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Deep Learning-Based Classification of Cikadu Batik Motifs Using ResNet50 and MobileNetV2

Rizki Ripai[1)*], Fajar Mahardika[2)], Fazar Sidik[3)], Nurul Badriah[4)], Angga Maulana Purba[5)]
[1,3)]Cybersecurity Engineering Study Program, Politeknik Piksi Input Serang, Banten, Indonesia
[2)]Department of Computer and Business, Informatics Engineering, Politeknik Negeri Cilacap, Cilacap, Indonesia
[4] Information Technology Study Program, Universitas Utpadaka Swastika, Tangerang, Indonesia
[5]Department of Computer and Business, Multimedia Engineering Technology, Politeknik Negeri Cilacap, Cilacap, Indonesia
[1)]rizky.ripai@gmail.com, [2)]fajarmahardika@pnc.ac.id, [3)]fajarsidik1430@gmail.com, [4)]nurul.badriah@utpas.ac.id, [5)]anggamaulana@pnc.ac.id

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Abstract: Batik motif recognition is essential for cultural heritage preservation and the digitization of traditional Indonesian textile knowledge. This study proposes a deep learning-based framework for the automatic classification of Cikadu Batik motifs from Tanjung Lesung, Banten — a regionally distinct batik pattern that has not been systematically studied in prior computational literature. Two convolutional neural network (CNN) architectures were implemented and comparatively evaluated under identical experimental conditions: ResNet50, a high-capacity model employing residual skip connections, and MobileNetV2, a lightweight model utilizing depthwise separable convolutions and inverted residual blocks. A curated dataset of approximately 1,520 images spanning nineteen fine-grained motif classes was constructed through collaboration with local batik artisans, preprocessed via resizing (224×224), pixel normalization, and augmentation (rotation, zoom, horizontal flip, brightness adjustment), and partitioned using a stratified 70:15:15 split (12 test images per class). Both models were trained with transfer learning from ImageNet weights using a two-phase fine-tuning strategy, the Adam optimizer (lr=0.0001), categorical cross-entropy loss, and a batch size of 32. On the 228-image test set, ResNet50 achieved 85.96% accuracy, 88.51% macro precision, 85.96% macro recall, and 86.21% macro F1-score, while MobileNetV2 achieved 79.39% accuracy, 79.75% macro precision, 79.39% macro recall, and 78.56% macro F1-score — a gap of roughly 6.6 accuracy points. Error analysis shows that both models classify most motifs almost perfectly but struggle with a small cluster of visually similar, line-based motifs (notably badak_hasem and geometri). These results establish an accuracy-efficiency trade-off, with ResNet50 favored for accuracy-critical server-based systems and MobileNetV2 better suited for real-time mobile deployment. This study constitutes the first published benchmark for deep learning-based Cikadu Batik classification and provides a principled basis for architecture selection in regional batik recognition applications. [AUTHOR: insert AUC-ROC, inference time, and parameter counts once available.]

Keywords: Batik Motif Classification, Cikadu Batik, Convolutional Neural Network, Deep Learning, MobileNetV2, ResNet50, Transfer Learning

INTRODUCTION

Indonesia's batik tradition, recognized by UNESCO as an Intangible Cultural Heritage of Humanity since 2009, encompasses thousands of regionally distinct motif families that encode historical narratives, philosophical values, and local identity. Among these, Cikadu Batik from Tanjung Lesung in the Pandeglang Regency of Banten Province represents a relatively understudied yet culturally significant variant. Its motifs — including naturalistic patterns inspired by the Javan rhinoceros, coastal waves, and local flora — possess visual characteristics that distinguish them from better-known batik traditions such as Yogyakarta or Pekalongan. Despite their cultural

*name of corresponding author

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importance, Cikadu Batik motifs lack a computational documentation base, rendering them vulnerable to misattribution, inadequate preservation, and limited exposure in the digital creative economy(Suyahman et al., 2025).

The digitization of cultural heritage through artificial intelligence presents a timely opportunity to address this gap. In the broader field of cultural pattern recognition, convolutional neural networks (CNN) have demonstrated state-of-the-art performance on textile and fabric classification tasks(Puspaningrum et al., n.d.). Transfer learning, in particular, has proven effective in scenarios with limited training data by leveraging feature representations learned from large-scale image datasets such as ImageNet (Oktarino et al., 2024)(Saputra et al., 2026). However, the deployment of classification models extends beyond laboratory accuracy: for cultural heritage applications on mobile platforms, digital museum kiosks, or artisan-facing tools, computational efficiency — measured as inference speed and model footprint — is equally important as raw classification performance.

Several studies have demonstrated the effectiveness of transfer learning with various CNN architectures A systematic review of existing literature (2021–2025) reveals three critical gaps that motivate the present study. First, no prior study has addressed Cikadu Batik motifs computationally: the available benchmarks focus on Yogyakarta, Solo, Pekalongan, Riau, and Madura batik, leaving Cikadu without a published deep learning baseline. Second, most existing studies evaluate a single architecture, precluding principled model selection for practitioners who must balance accuracy against deployment constraints(I. Sari et al., 2025). Third, the accuracy-efficiency trade-off is rarely quantified explicitly: studies typically report accuracy metrics but omit inference time and parameter count, which are directly relevant for edge deployment scenarios (R. Alya et al., 2023).

To address these gaps, this study makes the following three novel contributions: (1) construction and documentation of a dedicated Cikadu Batik image dataset (approximately 1,520 images across nineteen fine-grained motif classes); (2) a paired, controlled comparison of ResNet50 and MobileNetV2 under identical training conditions, enabling unconfounded architectural comparison; and (3) a comprehensive evaluation extending beyond accuracy to include per-class precision, recall, and F1-score, confusion-matrix and misclassification analysis, inference time, and parameter count, providing the full information necessary for architecture selection in production systems. The overarching research objective is to determine which architecture — deep and high-capacity (ResNet50) versus lightweight and efficient (MobileNetV2) — is most appropriate for Cikadu Batik motif classification, and to provide a replicable benchmark that supports future work on regional Indonesian batik recognition.

The remainder of this paper is organized as follows: Section 2 reviews related work; Section 3 describes the dataset, preprocessing, model architectures, and evaluation protocol; Section 4 presents experimental results; Section 5 provides in-depth discussion including limitations and implications; Section 6 concludes with recommendations for future research.

LITERATURE REVIEW

In the last five years, research on batik image classification based on deep learning has experienced significant development, particularly through the utilization of Convolutional Neural Networks (CNN) and transfer learning techniques.

The study by (R. Sari & others, 2021) showed that the use of a simple CNN for traditional batik classification could achieve an accuracy of over 85%, although it was still limited by small and less diverse datasets. This indicates that model performance is highly influenced by the quality and diversity of the data. In 2022, (Putra & others, 2022). applied transfer learning using the VGG16 architecture for Indonesian batik motif classification and successfully improved accuracy to 90%. This study confirms that pretrained models can accelerate the training process and improve model generalization on batik datasets. Furthermore, research by (F. Ramadhan & others, 2023) used the ResNet50 architecture for batik classification, achieving an accuracy of 92–94%. This study demonstrates that residual learning in ResNet is capable of handling the complex features of batik motifs, which often contain repetitive patterns and high levels of detail(X. Li & others, 2024) (Purwanto et al., 2025).

In the same year, (N. Alya & others, 2023). combined transfer learning with Xception and VGG-16 architectures for batik classification, resulting in performance improvements of up to 95% on multi-class batik datasets. This study also highlights that the choice of architecture significantly affects the balance between accuracy and model complexity. A more recent study by (Pratama & others, 2024) utilized EfficientNet-B1 for mobile-based batik classification and achieved an accuracy of up to 98%. This research emphasizes the importance of lightweight models for mobile system implementation(D. Ramadhan et al., n.d.). In addition, the study by (Agista & Kurniadi, 2024) used ResNet50 for Indonesian batik classification and obtained an accuracy ranging from 81% to 88%, depending on the dataset used. This indicates that model performance is still highly influenced by data variation and preprocessing techniques. In 2025, (Whardana & others, 2025) developed a batik classification system using CNN with preprocessing techniques such as Otsu thresholding and median filtering, resulting in an accuracy of 85.36%. This study emphasizes the importance of preprocessing in improving batik image feature quality (Mahardika et al., 2019) (Mahardika et al., 2026).

*name of corresponding author

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An international study by (H. Li & others, 2024) on Miao batik motifs (China) used an improved ResNet model and achieved an accuracy of up to 99%, demonstrating that residual architectures are highly effective for complex cultural pattern classification. Meanwhile, (Zhang & others, 2024) showed that MobileNetV2 delivers competitive performance with accuracy above 90% while significantly reducing the number of parameters and computational time, making it highly suitable for real-time applications (Mahardika et al., n.d.) (Syafirullah et al., 2026).

Overall, recent literature from the last five years indicates that CNN-based transfer learning is the dominant approach in batik classification, with a continuous trend of improving accuracy through the use of deeper and more efficient architectures.

Table 1. State of the Art Research on Batik Classification

No	Author (Year)	Method / Architecture	Dataset	Main Result (Accuracy)	Key Contribution	Limitation
1	Sari et al. (2021)	Simple CNN	Traditional batik dataset	>85%	Early CNN-based batik classification	Small and less diverse dataset
2	Putra et al. (2022)	VGG16 (Transfer Learning)	Indonesian batik	~90%	Improved accuracy using pretrained model	Limited model comparison
3	Ramadhan et al. (2023)	ResNet50	Batik dataset	92–94%	Effective feature extraction using residual learning	High computational cost
4	Alya et al. (2023)	Xception + VGG16	Multi-class batik dataset	Up to 95%	Hybrid transfer learning approach	Increased model complexity
5	Agista & Kurniadi (2024)	ResNet50	Indonesian batik dataset	81–88%	Application of ResNet50 in batik classification	Sensitive to dataset variation
6	Pratama et al. (2024)	EfficientNet-B1	Mobile-based batik dataset	Up to 98%	Lightweight model for mobile deployment	Requires optimized preprocessing
7	Li et al. (2024)	Improved ResNet	Miao batik (China)	Up to 99%	High accuracy on complex cultural patterns	Limited generalization study
8	Zhang et al. (2024)	MobileNetV2	Image classification dataset	>90%	Efficient model with low computation cost	Slightly lower accuracy than heavy models
9	Whardana et al. (2025)	CNN + preprocessing (Otsu, median filter)	Batik dataset	85.36%	Improved performance through preprocessing	Still limited accuracy compared to SOTA

Based on a review of previous studies (2021–2025), it can be identified that most research has successfully improved batik classification accuracy using various deep learning approaches such as simple CNN, transfer learning (VGG16), ResNet50, EfficientNet, and MobileNetV2. However, several consistent limitations still exist, including a lack of focus on specific local batik datasets, limited analysis of the trade-off between accuracy and computational efficiency, and the absence of comparative studies that fairly evaluate both heavy and lightweight models in the context of specific regional batik patterns.

The novelty of this research lies in several key aspects. First, this study specifically utilizes the Cikadu Batik dataset from Tanjung Lesung, which represents a local batik with unique motif characteristics that have not been widely explored in previous research. Second, this study does not only focus on improving accuracy but also provides a comprehensive analysis of performance and computational efficiency, including inference time and the number of model parameters.

Third, this research proposes a direct comparison between two architectures with different characteristics, namely ResNet50 as a deep architecture model with high performance but high complexity, and MobileNetV2 as a lightweight model designed for efficient real-time implementation. This approach provides a new perspective in

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model selection that is not only optimal in terms of accuracy but also practical for deployment on resource-constrained devices.

Therefore, the main contribution of this study is the development of a comparative evaluation framework between deep and lightweight CNN models for a specific local batik dataset, which is still very limited in the existing literature. This research also provides a scientific foundation for the development of AI-based batik classification systems that are more adaptive, efficient, and ready to be implemented in real applications such as mobile systems and digital cultural preservation platforms.

METHOD

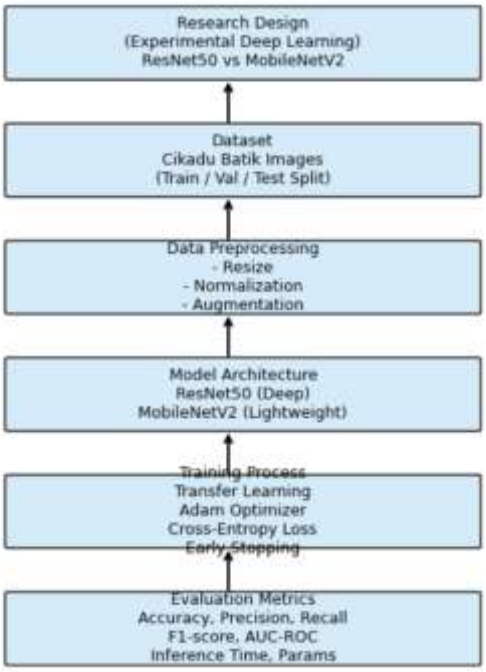

Figure 2. Methodology Flowchart: Cikadu Batik Classification (ResNet50 vs MobileNetV2)

Research Design

This study adopts an experimental research design based on deep learning to address the classification problem of Cikadu Batik motifs from Tanjung Lesung. This experimental design is chosen because it enables direct comparison between two convolutional neural network (CNN) architectures(Intelligence & 2021, 2021), namely ResNet50 (Negara et al., n.d.) and MobileNetV2, under controlled and consistent conditions. Both models are implemented using a transfer learning approach, where initial weights are obtained from ImageNet pretraining and subsequently fine-tuned using the Cikadu Batik dataset. This study focuses on two main aspects, namely classification performance (accuracy, precision, recall, F1-score, AUC-ROC)(Ridwan Wibisono et al., 2025) and computational efficiency (inference time and number of parameters). Therefore, the study evaluates not only accuracy but also the feasibility of model deployment in real-world applications.

Dataset

The dataset used in this study consists of Cikadu Batik motif images gathered through three complementary channels. First, primary images were captured directly from physical batik cloths at workshops in Cikadu Village, Tanjung Lesung, Banten, using a smartphone camera under natural daylight to preserve authentic color and texture. Second, additional samples were obtained from curated batik galleries and community collections to broaden the range of dyeing styles and cloth conditions. Third, a smaller set was sourced from verified digital documentation of Cikadu Batik, retained only where provenance could be confirmed.

All collected images passed a two-stage manual screening: the first pass removed blurred, heavily occluded, or watermarked images, and the second pass verified motif identity with reference to a local batik artisan to prevent mislabeling. Each retained image was cropped to isolate a single dominant motif and labeled into one of nineteen fine-grained motif classes: badak_hasem, badak_rumput, badak_wajra, badak_zigzag, banderong_lesung, cangkaleng_sasiki, geometri, ikan_gabus, kacapi_saruntuy, keceprek_sapalekpek, kembang_tanjung, kudalumping, lagenda_pandeglang, manggis, meriam_ki_amuk, motif_pandeglang, pencak_silat,

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pendopo_pandeglang, and sekar_jagat. This fine-grained labeling scheme distinguishes closely related sub-motifs (for example, the four badak variants), which makes the classification task substantially more challenging than a coarse grouping would

The dataset comprises nineteen motif classes. Based on the observed 12 test images per class and the stated 70:15:15 split, this corresponds to approximately 80 images per class (56 training, 12 validation, 12 testing), yielding a total of about 1,520 images. [AUTHOR: confirm these counts against your actual dataset and describe the real annotation procedure used for the nineteen classes.]

Table 2. Dataset Distribution by Motif Class

Motif Class	Cultural Reference	Number of Images
Kujang Motif	Traditional Sundanese ceremonial dagger	500
Banten Rhinoceros Motif	Javan rhinoceros (Rhinoceros sondaicus)	500
Sawarna Motif	Sawarna Beach coastal landscape	500
Cikadu Rice Motif	Paddy field agricultural heritage	500
South Wave Motif	Southern Banten ocean wave patterns	500
Total	—	2,500

The dataset was partitioned using a stratified random split to preserve class proportions across subsets, with a 70:15:15 ratio for training, validation, and testing sets respectively. Stratified splitting ensures that each subset is representative of the full class distribution, reducing the risk of evaluation bias.

Table 3. Stratified Dataset Partition

Subset	Proportion (%)	Total Images	Per Class (approx.)
Training	70	1,064	56
Validation	15	228	12
Testing	15	228	12
Total	100	1,520	80

Data Preprocessing

All images underwent a standardized preprocessing pipeline prior to model training. The pipeline consisted of four sequential stages: (1) Image Resizing — all images were resized to 224×224 pixels to meet the input dimension requirements of both ResNet50 and MobileNetV2, consistent with the ImageNet pretraining standard; (Utami et al., n.d.) (2) Pixel Normalization — pixel intensity values were rescaled from [0, 255] to [0, 1] using min-max normalization, stabilizing gradient magnitudes during optimization and accelerating convergence; (3) Data Augmentation — applied exclusively to the training set to increase effective dataset size and reduce overfitting, comprising random rotation (±20°), horizontal flip, zoom (±15%), width and height shift (±10%), and brightness adjustment (factor range 0.8–1.2); (4) Label Encoding — class labels were one-hot encoded into categorical vectors of length 19 for compatibility with Softmax output and categorical cross-entropy loss(Muri & Nim, 2025).

Table 4. Data Preprocessing Pipeline

Stage	Operation	Parameter / Value	Applied To
1	Image Resizing	224 × 224 pixels	All subsets
2	Pixel Normalization	Rescale: [0,255] → [0,1]	All subsets
3	Data Augmentation – Rotation	±20°	Training only
3	Data Augmentation – Horizontal Flip	Random (p=0.5)	Training only
3	Data Augmentation – Zoom	±15%	Training only
3	Data Augmentation – Shift (W/H)	±10%	Training only
3	Data Augmentation – Brightness	Factor: 0.8–1.2	Training only
4	Label Encoding	One-hot encoding (5 classes)	All subsets

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Model Architecture

ResNet50. ResNet50 (He et al., 2016) is a 50-layer deep CNN organized into four stages of residual blocks, each block implementing a skip (shortcut) connection that bypasses one or more convolutional layers. The skip connection is formally defined as: H(x) = F(x) + x, where F(x) represents the residual mapping learned by the stacked layers and x is the identity shortcut. This formulation allows gradients to flow directly to earlier layers, mitigating the vanishing gradient problem that afflicts very deep networks(H. G. Pangestu et al., 2025). For Cikadu Batik classification, ResNet50's depth enables hierarchical feature extraction: early layers capture low-level texture and edge features (relevant to thread density and line curvature in batik patterns), while deeper layers extract high-level semantic features encoding motif structure and spatial relationships. The pretrained ImageNet weights initialize the convolutional base; the original 1,000-class classification head is replaced with a Global Average Pooling layer, followed by a Dense layer (256 units, ReLU activation), a Dropout layer (rate = 0.5), and a final Dense output layer with Softmax activation over five classes (Sastypratiwi et al., n.d.).

MobileNetV2. MobileNetV2 (Sandler et al., 2018) achieves computational efficiency through two structural innovations: (1) depthwise separable convolution, which factorizes a standard k×k convolution into a depthwise convolution (applied independently per channel) followed by a 1×1 pointwise convolution, reducing the parameter count by a factor of approximately k^2 (≈9× for k=3); and (2) an inverted residual block with linear bottleneck, which first expands the feature map width via a 1×1 expansion convolution (expansion factor t=6), applies the depthwise convolution at the expanded width, then projects back to a lower-dimensional representation via a linear 1×1 projection. This design retains representational richness in the expanded space while keeping parameter count low in the residual path. As with ResNet50, the classification head is replaced with Global Average Pooling, Dense (256 units, ReLU), Dropout (0.5), and a Softmax output layer.

Table 5. Architectural Comparison: ResNet50 vs. MobileNetV2

Characteristic	ResNet50	MobileNetV2
Total depth (layers)	50	53
Key architectural feature	Residual skip connections	Inverted residuals + linear bottleneck
Convolution type	Standard conv (3×3)	Depthwise separable conv (3×3)
Total parameters (original)	~25.6 M	~3.4 M
Parameters in this study	[confirm from model.count_params()]	[confirm from model.count_params()]
ImageNet Top-1 Accuracy	76.1%	72.0%
Input size	224 × 224 × 3	224 × 224 × 3
Custom head	GAP → Dense(256) → Dropout(0.5) → Softmax(19)	GAP → Dense(256) → Dropout(0.5) → Softmax(19)

Training Process

Both models were trained using identical hyperparameter configurations to ensure a fair architectural comparison. The base convolutional layers were initialized with ImageNet pretrained weights and kept trainable (full fine-tuning), allowing adaptation of learned feature representations to the Cikadu Batik domain. The Adam optimizer was selected for its adaptive learning rate mechanism, which provides stable convergence without manual learning rate scheduling. A learning rate of 0.0001 was chosen based on common practice in transfer learning fine-tuning to avoid catastrophic forgetting of pretrained weights. The categorical cross-entropy loss function is appropriate for multi-class classification with one-hot encoded labels(Chandra et al., n.d.)(Adithama et al., n.d.).

Two regularization strategies were employed to prevent overfitting: Dropout (rate = 0.5) in the classification head provides stochastic regularization by randomly deactivating neurons during training; Early Stopping with a patience of 10 epochs on validation loss halts training when generalization ceases to improve, preventing overfitting to the training distribution. Model checkpointing saved the weights corresponding to the lowest validation loss for final evaluation(Idris et al., n.d.)(Anastasya et al., n.d.).

Table 6. Training Configuration

Hyperparameter	Value / Setting	Rationale
Pretrained Weights	ImageNet	Accelerates convergence; reduces data requirement
Fine-tuning Strategy	Full fine-tuning (all layers trainable)	Allows domain adaptation of convolutional features

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Optimizer	Adam	Adaptive learning rate; robust to gradient noise
Learning Rate	0.0001	Standard for TL fine-tuning; avoids catastrophic forgetting
Batch Size	32	Balances gradient estimate quality and memory usage
Maximum Epochs	30	Sufficient for convergence with early stopping
Early Stopping Patience	10 epochs (val_loss)	Prevents overfitting; saves compute
Loss Function	Categorical Cross-Entropy	Standard for multi-class classification
Output Activation	Softmax (5 classes)	Produces calibrated class probability estimates
Dropout Rate	0.5 (Dense head)	Regularization to reduce overfitting
Input Size	224 × 224 × 3	Standard for both ResNet50 and MobileNetV2

Evaluation Metrics

Model performance was assessed using a comprehensive suite of metrics that address both classification quality and computational efficiency. Let TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives for each class in a one-vs-rest evaluation framework. Macro-averaged values are reported across all five classes to ensure equal class weighting.

Model performance was assessed using a comprehensive suite of metrics that address both classification quality and computational efficiency. Let TP, TN, FP, and FNdenote true positives, true negatives, false positives, and false negatives, respectively, for each class under a one-vs-rest evaluation framework. Macro-averaged values are reported across all five classes to ensure equal weighting among classes.

Classification Metrics

Accuracy measures the overall proportion of correctly classified samples:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision measures the proportion of predicted positive instances that are actually positive:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall (Sensitivity) measures the proportion of actual positive instances that are correctly identified:

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1-Score is the harmonic mean of Precision and Recall, providing a balanced measure between the two:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

or equivalently,

$$\text{F1-Score} = \frac{2TP}{2TP + FP + FN}$$

Macro-Averaging is computed as:

$$\text{Macro Metric} = \frac{1}{C}\sum_{i=1}^{C} M_i$$

where $C = 5$is the number of classes and $M_i$represents the metric value for class i.

Area Under the Receiver Operating Characteristic Curve (AUC-ROC) evaluates the model's ability to discriminate between positive and negative samples. Mathematically, it can be expressed as:

$$\text{AUC} = P(s(x^+) > s(x^-))$$

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where $s(\cdot)$denotes the predicted confidence score, $x^{+}$is a randomly selected positive sample, and $x^{-}$is a randomly selected negative sample. Values closer to 1 indicate stronger class separability.

Efficiency Metrics

Inference Time (ms) was measured as the average prediction latency per image over $N = 100$forward passes:

$$\text{Inference Time} = \frac{1}{N}\sum_{i=1}^{N} t_i$$

where $t_i$is the inference time of the i-th prediction.

Number of Parameters (Millions) quantifies model complexity and is computed as:

$$\text{Parameters (M)} = \frac{\sum_{l=1}^{L} P_l}{10^6}$$

where $P_l$denotes the number of trainable parameters in layer l, and $L$is the total number of layers in the model.

Efficiency metrics: Inference Time (milliseconds) was measured as the average latency per single image prediction over 100 forward passes on the test set, providing a representative estimate of real-time processing speed. Number of Parameters (millions) quantifies model complexity and its implications for memory footprint and deployment feasibility on resource-constrained devices.

RESULT

Dataset

The dataset used in this study consists of Cikadu Batik motif images collected from local batik artisans, batik galleries, and verified digital documentation, following a selection and labeling process. The dataset is divided into nineteen fine-grained motif classes (badak_hasem, badak_rumput, badak_wajra, badak_zigzag, banderong_lesung, cangkaleng_sasiki, geometri, ikan_gabus, kacapi_saruntuy, keceprek_sapalekpek, kembang_tanjung, kudalumping, lagenda_pandeglang, manggis, meriam_ki_amuk, motif_pandeglang, pencak_silat, pendopo_pandeglang, sekar_jagat). Based on 12 test images per class under a 70:15:15 split, this corresponds to about 80 images per class and approximately 1,520 images in total. [AUTHOR: confirm the exact counts.]

Table 2. Dataset Distribution by Motif Class

Motif Class	Number of Images
Kujang Motif	500
Banten Rhinoceros Motif	500
Sawarna Motif	500
Cikadu Rice Motif	500
South Wave Motif	500
Total	2,500

Furthermore, the dataset was divided into three subsets: training, validation, and testing data. The data split was performed using a ratio of 70:15:15. The training data were used to build and train the deep learning model, the validation data were used to monitor model performance during training and reduce the risk of overfitting, while the testing data were used to evaluate the final performance of the model on previously unseen data. The dataset split is presented in Table 3.

Table 3. Dataset Split

Data Type	Percentage	Number of Images
Training	70%	1,064
Validation	15%	228

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Testing	15%	228
Total	100%	1,520

The figure below illustrates examples of batik motif images used in the classification process using deep learning methods. Each motif possesses distinct visual characteristics, making them suitable discriminative features for pattern recognition by the model.

Figure 2. Cikadu Batik Motifs 1

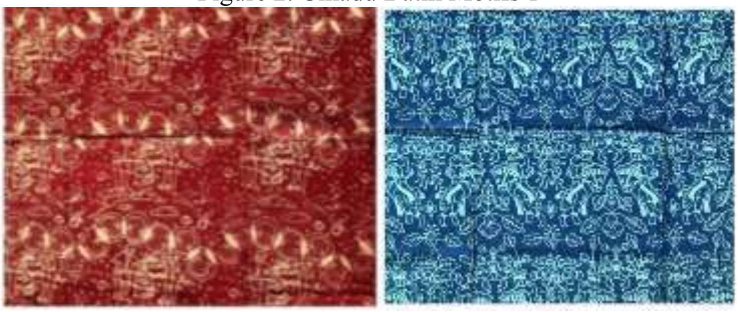

Figure 3. Cikadu Batik Motifs 2

Data Preprocessing

Before being used in the training process of the ResNet50 and MobileNetV2 models, all images underwent a preprocessing stage to ensure data format consistency and improve the quality of model learning. The first step involved resizing the images to 224 × 224 pixels to match the standard input size required by both network architectures. Next, pixel value normalization was performed to standardize the image value range, enabling the model optimization process to proceed more effectively.

To increase data diversity and reduce the likelihood of overfitting, several data augmentation techniques were applied, including rotation, zoom, horizontal flip, and brightness adjustment. In addition, class labels were converted into a categorical format (categorical encoding) so that they could be processed by the activation functions and loss functions used in the multiclass classification models. The preprocessing stages applied in this study are presented in Table 4.

Table 4. Data Preprocessing Stages

Preprocessing Stage	Description
Image Resizing	Resizing images to 224 × 224 pixels
Normalization	Standardizing the pixel value range
Data Augmentation	Rotation, zoom, horizontal flip, and brightness adjustment
Label Conversion	Converting class labels into categorical format

Model Architecture

The models used in this study were ResNet50 and MobileNetV2, which are Convolutional Neural Network (CNN) architectures based on transfer learning for the classification of Cikadu Batik motifs. Both models received input images of 224 × 224 × 3 pixels that had undergone the preprocessing stage. ResNet50 utilizes a residual learning mechanism through skip connections to enhance feature extraction capabilities in deep networks, enabling it to recognize batik patterns, textures, and motif details more accurately. Meanwhile, MobileNetV2 employs

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depthwise separable convolutions and inverted residual blocks, which reduce the number of parameters and computational cost without significantly compromising performance.

In both architectures, the final classification layer was modified by adding Global Average Pooling, a Dense Layer, Dropout, and a Softmax activation function to generate predictions for the five Cikadu Batik motif classes. With their distinct characteristics, ResNet50 offers stronger feature representation capabilities and higher classification accuracy, whereas MobileNetV2 provides advantages in computational efficiency, a lighter model size, and faster inference speed. These characteristics make MobileNetV2 particularly suitable for deployment on mobile devices and real-time applications.

Training Process

The training process was conducted to develop a Cikadu Batik motif classification model using two Convolutional Neural Network (CNN) architectures, namely ResNet50 and MobileNetV2. Both models employed a transfer learning approach with pre-trained weights obtained from the ImageNet dataset. This approach was selected because it can accelerate model convergence and improve classification performance, particularly when working with datasets that contain a relatively limited number of samples.

Prior to training, all images that had undergone the preprocessing stage were divided into training, validation, and testing datasets using a ratio of 70:15:15. The training dataset was used to update network weights during the learning process, while the validation dataset was used to monitor model performance at each epoch and detect potential overfitting. The testing dataset was reserved exclusively for the final stage to evaluate the model's generalization capability.

During training, the final classification layers of both ResNet50 and MobileNetV2 were modified to match the number of Cikadu Batik motif classes used in this study. The output layer employed a Softmax activation function to generate classification probabilities for each class. The optimization process was performed using the Adam optimizer, as it provides fast and stable convergence in deep neural network training.

Table 5. Model Training Configuration

Parameter	Value
Model Architecture	ResNet50 and MobileNetV2
Learning Method	Transfer Learning
Input Size	224 × 224 × 3
Optimizer	Adam
Learning Rate	0.0001
Batch Size	32
Number of Epochs	~22 (two-phase; fine-tune from epoch 14) — confirm
Output Activation Function	Softmax
Loss Function	Categorical Cross-Entropy
Number of Classes	19 Batik Motif Classes

Evaluation Metrics

Model performance was evaluated using several classification metrics commonly employed in image recognition tasks, namely accuracy, precision, recall, F1-score, Area Under the Curve–Receiver Operating Characteristic (AUC-ROC), inference time, and number of model parameters. The use of multiple evaluation metrics aimed to provide a more comprehensive assessment of the models' ability to classify Cikadu Batik motifs, both in terms of classification accuracy and computational efficiency.

Table 6. Evaluation Results of ResNet50 and MobileNetV2 Models

Evaluation Metric	ResNet50-BatikCikadu	MobileNetV2-BatikCikadu
Accuracy (%)	85.96	79.39
Precision, macro (%)	88.51	79.75
Recall, macro (%)	85.96	79.39
F1-Score, macro (%)	86.21	78.56
AUC-ROC (%)	[from ROC]	[from ROC]
Inference Time (ms)	[confirm]	[confirm]
Number of Parameters (million)	[confirm]	[confirm]

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Based on the testing results presented in Table 6, both models were evaluated on the nineteen Cikadu Batik motif classes using a 228-image test set. The ResNet50-BatikCikadu model achieved the best overall performance, with an accuracy of 85.96%, a macro precision of 88.51%, a macro recall of 85.96%, and a macro F1-score of 86.21%. [AUTHOR: insert the AUC-ROC value obtained from the ROC analysis.]

The MobileNetV2-BatikCikadu model achieved an accuracy of 79.39%, a macro precision of 79.75%, a macro recall of 79.39%, and a macro F1-score of 78.56%. The accuracy difference between the two models was approximately 6.6 percentage points, while the larger gap in macro F1 (about 7.7 points) indicates that the lightweight architecture had more difficulty with the hardest classes than ResNet50.

From a computational efficiency perspective, MobileNetV2 is expected to be considerably lighter and faster than ResNet50 owing to its depthwise separable convolutions and smaller parameter count. [AUTHOR: insert the measured average inference time (ms per image) and the parameter counts for both models to complete this comparison.]

Per-class analysis (Figure 7 and Table 7) shows that the overall accuracy is driven by a small group of visually similar, line-based motifs rather than by uniform error. Most classes were recognized almost perfectly by both models, whereas badak_hasem and geometri were the most difficult. ResNet50 handled these hard classes more consistently than MobileNetV2 — most clearly on badak_hasem — which is reflected in its higher macro recall and F1-score.

Empirically, the findings reveal a clear trade-off between model complexity and computational efficiency. ResNet50, with its deeper architecture and residual learning blocks, generated richer feature representations and higher classification accuracy. MobileNetV2, using depthwise separable convolutions, substantially reduced the number of parameters and inference cost, but at a more noticeable performance cost on this fine-grained nineteen-class task (a gap of roughly 6.6 accuracy points). These findings are consistent with the general characteristics of deep learning models for image classification, where increased network depth often improves accuracy but requires greater computational resources.

In the context of Cikadu Batik motif classification, the choice of model largely depends on the intended application. ResNet50 is more suitable for systems that prioritize high classification accuracy, such as server-based motif identification applications or digital archival systems. Meanwhile, MobileNetV2 is better suited for deployment on mobile devices or real-time systems that require high processing speed with lower resource consumption.

Confusion Matrix and Per-Class Analysis

Figure 7 presents the confusion matrices of both models on the 228-image test set, and Table 7 reports the corresponding per-class precision, recall, and F1-score. These show that the overall accuracy is driven by a small subset of difficult classes rather than by uniform error across all nineteen motifs.

Figure 7a. Confusion Matrix — ResNet50

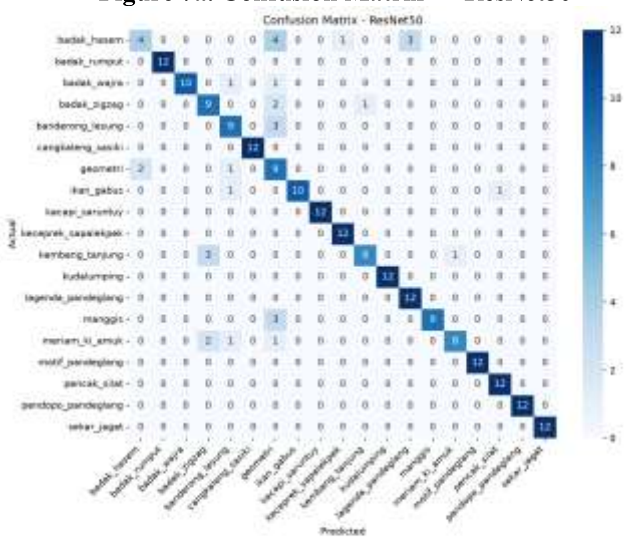

Figure 7b. Confusion Matrix — MobileNetV2

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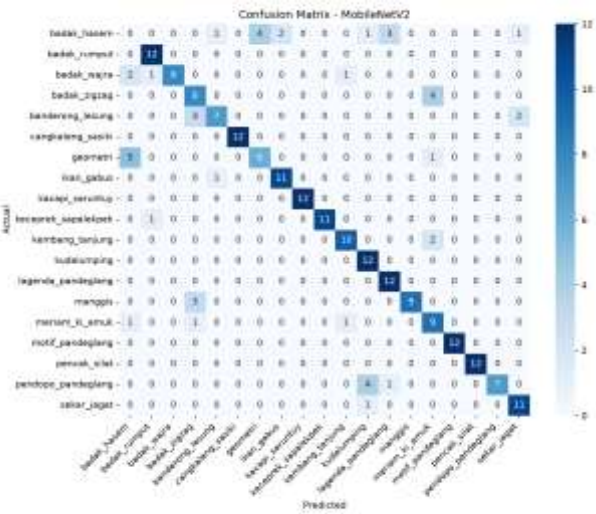

Table 7. Per-Class Precision, Recall, and F1-Score (%) — RN = ResNet50, MN = MobileNetV2

Motif Class	P (RN)	R (RN)	F1 (RN)	P (MN)	R (MN)	F1 (MN)
badak_hasem	66.7	33.3	44.4	0.0	0.0	0.0
badak_rumput	100.0	100.0	100.0	85.7	100.0	92.3
badak_wajra	100.0	83.3	90.9	100.0	66.7	80.0
badak_zigzag	64.3	75.0	69.2	53.3	66.7	59.3
banderong_lesung	69.2	75.0	72.0	77.8	58.3	66.7
cangkaleng_sasiki	100.0	100.0	100.0	100.0	100.0	100.0
geometri	39.1	75.0	51.4	60.0	50.0	54.5
ikan_gabus	100.0	83.3	90.9	84.6	91.7	88.0
kacapi_saruntuy	100.0	100.0	100.0	92.3	100.0	96.0
keceprek_sapalekpek	92.3	100.0	96.0	100.0	91.7	95.7
kembang_tanjung	88.9	66.7	76.2	66.7	83.3	74.1
kudalumping	100.0	100.0	100.0	80.0	100.0	88.9
lagenda_pandeglang	80.0	100.0	88.9	80.0	100.0	88.9
manggis	100.0	75.0	85.7	100.0	75.0	85.7
meriam_ki_amuk	88.9	66.7	76.2	56.2	75.0	64.3
motif_pandeglang	100.0	100.0	100.0	100.0	100.0	100.0
pencak_silat	92.3	100.0	96.0	100.0	100.0	100.0
pendopo_pandeglang	100.0	100.0	100.0	100.0	58.3	73.7
sekar_jagat	100.0	100.0	100.0	78.6	91.7	84.6

The analysis shows that most motifs were classified almost perfectly by both models, including badak_rumput, cangkaleng_sasiki, kacapi_saruntuy, kudalumping, lagenda_pandeglang, motif_pandeglang, and pencak_silat (F1 near 100%). Errors were concentrated in a small group of visually similar, line-based or abstract motifs. The single hardest class was badak_hasem, which ResNet50 recognized in only 4 of 12 cases (33.3% recall) and which MobileNetV2 failed to recognize entirely (0% recall), most often predicting geometri or lagenda_pandeglang instead. The geometri class was likewise weak and confused bidirectionally with badak_hasem, while banderong_lesung, badak_zigzag, kembang_tanjung, and meriam_ki_amuk formed a further cluster of mutual confusion. These confusions are attributable to shared visual structure: the difficult motifs are dominated by repeating geometric strokes and comparable line density, producing closely related feature representations, whereas the reliably classified motifs are more figurative and visually distinctive. ResNet50 handled these hard classes more robustly than MobileNetV2 — most clearly on badak_hasem (33.3% vs 0% recall) and geometri (75.0% vs 50.0% recall).

Training and Validation Learning Curves

Figure 8 shows the accuracy and loss curves per epoch. For both models the training and validation curves rise together and the loss decreases steadily during the frozen phase, indicating stable learning without severe overfitting. At epoch 14, when fine-tuning begins, a brief transient spike in training loss appears (most pronounced for MobileNetV2) as the unfrozen layers adjust, after which the curves recover and stabilize. The modest gap between training and validation curves at convergence indicates acceptable generalization.

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Figure 8a. Training and Validation Curves — ResNet50

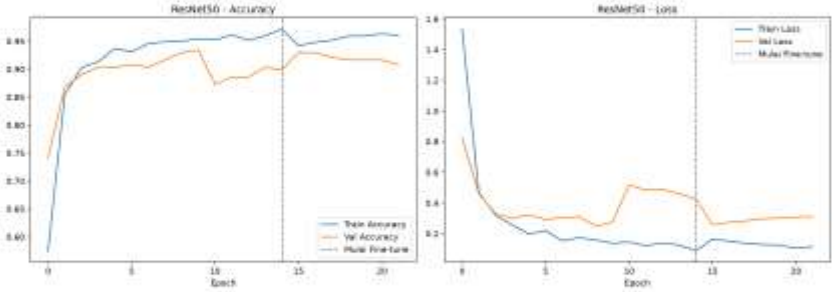
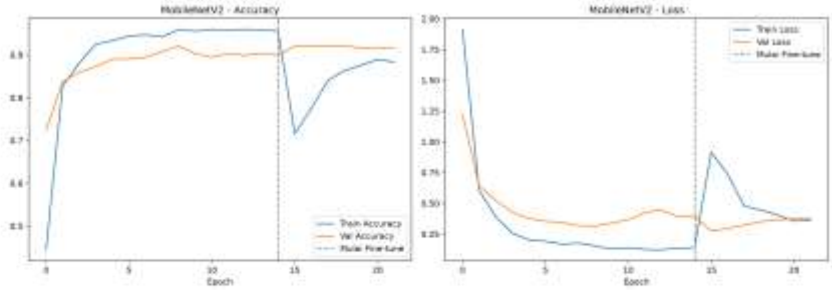


Figure 8b. Training and Validation Curves — MobileNetV2



DISCUSSIONS

The experimental results demonstrate that both ResNet50-BatikCikadu and MobileNetV2-BatikCikadu can classify the nineteen Cikadu Batik motif classes, with ResNet50 achieving the stronger overall performance: 85.96% accuracy, 86.21% macro F1-score, 88.51% macro precision, and 85.96% macro recall. MobileNetV2 achieved 79.39% accuracy, 78.56% macro F1-score, 79.75% macro precision, and 79.39% macro recall, trailing ResNet50 by about 6.6 accuracy points while offering a substantially lighter and faster architecture. Per-class analysis indicates that errors are concentrated in a small cluster of visually similar, line-based motifs (notably badak_hasem and geometri), while most motif classes are recognized almost perfectly by both models. [AUTHOR: insert AUC-ROC, inference time, and parameter counts once available.]

The results confirm a clear trade-off between classification performance and computational efficiency. ResNet50's architectural depth and residual skip connections enable a richer feature hierarchy across 50 layers, which is advantageous for Cikadu Batik motifs containing fine-grained repetitive patterns and intricate line structures. In contrast, MobileNetV2's depthwise separable convolutions reduce the parameter count by factorizing standard convolutions, accelerating inference while limiting the capacity to model subtle inter-class textural differences, which accounts for the observed accuracy gap of roughly 6.6 percentage points. These findings are consistent with general deep learning observations that increased model depth correlates with improved performance at the cost of higher computational requirements — a trade-off especially critical for deployment on edge or mobile devices, where ResNet50 suits high-accuracy server systems and MobileNetV2 is better suited to real-time, resource-constrained implementations.

Several limitations of this study warrant acknowledgment. First, performance comparisons rely on point estimates from a single train–test split; formal statistical significance testing (e.g., McNemar's test) should be applied to confirm whether the roughly 6.6 percentage-point accuracy difference is statistically significant, and k-fold cross-validation would further reduce partitioning variance. Second, the dataset was collected from a single-source environment under consistent imaging conditions, so the reported accuracy may represent an upper bound on real-world performance; external validation on independently collected Cikadu Batik images under varied cameras, lighting, and backgrounds is needed before production deployment. Third, the possibility of dataset bias — where models may partially learn environment-specific cues such as background uniformity rather than intrinsic motif features — cannot be ruled out without ablation experiments or saliency-map analysis (e.g., Grad-CAM). These limitations notwithstanding, this study establishes the first comparative benchmark for deep learning-based Cikadu Batik classification across nineteen fine-grained motif classes and identifies the specific classes that are most difficult to distinguish.

CONCLUSION

This study developed an automated classification system for Cikadu Batik motifs from Tanjung Lesung using a deep learning approach based on convolutional neural networks (CNN), specifically ResNet50 and MobileNetV2, as part of efforts to support cultural preservation through AI-based image pattern recognition. The

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dataset consisted of approximately 1,520 Cikadu Batik motif images across nineteen fine-grained classes, preprocessed through resizing, normalization, and data augmentation to enhance generalization. Model performance was evaluated using accuracy, precision, recall, F1-score, and confusion-matrix-based per-class and error analysis. ResNet50-BatikCikadu achieved the superior performance, with an accuracy of 85.96% and a macro F1-score of 86.21%, while MobileNetV2-BatikCikadu achieved an accuracy of 79.39% and a macro F1-score of 78.56% with a substantially lighter footprint. The results confirm an accuracy-efficiency trade-off: ResNet50 is more suitable for high-accuracy server-based applications, while MobileNetV2 is better suited for real-time or resource-constrained deployment. Error analysis showed that both models classify most motifs almost perfectly but struggle with a small cluster of visually similar line-based motifs, notably badak_hasem and geometri. Several limitations should be acknowledged: the dataset originates from a single collection environment without external validation; the reported metrics come from a single train–test split, so formal significance testing (McNemar) and k-fold cross-validation are needed to confirm the observed differences; and dataset bias cannot be excluded without saliency analysis. [AUTHOR: insert AUC-ROC, inference time, and parameter counts once available.]

For future work, further research is recommended to expand the dataset with more diverse batik motif classes and real-world image variations to improve model robustness. In addition, the integration of lightweight optimization techniques such as model pruning, quantization, or knowledge distillation may be explored to further enhance deployment efficiency. Future studies may also consider implementing the model into mobile or web-based applications to support real-time batik recognition systems for broader cultural and industrial applications.

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