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Evaluation of MobileNet-Based Deep Features for Yogyakarta Traditional Batik Motif Classification

Umar Muhdhor[1)*], Yohannes[2)]
[1,2)]Universitas Multi Data Palembang, Indonesia
[1)] umarmuhdhor_2226250042@mhs.mdp.ac.id, [2)] yohannesmasterous@mdp.ac.id

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Abstract: Batik is an Indonesian intangible cultural heritage that embodies profound philosophical, aesthetic, and cultural values. Yogyakarta batik motifs, such as Parang, Kawung, and Truntum, reflect Javanese wisdom and identity through distinctive geometric and floral patterns. In the digital era, artificial intelligence based image processing provides a promising approach to support the preservation and automatic recognition of traditional batik motifs. The objective of this study is to evaluate the effectiveness of MobileNet-based feature extraction combined with Support Vector Machine (SVM) classification for Yogyakarta batik motif recognition. The proposed method employs MobileNet as a convolutional feature extractor and SVM as a decision model to separate motif classes in the feature space. Experiments were conducted on 685 batik images consisting of three motif classes, with class imbalance handled using Synthetic Minority Over-sampling Technique (SMOTE). Model performance was evaluated using weighted accuracy, precision, recall, and F1-score under five-fold cross validation. The results show that MobileNetV3Large achieved the best performance with a weighted accuracy of 98.36%, followed by MobileNetV3Small and MobileNetV4Small. Statistical significance tests using the Friedman test and Wilcoxon signed-rank analysis confirm that the performance differences among the evaluated models are statistically significant. These findings indicate that MobileNetV3 architectures provide robust and discriminative feature representations for batik motif classification on limited yet structured datasets. This study contributes a validated MobileNet–SVM framework for batik recognition and supports ongoing efforts in the digital preservation of Indonesia's cultural heritage. Future work will explore larger motif sets and cross-dataset evaluation to further improve generalization performance.

Keywords: Batik Classification; Cultural Heritage Preservation; Deep Learning MobileNet; Support Vector Machine;

INTRODUCTION

Indonesia is known for its cultural diversity, and batik is one of its cultural heritages that carries philosophical, aesthetic, and national identity values. As a medium of artistic expression, this two-dimensional art form embodies high aesthetic value while reflecting the cultural identity of its people (Dani & Handayani, 2024). Each batik motif contains symbolic meanings rooted in animist and dynamic principles that have been passed down through generations through traditional practices (Dani & Handayani, 2024). The cultural importance of batik is internationally recognized, as UNESCO officially designated batik as an intangible cultural heritage of humanity on October 2, 2009, affirming its role as a symbol of Indonesian identity (Nafidanisa et al., 2025).

Yogyakarta is one of the main centers of batik development, producing distinctive motifs such as Kawung, Parang, and Truntum. These motifs are not merely decorative patterns, but visual representations of philosophical values that are commonly used in traditional ceremonies and social contexts. Despite their cultural significance, the identification and classification of batik motifs are still largely performed manually by experts. This manual process is inherently subjective, time-consuming, and difficult to scale, particularly when dealing with motifs that exhibit similar textures and repetitive geometric patterns (Nafidanisa et al., 2025). Such conditions highlight the need for an automated and objective classification system that can assist batik documentation and preservation.

*name of corresponding author

Recent advances in image processing and machine learning have opened new opportunities to address these challenges. Convolutional Neural Networks (CNN) have been widely adopted for image classification tasks due to their ability to extract hierarchical visual features ranging from low-level edges to complex textures and shapes. Several studies have reported promising results in batik classification, such as the integration of GLCM and CNN MobileNetV1 for five Yogyakarta batik motifs (Dani & Handayani, 2024). However, many existing works remain limited in scope, as they often involve a small number of motif classes and relatively constrained datasets. This limitation reduces their ability to represent the full diversity of Yogyakarta batik and increases the risk of misclassification for motifs with similar visual characteristics (Fanani et al., 2025; Ihdal, 2021). Comparable issues have also been observed in other regional studies, where Betawi batik classification using KNN and GLCM required extensive augmentation to stabilize performance (A. Akbar & Mulyana, 2022), and Semarang batik classification using a VGG16-based CNN demonstrated that data diversity and balance are critical factors for improving model generalization (Nafidanisa et al., 2025).

In this context, CNN is more appropriately viewed as a powerful feature extractor rather than a complete end-to-end classifier, particularly when dealing with limited and imbalanced datasets (Prayoga et al., 2023). Among various CNN architectures, MobileNet has gained attention due to its depthwise separable convolution mechanism, which enables efficient feature extraction with fewer parameters compared to conventional architectures (Wona et al., 2023). This characteristic makes MobileNet suitable for batik datasets that are relatively small while still benefiting from transfer learning using large-scale image datasets such as ImageNet (Wona et al., 2023). Nevertheless, features extracted by CNN models alone may not always produce stable classification results, especially under conditions of class imbalance and limited training samples.

To address this issue, Support Vector Machine (SVM) is often employed as a complementary classifier due to its robustness in handling small to medium-sized datasets and its ability to construct optimal decision boundaries using kernel functions. Several batik-related studies have demonstrated that SVM can provide more stable and consistent performance compared to pure CNN classifiers, particularly when data availability is limited, as reported in Nusantara batik research where SVM outperformed end-to-end CNN approaches (Arif et al., 2024). Despite this evidence, previous studies rarely provide a systematic evaluation of different MobileNet generations combined with SVM, nor do they rigorously assess performance robustness using imbalance handling, cross-validation, and statistical significance testing.

Based on these gaps, this study aims to systematically evaluate multiple generations of MobileNet architectures as feature extractors combined with SVM for the classification of Yogyakarta batik motifs. The main objectives of this research are to analyze the effectiveness of different MobileNet variants under limited and imbalanced data conditions, to assess classification robustness using cross-validation and statistical significance tests, and to identify the most suitable MobileNet backbone for batik motif recognition. By addressing dataset imbalance, overfitting risk, and evaluation bias, this study is expected to contribute a validated and reliable MobileNet–SVM framework that supports the digital preservation and automated recognition of Indonesian batik cultural heritage.

LITERATURE REVIEW

Recent developments in computer vision have demonstrated significant progress in the recognition and classification of traditional Indonesian batik motifs. Several studies have shown that Convolutional Neural Networks (CNN) are effective in learning hierarchical visual representations from complex textile patterns. Dani and Handayani (2024) reported high classification accuracy using CNN-based models for Yogyakarta batik motifs by exploiting spatial and texture features, while Nafidanisa et al. (2025) emphasized the importance of robust feature extraction when dealing with texture-rich and handcrafted batik images. Similar findings were reported by Sahpira and Yohannes (2025), who applied a MobileNetV2-based CNN with transfer learning to classify Palembang jumputan motifs, achieving high accuracy while maintaining computational efficiency. Although these studies confirm the suitability of CNN for batik motif recognition, most of them are limited to a small number of motif classes and relatively simple experimental settings, which restricts their ability to generalize across motifs with visually similar textures and repetitive geometric structures.

Beyond pure CNN approaches, several researchers have explored classical and hybrid machine learning techniques to address limitations related to small datasets and classification stability. Ihdal (2021) demonstrated that Support Vector Machine (SVM) performs well in recognizing textile visual patterns due to its margin-based decision mechanism, which is particularly effective for limited sample sizes. Fanani et al. (2025) further showed that hybrid models combining deep feature extraction with classical classifiers can improve both generalization and computational efficiency. These findings suggest that while CNN excels at feature extraction, end-to-end CNN classifiers may be prone to overfitting when applied to limited and imbalanced datasets, a condition commonly encountered in batik motif studies.

Lightweight CNN architectures have also gained attention as a practical solution for motif recognition tasks. Fathurrahman et al. (2025) highlighted the effectiveness of MobileNet-based architectures in reducing

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computational complexity without significantly sacrificing accuracy. Agni Nalendra et al. (2025) similarly found that MobileNet variants are capable of preserving micro-pattern features in ornamental motifs, which is crucial for distinguishing visually similar batik patterns such as Parang, Kawung, and Truntum. Despite these promising results, previous studies generally focus on a single MobileNet variant and rarely investigate how different generations of MobileNet architectures compare under the same experimental conditions. This lack of systematic comparison limits understanding of which MobileNet backbone is most suitable for texture-dominant cultural datasets.

Hybrid CNN–SVM approaches have been increasingly explored to combine the strengths of deep feature learning and robust classification. Studies by M. D. Akbar et al. (2022) and A. Akbar and Mulyana (2022) demonstrated that combining CNN-based feature extraction with SVM classification yields improved performance in texture and craft-motif recognition. Sinaga et al. (2024) further showed that optimized feature extraction enables reliable multi-class classification even in fine-grained motif datasets. Arif et al. (2024) provided empirical evidence that SVM can outperform end-to-end CNN classifiers in batik datasets with limited samples, supporting the argument that margin-based classifiers are more stable under constrained data conditions. Prayoga et al. (2023) reinforced this perspective by highlighting the theoretical role of CNN as a hierarchical feature extractor rather than a standalone classifier in small-scale image classification tasks.

From the perspective of cultural heritage preservation, AI-based motif classification has been shown to play an important role in digital archiving and automated documentation. Susanti (2024) and Wona et al. (2023) emphasized that accurate motif recognition systems can support the preservation and dissemination of cultural assets. Anggoro et al. (2023) demonstrated that CNN-based batik recognition systems can assist in maintaining regional identity through automated identification. Aras et al. (2022) and Hidayatillah and Jakfar (2022) further confirmed that combining CNN feature maps with SVM improves accuracy in fine-grained texture classification tasks, particularly for visually similar patterns.

Although existing studies provide a strong foundation for batik motif recognition, several research gaps remain. Most prior works rely on limited datasets without adequately addressing class imbalance and overfitting risks, and they often evaluate performance using a single train–test split without statistical validation. Moreover, the comparative effectiveness of different MobileNet generations combined with SVM has not been systematically analyzed, particularly in the context of Yogyakarta batik motifs. Therefore, this study seeks to address these gaps by providing a comprehensive evaluation of multiple MobileNet architectures integrated with SVM, incorporating imbalance handling, cross-validation, and statistical significance testing. By doing so, this research extends previous work and contributes a more rigorous and validated framework for batik motif classification.

METHOD

The methodology of this study was designed to provide a systematic, robust, and statistically validated framework for evaluating the performance of multiple MobileNet architectures in classifying Yogyakarta batik motifs. Unlike previous studies that relied on a single CNN backbone or a single train–test split, this research emphasizes comparative evaluation across MobileNet generations, explicit handling of data imbalance, and statistical validation of performance differences. The overall research workflow is illustrated in Figure 1 and arranged in a chronological sequence to ensure methodological rigor and reproducibility.

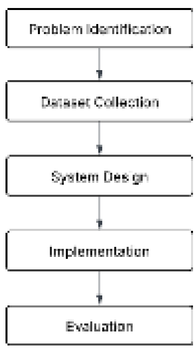

Fig. 1 Research Methodology Stages

The first stage involved problem identification through a comprehensive review of academic literature related to computer vision and batik motif recognition. Previous studies have reported that lightweight CNN architectures such as MobileNet are effective for image classification tasks with limited computational resources, while Support Vector Machine (SVM) often provides more stable decision boundaries than end-to-end convolutional classifiers on relatively small datasets (Arif et al., 2024; Setiaji & Huda, 2022). However, most existing works do not systematically compare different MobileNet generations, nor do they rigorously validate performance differences

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using statistical testing. These limitations motivated the proposed framework, which combines MobileNet feature extraction and SVM classification while explicitly focusing on cross-generation comparison and statistical robustness.

In the dataset collection stage, batik images were obtained from the publicly available batikv2 dataset (version 2) on Roboflow Universe, which contains images of traditional Indonesian batik motifs. From this dataset, three motifs characteristic of Yogyakarta batik were selected, namely Truntum, Kawung, and Parang. After data cleaning and organization, a total of 685 images were used, consisting of 548 images for training and 137 images for testing. The training set exhibited class imbalance, with 342 Truntum images, 88 Kawung images, and 118 Parang images, while the test set contained 85 Truntum, 22 Kawung, and 30 Parang images. This imbalance reflects realistic data conditions and motivates the need for explicit imbalance handling in the classification pipeline.

The system design stage, illustrated in Figure 2, outlines the technical pipeline of the proposed MobileNet–SVM framework. All images were resized to 224 × 224 pixels to match the input specifications of MobileNet architectures. Standard data augmentation techniques, including random rotation, horizontal flipping, and limited zooming, were applied to the training data to increase intra-class variation and reduce overfitting. Feature extraction was then performed using seven MobileNet variants, namely MobileNetV1, MobileNetV2, MobileNetV3Small, MobileNetV3Large, MobileNetV4Small, MobileNetV4Medium, and MobileNetV4Large. Each model was initialized with ImageNet pretrained weights and used as a fixed feature extractor, followed by a global average pooling layer to produce compact and discriminative feature vectors.

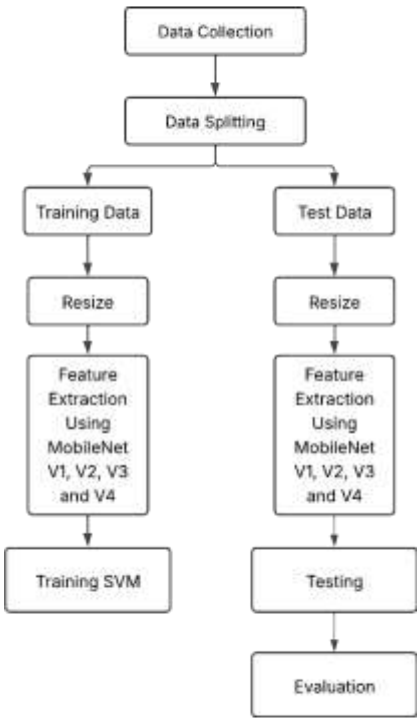

Fig. 2 System Design Scheme

To address the class imbalance in the training data, Synthetic Minority Over-sampling Technique (SMOTE) was applied at the feature level. SMOTE generated synthetic samples for minority classes so that each class in the training set contained an equal number of feature vectors (342 samples for Truntum, Kawung, and Parang). This strategy aims to improve class boundary learning while avoiding distortion of the original image distribution. The balanced feature set was subsequently used to train an SVM classifier with a radial basis function kernel. Hyperparameters, including the regularization parameter C and kernel parameter gamma, were optimized using GridSearch within a cross-validation framework to obtain an optimal classification margin for each MobileNet variant.

In the implementation and evaluation stage, a five-fold cross-validation protocol was employed to ensure reliable and unbiased performance estimation. For each fold, the SMOTE-balanced training features were divided into four folds for training and one fold for validation, and this process was repeated for all MobileNet variants. For every fold, a confusion matrix was constructed, containing true positive (TP), true negative (TN), false positive

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(FP), and false negative (FN) values. Based on these values, precision, recall, accuracy, and F1-score were computed using Eq. (1), Eq. (2), Eq. (3), and Eq. (4).

$$Precision = \frac{TP}{TP+FP} \times 100\% \quad (1)$$

$$Recall = \frac{TP}{TP+FN} \times 100\% \quad (2)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \quad (3)$$

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

Because the testing data were not artificially balanced, weighted precision, weighted recall, weighted accuracy, and weighted F1-score were used as the primary evaluation metrics. The weighted values were calculated by averaging per-class metrics using class proportions as weights, ensuring that minority classes such as Kawung and Parang contributed appropriately to the overall evaluation. The mean and standard deviation of these weighted metrics across the five folds were reported as the main performance indicators.

To validate whether the observed performance differences among MobileNet variants were statistically significant, a Friedman test was conducted on weighted accuracy values obtained from cross-validation. This was followed by pairwise Wilcoxon signed-rank tests comparing MobileNetV1 with each of the other models. Through this evaluation design, the proposed method not only compares classification performance but also provides statistical evidence to support model selection. Consequently, the methodological contribution of this study lies in its comprehensive evaluation framework, which integrates multi-generation MobileNet comparison, imbalance handling at the feature level, and statistical significance testing to identify a reliable backbone for Yogyakarta batik motif classification.

RESULT

The performance evaluation was conducted using five-fold cross validation with weighted metrics to ensure a fair assessment under class imbalance conditions. The comparative results of the seven MobileNet variants combined with SVM are summarized in Table 1 and visualized in Figure 3. Overall, the results indicate clear performance differences among the evaluated architectures.

MobileNetV3Large achieved the best overall performance, with a weighted accuracy of 98.36% ± 0.68%, weighted precision of 98.40% ± 0.65%, weighted recall of 98.36% ± 0.68%, and weighted F1-score of 98.33% ± 0.68%. This model consistently outperformed all other variants across all evaluation metrics. MobileNetV3Small ranked second with a weighted accuracy of 96.36% ± 2.70%, followed by MobileNetV4Small and MobileNetV4Medium, which both achieved weighted accuracies above 95%. Earlier architectures such as MobileNetV2 and MobileNetV1 showed lower performance, while MobileNetV4Large recorded the lowest weighted accuracy at 92.16% ± 1.67%.

Figure 3 further highlights these differences by illustrating the relative performance gaps across accuracy, precision, recall, and F1-score. The superiority of V3-based architectures is visually apparent, particularly when compared with earlier MobileNet generations and the larger V4 variant.

To verify whether these performance differences were statistically significant, a Friedman test was conducted on the weighted accuracy results. The test yielded $\chi^2 = 21.4505$ with $p = 0.001522$, indicating that the observed differences among the seven MobileNet variants are statistically significant. A post-hoc Wilcoxon signed-rank test using MobileNetV1 as the baseline showed that V3-based models consistently produced lower p-values compared to other variants, supporting their superior and more stable performance. These results confirm that the performance gains achieved by MobileNetV3Large are not caused by random variation but reflect a meaningful architectural advantage.

Table 1 Summary of Weighted Performance Metrics (Mean ± Std), 5-Fold CV

Model	Acc_mean (%)	Acc_std (%)	Prec_mean (%)	Prec_std (%)	Rec_mean (%)	Rec_std (%)	F1_mean (%)	F1_std (%)
MobileNetV1	93.43	1.76	93.97	1.52	93.43	1.76	93.06	2.02
MobileNetV2	94.17	1.95	94.71	1.62	94.17	1.95	93.93	2.10
MobileNetV3Small	96.36	2.70	96.40	2.72	96.36	2.70	96.17	2.92
MobileNetV3Large	**98.36**	**0.68**	**98.40**	**0.65**	**98.36**	**0.68**	**98.33**	**0.68**
MobileNetV4Small	95.62	1.34	95.88	1.20	95.62	1.34	95.34	1.49
MobileNetV4Medium	95.26	1.32	95.37	1.37	95.26	1.32	95.10	1.44
MobileNetV4Large	92.16	1.67	92.39	1.85	92.16	1.67	91.93	1.75

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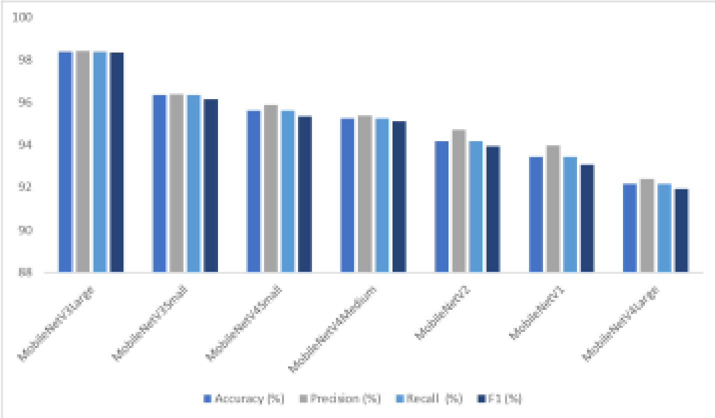

Fig. 3 Performance Comparison of Seven MobileNet Variants Using Weighted Metrics

DISCUSSIONS

The experimental results demonstrate that architectural refinement plays a more critical role than model size in batik motif classification. MobileNetV3Large outperforms all other variants because it integrates several architectural optimizations, including squeeze-and-excitation attention, improved depthwise separable convolution efficiency, and the h-swish activation function. These components enable the model to emphasize informative channels and capture subtle texture variations, which are essential for distinguishing visually similar batik motifs such as Kawung's repetitive circular patterns and Truntum's fine star-like ornaments.

MobileNetV3Small also exhibits strong performance, indicating that feature quality and representational efficiency are more influential than network depth or parameter count. However, its relatively higher standard deviation of ±2.70% suggests greater sensitivity to fold splits during cross validation. This instability may be attributed to the interaction between SMOTE-based feature balancing and limited sample diversity, which can cause variations in decision boundaries across folds.

In contrast, MobileNetV4Large underperforms despite being a newer architecture. This result suggests that increased architectural complexity does not necessarily improve performance when the dataset size is limited. The larger parameter space of MobileNetV4Large may lead to over-parameterization, reducing generalization capability and making the model less suitable for fine-grained texture recognition tasks under constrained data conditions.

The use of SMOTE successfully mitigated class imbalance during training, allowing minority motifs such as Kawung and Parang to contribute more effectively to the learning process. The application of weighted evaluation metrics ensured that real-world imbalance in the test set was properly reflected in the final performance assessment. Furthermore, the inclusion of statistical significance testing strengthens the reliability of the findings and provides a rigorous basis for selecting MobileNetV3Large as the most suitable backbone.

From a practical perspective, these results indicate that MobileNetV3Large offers an optimal balance between accuracy and efficiency for batik motif recognition. Its strong performance makes it suitable for deployment in mobile-based cultural preservation applications, digital batik archives, and educational tools. By identifying MobileNetV3 as the most effective backbone for limited yet structured batik datasets, this study provides a concrete technical recommendation that extends beyond prior CNN–SVM applications and contributes to the advancement of automated cultural heritage preservation systems.

CONCLUSION

This study systematically evaluated the performance of seven MobileNet architectures combined with a Support Vector Machine classifier for the classification of Yogyakarta batik motifs, with the primary objective of identifying the most effective lightweight backbone under limited and imbalanced dataset conditions. The experimental results demonstrate that MobileNetV3Large consistently outperforms other variants, achieving the highest weighted accuracy of 98.36%, followed by MobileNetV3Small and MobileNetV4Small. These findings confirm that architectural refinement, rather than model size alone, plays a crucial role in extracting discriminative texture features from complex batik motifs.

The integration of feature-level imbalance handling using SMOTE, weighted performance metrics, five-fold cross validation, and statistical significance testing ensures that the reported results are robust and reliable. By addressing common limitations in previous batik classification studies, such as class imbalance, overfitting risk, and the absence of statistical validation, this research provides a more rigorous evaluation framework. The main contribution of this study lies in delivering an empirically validated recommendation of MobileNetV3 as the most

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suitable backbone for batik motif recognition when combined with SVM, thereby extending prior CNN–SVM applications through comprehensive architectural comparison and statistical analysis.

Beyond its technical contribution, this study also offers practical implications for the development of mobile-based batik recognition systems, digital cultural archives, and educational applications supporting the preservation of Indonesian cultural heritage. Future research is encouraged to expand the number of batik motifs and regions, investigate rotation- and scale-invariant feature learning, and explore domain adaptation or cross-dataset evaluation strategies to further enhance model generalization and real-world applicability.

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*name of corresponding author