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# MULTI-OBJECTIVE OPTIMIZATION OF RESNET50 ARCHITECTURE USING GENETIC ALGORITHM FOR ENHANCED BATIK MOTIF CLASSIFICATION

**P.A.M. Zidane R.W.P.P Zer[1]; Dedy Hartama[2]; Agus Perdana Windarto[3]**

Informatic Engineering[1]
Informatics System[2]
Master's Program in Informatics[3]
STIKOM Tunas Bangsa, Pematangsiantar, Indonesia[1,2,3]
www.stikomtunasbangsa.ac.id[1,2,3]
zidanezer5@gmail.com*, dedyhartama@amiktunasbangsa.ac.id, agus.perdana@amiktunasbangsa.ac.id

(*) Corresponding Author
(Responsible for the Quality of Paper Content)



***Abstract***— *Automatic batik motif classification remains challenging due to the high visual similarity among many motifs, making manual differentiation difficult. This study proposes a weighted-sum multi-objective Genetic Algorithm (GA) to optimize a pre-trained ResNet50 model for batik motif classification. The novelty of this study lies in optimizing the top-layer architecture and transfer-learning hyperparameters of ResNet50 by jointly considering classification accuracy, trainable parameter count, and inference latency. Unlike many previous GA-based CNN studies that mainly focus on accuracy or construct architectures from scratch, this study employs GA as a resource-efficient optimizer for practical deployment. The research used a quantitative experimental design with a secondary dataset of 3,550 batik images from five motif classes, namely Kawung, Megamendung, Parang, Sidomukti, and Truntum. The optimization process searched for the best configuration of four hyperparameters, namely the number of neurons in the dense layer, dropout rate, learning rate, and fine-tuning depth, while Adam was used as a fixed optimizer throughout the experiments. The results show that the proposed model improved classification accuracy from 84.00% to 90.00%, reduced trainable parameters by 94.4% from 23.59 million to 1.31 million, and decreased inference time by 29.4% compared with the baseline ResNet50 model. These findings indicate that the proposed method can achieve a favorable balance between predictive performance and computational efficiency for cultural heritage recognition on resource-constrained devices.*

***Keywords***: *Batik Classification, Genetic Algorithm, Multi-Objective Optimization, ResNet50, Transfer Learning.*

**Intisari**—*Klasifikasi motif batik otomatis tetap menjadi tantangan karena kesamaan visual yang tinggi di antara banyak motif, sehingga perbedaan manual menjadi sulit. Studi ini mengusulkan Algoritma Genetika (GA) multi-objektif berbobot untuk mengoptimalkan model ResNet50 yang telah dilatih sebelumnya untuk klasifikasi motif batik. Keunikan dari studi ini terletak pada pengoptimalan arsitektur lapisan atas dan hiperparameter transfer-learning dari ResNet50 dengan mempertimbangkan secara bersamaan akurasi klasifikasi, jumlah parameter yang dapat dilatih, dan latensi inferensi. Tidak seperti banyak studi CNN berbasis GA sebelumnya yang terutama fokus pada akurasi atau membangun arsitektur dari awal, studi ini menggunakan GA sebagai pengoptimal yang efisien sumber daya untuk penerapan praktis. Penelitian ini menggunakan desain eksperimen kuantitatif dengan dataset sekunder sebanyak 3.550 gambar batik dari lima kelas motif, yaitu Kawung, Megamendung, Parang, Sidomukti, dan Truntum. Proses optimisasi mencari konfigurasi terbaik dari empat hiperparameter, yaitu jumlah neuron di lapisan padat, tingkat dropout, laju pembelajaran, dan kedalaman fine-tuning, sementara Adam digunakan sebagai optimizer tetap sepanjang eksperimen. Hasilnya menunjukkan bahwa model yang diusulkan meningkatkan akurasi klasifikasi dari*

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*84,00% menjadi 90,00%, mengurangi parameter yang dapat dilatih sebesar 94,4% dari 23,59 juta menjadi 1,31 juta, dan mengurangi waktu inferensi sebesar 29,4% dibandingkan dengan model ResNet50 dasar. Temuan ini menunjukkan bahwa metode yang diusulkan dapat mencapai keseimbangan yang menguntungkan antara kinerja prediktif dan efisiensi komputasi untuk pengenalan warisan budaya pada perangkat dengan sumber daya terbatas.*

***Kata Kunci**: Klasifikasi Batik, Algoritma Genetika, Optimasi Multiobjektif, ResNet50, Transfer Learning.*

## INTRODUCTION

Indonesian batik is an intangible cultural heritage recognized by UNESCO and holds significant philosophical and aesthetic value [1], [2]. However, the high visual complexity of batik motifs and the similarity among patterns make manual identification difficult, subjective, and error-prone [3]. Therefore, developing an automatic classification system is important to support the documentation and digital preservation of this cultural heritage through Deep Learning-based motif recognition [4], [5].

In recent years, Deep Learning, particularly Convolutional Neural Networks (CNNs), has become a dominant approach for image classification tasks [6]. Among various CNN architectures, ResNet50 has shown strong performance due to its residual connections, which help mitigate the vanishing gradient problem and enable effective feature extraction in deep networks [7], [8]. In parallel, optimization methods such as Genetic Algorithms (GA) have also been widely used to identify suitable architectural and hyperparameter configurations [9], [10], [11].

ResNet50 has demonstrated high accuracy on standard benchmark datasets such as ImageNet [12], [13]. Its strength lies in its ability to preserve gradient flow and capture complex visual features effectively [14], [15]. However, applying the standard ResNet50 architecture directly to more specific tasks such as batik motif classification may be inefficient [5]. With approximately 23 million parameters, the model tends to require high computational resources and may increase the risk of overfitting when trained on relatively small datasets. In addition, its default hyperparameter settings are not always well suited to the visual characteristics of batik images [16], [17], [18].

One of the main challenges in CNN development is determining an optimal combination of architecture and hyperparameters. Conventional approaches such as trial-and-error are inefficient and time-consuming [19], [20], [21]. Moreover, many automated optimization methods remain single-objective, focusing primarily on accuracy while giving limited attention to computational efficiency, including trainable parameter count and inference latency. As a result, the resulting models may achieve high accuracy but remain difficult to deploy on resource-constrained devices [22], [23].

To address this issue, this study employs a multi-objective optimization approach using Genetic Algorithms. GA was selected because of its capability to explore a large search space and identify near-optimal solutions efficiently [24], [25]. Unlike previous approaches that mainly emphasize predictive performance, this study seeks to balance accuracy and model efficiency by minimizing trainable parameters and inference time without sacrificing classification performance. In this way, the resulting model is expected to be more suitable for deployment on resource-constrained devices [26], [27].

Although Neural Architecture Search (NAS) has become a prominent approach for automated network design, its implementation generally requires substantial computational resources, making it less practical for small-scale cultural heritage datasets [28], [29], [30]. In batik motif recognition, prior studies have mainly emphasized classification accuracy, while limited attention has been given to balancing representational strength and computational efficiency within transfer-learning settings [3], [31], [32].

Therefore, this study addresses this gap by formulating a weighted-sum multi-objective Genetic Algorithm framework that optimizes the top-layer architecture and transfer-learning hyperparameters of a pre-trained ResNet50. Rather than constructing a new architecture from scratch, the proposed approach positions GA as an efficient optimizer that jointly considers classification accuracy, trainable parameter count, and inference latency [33], [34]. In this way, the study contributes a more practical and lightweight solution for cultural heritage recognition on resource-constrained device.

## MATERIALS AND METHODS

### Related Work

The application of Convolutional Neural Networks (CNNs), particularly ResNet50, to batik motif classification has been widely explored.

Prasetyo et al. demonstrated that implementing transfer learning on CNN with data augmentation achieved high classification performance on Indonesian batik motifs, confirming the strong feature extraction capability of deep architectures [35]. However, despite its promising classification performance, challenges related to parameter efficiency and computational cost remain important concerns for practical deployment, especially in real-world cultural heritage applications. Similar observations were reported by Sastypratiwi and Muhardi, who found that CNN-based models can produce good classification accuracy, yet their efficiency on relatively small batik datasets is still limited, thereby requiring further optimization through transfer learning strategies or lighter model designs [3].

Beyond the batik domain, several studies have employed Genetic Algorithms to optimize CNN architectures and hyperparameters. Lehana et al. showed that GA can reduce the number of model parameters while maintaining classification performance [10]. Ferreira et al. applied GA to optimize CNN models for acute leukemia classification and reported improvements in both efficiency and accuracy [9]. Likewise, Munsarif et al. demonstrated that GA-based optimization improved model effectiveness in handwriting recognition tasks [21]. These studies indicate that GA is a promising optimization method for enhancing CNN performance across classification problems, particularly when the search space involves multiple architectural and training parameters.

More recent studies have begun to incorporate multi-objective optimization into neural network design in order to balance predictive performance and computational efficiency. Santoso et al., for example, used a multi-objective optimization approach within Neural Architecture Search to jointly consider accuracy, model size, and inference speed [20]. This direction is highly relevant for practical image classification systems, especially those intended for deployment on resource-constrained devices. Nevertheless, in the context of batik motif recognition, existing studies still tend to emphasize classification accuracy, while limited attention has been given to systematically balancing feature representation strength, parameter efficiency, and inference latency within a transfer-learning framework.

Based on this gap, the present study proposes a weighted-sum multi-objective Genetic Algorithm framework to optimize a pre-trained ResNet50 model for batik motif classification. Unlike prior studies that either focus only on CNN accuracy in batik recognition or apply GA in other classification domains, this study integrates both perspectives by optimizing the top-layer architecture and transfer-learning hyperparameters of ResNet50 while jointly considering classification accuracy, trainable parameter count, and inference latency. In this way, the study contributes a more practical and lightweight solution for cultural heritage recognition on resource-constrained devices.

### Data Collection

This research utilized a dataset of 3,550 Indonesian batik images sourced from Kaggle, distributed across five categories: Kawung, Megamendung, Parang, Sidomukti, and Truntum. To ensure robust generalization and support multi-objective optimization, the data was partitioned via stratified sampling into a training set (2,800 images) for weight optimization, a validation set (700 images) for Genetic Algorithm fitness evaluation, and a dedicated test set (50 images). The test set, consisting of 10 images per class, was reserved as a held-out blind evaluation set to assess performance on unseen data. This experimental design strictly isolates the final evaluation from the optimization phase, thereby preventing data leakage and ensuring an objective assessment of the model's true predictive capability.

### Data Pre-Processing

This research utilizes a secondary dataset comprising images of Indonesian Batik motifs, categorized into five groups: Kawung, Megamendung, Parang, Sidomukti, and Truntum. The total quantity of batik images utilized amounts to 3,550. To guarantee compatibility with the model architecture, all images are subjected to pre-processing procedures, including resizing to 224 x 224 pixels and normalization of pixel values. The distribution of the dataset is thoroughly detailed in Table 1.

Table 1. Number of Images

| No | Type of Batik | Number of Images |
|---|---|---|
| 1 | Kawung | 710 |
| 2 | Megamendung | 710 |
| 3 | Parang | 710 |
| 4 | Sidomukti | 710 |
| 5 | Truntum | 710 |
| | Total | 3.550 |

Source: (Dionisiusdh, 2026) [36]

Table 1 presents data sourced from Kaggle whose data has been categorized by type. Here is an example of a picture used for each type of batik motif.

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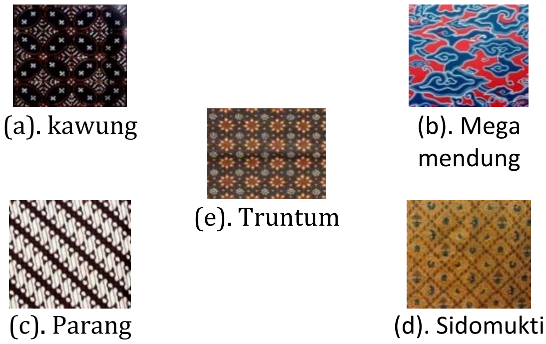
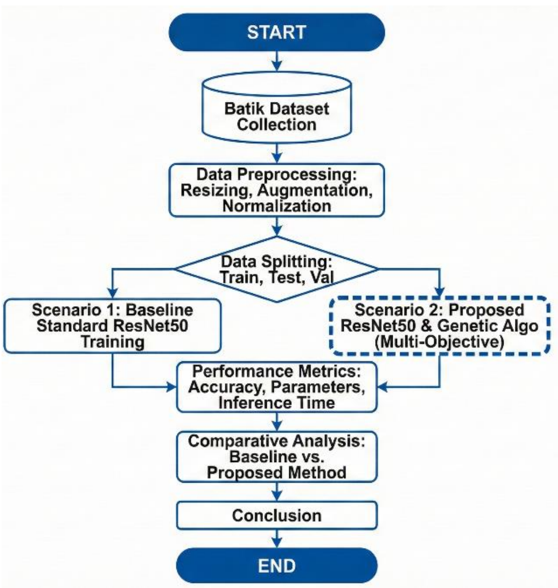


Source: (Dionisiusdh, 2026) [36]
Figure 1. Image of Batik Motif

Figure 1 shows examples of photos of batik motifs, especially Kawung, Megamendung, Parang, Sidomukti, and Truntum. This dataset is evenly distributed among the five classes and shows a distinctive diversity of colors and motifs.

**Research Framework**

To accomplish the objective of enhancing the classification accuracy of Batik Motifs utilizing the ResNet50 Architecture in conjunction with the Multi-Objective Genetic Algorithm, this study was conducted through a series of methodical stages. Each stage is crafted to guarantee that the model development process remains well-organized, efficient, and consistent with established deep learning best practices. Broadly speaking, this study contrasts two primary scenarios: a baseline model with a fixed configuration and an experimental model that is dynamically optimized utilizing Genetic Algorithms (GA). The research pipeline diagram is presented in Figure 2.



Source: (Research Result 2026)
Figure 2. Research Framework

1. Data Collection

This study uses secondary data obtained from a public repository known as 'Dataset Motif Batik'. The dataset includes a total of 3,550 digital images divided into five categories of batik motifs, namely Kawung, Megamendung, Parang, Sidomukti, and Truntum. For experimental purposes, the data were divided into three subsets: 2,800 images were used as training data, 700 images as validation data, and 50 images as test data. This division is designed to ensure models can be optimally trained, validated during the process of genetic evolution, and objectively tested at the final stages.

2. Pre-processing

Data pre-processing begins with resizing the image to a dimension of 224x224 pixels as per the ResNet50 architecture, as well as pixel normalization scale 0-1 for model convergence acceleration. To mitigate overfitting and enrich feature variation, data augmentation applied to the training data includes: 20° random rotation, 10% width/height shift, 10% shear and zoom, and horizontal flip.

3. Model Architecture Design

The basic architecture used is ResNet50, which has been pre-trained on the ImageNet dataset. This architecture was chosen because of its ability to extract complex features through residual learning mechanisms. In this study, ResNet50 functions as a *feature extractor* (backbone). The classifier head section is modified by adding a *Global Average Pooling* layer, followed by *a Dense Layer* (with the optimized number of neurons), a *Dropout* layer, and an *Output layer with* a Softmax *activation function* for the 5-class classifications.

4. GA Optimization

The method proposed in this study utilizes Genetic Algorithms with a multi-objective approach to automatically optimize hyperparameters and transfer learning strategies in the ResNet50 architecture. Each individual in the population represents a candidate model configuration, encoded as a chromosome consisting of four optimization variables, namely the number of dense-layer neurons, dropout rate, learning rate, and fine-tuning depth. Adam was used as a fixed optimizer throughout the experiments and was therefore not included as an optimized variable. The search space range for each hyperparameter is detailed in Table 2.

Table 2. Hyperparameter Search Space for GA Optimization

| Hyperparameter (Gene) | Search Space Range / Values |
|---|---|
| Neurons (Dense) | 32, 64, 128, 256, 512 |
| Dropout Rate | 0.1 – 0.5 |
| Learning Rate | $10^{-5}$ – $10^{-2}$ |
| Fine-tuning Depth (Unfreeze) | 0 – 5 (Layers) |

Source: (Research Result 2026)

To evaluate the qualities of each individual in the population and direct the evolutionary process towards optimal solutions, the study formulated a weighted fitness function (F) that is mathematically defined as follows:

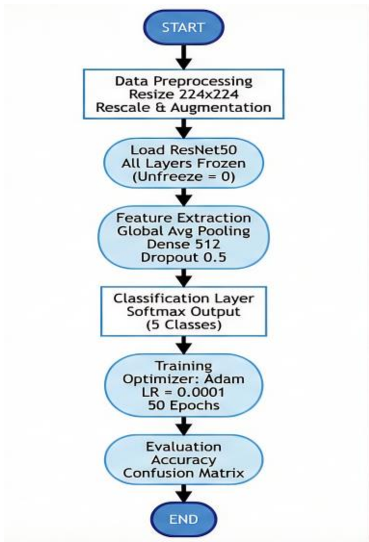
$$F = (w_1 \cdot Accuracy) - (w_2 \cdot Parameters) - (w_3 \cdot Inference\ Time) \quad (1)$$

The weighting factors for the multi-objective fitness function ($w\_1$=0.6, $w\_2$=0.3, and $w\_3$=0.1) were strategically determined through empirical preliminary testing. Accuracy ($w\_1$) is assigned the highest priority to ensure the model maintains its primary predictive capability. The weight for model complexity ($w\_2$=0.3) is set significantly higher than inference time ($w\_3$=0.1) to act as a rigorous penalty against 'architectural bloat,' ensuring the GA favors leaner architectures that are fundamentally more efficient for mobile deployment. This specific balance was found to produce the most stable convergence toward models that satisfy both performance and resource constraints.

The generalization capability and overall effectiveness of the model were evaluated using a comprehensive set of metrics, including accuracy for overall performance and precision, recall, and F1-score for class-specific analysis of batik motifs. Beyond predictive performance, the model's efficiency was also assessed through the number of trainable parameters and inference latency, ensuring that the resulting architecture remained lightweight and responsive for practical implementation. Because the held-out testing subset in this study was relatively limited, performance differences between the baseline and optimized models were interpreted descriptively. More rigorous statistical validation using a larger evaluation set is recommended for future work.

**ResNet50 Architecture**

This study establishes a baseline model using the standard ResNet50 architecture that implements the ImageNet pre-trained weight-based Transfer Learning strategy. This approach utilizes the ResNet50 backbone as a feature extractor, with the condition that the entire convolutional layer is frozen to maintain basic feature extraction capabilities without updating the weights during training. The structure is then equipped with a classifier head that is arranged manually, including a Global Average Pooling layer, followed by a Dense Layer with a capacity of 512 neurons with a ReLU activation function, a Dropout layer with a ratio of 0.5 as regularization, and an Output layer with 5 neurons using the Softmax activation function. Figure 3 shows the architecture.




Source: (Research Result, 2026)

Figure 3. ResNet50 Architecture

Figure 3 illustrates the standard ResNet50 model training technique applying a static hyperparameter configuration that adopts conventional standards in image classification. This mechanism uses an Adam optimizer with a fixed learning rate of 0.0001 to minimize the *Categorical Cross-entropy* loss function for 50 epochs with a batch size of 32. The approach was established as an objective benchmark to validate the significance of the performance and efficiency improvements offered by the proposed Genetic Algorithm optimization method.

**Proposed Method**

This study presents a method for optimizing Convolutional Neural Network design using Multi-Objective Genetic Algorithms to enhance batik motif classification performance. This method, unlike traditional approaches that primarily emphasize maximizing accuracy, aims to attain an optimal equilibrium among three competing objectives: prediction accuracy, model size reduction, and inference time minimization. The optimization

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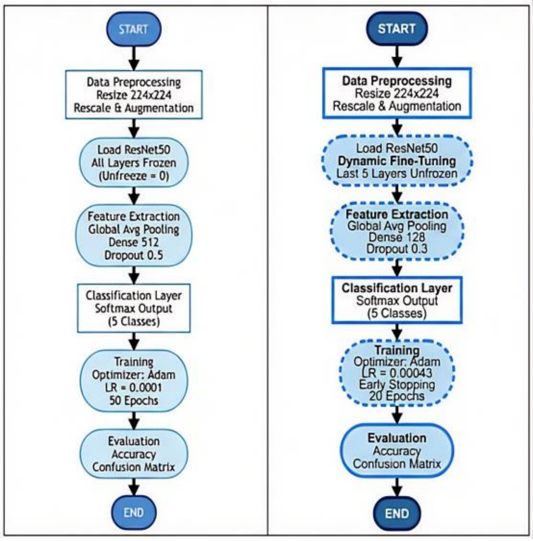
procedure commences with the delineation of a search space, whereby each candidate model configuration is depicted as a chromosome comprising four optimization variables: the quantity of neurons in the dense layer, the dropout rate, the learning rate, and the fine-tuning depth. Adam was used as a fixed optimizer throughout the experiments and was hence excluded as an optimized variable. This method enables the model to adjust dynamically to the attributes of the given dataset without requiring significant user intervention.

To evaluate the quality of each individual in the population, this study formulated a weighted fitness function that simultaneously accommodates three competing objectives: (1) maximization of validation accuracy (60% priority weight), (2) minimization of model complexity based on the number of trainable parameters (30% weight), and (3) minimization of inference time (10% weight). This mechanism encourages the algorithm to explore the solution space in order to identify a model configuration that is not only accurate, but also compact and efficient for practical implementation in resource-constrained environments. The workflow of the proposed method is illustrated systematically in Figure 4.




Source: (Research Result 2026)

Figure 4. Proposed Method

Referring to Figure 4, the optimization process begins with the initialization of a population of 10 individuals with a random gene configuration. Each individual then enters the Fitness Evaluation stage (the primary process block), where the model is partially trained to measure their performance. This assessment is based on three competing objectives: (1) Accuracy (weight 0.6), (2) Model Size (calculated from normalization of the number of parameters, weight 0.3), and (3) Inference Time (average prediction speed, weight 0.1). The scores of the three objectives were combined into one fitness value using the weighted sum method.

Individuals with high fitness scores are then selected through a selection process to become the parent, who then undergo genetic surgery in the form of Crossover and Mutation to produce new generations. This cycle repeats for 20 generations until the algorithm converges on the optimal solution. The specific operational parameters used to control the evolutionary behavior of the Genetic Algorithm in this study are summarized in Table 3.

Table 3. Genetic Algorithm Operational Parameters

| Parameter | Value |
|---|---|
| Population Size | 10 individuals |
| Max Generations | 20 Generations |
| Crossover Rate | 0.8 |
| Mutation Rate | 0.1 |
| Selection Method | Best Individual |

Source: (Research Result 2026)

Once the evolution process is complete, the configuration with the highest fitness value is designated as the "Best Solution". This solution is then used to build a final model that is fully retrained (Full Training) for 20 epochs with an Early Stopping mechanism to ensure the model achieves maximum performance without overfitting.

## RESULTS AND DISCUSSION

At this stage, the results of experiments and in-depth analysis on the application of Multi-Objective Genetic Algorithms for the optimization of the ResNet50 architecture in the classification of batik motifs are described. The discussion began with an analysis of the evolution process of searching for optimal parameters, which was then followed by a comparative evaluation between the performance of the baseline model and the optimization result model. The primary focus of the discussion was on the effectiveness of the proposed method in balancing the trade-off between classification accuracy and computational efficiency, as well as validation of model robustness through visualization analysis of prediction errors.

### Multi-Objective Genetic Algorithm Optimization Analysis

The optimization of the ResNet50 architecture was carried out using Multi-Objective

Genetic Algorithms for 20 generations to balance accuracy and efficiency. The evolutionary process shows a positive convergence trend, in which the mechanism of selection and crossover manages to progressively increase the average fitness value of the population towards the optimal point. At the end of the evolution, the algorithm identifies the best configuration *(Winning Solution)* with the highest fitness score of 0.8591.

Table 4. Optimal Hyperparameter Configuration of Genetic Algorithm Results

| Metric | ResNet50 | ResNet 50 Proposed |
|---|---|---|
| Dense Layer | 512 Neuron | 128 Neuron |
| Dropout | 0.5 | 0.3 |
| LR | 0.0001 | 0.00043 |
| Unfreeze | 0 | 5 Layers |
| Optimizer | Adam | Adam |
| Est. Param | 23.587.717 | 1.313.541 |
| Est. Time | 0.1450 s/img | 0.1023 s/img |

Source: (Research Result, 2026)

Based on Table 4, it can be seen that the Genetic Algorithm managed to drastically reduce redundancy by 94.4%. The use of 128 neurons on the classifier head proved to be sufficient to distinguish batik features without burdening memory. The algorithm's decision to fine-tune the last 5 layers is the most crucial aspect of the success of this model.

Viewed from the theory of Representation Learning, the early layers of CNN generally capture generic visual features such as borders, lines, and basic textures that are universal to the ImageNet dataset. However, batik motifs have very specific and repetitive geometric characteristics. By opening up the last 5 layers, the model is given the flexibility to adjust the representation of high-level semantic features to align with the batik domain, without undermining the foundation of the basic visual features that have been studied beforehand.

This 5-layer depth is identified by GA as a sweet spot that prevents catastrophic forgetting while minimizing the number of parameters that must be retrained. This strategy directly resulted in an increase in inference speed by 29.4% (from 0.1450 seconds to 0.1023 seconds per image), making the optimization model very feasible to implement on devices with limited resources.

**Image Data Pre-processing Result**

The dataset used in this study comprised 3,550 batik images and was divided into 2,800 images for training, 700 images for validation, and 50 images for testing, corresponding to approximately 78.87%, 19.72%, and 1.41% of the total dataset, respectively. The training set was used for model learning, the validation set was used during the optimization process, and the testing set was reserved for final evaluation, as presented in Table 5.

Table 5. Images Data Splitting

| No | Data Splitting | Class | Amount |
|---|---|---|---|
| 1 | Training | Kawung | 560 |
| 2 | | Megamendung | 560 |
| 3 | | Parang | 560 |
| 4 | | Sidomukti | 560 |
| 5 | | Truntum | 560 |
| 6 | Validation | Kawung | 140 |
| 7 | | Megamendung | 140 |
| 8 | | Parang | 140 |
| 9 | | Sidomukti | 140 |
| 10 | | Truntum | 140 |
| 11 | Testing | Kawung | 10 |
| 12 | | Megamendung | 10 |
| 13 | | Parang | 10 |
| 14 | | Sidomukti | 10 |
| 15 | | Truntum | 10 |

Source: (Research Result, 2026)

Table 5 displays the distribution of batik motif imagery datasets, categorized by type, along with the corresponding number of images available for each class. This dataset is segmented into three primary subsets: training, validation, and testing, each of which has a specific role in the model development cycle. In the training subset, a total of 2,800 images were allocated covering five main motif classes: Kawung, Megamendung, Parang, Sidomukti, and Truntum, where each class had 560 images that had been enriched through data augmentation techniques. Meanwhile, the validation phase uses 700 images (140 images per class), which serves as a vital reference for fitness functions in the optimization of Genetic Algorithms, and the testing phase uses 50 images (10 images per class) for final evaluation.

All photos have also gone through a resizing process to a dimension of 224 x 224 pixels and normalization of pixel values. The distribution and treatment of this data is designed following the principles of Deep Learning, where dominant and varied trained data allows the model to learn complex features effectively, validation data oversees the optimal architecture search process, and test data ensures objective measurement of the accuracy of previously unobserved data. With this approach, the model is anticipated to effectively generalize and attain optimal performance in classifying batik motifs that exhibit a high degree of similarity.

**Image Data Classification Result**

At this phase, comparative assessments were performed to categorize the batik motif image data utilizing two distinct configurations of Convolutional Neural Network architecture: the

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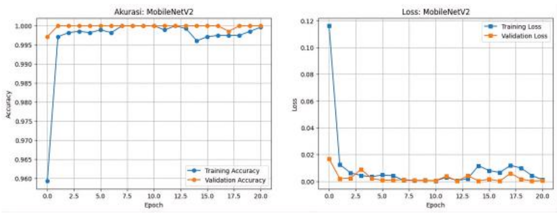
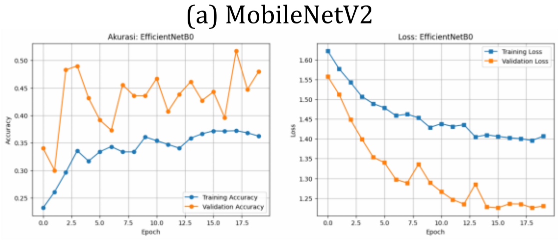
conventional ResNet50 model (Baseline) and the ResNet50 model that has been enhanced via optimization with the Multi-Objective Genetic Algorithm (Proposed Method).

**Loss and Accuracy Curve**

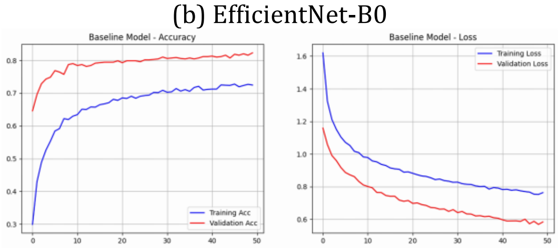
At this stage, an in-depth evaluation of the convergence stability of the model was carried out through learning curves analysis. To provide a comprehensive assessment, a comparison was made between the proposed model (GA-Optimized ResNet50), the baseline architecture (ResNet50 Standard), and the two standard lightweight architectures (MobileNetV2 and EfficientNet-B0). Figure 5 presents a comparison of the accuracy and loss curves of the four models to identify the symptoms of overfitting or underfitting.



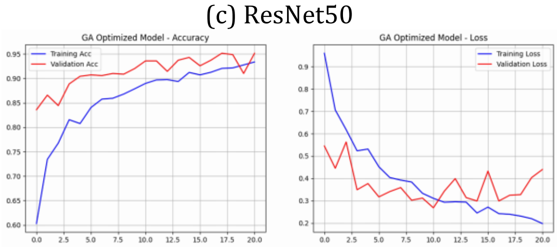
(a) MobileNetV2



(b) EfficientNet-B0



(c) ResNet50



(d) ResNet50 Proposed

Source: (Research Result 2026)

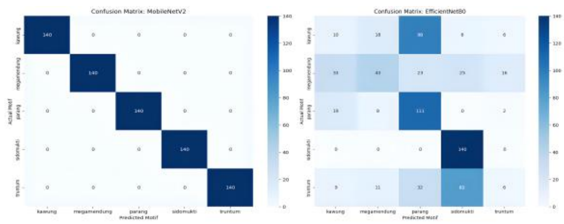
Figure 5. Training Validation Loss

Based on Figure 5, it can be seen that there is a significant difference in convergence characteristics between the four architectures. In Figure 5a, MobileNetV2 shows a very high convergence speed with an accuracy of up to 100%, but as noted in Table 8, this is compensated for by a much larger number of parameters (2.92 million parameters). On the other hand, EfficientNet-B0 (Figure 5b) shows a failure to capture batik features optimally (underfitting), where the accuracy curve is held at 44.57% with unstable loss fluctuations.

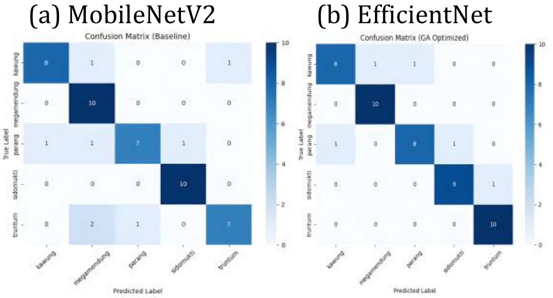
A comparison between ResNet50 Baseline (Figure 5c) and GA-Optimized ResNet50 (Figure 5d) shows the success of genetic algorithm optimization. In the baseline model, the training loss curve remains above the validation curve, indicating that the standard architecture is too rigid to capture the details of complex batik patterns. However, in the proposed model (Figure 5d), a very stable and smooth convergence trend can be seen. The tight gap between the training and validation curves proves that the unfreezing strategy in the last 5 layers has succeeded in creating a "robust" model, able to generalize well on new data without overfitting, even though the number of parameters has been cut to just 1.31 million parameters.

**Confusion Matrix**

Confusion matrix analysis provides an in-depth picture of the model's classification performance by identifying specific areas where misclassification occurs. To provide a comprehensive robustness evaluation, Figure 6 presents a comparison of the error matrix of the four models tested: the proposed architecture, the baseline architecture, and the two standard lightweight architectures (MobileNetV2 and EfficientNet-B0) as benchmarks for feature extraction effectiveness.



(a) MobileNetV2 (b) EfficientNet




(c) ResNet50 (d) ResNet50 Proposed

Source: (Research Result 2026)

Figure 6. Confusion Matrix

Based on Figure 6, there is a significant difference in the ability of each model to handle the inter-class visual similarity in batik motifs. In Figure 6a, MobileNetV2 shows a perfect classification of all classes, but this performance requires a much larger number of parameters than the proposed model. A contrast phenomenon was seen in EfficientNet-B0 (Figure 6b) which experienced massive feature extraction failures, where prediction errors were randomly spread across almost the entire class with an average accuracy of only 44.57%. This proves that the use of theoretically more modern architecture does not guarantee robustness in recognizing complex batik geometric patterns without specific optimization.

The comparison between ResNet50 Baseline (Figure 6c) and GA-Optimized ResNet50 (Figure 6d) shows the real impact of hyperparameter optimization resulting from Genetic Algorithm. In the baseline model, there are many misclassifications especially in the 'Parang' and 'Truntum' categories (with a recall value of only 0.70), where the original motif image is often misidentified as another class. However, in the proposed model (Figure 6d), the error was significantly suppressed. The proposed model shows a sharp increase in precision in the 'Megamendung' motif (increased from 0.71 to 0.91) as well as a minimization of defects in the 'Truntum' class to reach the optimal recall level. This success confirms that the unfreezing strategy in the last 5 layers provides the right flexibility for the model to learn the complex semantic features of batik, resulting in a classification system that is much more robust than other industry-standard models.

Table 6. Classification Report ResNet50 Baseline

| | Precision | Recall | F1-Score |
|---|---|---|---|
| Kawung | 0.89 | 0.80 | 0.84 |
| Megamendung | 0.71 | 1.00 | 0.83 |
| Parang | 0.88 | 0.70 | 0.78 |
| Sidomukti | 0.91 | 1.00 | 0.95 |
| Truntum | 0.88 | 0.70 | 0.78 |
| Accuracy | **0.84** | **0.84** | **0.84** |
| Macro Avg | 0.85 | 0.84 | 0.84 |

Source: (Research Result, 2026)

Table 7. Classification Report ResNet50 Proposed

| | Precision | Recall | F1-Score |
|---|---|---|---|
| Kawung | 0.89 | 0.80 | 0.84 |
| Megamendung | 0.91 | 1.00 | 0.95 |
| Parang | 0.89 | 0.80 | 0.84 |
| Sidomukti | 0.91 | 0.90 | 0.90 |
| Truntum | 0.90 | 1.00 | 0.95 |
| Accuracy | **0.91** | **0.90** | **0.90** |
| Macro Avg | 0.90 | 0.90 | 0.90 |

Source: (Research Result, 2026)

Through the integration of the data in Tables 6 and 7, it is clear that the proposed model achieves more stable prediction performance across all metrics. The increase in total accuracy from 84% to 90%, driven by significant improvements in precision values and recall across almost the entire motif class, proves that the solutions generated by the Multi-Objective Genetic Algorithm are not only parametrically efficient but also have reliable accuracy for practical implementation in resource constrained environments.

**Model Evaluation Performance**

The final stage of evaluation was carried out by conducting thorough benchmarking to validate the efficiency and performance of the proposed model against the basic architecture as well as the industry-standard lightweight architecture. A summary of the performance comparison is presented in Table 8.

Table 8. Testing Result

| Model | Accuracy | Parameters | Inference Time (s/img) |
|---|---|---|---|
| ResNet50 | 84.00% | 23,587,717 | 0.1450 s |
| MobileNetV2 | 100.00% | 2,916,421 | 0.0128 s |
| EfficientNet-B0 | 44.57% | 4,708,008 | 0.0200 s |
| GA-Optimized ResNet50 | 90.00% | 1,313,541 | 0.1023 s |

Source: (Research Result, 2026)

Based on Table 8, the proposed model (GA-Optimized ResNet50) showed a more favorable balance between accuracy and efficiency within the ResNet50 optimization framework. Compared with the baseline model, the proposed model substantially reduced the number of trainable parameters while also improving classification performance. Although MobileNetV2 achieved perfect accuracy, it still used more parameters than the proposed model, whereas EfficientNet-B0 failed to deliver competitive performance on this dataset. The ability of the proposed model to reduce trainable parameters by 94.4% relative to the original ResNet50 architecture, while still improving predictive performance, indicates the practical value of the proposed weighted-sum multi-objective Genetic Algorithm for resource-efficient model optimization.

## CONCLUSION

This study developed a ResNet50-based CNN optimized with a Multi-Objective Genetic Algorithm for classifying Indonesian Batik motifs. The proposed approach effectively balances predictive

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performance and computational efficiency, improving classification accuracy by 6% (from 84% to 90%), reducing trainable parameters by 94.4% (from 23.59M to 1.31M), and increasing inference speed by 29.4%. Analysis shows that fine-tuning the last five layers of ResNet50 captures domain-specific features without full-network retraining. Benchmarking against EfficientNet-B0 further highlights the model's parameter efficiency. However, the study used a limited testing subset, so the reported performance should be considered an initial empirical indication rather than a definitive measure of generalization. Future work should validate the approach on larger and more diverse datasets, explore optimization on lightweight backbones such as MobileNetV3, and investigate integration into mobile applications for real-time testing.

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