Enhanced Semarang batik classification using deep learning: a comparative study of CNN architectures

Edy Winarno[1], Achmad Solichan[1], Aditya Putra Ramdani[1], Wiwien Hadikurniawati[2], Anindita Septiarini[3], Hamdani Hamdani[3]
[1]Department of Information Technology, Faculty of Engineering and Computer Science, Universitas Muhammadiyah Semarang, Semarang, Indonesia
[2]Department of Informatics Engineering, Faculty of Information Technology and Industry, Universitas Stikubank, Semarang, Indonesia
[3]Department of Informatics, Faculty of Engineering, Mulawarman University, Samarinda, Indonesia

Article Info

Article history:

Received Sep 23, 2024
Revised Jul 8, 2025
Accepted Jul 29, 2025

Keywords:

Backbone
Batik pattern
Deep learning
DenseNet-121
Fabric classification

ABSTRACT

Batik is an important part of Indonesia's cultural heritage, with each region producing unique designs. In Central Java, Semarang is known for its distinctive batik patterns that reflect rich local traditions. However, many people are still unfamiliar with these designs, which threatens their preservation. This study develops an automated system to classify Semarang batik patterns, showing how technology can help safeguard cultural heritage. A convolutional neural network (CNN) approach was used to recognize ten batik types, including *Asem Arang*, *Asem Sinom*, *Asem Warak*, *Blekok*, *Blekok Warak*, *Gambang Semarangan*, and *Kembang Sepatu*. Pre-processing steps—such as image resizing, cropping, flipping, and rotation—improved model performance and reduced complexity. Five CNN architectures (MobileNetV2, ResNet-50, DenseNet-121, VGG-16, and EfficientNetB4) were tested using 224×224 input size, Adam optimizer, ReLU activation, and categorical cross-entropy loss. Results show VGG-16, ResNet-50, and DenseNet-121 achieved perfect accuracy (1.0) on a dataset of 3,000 locally collected images. These findings highlight CNN models' strong potential for batik pattern recognition, supporting digital preservation of Indonesian culture.

Corresponding Author:

Edy Winarno
Department of Information Technology, Faculty of Engineering and Computer Science
Universitas Muhammadiyah Semarang
St. Kedungmundu Raya 118, Semarang, Indonesia
Email: edywin@unimus.ac.id

1. INTRODUCTION

Various regions have distinct cultural legacies, particularly in the form of intricately woven pattern elements such as traditional cube patterns [1], archaeological pottery [2], and traditional fabrics [3]–[5]. Among these, batik stands out as a remarkable cultural asset of Indonesia, officially recognized by UNESCO as an intangible cultural heritage. Indonesian artisans use wax-resist dyeing techniques to create batik masterpieces, a tradition that dates back thousands of years. Batik displays many fascinating patterns and motifs, often rich in symbolism [6]. Techniques such as writing (*tulis*), stamping (*cap*), and printing are integral to batik production [7]. Batik holds profound cultural significance in Indonesia, is essential to ceremonies, celebrations, and daily life, and serves as a popular souvenir. Sustainable conservation efforts and innovative advancements are urgently needed to preserve the rich artistic tradition of batik [8].

Semarang batik, originating from Central Java, exemplifies a unique regional style [9]. Its designs blend Chinese and Arabic influences and feature motifs such as tamarind fruits, peacocks, roses, storks, and blekok birds. Landmarks like *Tugu Muda* and *Lawang Sewu* are also frequently depicted. Distinctive bottom-line patterns and vibrant color motifs characterize Semarang batik, adding to its regional identity.

Indonesia's tourism industry benefits significantly from the diversity of batik patterns, including Semarang batik. Many domestic and international tourists are fascinated by batik and seek to understand its history and production processes. However, one major challenge is accurately identifying and classifying specific batik patterns, which hinders deeper cultural engagement and appreciation. Traditional recognition methods rely heavily on expert knowledge, which is not always accessible. Thus, an automated and accurate model for recognizing batik patterns is needed.

Additionally, in order to gain a thorough understanding of Semarang batik, namely its motifs, it would be helpful to know the name of the particular batik motif. You can accomplish this by using internet search engines or consulting reputable sources like books. Often, we see pictures of batik without knowing the name of the pattern, which makes it difficult for us to learn more about the batik. Therefore, creating a method that can simplify the process of classifying Semarang batik designs is essential.

The classification of traditional fabric was successfully developed using machine learning [10]–[15] and deep learning using various architectures [16]–[21]. East Kalimantan batik was classified using color attributes derived from red-green-blue (RGB) color spaces. The use of the gray level co-occurrence matrix (GLCM) allowed for the extraction of textural information. In the following, the decision tree classifier was fed the gathered features. Each of the four batik regions—Burung Enggang, Batang Garing, Tameng, and Shaho—contributes 100 images to the broader dataset used for this study. The method produced optimal performance, indicating an accuracy value of 99.9% [22]. Support vector machines (SVM) and backpropagation neural networks (BPNN) were used to develop batik's pattern recognition model. While recognizing the motif of batiks, the SVM approach takes an average of 0.77 milliseconds to process, whereas the BPNN method takes an average of 3.59 milliseconds. The SVM approach yielded an accuracy of 88.33% for categorizing batik's pattern test data, whereas the BPNN method yielded an accuracy of 76.25% [23].

Mulwin-local binary pattern (LBP) feature extraction was suggested for batik image categorization. The classification process was solved using the deep neural network technique. Previously, image segmentation using the watershed approach included feature extraction. This feature extraction algorithm combines 3–4 window types. For excellent results, 6×6, 9×9, 12×12, and 15×15 pixels or a combination of 3 or 4 windows were employed. Several experiments used more training images than test images, although classification accuracy and precision exceeded 72.88%. Adding picture classes and more training images than test images increased classification accuracy to over 81.65%. Using the same rotation but different scales, further studies with more training images than test images achieved a classification accuracy of over 93.68% with 12 classes. Even with only 10 drawing classes, accuracy exceeded 98%. Further study can increase the reliability of this algorithm's batik picture classification [17]. A deep learning method was carried out to classify batik. The process was based on VGG16 architecture with a random forest as the classifier. The test from the method uses the public batik dataset, which was widely used in the previous study. Measurement parameters using precision, recall, F-score, and accuracy to evaluate the proposed method performance. The result shows that the proposed method outperformed the existing one based on color and texture features. The precision, recall, F-score, and accuracy reach ±97% [24].

In prior research, the classification of batik images was applied using the convolutional neural network (CNN) method with ResNet architecture. The original batik image datasets consist of 300 images with 50 classes. The augmentation process produces 1,200 new images with the same number of classes. The testing scenario compares the accuracy between original data and augmented data with a ratio of 80:20 for data training and testing. The confusion matrices show the model provides the highest accuracy performance at 96% [16]. A model for classifying nine Solo batik patterns was developed using complex symbols, patterns, dots, and natural designs. It employed hidden layers ranging from 1 to 4, is to determine the optimal number of layers to achieve the best accuracy. The input image is a 100×100 pixel image. Afterward, the feature extraction process utilized three convolution layers' 3×3 feature maps. Subsequently, the dropout was added for regularization, with parameters between 0.1 and 0.9. This model also optimized using Adam method. A 3-layered CNN obtained the best accuracy results with a dropout value of 0.2 runs for 20 epochs with an accuracy value of 97.77% [19].

The development of the batik categorization has been the subject of extensive prior research. It remains difficult, nevertheless, because the features used might not be selective, and lighting often affects the results of feature extraction in batik images. The current approach to Semarang batik pattern classification is inadequate, and this research intends to rectify that. *Blekok*, *Blekok Warak*, *Asem Arang*, *Asem Sinom*, *Gambang Semarangan*, and *Kembang Sepatu* are the ten categories into which the Semarang batik dataset was divided [25]. Justifying the best CNN architecture for learning the batik Semarang classification model is the main objective of this study. In previous research, the classification of batik, specifically Semarang batik, has been conducted using machine learning with a total of 5 classes. In this study, the classification of Semarang batik patterns is carried out with a larger number of classes, namely 10 classes. The Semarang batik classification model is developed using deep learning.

This study addresses this challenge by proposing a deep learning approach using CNNs to classify Semarang batik patterns automatically. Unlike previous research that often focused on general batik recognition, this study advances the field by systematically comparing the performance of five different CNN architectures—MobileNetV2, ResNet-50, DenseNet-121, VGG-16, and EfficientNetB4—on a localized Semarang batik dataset.

This paper is structured as follows: section 2 details the dataset used, preprocessing techniques, and the deep learning model architecture implemented for Semarang batik pattern classification. Section 3 presents the experimental results, comparing the accuracy and effectiveness of the proposed model with previous approaches. Finally, section 4 summarizes the improvements achieved and discussing potential directions for future research.

2. METHOD

The main objective of this study is to develop a robust model to classify the Semarang batik pattern with high accuracy. The model determined the difference in 10 classes of the Semarang batik pattern. This model has several main processes: data acquisition, preprocessing, augmentation, and learning. This study employed the CNN method in the learning process for the image classification of Semarang batik. It was deemed appropriate for this pattern recognition problem. The overview of the proposed model for classifying the Semarang batik pattern is depicted in Figure 1.

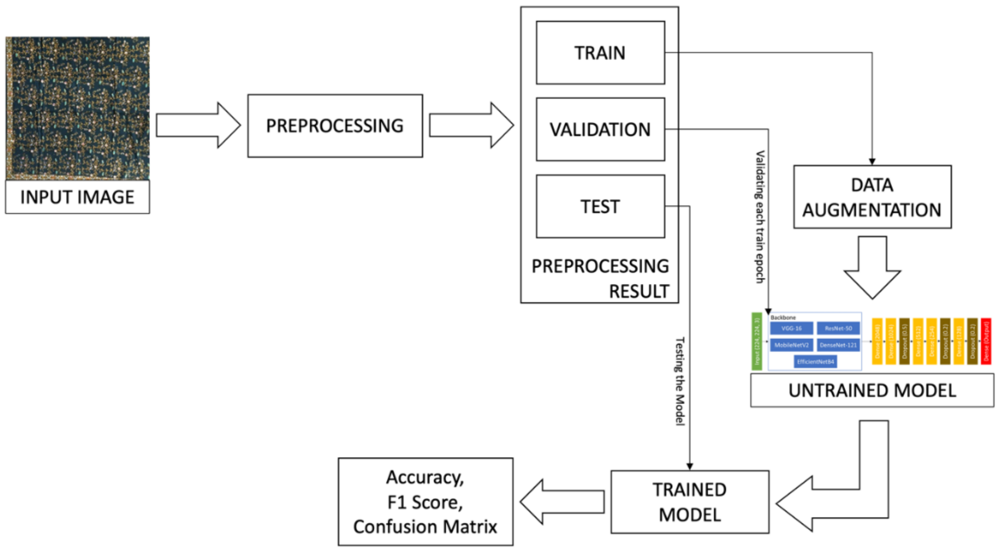


Figure 1. The overview of the proposed model for classifying the Semarang batik pattern

2.1. Data acquisition

The dataset consists of ten distinct class patterns: *Asem Arang*, *Asem Sinom*, *Asem Warak*, *Blekok*, *Blekok Warak*, *Gambang Semarangan*, *Kembang Sepatu*, *Semarangan*, *Tugu Muda*, and *Warak Beras Utah*. The number of images acquired for each class is 300, resulting in 3,000 images. The images were taken indoors under controlled lighting conditions using the built-in camera of an iPhone 6s. The camera should be positioned at a distance of around 30–60 cm from the item, with the camera's orientation straight to the object. The images were stored in JPEG format and have a dimension of 3024×4032 pixels [25]. An example of the image patterns from the Semarang batik collection is presented in Figure 2. The figure illustrates several motifs, including; (a) *Asem Arang*, (b) *Asem Sinom*, (c) *Asem Warak*, (d) *Blekok*, (e) *Blekok Warak*, (f) *Gambang Semarangan*, (g) *Kembang Sepatu*, (h) *Semarangan*, (i) *Tugu Muda*, and (j) *Warak Beras*.

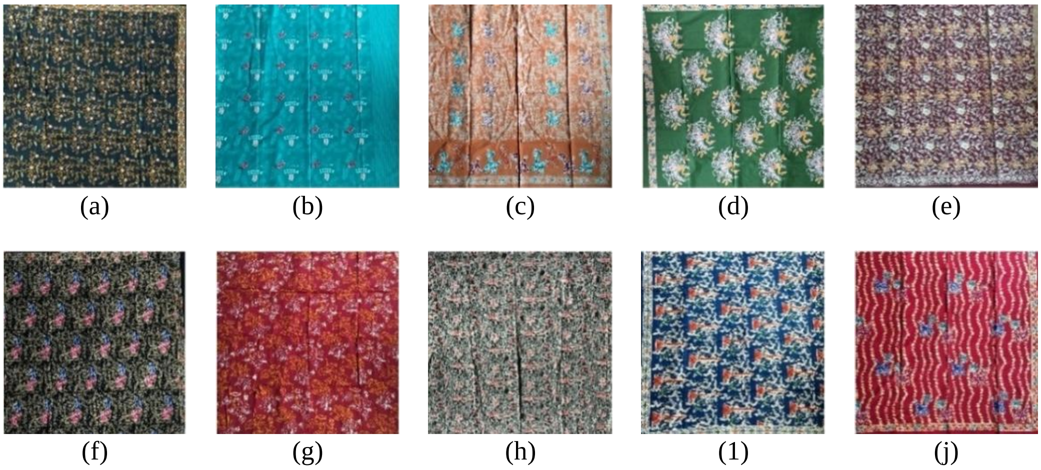


Figure 2. The image pattern example of the Semarang batik collection; (a) *Asem Arang,* (b) *Asem Sinom,* (c) *Asem Warak,* (d) *Blekok,* (e) *Blekok Warak,* (f) *Gambang Semarangan,* (g) *Kembang Sepatu,* (h) *Semarangan,* (i) *Tugu Muda,* and (j) *Warak Beras*

2.1.1. Pre-processing

In this study, the first step was resizing them into the same size of pixels. The images were resized from 3024×4032 pixels into 224×224 pixels [26]-[29]. Afterward, the dataset was split into three stages: training, validation, and testing. The dataset was split into three stages: training, validation, and testing. The validation and testing sets have a similar number of data. This study considers four scenarios for splitting the dataset into training, validation, and testing sets, as shown in Table 1. These scenarios include scenario-1 (60%, 20%, and 20%), scenario-2 (70%, 15%, and 15%), scenario-3 (80%, 10%, and 10%), and scenario-4 (90%, 5%, and 5%). Meanwhile, the previous study used a dataset split of 70% for training and 30% for testing [30].

Table 1. The scenarios for splitting the dataset

Scenario	Training (%)	Validation (%)	Testing (%)
Scenario-1	60	20	20
Scenario-2	70	15	15
Scenario-3	80	10	10
Scenario-4	90	5	5

2.1.2. Data augmentation

Data augmentation increases data variety without collecting and manually labeling new data [31]. This study compared the results that using augmentation and no augmentation. Augmentation was only applied in the training set. Several augmentation techniques were carried out, including flipping horizontally, flipping vertically, flipping horizontally, followed by flipping vertically. Subsequently, the original image and all the flipping results were rotated 90° to the right [32]. Lastly, the original image and all the results of flipping and rotation images were center cropped (without changing the size of the image) [31]. Therefore, each original image produced 15 new augmented images. Figure 3 presents the results of image augmentation, consisting of; (a) the original image, (b) horizontal flip, (c) vertical flip, (d) combined horizontal and vertical flip, (e) original with a 90° right rotation, (f) horizontal flip with a 90° right rotation, (g) vertical flip with a 90° right rotation, and (h) combined horizontal and vertical flip with a 90° right rotation.

In this study, the model was developed by applying CNN. The first layer of the neural network was the input layer. Since the input image size was 224×224 pixels, the input layer should be (224, 224, 3). The third input layer indicates the image channel of RGB. Subsequently, the convolutional and max pooling layers were required for extracting image features [33], [34]. The architecture of convolutional and max pooling was formed as the backbone. This study employed five backbones including VGG-16, MobileNetV2, ResNet-50, DenseNet-121, and EfficientNetB4. All the backbones are applied using transfer learning from IMAGENET weight. All the layers were trained with new data to shorten training time (fine-tuning).

The following backbone layer, the fully connected layer or dense layer, was needed to calculate the feature extracted from the backbone. The dropout layer was used to reduce the neural network's overfitting [32]. The illustration of neural network architecture is depicted in Figure 4. The dense layer has a number inside parentheses. It indicates the number of units (output space) except the dense (output) layer. It became the value of 10 because the neural network was classified into ten classes. The dropout layer was implemented to drop the fraction of the input units.

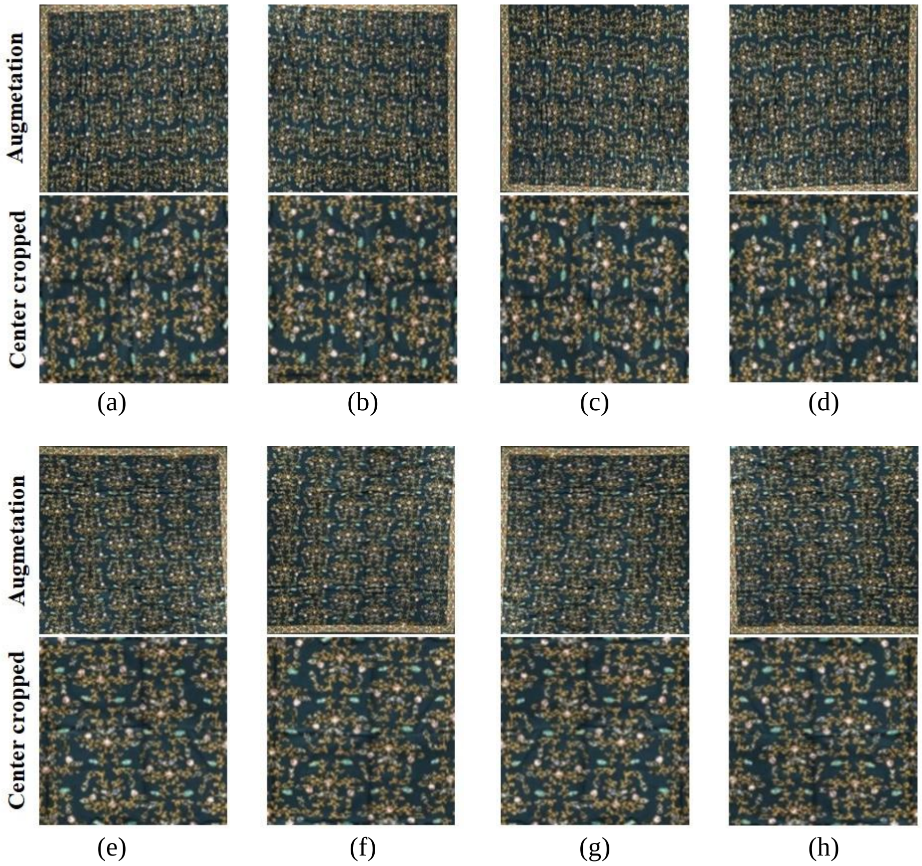


Figure 3. The image example of the augmentation result; (a) original, (b) flip horizontal, (c) flip vertical, (d) flip horizontal and vertical, (e) original+rotation 90° right, (f) flip horizontal+rotation 90° right, (g) flip vertical+rotation 90° right, and (h) flip horizontal and vertical+rotation 90° right

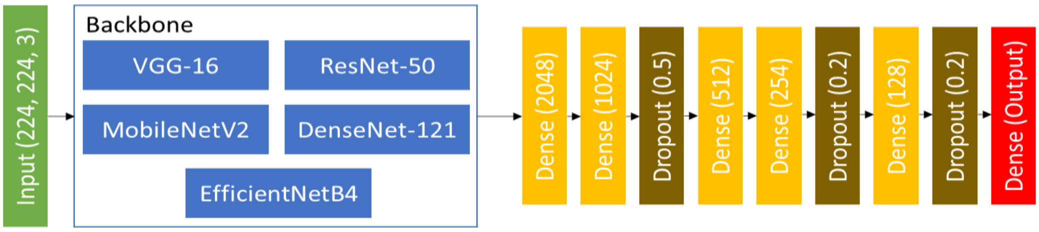


Figure 4. The architecture of neural network for Semarang batik classification

2.1.3. Evaluation

Two parameters were used to evaluate the proposed model's performance: accuracy and F1-score that computed using (1) and (2), respectively [33]. The output of prediction consists of four inputs, namely TP, TN, FP, and FN. TP stands for true positive, in which the model can detect a positive sample correctly; TN stands for true negative, where the model can detect a negative sample correctly; FP stands for false positive, where the model gives a false result to detect a negative sample; and FN stands for false negative where model give false result for detecting positive sample [35]. We also visualize the result in a confusion matrix [36]. The multi-class confusion matrix was used to determine the evaluation parameters. A common method to show the degree to which classification systems work is with a confusion matrix, which shows the details of correctly and incorrectly categorized data [5], [37].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$F1\ score = \frac{2TP}{2TP+FP+FN} \quad (2)$$

3. RESULTS AND DISCUSSION

This study compared several backbones to develop the optimal model. Each backbone employed the data with and without augmentation. Tensorflow library and the Adam optimizer with 1×10^{-4} learning rate (LR) were applied in all experiment scenarios. The loss function and activation function for the dense layer were used categorical cross-entropy and rectified linear unit (ReLU), except for the output layer, which used softmax activation. The model was formed for classifying 10 classes of Semarang batik. The model hyperparameter used is presented in Table 2.

Table 2. Model hyperparameter

Model parameter	Parameter name	Descriptions
Optimizer	Adam optimizer	LR=1×10^{-4}
Loss function	Categorical cross entropy	-
Dense activation function	ReLU and softmax	Softmax is only for output layer

Training epochs were limited to 50. Node explosions in the training model may overfit. The outcome did not match the validation prediction. Early termination fixed this problem [36]. An early stop was implemented to reduce training time. This study defines three early stop condition: i) when training and validation accuracy reaches 99.8%, and training and validation loss is less than or equal to 5%; ii) when validation accuracy reaches 100%, validation loss is less than or equal to 5% and training accuracy reach 99%, and iii) when validation accuracy reaches 100%, and validation loss is less than or equal to 1%.

Several tests were conducted to validate the appropriate backbone for developing the Semarang batik classification model. The model evaluation was employed using various backbones and augmentation processes. The model performance was indicated by the training time (s) and the value of accuracy and score as the evaluation parameters. The experiments were applied based on the split of dataset scenarios, namely scenario-1 (60%:20%:20%), scenario-2 (70%:15%:15%), scenario-3 (80%:10%:10%), and scenario-4 (90%:5%:5%). Tables 3–6 highlight the results of comparing the batik Semarang classification model's performance for each scenario utilizing different backbones.

Table 3. The comparison of the model's performance using various backbones for scenario-1

Model	Augmentation	Training epoch	Training time (s)	Accuracy (%)	F1 score (%)
VGG-16	No	23	777	100	100
MobileNetV2	No	9	244	100	100
ResNet-50	No	5	267	100	100
DenseNet-121	No	3	209	99.8	99.8
EfficientNetB4	No	10	796	100	100
VGG-16	Yes	2	915	100	100
MobileNetV2	Yes	8	2727	99.6	99.6
ResNet-50	Yes	11	6503	100	100
DenseNet-121	Yes	1	782	100	100
EfficientNetB4	Yes	2	2171	99.8	99.8

Table 4. The comparison of the model's performance using various backbones for scenario-2

Model	Augmentation	Training epoch	Training time (s)	Accuracy (%)	F1 score (%)
VGG-16	No	19	696	100	100
MobileNetV2	No	7	231	100	100
ResNet-50	No	8	439	100	100
DenseNet-121	No	2	191	99.7	99.7
EfficientNetB4	No	13	1149	100	100
VGG-16	Yes	5	2806	100	100
MobileNetV2	Yes	1	481	99.7	99.7
ResNet-50	Yes	5	3818	100	100
DenseNet-121	Yes	1	963	100	100
EfficientNetB4	Yes	2	2643	100	100

Table 5. The comparison of the model's performance using various backbones for scenario-3

Model	Augmentation	Training epoch	Training time (s)	Accuracy (%)	F1 score (%)
VGG-16	No	45	1845	100	100
MobileNetV2	No	11	356	99.6	99.6
ResNet-50	No	5	331	99.6	99.6
DenseNet-121	No	2	197	100	100
EfficientNetB4	No	14	1603	99.3	99.3
VGG-16	Yes	3	1912	100	100
MobileNetV2	Yes	3	1500	99.6	100
ResNet-50	Yes	6	5246	100	100
DenseNet-121	Yes	1	1176	100	100
EfficientNetB4	Yes	2	2977	99.3	99.3

Table 6. The comparison of the model's performance using various backbones for scenario-4

Model	Augmentation	Training epoch	Training time (s)	Accuracy (%)	F1 score (%)
VGG-16	No	26	1414	100	100
MobileNetV2	No	6	303	100	100
ResNet-50	No	10	718	100	100
DenseNet-121	No	2	237	100	100
EfficientNetB4	No	6	762	100	100
VGG-16	Yes	1	729	100	100
MobileNetV2	Yes	4	2133	100	100
ResNet-50	Yes	5	4909	100	100
DenseNet-121	Yes	1	1337	100	100
EfficientNetB4	Yes	5	8227	100	100

The high accuracy and F1 score values obtained show the optimal model performance. In addition, based on low training time and number of epochs. Table 3 (scenario-1) shows that MobileNetV2 with augmentation yields the lowest accuracy value of 99.6%. Meanwhile, DenseNet-121 without augmentation and EfficientNetB4 with augmentation produced a higher accuracy value of 99.8%. The reminder backbones achieved an accuracy value of 100%. Hence, the best backbone was MobileNetV2 without augmentation, revealing it has the fastest training time of 244s with a low epochs number of 9. The visualization of the model performance for scenario-1 is depicted in Figure 5.

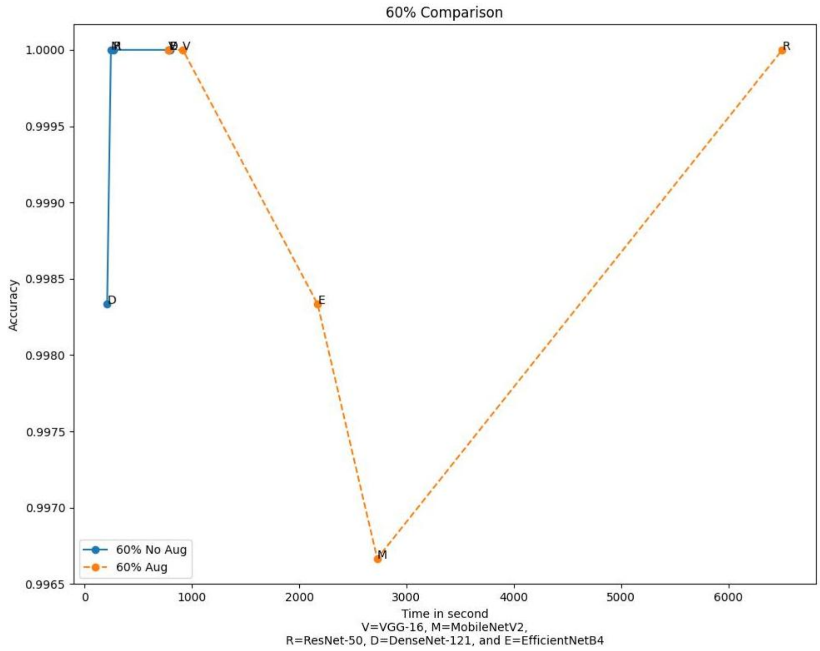


Figure 5. The visualization of the model performance for scenario-1

Table 4 (scenario-2) presents that DenseNet-121 without augmentation and MobileNetV2 with augmentation yields the lowest accuracy value of 99.7%. Meanwhile, the reminder backbones achieved an accuracy value of 100%. The MobileNetV2 without augmentation was obtained the best backbone, as it demonstrated the shortest training time of 231s with a few epochs of 7 total. Figure 6 visually represents the model's performance in scenario 2.

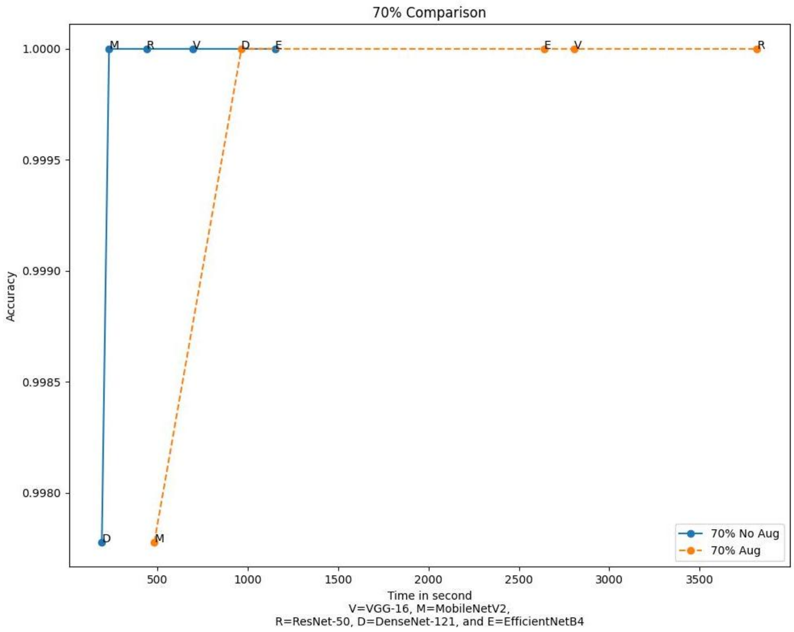


Figure 6. The visualization of the model performance for scenario-2

Table 5 (scenario-3) shows that EfficientNetB4 with and without augmentation yields the lowest accuracy value of 99.3%. Meanwhile, MobileNetV2 (with and without augmentation) and ResNet-50 without augmentation produced a higher accuracy value of 99.6%. The reminder backbones achieved an accuracy value of 100%. Hence, the best backbone was DenseNet-121 without augmentation, revealing it has the fastest training time of 197s with a low epoch number of 2. The visualization of the model performance for scenario-3 is depicted in Figure 7. Furthermore, Table 6 (scenario-4) presents all the backbones that successfully achieved an accuracy value of 100%. Hence, the best backbone was DenseNet-121 without augmentation; it indicates the fastest training time of 237s with a low number of epochs of 2. Figure 8 visually represents the model's performance in scenario 4.

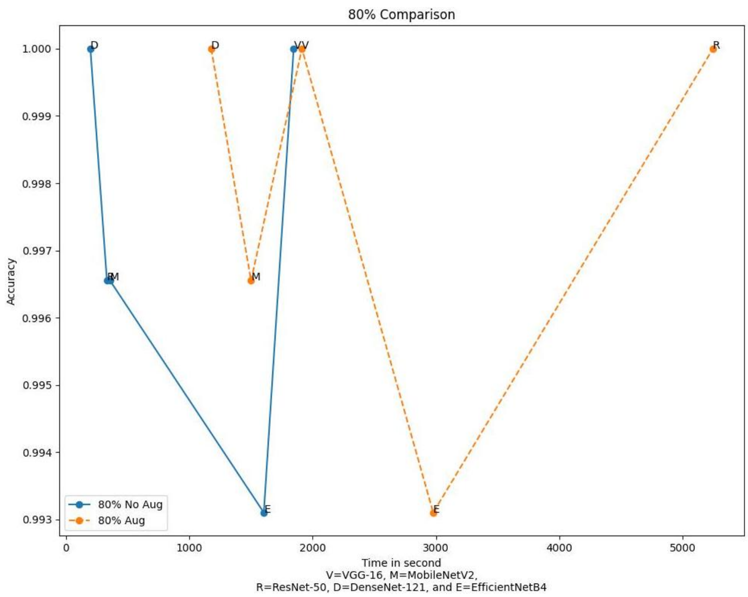


Figure 7. The visualization of the model performance for scenario-3

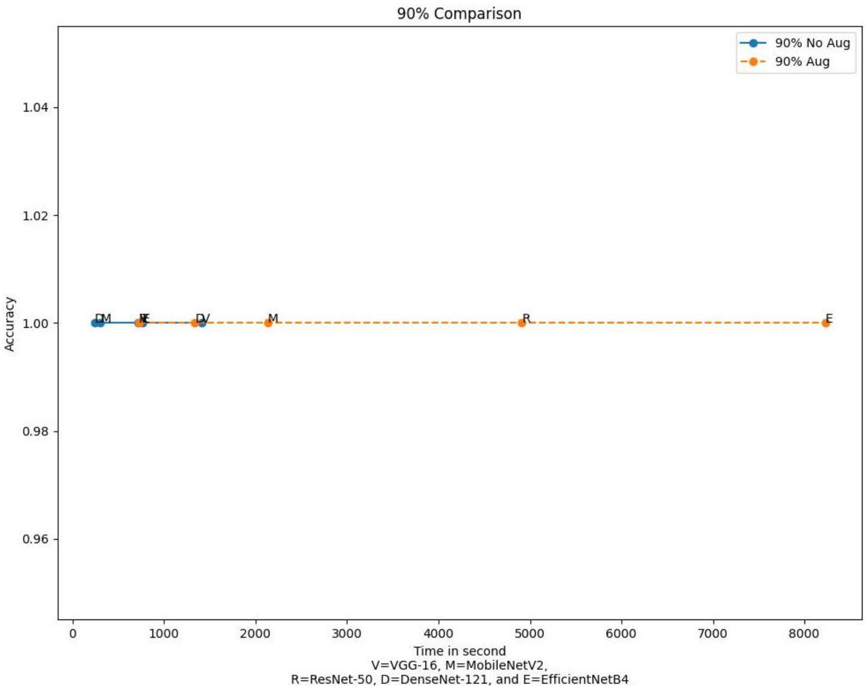


Figure 8. The visualization of the model performance for scenario-4

The model was developed for classifying 10 classes of Semarang batik: *Asem Arang* (0), *Asem Sinom* (1), *Asem Warak* (2), *Blekok* (3), *Blekok Warak* (4), *Gambang Semarangan* (5), *Kembang Sepatu* (6), *Semarangan* (7), *Tugu Muda* (8), and *Warak Beras Utah* (9). According to the experiment, misclassification occurs frequently in classes *Asem Sinom*, *Gambang Semarangan*, and *Asem Warak*. Details of these errors are shown in the confusion matrix in Figure 9 (in Appendix). There were 2 errors that occurred in class Asem Sinom, which were classified as class 3 as shown in Figure 9(a), resulting in an accuracy value of 99.6% (see Table 2). Class *Gambang Semarangan* was incorrectly classified as class Semarangan with 1 image, as shown in Figure 9(b), resulting in an accuracy value of 99.8% (see Table 2). Subsequently, class *Gambang Semarangan* was misclassified as class *Warak Beras Utah*, as shown in Figure 9(c), resulting in an accuracy value of 99.7% (see Table 3). Furthermore, class *Asem Warak* was incorrectly classified as class *Blekok* with 1 image (Figure 9(d)), and was classified as class *Asem Arang* and *class Blekok Warak* with a total of 2 images (Figure 9(e)) resulting in an accuracy value of 99.6% and 99.3%, as shown in Table 4 respectively.

Regarding the data augmentation, it reveals that the augmentation process is not needed due to without augmentation, the classification model successfully achieves the maximum value of accuracy and score of 100%. Data augmentation makes the model training time longer; in some models, it guarantees perfect accuracy and F1 score (VGG-16, ResNet-50, and DenseNet-121). According to the four scenarios of the data split method, the best model has been justified. The best performance of the Semarang batik classification model based on dataset split is summarized in Table 7. Table 7 shows the DenseNet-121 backbone obtains the fastest training time of 197s and takes 2 epochs to build the Semarang batik classification model. The model was formed using the dataset split of 80%:10%:10% for the training, validation, and testing set, respectively.

Table 7. The various training times from the best performance result of the Semarang batik classification model

Dataset split	Model	Training epoch	Training time
60%:20%:20%	MobileNetV2	9	244
70%:15%:15%	MobileNetV2	7	231
80%:10%:10%	DenseNet-121	2	197
90%:5%:5%	DenseNet-121	2	237

Table 8 provides a brief overview of the development studies concerning different batik classification methods constructed using deep learning and machine learning techniques, and it also summarizes the performance results of the fabric classification method from multiple prior studies and the proposed method. Prior research made use of several backbones applied to local datasets. Similar motifs and datasets were utilized in a study about the Semarang batik classification [25].

Table 8. An overview of previous studies on traditional fabric classification

No.	Method	Accuracy (%)
1	The GLCM consisting of correlation, energy, homogeneity, and contrast were applied combining with quadratic SVM [10].	90.3
2	The combination of GLCM and artificial neural network (ANN) [11].	90.48
3	CNN using ResNet-50 backbone [16].	96
4	Mulwin-LBP algorithm for feature extraction and deep neural network for the classifier [17].	98
5	The color and texture features applied using color moments in the RGB color spaces and the GLCM with the decision tree classifier [22].	99.9
6	The combination of color moments, area based invariant moments, GLCM, and LBP with the ANN classifier [25].	99.76
7	Proposed model using CNN with DenseNet-121 backbone.	100

The study demonstrates that deep learning-based classification achieves 100% accuracy under specific conditions, yet it does not extensively compare its performance with traditional machine learning approaches, such as SVM or decision trees, in terms of computational efficiency and practical deployment. Additionally, the paper could benefit from a deeper exploration of real-world applicability, such as the integration of this model into mobile applications or museum databases for automatic batik recognition.

The findings indicate that CNN-based approaches, particularly DenseNet-121, significantly enhance classification accuracy. However, challenges such as sensitivity to lighting variations, image distortions, and scalability to larger datasets remain unaddressed. Future research should focus on optimizing computational efficiency, experimenting with self-supervised learning techniques, and expanding the dataset with diverse batik motifs to improve robustness. Furthermore, incorporating explainable AI (XAI) methods could enhance the interpretability of classification decisions, making the model more accessible for cultural heritage preservation initiatives and practical applications in textile industries.

The primary problem addressed in the research is the challenge of accurately classifying batik patterns into 10 distinct classes due to their intricate designs and similarities. To overcome this, the study explores multiple CNN backbones, including MobileNetV2, ResNet-50, VGG-16, DenseNet-121, and EfficientNetB4, comparing their performance based on accuracy, F1-score, training time, and the impact of data augmentation. The experimental results demonstrate that all models achieved high accuracy, with some architectures such as VGG-16, ResNet-50, and DenseNet-121 reaching 100% accuracy without the need for augmentation. However, the study highlights that while data augmentation can improve model generalization, it also significantly increases training time. Additionally, the research identifies common misclassification patterns in specific batik classes and addresses the importance of selecting the optimal CNN backbone to balance accuracy and computational efficiency. Ultimately, the study confirms that DenseNet-121 is the most efficient model, achieving the best trade-off between training time and classification performance.

4. CONCLUSION

This study investigated the performance of CNNs using various backbones to build an automated classification model for Semarang batik, comprising ten distinct classes*: Asem Arang, Asem Sinom, Asem Warak, Blekok, Blekok Warak, Gambang Semarangan, Kembang Sepatu, Semarangan, Tugu Muda,* and *Warak Beras Utah*. The DenseNet-121 emerged as the best-performing model, achieving a perfect classification accuracy of 100% with the fastest training time of 237 seconds without data augmentation. While all tested models (MobileNetV2, ResNet-50, VGG-16, DenseNet-121, and EfficientNetB4) attained 100% accuracy under the given experimental settings, DenseNet-121 demonstrated the most optimal balance between performance and efficiency, making it highly suitable for real-time or resource-constrained applications. The primary variation among models was observed in training duration, with EfficientNetB4 requiring the longest training time (8,227 seconds) when data augmentation was applied. Future research directions include enhancing the model's robustness and generalization capabilities by incorporating larger and more diverse datasets that capture variations in lighting conditions, fabric textures, and perspective angles. Additionally, deploying the model in real-world mobile or web-based applications could facilitate broader public access and contribute significantly to the digital preservation of Indonesia's batik heritage.

ACKNOWLEDGMENTS

Thanks to the Research Centre for Artificial Intelligence, Faculty of Engineering and Computer Science, Universitas Muhammadiyah Semarang, Indonesia, which has supported this research.

FUNDING INFORMATION

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. However, the publication and dissemination costs were financially supported by the Faculty of Engineering and Computer Science, Universitas Muhammadiyah Semarang.

AUTHOR CONTRIBUTIONS STATEMENT

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

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Edy Winarno	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Achmad Solichan		✓		✓		✓	✓			✓		✓		
Aditya Putra Ramdani		✓	✓			✓		✓	✓		✓			
Wiwien Hadikurniawati		✓		✓	✓		✓	✓		✓		✓	✓	✓
Anindita Septiarini	✓	✓		✓	✓		✓			✓	✓			
Hamdani Hamdani	✓			✓	✓			✓		✓	✓			

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

Authors state no conflict of interest.

INFORMED CONSENT

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

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author [AS] on request.

REFERENCES

[1] Y. Choi, Y. J. Yang, and H. G. Sohn, "Resilient cultural heritage through digital cultural heritage cube: Two cases in South Korea," *Journal of Cultural Heritage*, vol. 48, pp. 36–44, Mar. 2021, doi: 10.1016/j.culher.2021.01.007.

[2] L. Di Angelo, P. Di Stefano, and E. Guardiani, "A review of computer-based methods for classification and reconstruction of 3D high-density scanned archaeological pottery," *Journal of Cultural Heritage*, vol. 56, pp. 10–24, Jul. 2022, doi: 10.1016/j.culher.2022.05.001.

[3] M. A. Rasyidi and T. Bariyah, "Batik pattern recognition using convolutional neural network," *Bulletin of Electrical Engineering and Informatics*, vol. 9, no. 4, pp. 1430–1437, Aug. 2020, doi: 10.11591/eei.v9i4.2385.

[4] A. Septiarini, R. Saputra, A. Tedjawati, M. Wati, and H. Hamdani, "Pattern Recognition of Sarong Fabric Using Machine Learning Approach Based on Computer Vision for Cultural Preservation," *International Journal of Intelligent Engineering and Systems*, vol. 15, no. 5, pp. 284–295, Oct. 2022, doi: 10.22266/ijies2022.1031.26.

[5] E. Winarno, W. Hadikurniawati, A. Septiarini, and H. Hamdani, "Analysis of color features performance using support vector machine with multi-kernel for batik classification," *International Journal of Advances in Intelligent Informatics*, vol. 8, no. 2, pp. 151–164, Jul. 2022, doi: 10.26555/ijain.v8i2.821.

[6] P. R. Wahyuni, "The Influence of Price and Product Quality on Batik Purchasing Decisions: Evidence from Sumenep Regency, Indonesia," *International Journal of Social Science and Human Research*, vol. 6, no. 09, Sep. 2023, doi: 10.47191/ijsshr/v6-i9-53.

[7] M. Isa, M. F. Wajdi, L. Mangifera, A. Mardalis, and N. H. Kamarulzaman, "Value Chain and Stakeholders' Analyses of Batik Tulis Industry in Indonesia," *Journal of Evolutionary Studies in Business*, vol. 8, no. 2, pp. 138–167, Jul. 2023, doi: 10.1344/jesb2023.8.2.38898.

[8] K. Oginawati *et al.*, "Occupational lead exposure health risk assessment and heme biosynthesis: A study on batik artisans in yogyakarta, Indonesia," *Heliyon*, vol. 9, no. 9, pp. 1–17, Sep. 2023, doi: 10.1016/j.heliyon.2023.e19994.

[9] S. Susanti, S. F. Pradigdo, F. Arifan, Y. Pratama, and A. Katherinatama, "Pigment extraction from shallot peel as natural dyes for Semarang typical batik manufacture," in *AIP Conference Proceedings*, 2023, doi: 10.1063/5.0142860.

[10] B. J. Filia *et al.*, "Improving batik pattern classification using CNN with advanced augmentation and oversampling on imbalanced dataset," *Procedia Computer Science*, vol. 227, pp. 508-517, 2023, doi: 10.1016/j.procs.2023.10.552.

[11] A. A. Kasim, R. Wardoyo, and A. Harjoko, "Batik classification with artificial neural network based ontexture-shape feature of main ornament," *International Journal of Intelligent Systems and Applications*, vol. 9, no. 6, pp. 55–65, Jun. 2017, doi: 10.5815/ijisa.2017.06.06.

[12] R. Andrian, B. Hermanto, and R. Kamil, "The Implementation of Backpropagation Artificial Neural Network for Recognition of Batik Lampung Motive," *Journal of Physics: Conference Series*, vol. 1338, no. 1, pp. 1–11, Oct. 2019, doi: 10.1088/1742-6596/1338/1/012062.

[13] A. H. Rangkuti, A. Harjoko, and A. Putra, "A Novel Reliable Approach for Image Batik Classification That Invariant with Scale and Rotation Using MU2ECS-LBP Algorithm," *Procedia Computer Science*, vol. 179, pp. 863–870, 2021, doi: 10.1016/j.procs.2021.01.075.

[14] A. A. Kasim, M. Bakri, and A. Septiarini, "The Artificial Neural Networks (ANN) for Batik Detection Based on Textural Features," in *Proceedings of the Proceedings of the 7th Mathematics, Science, and Computer Science Education International Seminar, MSCEIS 2019*, EAI, 2020, pp. 1–9, doi: 10.4108/eai.12-10-2019.2296538.

[15] V. M. Ngo, T. V. T. Duong, T. B. T. Nguyen, P. T. Nguyen, and O. Conlan, "An efficient classification algorithm for traditional textile patterns from different cultures based on structures," *Journal on Computing and Cultural Heritage*, vol. 14, no. 4, pp. 1–22, Dec. 2021, doi: 10.1145/3465381.

[16] B. S. Negara, E. Satria, S. Sanjaya, and D. R. D. Santoso, "ResNet-50 for Classifying Indonesian Batik with Data Augmentation," in *2021 International Congress of Advanced Technology and Engineering (ICOTEN)*, Jul. 2021, pp. 1–4, doi: 10.1109/ICOTEN52080.2021.9493488.

[17] A. H. Rangkuti, M. M. Ramadhan, and A. H. Aslamia, "Reliable Batik Image Classification : Mulwin-LBP Algorithm and Deep Neural Network," in *2021 3rd International Symposium on Material and Electrical Engineering Conference (ISMEE)*, Nov. 2021, pp. 96–101, doi: 10.1109/ISMEE54273.2021.9774230.

[18] A. E. Minarno, M. Y. Hasanuddin, and Y. Azhar, "Batik images retrieval using pre-trained model and K-Nearest Neighbor," *JOIV: International Journal on Informatics Visualization*, vol. 7, no. 1, pp. 115–121, Mar. 2023.

[19] D. A. Anggoro, A. A. T. Marzuki, and W. Supriyanti, "Classification of Solo Batik patterns using deep learning convolutional neural networks algorithm," *Telkomnika (Telecommunication Computing Electronics and Control)*, vol. 22, no. 1, pp. 232–240, 2024, doi: 10.12928/TELKOMNIKA.v22i1.24598.

[20] I. M. A. Agastya and A. Setyanto, "Classification of Indonesian batik using deep learning techniques and data augmentation," in *2018 3rd International Conference on Information Technology, Information System and Electrical Engineering (ICITISEE)*, Yogyakarta, Indonesia, Nov. 2018, pp. 27–31, doi: 10.1109/ICITISEE.2018.8720990.

[21] D. G. T. Meranggi, N. Yudistira, and Y. A. Sari, "Batik Classification Using Convolutional Neural Network with Data Improvements," *International Journal on Informatics Visualization*, vol. 6, no. 1, pp. 6–11, Mar. 2022, doi: 10.30630/joiv.6.1.716.

[22] A. Tejawati *et al.*, "Batik Pattern Classification Using Decision Tree Based on Color-Texture Features," in *2023 Sixth International Conference on Vocational Education and Electrical Engineering (ICVEE)*, Surabaya, Indonesia, Oct. 2023, pp. 347–352, doi: 10.1109/ICVEE59738.2023.10348243.

[23] W. Herulambang, M. N. Hamidah, and F. Setyatama, "Comparison of SVM and BPNN Methods in the Classification of Batik Patterns Based on Color Histograms and Invariant Moments," in *2020 International Conference on Smart Technology and Applications (ICoSTA)*, Feb. 2020, pp. 1–4, doi: 10.1109/ICoSTA48221.2020.1570615583.

[24] D. M. S. Arsa and A. A. N. H. Susila, "VGG16 in Batik Classification based on Random Forest," in *Proceedings of 2019 International Conference on Information Management and Technology (ICIMTech)*, Aug. 2019, pp. 295–299, doi: 10.1109/ICIMTech.2019.8843844.

[25] E. Winarno, A. Septiarini, W. Hadikurniawati, and H. Hamdani, "The Hybrid Features and Supervised Learning for Batik Pattern Classification," *Journal on Computing and Cultural Heritage*, vol. 17, no. 2, pp. 1–13, Jun. 2024, doi: 10.1145/3631131.

[26] X. Fu, S. Liu, C. Li, and J. Sun, "MCLNet: An multidimensional convolutional lightweight network for gastric histopathology image classification," *Biomedical Signal Processing and Control*, vol. 80, Feb. 2023, doi: 10.1016/j.bspc.2022.104319.

[27] K. Oya, K. Kokomoto, K. Nozaki, and S. Toyosawa, "Oral squamous cell carcinoma diagnosis in digitized histological images using convolutional neural network," *Journal of Dental Sciences*, vol. 18, no. 1, pp. 322–329, Jan. 2023, doi: 10.1016/j.jds.2022.08.017.

[28] W. M. Salama, M. H. Aly, and Y. Abouelseoud, "Deep learning-based spam image filtering," *Alexandria Engineering Journal*, vol. 68, pp. 461–468, Apr. 2023, doi: 10.1016/j.aej.2023.01.048.

[29] L. M. Tassis and R. A. Krohling, "Few-shot learning for biotic stress classification of coffee leaves," *Artificial Intelligence in Agriculture*, vol. 6, pp. 55–67, 2022, doi: 10.1016/j.aiia.2022.04.001.

[30] R. Mohammedqasem *et al.*, "Multi-objective deep learning framework for COVID-19 dataset problems," *Journal of King Saud University - Science*, vol. 35, no. 3, pp. 1–8, Apr. 2023, doi: 10.1016/j.jksus.2022.102527.

[31] C. Chen *et al.*, "Enhancing MR image segmentation with realistic adversarial data augmentation," *Medical Image Analysis*, vol. 82, pp. 1–15, Nov. 2022, doi: 10.1016/j.media.2022.102597.

[32] F. L. de la Rosa, J. L. Gómez-Sirvent, R. Sánchez-Reolid, R. Morales, and A. Fernández-Caballero, "Geometric transformation-based data augmentation on defect classification of segmented images of semiconductor materials using a ResNet50 convolutional neural network," *Expert Systems with Applications*, vol. 206, p. 117731, Nov. 2022, doi: 10.1016/j.eswa.2022.117731.

[33] Y. Y. Chen, Y. H. Lin, C. C. Kung, M. H. Chung, and I. H. Yen, "Design and implementation of cloud analytics-assisted smart power meters considering advanced artificial intelligence as edge analytics in demand-side management for smart homes," *Sensors*, vol. 19, no. 9, pp. 1–26, May 2019, doi: 10.3390/s19092047.

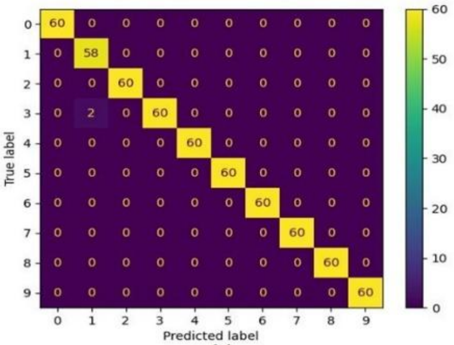
[34] M. Ibrahim, A. Shaawat, and M. Torki, "Covariance Pooling Layer for Text Classification," *Procedia CIRP*, vol. 189, pp. 61–66, 2021, doi: 10.1016/j.procs.2021.05.070.

[35] A. Koivu, J. P. Kakko, S. Mäntyniemi, and M. Sairanen, "Quality of randomness and node dropout regularization for fitting neural networks," *Expert Systems with Applications*, vol. 207, pp. 1–10, Nov. 2022, doi: 10.1016/j.eswa.2022.117938.

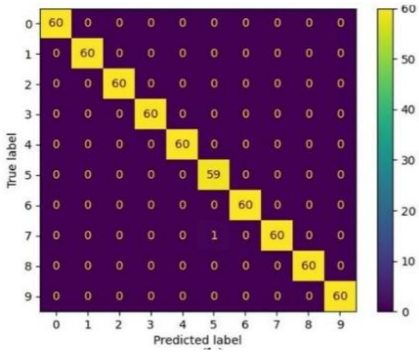
[36] K. Yildirim *et al.*, "Deep learning-based PI-RADS score estimation to detect prostate cancer using multiparametric magnetic resonance imaging," *Computers and Electrical Engineering*, vol. 102, p. 108275, Sep. 2022, doi: 10.1016/j.compeleceng.2022.108275.

[37] E. A. B. Ibrahim *et al.*, "Evaluation of texture feature based on basic local binary pattern for wood defect classification," *International Journal of Advances in Intelligent Informatics*, vol. 7, no. 1, pp. 26-36, Mar. 2021, doi: 10.26555/ijain.v7i1.393.

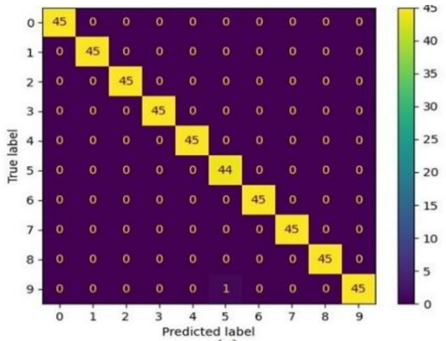
APPENDIX



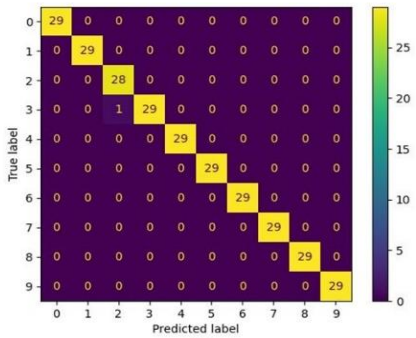
(a)



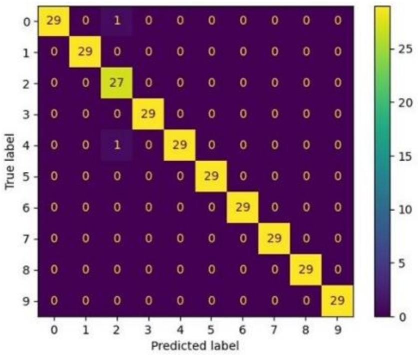
(b)



(c)



(d)



(e)

Figure 9. Confusion matrix for classification model of Semarang batik with various misclassifications; (a) *Asem Sinom* as class 3, (b) *Gambang Semarangan* as class 7, (c) *Gambang Semarangan* as class 9, (d) *Asem Warak* as class 3, and (e) *Asem Warak* as class 0 & 4

BIOGRAPHIES OF AUTHORS

Edy Winarno is a lecturer in the Bachelor's program in Information Technology at Muhammadiyah University of Semarang. He graduated from Doctoral degree in computer science from Gadjah Mada University, Indonesia, specializing in image processing and, computer vision. He is also a researcher and got a grant from the Ministry of Education, Culture, Research, and Technology of Indonesia from 2011 until the present. His research interests in artificial intelligence, image processing, security, and computer vision. He can be contacted at email: edywin@unimus.ac.id.

Achmad Solichan earned his Master's degree in Information Systems from Universitas Diponegoro in 2012. His research interests include artificial intelligence and energy optimization. Currently serving as a lecturer in the Bachelor's program in Information Technology at Universitas Muhammadiyah Semarang. He can be contacted at email: solichan@unimus.ac.id.

Aditya Putra Ramdani is a lecturer in the Bachelor's program in Information Technology at Muhammadiyah University of Semarang. He graduated with a Master's degree in Computer Engineering from Dian Nuswantoro University Semarang in 2020. His research focuses on artificial intelligence and cyber security. He can be contacted at email: adityaputraramdani@unimus.ac.id.

Wiwien Hadikurniawati received the bachelor's degree in electrical engineering from Semarang University, Indonesia, in 1999, and the master's degree in information systems from Diponegoro University, Indonesia, in 2010. She is currently a Lecturer with the Faculty of Information Technology and Industry, Stikubank University, Indonesia. Her research interests include machine learning and decision-making. She can be contacted at email: wiwien@edu.unisbank.ac.id.

Anindita Septiarini is a professor at the Department of Informatics at Mulawarman University, Indonesia. She holds a Doctoral degree in computer science from Gadjah Mada University, Indonesia, specializing in image analysis. She is also a researcher and got a grant from the Ministry of Education, Culture, Research, and Technology of Indonesia from 2016 until the present. Her research interests lie in artificial intelligence, especially pattern recognition, image processing, and computer vision. She has received national awards such as scientific article incentives from the Ministry of Education, Culture, Research, and Technology of Indonesia in 2017 and 2019. She held several administrative posts with the Department of Informatics, Mulawarman University, Indonesia, from 2018 to 2020, including the Head of Department and the Head of Laboratory. She can be contacted at email: anindita@unmul.ac.id.

Hamdani Hamdani is a professor in Department of Informatics at Mulawarman University, Indonesia. He is a lecturer and researcher since 2005 at Mulawarman University, Indonesia. His research interests lie in the field of artificial intelligence, especially pattern recognition, decision support system, and expert system. He received her bachelor's degree in 2002 from Ahmad Dahlan University, Indonesia, his master's degree in 2009 from Gadjah Mada University, Indonesia, and her doctoral degree in computer science in 2018 from Gadjah Mada University Indonesia. He can be contacted at email: hamdani@unmul.ac.id.