to the training accuracy, showing that this model was not too overfit on the training data. The test accuracy of 92.50% is the lowest among all models, indicating that InceptionV3 could be more effective in generalizing on previously unseen batik data than other models.

The fourth experiment in phase one was carried out using the VGG16 model. This model uses a simple but effective architecture with many layers of small convolution. The VGG16 model has added a classification layer on top of the VGG16 feature output and fine-tuned the batik besurek dataset. Based on the experimental results, VGG16 has a high training accuracy of 99.67%, which shows that the model learns the features from the training data very well. The validation accuracy of 96.02% shows that the VGG16 model can still generalize well despite the decrease in training accuracy. A test accuracy of 95.00% also indicates good performance but is slightly lower than ResNet50. The results of the comparison of the performance of each model in the experiment in phase one can be seen in Figure 3.

Based on the performance comparison results, ResNet50 is the best-performing model overall, with the highest accuracy on training, validation, and test data. This shows that ResNet50 can learn and generalize data very well. The VGG16 model also shows excellent performance but slightly lower accuracy than the ResNet50 model, especially in test data processing. MobileNetV2 achieves excellent accuracy and higher efficiency compared to VGG16 and ResNet50, but performs below the ResNet50 model overall. InceptionV3 has reasonable training and validation accuracy but shows lower testing accuracy and problems, especially in generalizations on the new batik besurek data.

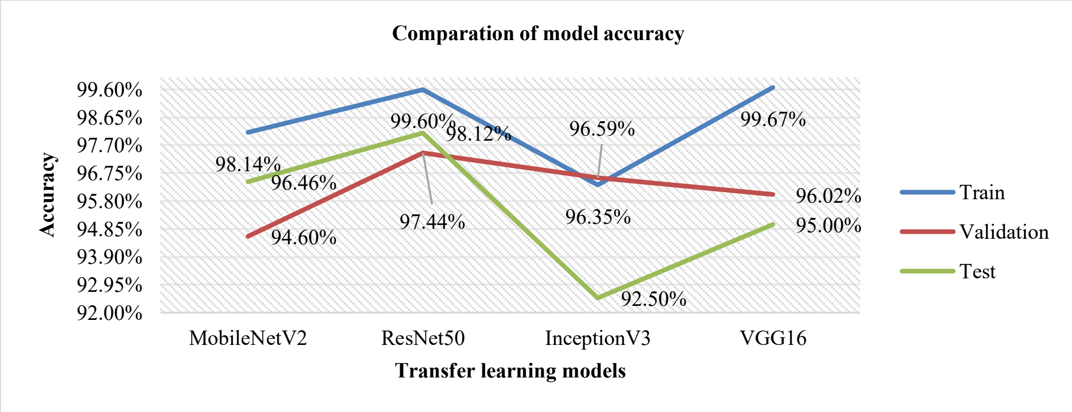

Figure 3. Comparation of transfer learning performance

The experiment in the second phase was carried out by improving the best transfer learning model in the second phase of the experiment. Improvements were made by adding mixed contrast enhancement, activation function, and optimizer for the batik besurek textile motif classification. The first experiment in the second phase uses ResNet50 with Adam optimizer, ReLU activation function and retinex as the contrast enhancement method. Based on the experiment results, the training stage obtained an accuracy score of 99.87%, indicating that this model can learn the training data more effectively after adding contrast enhancement techniques such as retinex. The validation accuracy in this experiment of 99.15% shows that the model is also very good at generalizing to the validation data. A test accuracy of 96.25% indicates significant overfitting of training and validation data, resulting in performance degradation in the new test data.

The second phase experiment uses ResNet50 with Adam optimizer, ReLU activation function and retinex and GC as contrast enhancement methods. At the training stage, this model obtained 100% accuracy, showing that the model has fully memorized the existing batik besurek data. There was a decrease in training accuracy at the validation stage, with a validation accuracy of 98.29%, which showed that the model could still generalize the batik besurek data well. At the testing stage, an accuracy of 97.29% was obtained, which showed excellent performance in the batik besurek data. The GC technique helps to improve the quality of test results compared to using retinex only.

The third experiment in the second phase uses ResNet50 with Adam optimizer, ReLU activation function, and CLAHE as the contrast enhancement method. At the training stage, the model gained 100% accuracy, indicating that the model can memorize the batik data thoroughly. The accuracy of the validation data of 95.17% decreased compared to other models, indicating that the model may be slightly overfitted with training data. The accuracy in the test reached the highest value of 98.75%, which shows that CLAHE effectively improves the performance of the ResNet50 model on batik besurek data.

The fourth experiment in the second phase uses ResNet50 with Adam optimizer, ReLU activation function, and CLAHE and GC as contrast enhancement methods. In the training stage, the model obtained an accuracy score of 99.60%, which indicates good training performance without significant overfitting. The validation accuracy got a score of 97.73%, which shows that the model can generalize the validation data well. At the test stage, the model accuracy of only 95.00% represents a decrease compared to the single CLAHE configuration. This may be due to the interaction between CLAHE and GC, which is less than optimal for the test data. The results of the comparison of the performance of each model in the experiment in the second phase can be seen in Table 2.

Table 2. Comparation of ResNet50 improvement performance

Experiment	Train (%)	Improvement (%)	Validate (%)	Improvement (%)	Test (%)	Improvement (%)
ResNet50	99.60	-	97.44	-	98.12	-
ResNet50+Adam+ReLU+retinex	99.87	(+) 0.27	99.15	(+) 1.71	96.25	(-) 1.87
ResNet50+Adam+ReLU+retinex+GC	100	(+) 0.40	98.29	(+) 0.85	97.29	(-) 0.83
ResNet50+Adam+ReLU+CLAHE	100	(+) 0.40	95.17	(-) 2.27	98.75	(+) 0.63
ResNet50+Adam+ReLU+CLAHE+GC	99.60	(+) 0.00	97.73	(+) 0.29	95.00	(-) 3.12

The ResNet50 model with Adam optimizer, ReLU activation function and CLAHE as the contrast enhancement method obtained the highest test accuracy (98.75%), showing that CLAHE is very effective in improving performance on batik besurek data. The ResNet50 model with Adam optimizer, ReLU activation function, and retinex and GC as contrast enhancement methods showed excellent test accuracy (97.29%) with high validation accuracy, signaling a good balance between training and generalization. Some models show 100% training accuracy, which may signal overfitting, especially in models that show a decrease in accuracy in the test data. Based on comparing accuracy values, ResNet50 with Adam optimizer, ReLU activation function, and CLAHE as the contrast enhancement method is the best combination. Several evaluation matrices such as accuracy, loss, precision, recall, F1-score, and confusion matrix were used to analyze the results of the ResNet50 model with Adam optimizer, ReLU activation function, and CLAHE as contrast enhancement methods in more detail. The first evaluation is based on the loss and accuracy graph of the training data and validation data seen in Figure 4.

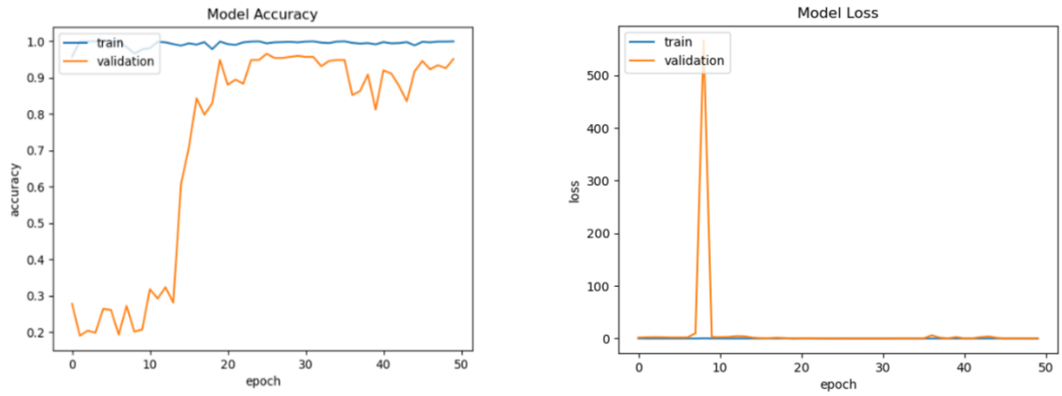

Figure 4. Accuracy and loss value of ResNet50 with Adam, ReLU and CLAHE

Based on the accuracy and loss graphs, the ResNet50 model with Adam optimizer, ReLU activation function, and CLAHE shows high training accuracy (about 95-100%) and low training loss and very low validation accuracy (about 27-20%) at the beginning of the epoch. This indicates that the model is overfitting the training data and cannot generalize the validation data well. From the 21st to the 30th epoch, the model showed a stable validation accuracy of around 94-97%. The training accuracy is very high, and the model can perform well on the validation data. Despite some fluctuations, the model remains in good performance on validation data. The block diagram of the proposed approach can be seen in Figure 5.

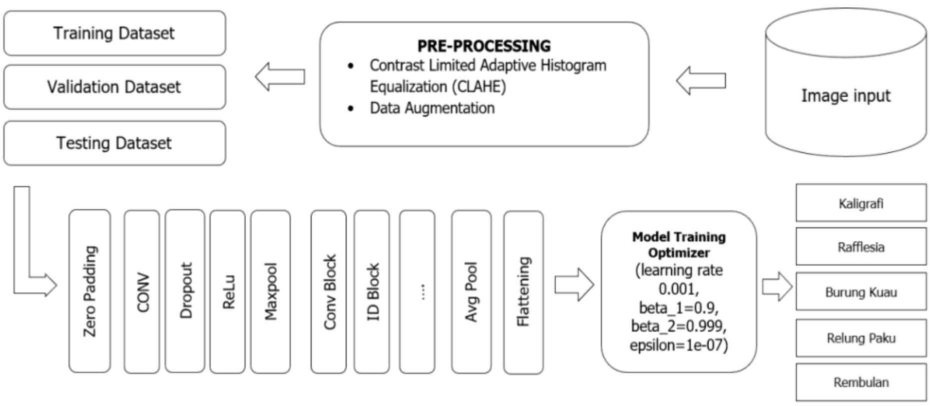

Figure 5. Block diagram of proposed ResNet50 model with modification

Validation accuracy peaked at around 96% in the 26th epoch, and subsequent epochs slightly declined to around 95%. The training accuracy remains stable, indicating that the model has achieved stability in training and validation data. The model showed significant performance improvements from the start of training, with validation accuracy increasing consistently after a few initial epochs. By the end of the training, the model achieved excellent validation performance, indicating that the model had successfully avoided overfitting and could generalize well on the validation data. The second evaluation can be seen from the precision, recall and F1-score values in Table 3.

Table 3. Evaluation matrix of ResNet50 with Adam, ReLU, and CLAHE

Class	Precision	Recall	F1-score
Burung kuau	0.96	1.00	0.98
Kaligrafi	1.00	0.98	0.99
Raflesia	0.98	1.00	0.99
Relung paku	1.00	1.00	1.00
Rembulan	1.00	0.96	0.98

Based on the results of the classification model evaluation metrics in the form of precision, recall, and F1-score for each class in the batik besurek dataset, the *burung kuau* class got a precision value of 0.96, which shows that 96% of the model's predictions on the *burung kuau* data are correct. A recall value of 1.00 indicates that the model successfully detected all instances of *burung kuau*. An F1-score of 0.98 for the bird kuau data class shows excellent model performance with a good balance between precision and recall.

The *kaligrafi* class gets a precision of 1.00, indicating that all *kaligrafi* predictions are correct. A recall value of 0.98 for the *kaligrafi* class indicates that 98% of *kaligrafi* data are successfully detected. An F1-score of 0.99 for the *kaligrafi* class indicates excellent model performance with a good balance between precision and recall. Then, the rafflesia class gets a precision of 0.98, indicating that 98% of the rafflesia data predictions are correct. The recall value for the rafflesia data class is 1.00, indicating that the model detected all rafflesia instances successfully. An F1-score of 0.99 for the rafflesia data class shows excellent performance with a good balance between precision and recall.

The *relung paku* class gets a precision of 1.00, indicating that all *relung paku* predictions are correct. A recall value 1.00 for the *relung paku* data class indicates that all *relung paku* instances were successfully detected. An F1-score of 1.00 for the *relung paku* data class shows perfect performance with an optimal balance between precision and recall. The *rembulan* class gets a precision of 1.00, indicating that all moon predictions are correct. A recall value of 0.96 for the *rembulan* data class indicates that the model successfully detected 96% of the lunar instances. An F1-score of 0.98 for the *rembulan* data class indicates excellent performance with a good balance between precision and recall.

The best-in-class performance uses the ResNet50 model with Adam optimizer, ReLU activation function, and CLAHE, which is the *relung paku* class. The class has the highest F1-score of 1.00, demonstrating excellent performance and a perfect balance between precision and recall. The third evaluation can be seen from the confusion matrix value of the experiment results with the test data seen in Figure 6.

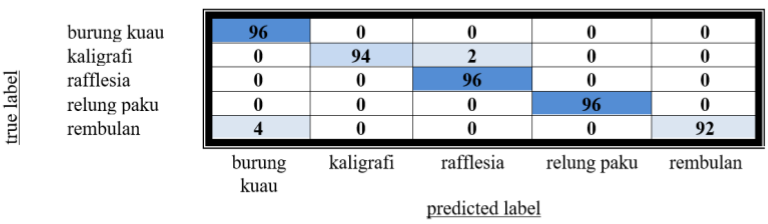

Figure 6. Confusion matrix of ResNet50 with Adam, ReLU and CLAHE

The confusion matrix evaluation was seen based on the values of true positives (TP), false positives (FP), false negatives (FN) and accuracy (ACC) for each class, namely *burung kuau*, *kaligrafi*, raflesia, *relung paku*, and *rembulan*. The data class *burung kuau* gets a TP value of 96, meaning the amount of data is correctly classified as *burung kuau*. An FP value of 0 means that no data from other classes are incorrectly classified as *burung kuau*. FN value of 0 means no *burung kuau* data incorrectly classified to other classes. An accuracy of 100% means that all data on *burung kuau* are classified correctly. The *kaligrafi* data class gets a TP value of 94 data correctly classified as *kaligrafi*. An FP value of 0 indicates that no data from other classes is incorrectly classified as *kaligrafi*. An FN value of 2 indicates that the amount of data from *kaligrafi* is incorrectly classified into another class. The class accuracy of 97.92% of the *kaligrafi* data is correctly classified.

The rafflesia data class gets a TP value of 96 data, meaning the amount of data is correctly classified as rafflesia. An FP value of 0 means that no data from other classes is incorrectly classified as rafflesia. An FN value of 0 means no rafflesia data is misclassified to another class. The accuracy of the class is 100% which means that all the rafflesia data is correctly classified. The *relung paku* data class gets a TP value of 96 data, meaning the amount of data is correctly classified as a *relung paku*. An FP value of 0 means that no data from other classes is incorrectly classified as a *relung paku*. An FN value of 0 which means no data *relung paku* are misclassified to other classes. The accuracy of the class is 100% which means that all *relung paku* data is correctly classified. The *rembulan* data class gets a TP value of 92, meaning the amount of data is correctly classified as *rembulan*. An FP value of 0 data indicates that the number from other classes is incorrectly classified as *rembulan*. An FN value of 4 indicates the amount of data from the *rembulan* classified into another class. The accuracy of the class was 95.83%, of the *rembulan* data was correctly classified.

Using ResNet50 with the Adam optimizer, ReLU activation function, and CLAHE preprocessing is highly effective for batik motif classification. ResNet50, a deep convolutional neural network, leverages residual connections to avoid vanishing gradient issues, enabling it to learn complex patterns within intricate batik motifs. The Adam optimizer, known for its adaptability and efficiency, enhances the model's convergence, making it well-suited for handling high-variation data like batik patterns. ReLU further aids by adding non-linearity and sparsity, helping the model focus on essential features. CLAHE preprocessing enhances contrast in batik images, making subtle details more pronounced and boosting feature extraction, ultimately improving classification accuracy for intricate batik motifs.

Future research could explore enhancing batik motif classification by combining ResNet50 with advanced techniques such as attention mechanisms or feature fusion methods to further refine intricate pattern recognition. Experimenting with other optimizers like RMSprop or gradient clipping may also stabilize training and improve performance on complex, high-variance batik patterns. Additionally, using transfer learning from other domains or employing hybrid models that integrate CNNs with transformers could yield more robust feature representations. Expanding the batik dataset and testing the model on various motif styles, colors, and fabric textures could provide insights into the adaptability of ResNet50, further advancing automated batik classification techniques.

4. CONCLUSION

Digital image processing is done on images to obtain specific results according to needs. Using digital image processing, we can classify several similar batik besurek images. This method can be one way to solve the problem of the introduction of batik besurek motifs. Based on the experiment results, ResNet50 performed at the first-best with a training accuracy of 99.60%, a validation accuracy of 97.44%, and a testing accuracy of 98.12%. The MobileNetV2 model obtained the second-best performance with a training accuracy of 98.14%, a validation accuracy of 94.60% and a testing accuracy of 96.46%. The VGG16 model performed at the third highest, with a training accuracy of 99.67%, a validation accuracy of 96.02%, and a testing accuracy of 95.00%. The InceptionV3 model performed at the third highest, with a training accuracy of 96.35%, a validation accuracy of 96.59%, and a testing accuracy of 92.50%. The ResNet50 model with Adam optimizer, ReLU activation function and CLAHE as the contrast enhancement method obtained the highest test accuracy (98.75%), showing that CLAHE is very effective in improving performance on batik besurek data. Then, this model also shows high training accuracy (about 95-100%) and low training loss and very low validation accuracy (about 27-20%) at the beginning of the epoch. This indicates that the model is overfitting the training data and cannot generalize the validation data well.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the author, [MU]. The data are not publicly available due to certain restrictions.

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