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Enhanced Semarang Batik Classification using MobileNetV2 and Data Augmentation

Emila Khoirunnisa[1)], Farrikh Alzami[2)*], Ricardus Anggi Pramunendar[3], Rama Aria Megantara[4], Muhammad Naufal[5], Harun Al-Azies[6], Sri Winarno[7]
[1,3,4,5,6,7)]Informatics Engineering, Facullty of Computer Science, Universitas Dian Nuswantoro, Indonesia
[2)] Information Systems, Faculty of Computer Science, Universitas Dian Nuswantoro, Indonesia
[1]111202113709@mhs.dinus.ac.id, [2]alzami@dsn.dinus.ac.id, [3]ricardus.anggi@dsn.dinus.ac.id, [4]aria@dsn.dinus.ac.id, [5]m.naufal@dsn.dinus.ac.id, [6]harun.alazies@dsn.dinus.ac.id, [7]sri.winarno@dsn.dinus.ac.id

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Abstract: Batik, an Indonesian cultural heritage recognized by UNESCO, faces challenges in pattern identification and documentation, particularly for the younger generation. Previous studies on batik classification have shown limitations in handling small datasets and maintaining accuracy with limited computational resources. This research proposes an enhanced classification approach for Semarang Batik motifs using MobileNetV2 architecture combined with strategic data augmentation techniques. The study utilizes a dataset of 3,020 images comprising 10 distinct Semarang Batik motifs, implementing horizontal flipping, rotation, and zoom transformations to address dataset limitations. Our methodology incorporates transfer learning through ImageNet pre-trained weights and custom layer modifications to optimize the MobileNetV2 architecture for batik-specific features. The model achieves 100% accuracy on validation data, with precision, recall, and F1-scores consistently above 0.98 across all classes. The confusion matrix analysis reveals minimal misclassification between similar motif patterns, particularly in the Batik Blekok Warak and Batik Kembang Sepatu classes. This research contributes to cultural heritage preservation by providing an efficient, resource-conscious solution for automated batik pattern recognition, potentially supporting educational and commercial applications in the batik industry.

Keywords: Batik Pattern Recognition; MobileNetV2; Deep Learning Classification; Data Augmentation; Cultural Heritage Preservation; Computer Vision

INTRODUCTION

Batik, an Indonesian national cultural heritage recognized by UNESCO (Al-shami et al., 2024; Filia et al., 2023), popular for its dyeing technique using wax resist that produces unique patterns based on regions in Indonesia (Hu et al., 2021). Each region has unique batik patterns, reflecting their respective local cultures. However, the vast diversity of these patterns presents significant challenges in identification and documentation (Filia et al., 2023; Rangkuti et al., 2021). The reason is that many patterns are easily recognizable, while others are difficult to distinguish, especially by the younger generation. This raises concerns regarding the sustainability of batik heritage, especially in disseminating knowledge to the next generation, as well as the threat of batik extinction in some regions.

The complexity of batik pattern recognition stems from several factors. First, the intricate nature of batik motifs involves multiple layers of patterns, varying color combinations, and subtle design elements that require expert knowledge to distinguish. Second, the traditional method of pattern identification relies heavily on expert craftspeople, whose knowledge is often not well-documented or systematically organized. Third, the increasing demand for batik authentication and classification, particularly in commercial and educational contexts, necessitates an automated and accurate recognition system (Rangkuti et al., 2021).

Previous studies have explored various approaches to batik pattern classification using machine learning techniques, particularly Convolutional Neural Networks (CNN) (Filia et al., 2023; Ihsan, 2023; Rangkuti et al., 2021).While these studies demonstrated promising results, they faced several limitations. Most notably, they required substantial computational resources, making them impractical for real-world applications. Additionally, existing research has not adequately addressed the challenge of limited dataset availability, which is common in cultural heritage domains. The varying quality and consistency of batik images further complicate the classification task, especially when dealing with traditional patterns that may have subtle variations.

*name of corresponding author

To address these challenges, this research proposes an efficient approach using MobileNetV2 architecture (Alsaheel et al., 2023; Alzami et al., 2024; Arnia et al., 2024; Asghar et al., 2024; Utomo et al., 2021). MobileNetV2 is specifically chosen for its ability to maintain high accuracy while requiring minimal computational resources, making it ideal for practical applications (Dang et al., 2022; Hosseini et al., 2023). The architecture employs depthwise separable convolution to reduce computation and parameters (Abraham et al., 2023; Jadon et al., 2020; Mabrouk et al., 2023) combined with inverted residuals and linear bottlenecks for efficient feature extraction (Ahad et al., 2023; Alsaheel et al., 2023; Arnia et al., 2024; Asghar et al., 2024). Despite its lightweight design (Rashid et al., 2022), MobileNetV2 has proven effective in various classification tasks, making it particularly suitable for the complex nature of batik pattern recognition.

This research makes several key contributions to the field of batik motif classification. It develops an efficient and accurate classification system for Semarang batik motifs using the lightweight and effective MobileNetV2 architecture. This approach addresses the challenge of limited batik pattern datasets by introducing an optimized data augmentation strategy, enhancing the model's robustness and accuracy. Additionally, the study provides a comprehensive evaluation of model performance across various batik motif classes, ensuring the reliability and generalizability of the classification system. Furthermore, it demonstrates the feasibility of implementing high-accuracy batik classification on resource-constrained devices, enabling practical applications on devices with limited computational resources. Overall, the proposed approach significantly contributes to the recognition of batik motifs, supporting the preservation of Indonesian cultural heritage in the digital era.

The proposed approach focuses on ten distinct Semarang batik motifs, employing strategic data augmentation techniques to enhance model generalization while maintaining the essential characteristics of each pattern. This research aims not only to achieve high classification accuracy but also to provide a practical solution that can be implemented in real-world applications for cultural heritage preservation and education.

LITERATURE REVIEW

MobileNetV2 is a lightweight convolutional neural network (CNN) architecture designed primarily for mobile and edge devices, emphasizing efficiency and performance. Its architecture builds upon the principles of depthwise separable convolutions, which significantly reduce the number of parameters and computational cost compared to traditional convolutional layers. This design enables MobileNetV2 to maintain a high level of accuracy while being resource-efficient, making it suitable for various applications, particularly in medical imaging and real-time classification tasks. The MobileNetV2-based approach offers significant advantages, both in terms of computational efficiency and scientific contribution, particularly in fields that rely on advanced image analysis technologies.

One of the notable applications of MobileNetV2 is in the medical field, where it has been utilized for diagnosing diseases from imaging data. For instance, Zhang et al. employed MobileNetV2 as the backbone for a model aimed at diagnosing COVID-19 from CT images, leveraging transfer learning to mitigate overfitting due to limited data availability (Zhang et al., 2022). Similarly, Shamrat et al. customized MobileNetV2 for high-precision multiclass classification of lung diseases from chest X-ray images, demonstrating its adaptability and effectiveness in medical diagnostics (Shamrat et al., 2023). These studies highlight MobileNetV2's capability to perform well even in scenarios with constrained datasets, which is a common challenge in medical imaging.

Moreover, MobileNetV2 has been integrated into frameworks for detecting deep fakes in healthcare, showcasing its versatility beyond traditional medical applications. Alsaheel's research involved training MobileNetV2 alongside other CNN models to distinguish between authentic and manipulated medical images, indicating its robustness in handling diverse image classification tasks (Alsaheel et al., 2023). This adaptability is further evidenced by its application in melanoma image classification, where Indraswari et al. demonstrated the network's efficacy in identifying skin cancer from images (Indraswari et al., 2022). Such applications underline the importance of MobileNetV2 in enhancing diagnostic accuracy across various medical conditions.

In addition to its applications in healthcare, MobileNetV2 has been employed in agricultural contexts, such as the detection of guava leaf diseases. Rashid et al. proposed a hybrid model that utilized MobileNetV2 as an encoder in a segmentation framework, illustrating its effectiveness in agricultural image analysis (Rashid et al., 2022). This cross-disciplinary utilization of MobileNetV2 emphasizes its flexibility and potential for broader applications beyond conventional domains.

In matter of batik field, MobileNetV2 was shown to outperform other models like InceptionV3 and VGG19 in batik image retrieval tasks when used in conjunction with K-Nearest Neighbor (KNN) for re-ranking, achieving notable precision improvements (Minarno et al., 2023). This highlights MobileNetV2's capability to handle complex image classification tasks effectively, making it suitable for the intricate patterns found in batik designs. Then, Andrian's research utilized data augmentation methods such as rotation and brightness adjustments to improve the model's robustness against variations in the dataset, resulting in high classification accuracy (Andrian et al., 2024). This approach is essential in the context of batik classification, where the diversity of patterns can pose challenges for machine learning models.

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METHOD

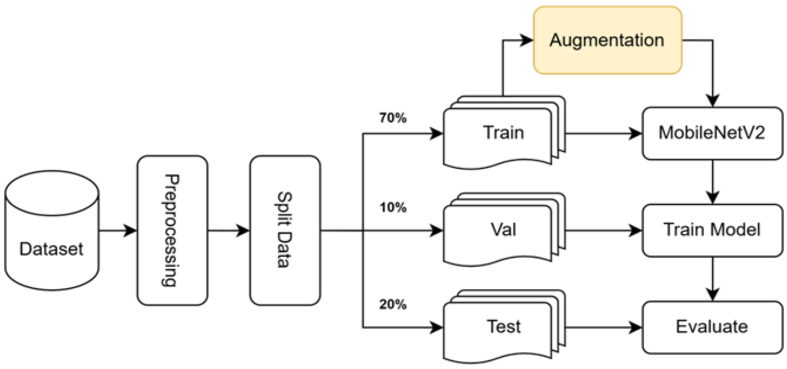

Fig. 1 Experiment Method

This research implements a systematic approach to classify Semarang batik motifs using the MobileNetV2 architecture. Fig. 1 illustrates the complete methodology framework, consisting of five main stages: dataset preparation, preprocessing, data augmentation, model development, and evaluation. Each stage is designed to address specific challenges in batik pattern recognition while maintaining computational efficiency.

The initial step begins with collecting the dataset, then preprocessing is carried out on the dataset. The dataset is then divided into train, val, and test. In the train data, augmentation is performed to add variety to the dataset. After augmentation, MobileNetV2 architecture is applied as a base model that has been pre trained using ImageNet. The model is trained using the augmented data, while validation data is used to monitor the performance of the model. After training, evaluation is done by calculating accuracy, confusion matrix, as well as metrics such as precision, recall, and F1-score to measure the performance of the model in batik motif classification.

Dataset

The dataset comprises 3,020 high-resolution images of Semarang batik patterns, encompassing ten distinct motif classes (Fig. 2). These images were collected from the Kaggle platform (Edy Winarno & Fazri Gading, n.d.), representing authentic Semarang batik patterns with varying lighting conditions, angles, and scales. Table 1 presents the distribution of images across classes, demonstrating a relatively balanced dataset with approximately 300 images per class.

The selected motifs represent significant cultural elements of Semarang:

a. Asem Arang and Asem Sinom: Characterized by tamarind leaf patterns.
b. Setting 5 mm for the left protrudes in.
c. Gambang Semarangan: Incorporating traditional musical instrument patterns.
d. Other motifs: Representing local landmarks and cultural symbols.

Fig. 2 Image of Batik Motif (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 Utah

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Table 1. Initial Dataset Composition

Name	Number
Asem Arang	308
Asem Sinom	300
Asem Warak	300
Blekok	300
Blekok Warak	300
Gambang Semarangan	308
Kembang Sepatu	300
Semarangan	304
Tugu Muda	300
Warak Beras Utah	300
Total	3020

Preprocessing

In the preprocessing step, the author resizes each image in the dataset by 224x224 pixels according to the input size required by the MobileNetV2 architecture. The original images from the Semarang batik dataset have varying resolutions, so this size adjustment is important to ensure consistency and speed up performance. The resize process is done using the cv2.resize function from the OpenCV library. The choice of 224x224 size is based on the MobileNetV2 architecture specification (Indraswari et al., 2022), which has been trained using ImageNet datasets with the same image size. Resizing images to a uniform size has several important benefits, including maintaining the suitability of the input for the model and reducing the computational burden, as smaller images can be processed more efficiently (Kurniastuti et al., 2024; Saifullah et al., 2023).

In this study, the author did not perform the stage of converting the image to grayscale as is commonly practiced in image detection. The reason is that Batik motifs and patterns are not only determined by geometric patterns, but also color combinations that characterize each motif. Therefore, retaining the color information in the image is important to support the classification accuracy. Since color image processing has a higher complexity than grayscale, it will be helped by the implementation of MobileNetV2.

After preprocessing, the dataset is then divided into three separate subsets, namely train, validation, and test, with a ratio of 70% for train, 20% for test, and 10% for validation. The 70:20:10 split ratio was chosen based on empirical studies in similar pattern recognition tasks, providing sufficient data for training while ensuring robust validation and testing.

Data splitting is conducted by randomizing the images in each class first. This is important to avoid any bias that may arise if the data is sorted based on a particular pattern. After the randomization process, the image files are copied to the appropriate folders using the shutil.copy function, so that the folder structure is maintained and each image is treated separately during dataset sharing. This process ensures that the model is trained with representative data from each class, tested with separate data, and validated with data that has not been used during training.

Data Augmentation

Data Augmentation is a technique used to enrich the diversity of a dataset by creating variations of existing images (Ahad et al., 2023; Beddiar et al., 2023). In the context of Semarang batik classification, this technique is important to improve model generalization and reduce the risk of overfitting (Shamrat et al., 2023). Overfitting occurs when a model fits too well to the training data, so the model cannot generalize well to data it has never seen before and difficulty maintaining high accuracy when tested on new data (Indraswari et al., 2022).

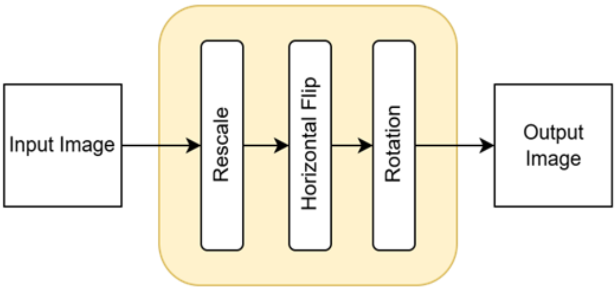

Fig. 3 Data Augmentation

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This research utilizes the ImageDataGenerator of Keras TensorFlow, which allows random application of various transformations to each batch of images during training. Seen in Fig. 3, the author configured the ImageDataGenerator for training to include pixel normalization to the 1/255 range, horizontal inversion, rotation up to 20 degrees, zoom up to 20%, and horizontal and vertical shift. As for the validation and testing datasets, the author only applies normalization. This augmentation technique not only enriches the variety of datasets but also plays an important role in improving the generalization of the model to be able to recognize patterns even if the image undergoes changes in position, orientation, or scale.

Pixel normalization keeps the training process stable by reducing pixel values, thus preventing gradients from blowing out or disappearing. Horizontal inversion helps the model recognize patterns even when the image is upside down, while rotation and zoom increase the model's resilience to changes in orientation and scale. Horizontal and vertical shifts allow the model to remain accurate despite shifts in the position of objects. Overall, these augmentation techniques prevent overfitting and make the model more adaptive to variations of different shapes and sizes, without the need for manual addition of new data.

MobileNetV2

Deep CNN architecture is known for delivering superior performance in image classification, object identification, and image segmentation tasks. Previous research has also shown significant results in image classification using CNN architecture. In this research, the architecture model used is MobileNetV2, which is a Convolutional Neural Network (CNN) model. MobileNetV2 proved to be effective for image classification tasks.

After the basic model is initialized using the ImageNet dataset (Khandakar et al., 2021; Nasir et al., 2023; Zhang et al., 2022), several additional layers that can be seen in Fig. 4 are added to adapt the model to the Batik pattern classification task. ImageNet, which serves as the foundation for images utilized in competitions, has significantly contributed to advancements in the construction and training of convolutional neural networks (Hossain et al., 2022). The layers include Global Average Pooling to reduce the output dimension of the base model, followed by a Dense layer with 1024 neurons and a ReLU activation function to capture non-linear relationships. Batch Normalization is then applied to stabilize the training process, while the Flatten layer converts the output into a 1D vector form to be passed on to the subsequent layers. In addition, a Dropout layer with a rate of 0.5 is added to prevent overfitting (Jadon et al., 2020), and an output layer with softmax activation is used to classify the images into 10 different classes according to the Semarang Batik dataset.

Table 2. Hyperparameter Value for Training Model

Hyperparameter	**Value**
Batch Size	32
Epochs	25
Learning Rate	0.0001

Seen in Table 2, the model was compiled using the Adam optimizer with a learning rate of 0.0001. The loss function used is categorical crossentropy, suitable for the multi-class classification task (Ahad et al., 2023; Wibawa et al., 2024) on the Batik dataset which has 10 classes. The training process is performed for 25 epochs with a batch size of 32, and uses two callbacks, namely EarlyStopping to stop training if there is no improvement in the validation loss within 10 epochs, and ReduceLROnPlateau to decrease the learning rate if the validation loss stagnates. These hyperparameters are designed to ensure effective training without overfitting.

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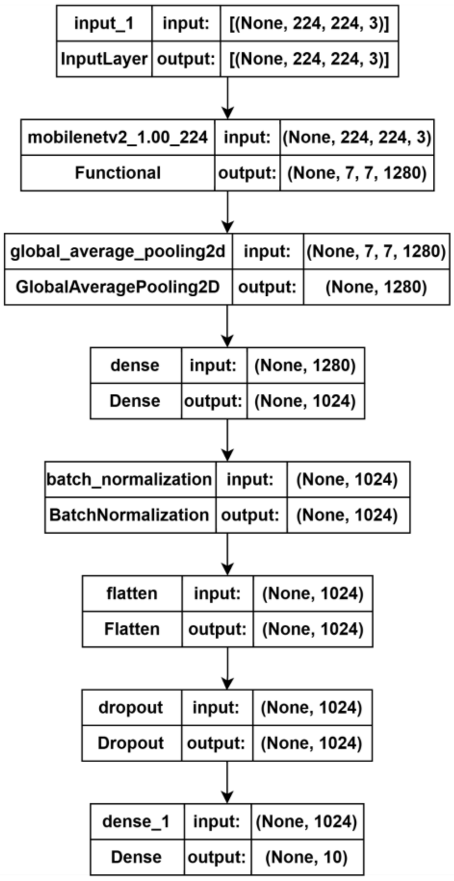

Fig. 4 Layers of MobileNetV2

Evaluation

The evaluation process involves measuring the accuracy of the model using test data. Accuracy is calculated by checking how many predictions are correct compared to the total predictions generated. The accuracy results provide an overview of the model's ability to recognize patterns that have been learned from the training data.

To get a more in-depth analysis, a confusion matrix is used which shows the comparison between the original label and the label predicted by the model. Through the confusion matrix, we can identify the classes where the model makes frequent errors. In addition, a classification report that includes metrics such as accuracy, precision, recall, and F1-score is also calculated.

After preprocessing, the dataset is then divided into three separate subsets, namely train, validation, and test, with a ratio of 70% for train, 20% for test, and 10% for validation. The 70:20:10 split ratio was chosen based on empirical studies in similar pattern recognition tasks, providing sufficient data for training while ensuring robust validation and testing.

a. Accuracy

Accuracy measures the percentage of correct predictions out of all test data.

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

b. Precision

Precision measures how precise the model is in predicting a particular class, i.e. the proportion of correct positive predictions compared to all positive predictions.

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

c. Recall

Recall measures the model's ability to find all true positive instances in the data.

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

d. F1-Score

F1-Score is the harmonic mean of precision and recall, which is useful when there is an imbalance between the two.

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

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Where, True Positive (TP) refers to the number of correct predictions of positive cases by the method, False Positive (FP) refers to the number of incorrect predictions of positive cases, True Negative (TN) refers to the number of correct predictions of negative cases, and False Negative (FN) refers to the number of incorrect predictions of negative cases by the method. While accuracy is important for measuring overall prediction success, precision, recall, and F1-score offer deeper insights, especially in identifying class-specific weaknesses. By considering these four metrics, the evaluation becomes more thorough and allows for a more accurate analysis of the model's ability to handle pattern variations in the dataset.

RESULTS

In this section, the experimental results of MobileNetV2 are presented to measure the effectiveness of the architecture in classifying Semarang Batik motifs. The total 3020 images in the Semarang Batik dataset are divided into three parts, namely training, test, and validation with 2112, 602, and 306 images respectively.

Fig. 5 Sample Augmentation Technique for Batik Blekok

Training is done for 25 epochs with a batch size of 32. The optimizer used is Adam with a learning rate of 0.0001. Data augmentation is applied using ImageDataGenerator, with pixel normalization to 1/255 range, horizontal flip, and rotation up to 20 degrees. The sample after data augmentation is presented in Fig. 5.

Table 3. Model Performance of MobileNetV2 on Test Data

Classes	Precision	Recall	F1-Score	Support
Asem Arang	1.00	1.00	1.00	60
Asem Sinom	1.00	1.00	1.00	60
Asem Warak	1.00	1.00	1.00	61
Blekok	1.00	1.00	1.00	60
Blekok Warak	0.98	1.00	0.99	60
Gambang Semarangan	1.00	1.00	1.00	61
Kembang Sepatu	1.00	0.98	0.99	60
Semarangan	1.00	1.00	1.00	60
Tugu Muda	1.00	0.98	0.99	60
Warak Beras Utah	1.00	1.00	1.00	60
Macro Average	1.00	1.00	1.00	602
Accuracy		1.00		602

Based on the model performance evaluation results shown in Table 3, the MobileNetV2 model shows excellent classification capabilities, with an overall accuracy of 100%. In addition, the precision, recall, and F1-score values for almost all classes reach 1.00, indicating that the model is consistently able to identify each batik motif accurately and correctly. However, there are exceptions in two classes, namely Batik Blekok Warak and Batik Kembang Sepatu.

In the Batik Blekok Warak class, the precision is recorded at 0.98, indicating a slight prediction error, where several images from other classes are classified as Blekok Warak. Meanwhile, the recall for the Batik Kembang Sepatu class also decreased slightly to 0.98, indicating that there are 1 or 2 images from this class that are misclassified as other classes. Even so, both classes still have an F1-score of 0.99, reflecting the model's consistent and strong performance in identifying patterns, despite a slight prediction error.

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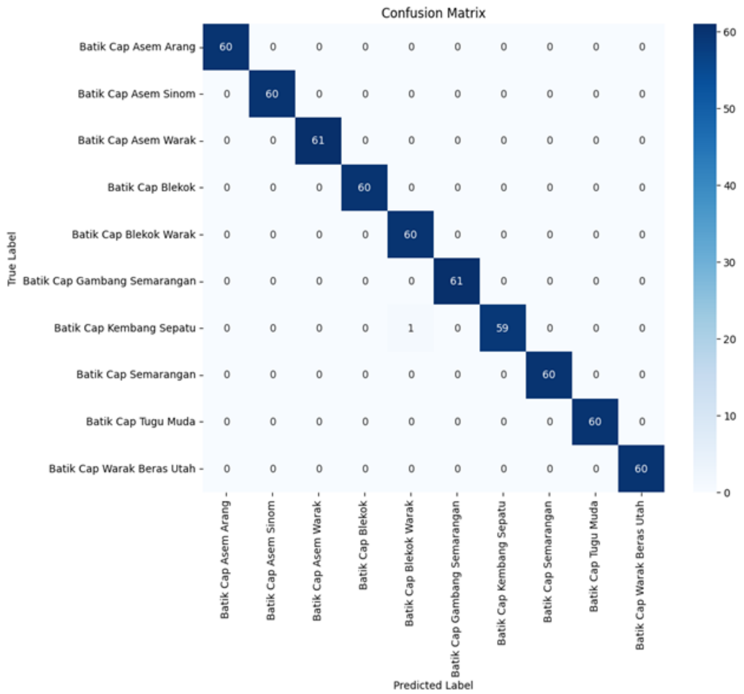

Fig. 6 Confusion Matrix

Further analysis through the confusion matrix in Fig. 6 strengthens this finding. In the confusion matrix, it can be seen that one image from the Batik Kembang Sepatu class is misclassified as Batik Blekok Warak, in accordance with the decrease in recall detected in the Batik Kembang Sepatu class. This indicates a similarity in pattern between the two classes, which makes it difficult for the model to distinguish them. On the other hand, prediction errors in the Batik Blekok Warak class are seen from several incorrect predictions from or to this class, in accordance with the decrease in precision recorded.

The use of data augmentation has a significant impact on improving performance across classes. Augmentation techniques such as rotation and horizontal flip help enrich the variation in the training data, so that the model is able to recognize batik motif patterns better. Thus, The implemented augmentation strategy showed significant benefits:

a. Enhanced model generalization across variable pattern presentations.
b. Effective handling of limited dataset size.
c. Maintained pattern recognition integrity despite transformations.

In addition to the overall performance shown in Table 3 and Fig. 6, Fig. 7 provides further insight into the model training and validation process through the accuracy and loss graphs. These graphs illustrate the development of model accuracy and loss over 25 epochs.

Based on accuracy graph, the training accuracy reaches 100% since the 2nd epoch and remains stable until the end of training. Meanwhile, the validation accuracy reaches a high value with an average of 98%-99% and also shows stability after the first few epochs. Although there are slight fluctuations at some endpoints of training, the difference between training and validation accuracy is very small, indicating that the model is able to generalize well on data that was not seen during training.

The loss graph shows that the training loss value decreases significantly and rapidly towards 0.0 in the first few epochs. After the 5th epoch, the loss value remains at a very low level and does not increase. The validation loss also decreases sharply in the early epochs and reaches a stable value close to 0.05, with slight fluctuations at the end of training. Thus, Absence of significant oscillations, suggesting optimal learning rate selection.

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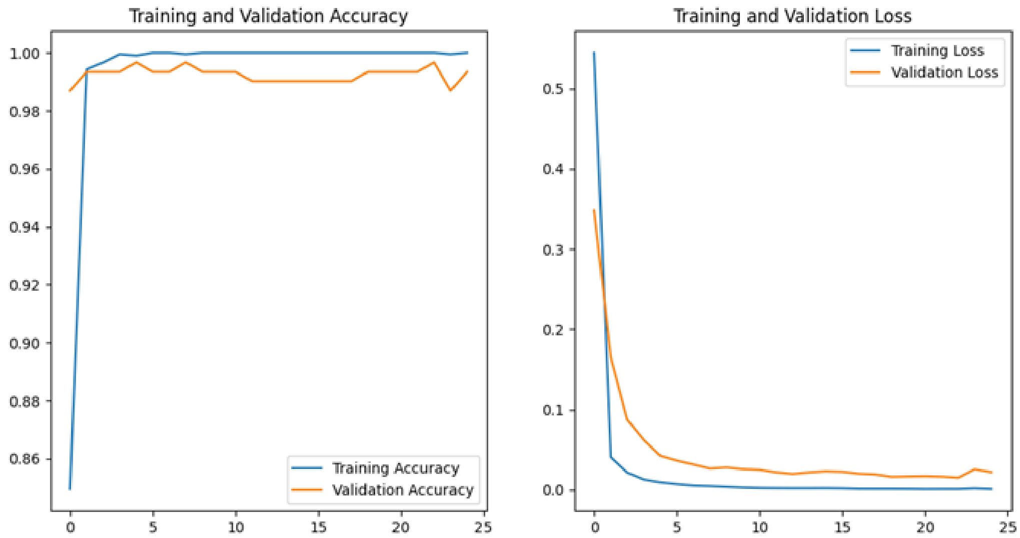

Fig. 7 Accuracy Graph and Loss Graph

There is no significant increase in validation loss compared to training loss indicating that the model is not overfitting. This shows that the use of the known efficient MobileNetV2 architecture and data augmentation techniques has helped the model learn important features of each class without getting stuck in the specific patterns of the training data.

Our results demonstrate several advantages compared to existing approaches:

a. Higher accuracy while maintaining computational efficiency.
b. Robust performance across diverse motif classes.
c. Practical applicability for real-world implementation.

The model's performance suggests several practical applications:

a. Integration into mobile applications for batik recognition.
b. Educational tools for cultural heritage preservation.
c. Quality control systems in batik production.

While the model shows excellent performance, several areas warrant further investigation:

a. Expansion to include more regional batik patterns.
b. Investigation of model performance under varying image quality conditions.
c. Development of explainable AI components for pattern recognition.

DISCUSSIONS

The experimental results demonstrate the effectiveness of MobileNetV2 in classifying Semarang Batik motifs, with the model achieving 100% accuracy across 10 distinct motifs and high precision and recall scores. The success of the model can be attributed to several key factors, including the efficiency of MobileNetV2's architecture, the impact of data augmentation strategies, and the model's strong pattern recognition capabilities. The use of depthwise separable convolutions in MobileNetV2 allowed the model to efficiently capture intricate batik patterns while maintaining low computational cost, making it suitable for deployment on resource-constrained devices. Additionally, the augmentation techniques, such as rotation, flipping, and zoom transformations, enhanced the model's ability to generalize across variations in the batik motifs, compensating for the limited dataset size. This approach successfully addressed the challenges posed by the dataset limitations, allowing the model to perform consistently across diverse classes of motifs.

The model demonstrated an impressive ability to distinguish subtle differences between motifs, although some misclassifications occurred, such as between Batik Blekok Warak and Kembang Sepatu, which highlight the difficulty of differentiating between similar motif elements. Despite this, the overall performance indicates the model’s effective feature extraction capabilities and its robustness in recognizing batik patterns. The dataset was handled effectively through transfer learning from ImageNet, enabling the model to leverage pre-trained features and adapt them to the task at hand.

While the results are promising, there are areas for further improvement. Expanding the dataset to include a wider variety of regional batik patterns and incorporating more diverse image capture conditions would improve the model's generalization. Exploring lighter architecture variants and integrating explainable AI features could enhance the model’s interpretability and usability. Furthermore, enabling real-time classification and developing

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mobile applications would extend the model's practical applications, making it more accessible for users in cultural heritage preservation and related fields.

In conclusion, this research demonstrates that MobileNetV2 is a powerful tool for batik motif classification, balancing high accuracy and efficiency while addressing the challenges of limited datasets. The model's performance opens up possibilities for similar applications in the preservation and recognition of other cultural artifacts, offering valuable contributions to both technological innovation and cultural heritage preservation.

CONCLUSION

This study successfully demonstrates the effectiveness of MobileNetV2 in classifying Semarang batik motifs, achieving 100% accuracy across 10 distinct motifs, with precision and recall scores of at least 0.98 for all classes. The proposed system addresses dataset limitations through optimized data augmentation while maintaining efficiency and practicality for real-world applications. These findings provide significant contributions to cultural heritage preservation through digital documentation of batik patterns, serve as an educational tool for younger generations, and assist in authentication and classification tasks. The proposed approach also offers promising applications in industry, such as quality control in batik production and pattern verification for e-commerce. Future research should focus on expanding the dataset, exploring advanced lightweight architectures, and developing user-friendly applications to maximize its utility and accessibility.

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