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FINE-TUNING RESNET50V2 WITH ADAMW AND ADAPTIVE TRANSFER LEARNING FOR SONGKET CLASSIFICATION IN LOMBOK

Erfan Wahyudi[1], Bahtiar Imran[2*]; Zaeniah[3]; Surni Erniwati[4]; Muh Nasirudin Karim[5], Zumratul Muahidin[6]

Manajemen Keamanan dan Keselamatan Publik[1],
Institut Pemerintahan Dalam Negeri, Praya, Indonesia[1]
https://www.ipdn.ac.id/ipdn_ntb[1]

Rekayasa Sistem Komputer[2, 5], Sistem Informasi[3, 6], Manajemen Informatika[4]
Universitas Teknologi Mataram, Mataram, Indonesia[1, 2, 3, 4]
https://utmmataram.ac.id[2, 3, 4, 5, 6]
erfan.wahyudie@gmail.com[1], bahtiarimranlombok@gmail.com[2*], zaen1989@gmail.com[3],
mentari1990@gmail.com[4], karimnasirundin@gmail.com[5], muahidinzumratul@gmail.com[6]
(*) Corresponding Author

Abstract— *This study aims to develop a classification system for traditional Lombok songket fabric patterns using the ResNet50V2 architecture, optimized through fine-tuning and the AdamW optimizer. The data were collected directly from songket artisans in Lombok and categorized into three groups based on the origin of the patterns: Sade, Sukarara, and Pringgasela. The model was trained with data augmentation techniques, including rotation, shifting, and zooming, to increase data diversity. During the training process, fine-tuning was applied to the last layer of ResNet50V2, and optimization was performed using AdamW with a learning rate of 0.0001. The model was evaluated using a confusion matrix, classification report, and analysis of accuracy and loss. The experimental results showed that the model achieved 100% accuracy at the 15th epoch. Furthermore, experiments with different parameters (epochs, batch size, and learning rate) demonstrated that the 15th epoch provided the best results with 100% accuracy, while using higher epochs (30 and 40) did not necessarily yield better outcomes. This model is effective in identifying songket fabric patterns with good classification results for each class. Although the results are excellent, increasing the dataset size and exploring more complex model architectures could further enhance performance. Overall, this study demonstrates the significant potential of deep learning technology in classifying songket patterns with reliable accuracy in real-world applications.*

Keywords: *data augmentation, deep learning, fine-tuning, ResNet50V2, songket pattern classification.*

Abstrak—*Penelitian ini bertujuan untuk mengembangkan sistem klasifikasi motif kain songket khas Lombok menggunakan arsitektur ResNet50V2 yang dioptimalkan melalui fine-tuning dan AdamW optimizer. Data dikumpulkan langsung dari pengrajin songket di daerah Lombok dan dibagi menjadi tiga kategori berdasarkan asal motifnya yaitu Sade, Sukarara, dan Pringgasela. Model dilatih dengan augmentasi data, termasuk rotasi, pergeseran, dan zooming untuk meningkatkan keragaman data. Selama proses pelatihan, dilakukan fine-tuning pada lapisan terakhir ResNet50V2 dan optimasi menggunakan AdamW dengan learning rate 0.0001. Model dievaluasi menggunakan confusion matrix, classification report, dan analisis akurasi dan loss. Hasil eksperimen menunjukkan bahwa model berhasil mencapai akurasi 100% pada epoch ke-15. Selain itu, eksperimen dengan berbagai parameter (epoch, batch size, dan learning rate) menunjukkan bahwa epoch ke-15 memberikan hasil terbaik dengan akurasi 100%, sedangkan penggunaan epoch yang lebih tinggi (30 dan 40) tidak selalu memberikan hasil yang lebih baik. Model ini efektif dalam mengidentifikasi pola kain songket dengan hasil klasifikasi yang baik pada setiap kelas. Meskipun hasilnya sangat baik, peningkatan jumlah data dan eksplorasi arsitektur model yang lebih kompleks dapat meningkatkan kinerja lebih lanjut. Secara keseluruhan, penelitian ini menunjukkan potensi besar dari teknologi deep learning dalam mengklasifikasikan motif songket, dengan akurasi yang dapat diandalkan di dunia nyata.*

***Kata Kunci**: augmentasi data, pembelajaran mendalam, penyesuaian parameter, ResNet50V2, klasifikasi motif songket.*

INTRODUCTION

Songket is a traditional woven fabric that features various patterns, each of which carries its own meaning and philosophy. Due to the diversity of patterns, not everyone is able to recognize and distinguish one pattern from another (Das et al., 2021; He et al., 2021; Welamo1 & Deng1Sanpeng, 2021; Yullyana et al., 2022). The patterns and textures of woven fabrics in Indonesia are diverse, adapting to the unique characteristics of each region. One such region with a distinct uniqueness in songket fabric is Lombok, an island in the province of West Nusa Tenggara. Known as a tourist destination, Lombok offers a rich cultural heritage, one of which is the distinctive Lombok songket, a prominent product of the region (Hambali & Mahayadi, 2021; Ilahi et al., 2022; Imran & Efendi, 2020). To accurately identify the differences in texture between each type of songket, a classification method utilizing technology or computer-based systems is needed (Kartika et al., 2022; Lesiangi et al., 2021). With the help of this technology, the analysis process can be conducted more objectively and efficiently, allowing the unique characteristics of each songket to be recognized more precisely (Gültekin et al., 2021; Tasnim et al., 2023; Yildiz, 2020).

Several previous studies have addressed this issue using various methods. Study (Yullyana et al., 2022) employed Content-Based Image Retrieval (CBIR) with a graph matching method for classifying songket fabric, achieving an F1-score of 91.05% using the VF2 algorithm and an F1-score of 53.36% with Graph Edit Distance (GED ≤ 8). Study (Yuhandri et al., 2017a) extracted object features from songket fabric using the Chain Code algorithm. The results indicated that the Chain Code algorithm could identify the number of objects, chain code lengths, and the probability of the appearance of each chain code in the songket pattern. Study (Yuhandri et al., 2017b) focused on pattern recognition and classification using artificial neural networks, achieving a precision of 98%. Similarly, study (Hambali & Mahayadi, 2021) employed Convolutional Neural Networks (CNN) for classifying Lombok's traditional songket fabric, obtaining an accuracy of 86.36%. Study (Al Sasongko et al., 2022) applied the Gray Scale Matrix technique for Lombok songket pattern identification based on Backpropagation learning, with the best results achieved at a 0° angle, yielding an accuracy of 88.33%. Study (Hussain et al., 2020) used Deep Convolutional Neural Networks for recognizing and classifying woven fabric patterns, showing that the proposed model was robust and achieved high accuracy despite changes in the fabric's physical properties, outperforming baseline approaches and the pre-trained VGGNet deep learning model. Finally, study (Kahraman & Durmu¸so˘glu, 2022) focused on fabric defect classification using capsule networks, achieving a performance score of 98.7% in fabric defect detection with Capsule Networks.

The purpose of this study is to develop a songket pattern classification system using Convolutional Neural Networks (CNN) with the ResNet50V2 architecture, optimized through fine-tuning and the AdamW optimizer. The selection of the ResNet50V2 architecture is based on its superior capability in image classification with a high level of accuracy. Furthermore, ResNet50V2 has been proven effective in various image classification tasks due to its deep network structure, which enables it to extract features comprehensively without experiencing performance degradation (Duklan et al., 2024; Hindarto, 2023). The dataset was collected directly from songket weavers in West Nusa Tenggara and divided into 80% for training and 20% for testing. To improve model performance, adaptive transfer learning was applied, with fine-tuning on the final layers of ResNet50V2. The training process utilized ReduceLROnPlateau to dynamically adjust the learning rate, while data augmentation was applied to enhance the model's robustness against variations in pattern, lighting, and image orientation. Evaluation was performed using a Confusion Matrix, Classification Report, and visualizations of accuracy and loss. Additionally, the prediction results were visualized to analyze the effectiveness of the model in automatically recognizing songket patterns. This approach is expected to improve the efficiency and accuracy of songket pattern identification based on deep learning.

MATERIALS AND METHODS

Data Collection

The data collection in this study was conducted directly at the songket weaving centers located in Lombok, specifically in the villages of Sade, Sukarara, and Pringgasela. The data acquisition process utilized a high-resolution DSLR camera, where each image was taken from a distance of approximately one meter to ensure that the details of the songket patterns were clearly captured. The raw data obtained had a resolution of 4000 × 4000 pixels, allowing for more accurate analysis during the classification and identification of weaving patterns.

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Data Labeling

In the data labeling phase, the collected images were categorized into three main folders based on the origin of the patterns, namely Songket Sade, Songket Sukarara, and Songket Pringgasela. This categorization was done to facilitate the classification process in the subsequent stages of processing. With a structured labeling system, the model can more easily recognize the distinct characteristics of each type of songket, thus improving the accuracy of the identification and classification of weaving patterns.

Data Preprocessing

In the Data Preprocessing stage, the collected images undergo several adjustments before being used for model training. First, each image is resized to 800×800 pixels to match the ResNet50V2 architecture. Next, normalization is performed by dividing the pixel values by 255 to scale them within the range of [0,1], which helps accelerate model convergence during training. Additionally, data augmentation techniques are applied, such as rotating by 5 degrees, shifting the width and height by 5%, shear transformation, and zooming within a 5% range. These augmentations are applied to increase the diversity of the training data and help the model become more robust to variations in songket patterns. Finally, horizontal flipping is also applied to capture possible pattern variations that may arise from different orientations.

The formula used for Image Normalization (Pei et al., 2023):

$$I_{norm} = \frac{I}{255} \quad (1)$$

Where I is the pixel matrix of the original image and I_{norm} is the image that has been normalized to the range [0, 1]

Data Augmentation:

Rotation, shift, shear, zoom, and flip are performed using affine transformations.

$$I' = T(I) \quad (2)$$

With T as the transformation that includes:

1. Rotation: $T_{rot}(\theta)$
2. Translation: $T_{trans}(x, y)$
3. Scaling: $T_{scale}(s)$
4. Horizontal flip: T_{flip}

Model Architecture

This study uses ResNet50V2, a deep learning model based on Convolutional Neural Networks (CNN) that has been pre-trained with ImageNet. The model is utilized as a feature extractor by removing its classification layers (include_top=False), retaining only the convolutional base. To improve computational efficiency, only the last 50 layers of ResNet50V2 are made trainable (trainable=True), while the other layers are frozen (trainable=False). Additional layers are then added on top of the feature extractor to tailor it for the songket pattern classification task. After the output from ResNet50V2 passes through the GlobalAveragePooling2D layer, normalization is applied using BatchNormalization to reduce internal covariate shift. Subsequently, a dense layer with 512 neurons and a ReLU activation function is used to enhance feature representation. Regularization is applied via BatchNormalization and a dropout rate of 0.4 to prevent overfitting. Finally, a dense layer with a number of neurons corresponding to the number of classes and a softmax activation function is used to produce classification probabilities. The model is optimized using the AdamW optimizer with an initial learning rate of 0.0001 and weight decay of 1e-4, and categorical cross-entropy loss is used as the loss function.

The formula used for ResNet uses residual learning (Kim et al., 2023):

$$y = F(x, \{W_i\}) + x \quad (3)$$

With $F(x, \{W_i\})$ as the learned transformation function, and x is the input from the previous layer.

Global Average Pooling (Dogan, 2023):

$$\text{GAP} = \frac{1}{N}\sum_{i=1}^{N} f_i \quad (4)$$

Batch Normalization (Dogan, 2023):

$$\hat{x}_i = \frac{x_i - \mu}{\sqrt{\sigma^2 + \epsilon}} \quad (5)$$

Where μ dan σ^2 is the batch mean variance.

Dropout for Regularization:

$$y = M.x \quad (6)$$

Where M is the dropout mask matrix with elements 0 or 1. Softmax Activation for Classification (Dogan, 2023) :

$$P(y_i) = \frac{e^{z_i}}{\sum_j e^{z_i}} \quad (7)$$

Where z_i is the output of the last layer.

Loss Function (Categorical Crossentropy):

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \quad (8)$$

With y_i as the true label and $\hat{y}_i$ as the model's prediction.

Fine-Tuning the Model

After the base ResNet50V2 model is applied, fine-tuning is performed to enhance the accuracy of songket pattern classification. In the initial phase of training, only the added layers are trained, while the weights in ResNet50V2 are kept frozen to retain the features learned from ImageNet. After several epochs, the last 50 layers of ResNet50V2 are unfrozen, allowing the higher-level features to be updated according to the characteristics of the songket dataset. To ensure optimal fine-tuning, Early Stopping is employed by monitoring the validation accuracy. If there is no improvement in accuracy for five consecutive epochs, the training is automatically stopped to avoid overfitting. Additionally, ReduceLROnPlateau is implemented to adaptively reduce the learning rate by 50% if the validation loss does not decrease after three epochs. This strategy allows the model to converge more stably and learn the features of songket patterns more effectively.

Hyperparameter Tuning

In the model used in this study, hyperparameter tuning was performed using a manual approach, where specific parameter values were explicitly determined based on previous experimental considerations. The key hyperparameters adjusted in this model include the learning rate, dropout rate, and the number of layers unfrozen for fine-tuning.

The model employs the AdamW optimizer with an initial learning rate of 0.0001 and a weight decay of 1e-4. AdamW was chosen for its ability to mitigate overfitting through weight decay regularization, which helps improve the model's generalization. Additionally, a dropout rate of 0.4 was applied after the fully connected layer to further reduce the risk of overfitting. To enhance training stability, two additional techniques were implemented: Early Stopping and ReduceLROnPlateau. Early Stopping terminates training if the validation accuracy does not improve for five consecutive epochs, thereby preventing overfitting. Meanwhile, ReduceLROnPlateau adaptively reduces the learning rate by a factor of 0.5 if the validation loss does not improve for three consecutive epochs, with a minimum learning rate threshold of 1e-6.

Optimization with AdamW:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t \quad (9)$$

$$m_t = \beta_2 v_{t-1} + (1-\beta_2) g_t^2 \quad (10)$$

$$\theta_t = \theta_{t-1} - \eta \frac{m_t}{\sqrt{v_t + \epsilon}} + \leftthreetimes\, \theta_{t-1} \quad (11)$$

Di mana $\leftthreetimes$ adalah weight decay.

Training the Model

The model training process is conducted using the ResNet50V2 architecture, which has been modified for songket image classification. The model is trained on a dataset that has undergone augmentation to enhance its ability to generalize across variations in the images. The training scheme uses categorical cross-entropy loss function, as the dataset contains multiple classes, and the AdamW optimizer with an initial learning rate of 0.0001 and weight decay of 1e-4 to reduce the risk of overfitting. To improve training efficiency, a fine-tuning strategy is implemented by unfreezing only the last 50 layers of ResNet50V2, while the other layers remain frozen to retain the pretrained weights. Additionally, Early Stopping with a patience of 5 is used to halt training if validation accuracy does not improve within five consecutive epochs. The ReduceLROnPlateau technique is also employed to adjust the learning rate if the validation loss does not improve within three consecutive epochs.

Model Evaluation

The model evaluation is conducted to assess its performance in accurately classifying songket images. After the training process is completed, the model is tested using validation data, where the predictions made by the model are compared with the actual labels. The prediction results are evaluated using a confusion matrix, which is visualized as a heatmap to examine the distribution of classification errors between the classes. Additionally, a classification report is generated, including metrics such as precision, recall, F1-score, and accuracy for each class. The overall accuracy of the model is also calculated using the accuracy score. Apart from numerical evaluation, a visual analysis is performed by displaying several validation images along with their corresponding model predictions. The formula used (Kahraman & Durmu¸so˘glu, 2022).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (12)$$

Where TP = True Positives, TN = True Negatives, FP = False Positives, dan FN = False Negatives.

Confusion Matrix:
The Confusion Matrix (CM) has a size of $N \times N$ with elements:
CM_{ij} = The number of predictions for class j that actually belong to class i (13)

Classification Report (Precision, Recall, F1-Score):

$$Precision = \frac{TP}{TP+FP} \quad (14)$$

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$$Recall = \frac{TP}{TP+FN} \quad (15)$$

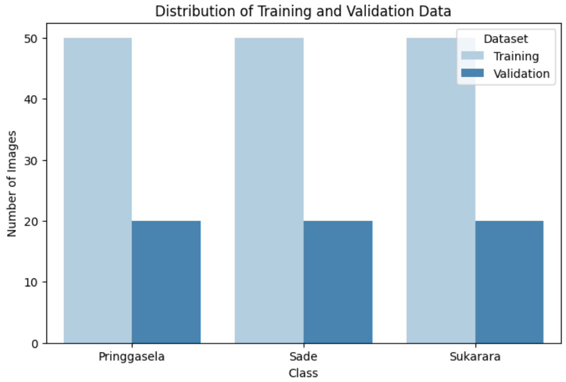
$$\text{F1} - \text{Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (16)$$

RESULTS AND DISCUSSION

Dataset

The dataset used in this study consists of images of traditional Lombok songket fabrics, categorized into several classes based on their patterns. It is divided into two main subsets: the training set, which is used to train the model, and the validation set, which is used to evaluate the model's performance. The dataset was collected over a duration of two days and is stored in the directories "./dataset1/train" for training data and "./dataset1/validation" for validation data. Each songket category is placed in a separate folder within these directories, allowing ImageDataGenerator to automatically process and augment the data.

The dataset consists of a total of 210 images, with 150 images used for training and 60 images for validation. The training dataset contains three classes: Pringgasela, Sade, and Sukarara, with each class containing 50 images. Similarly, the validation dataset consists of three classes: validation_pringgasela, validation_sade, and validation_sukarara, with each class containing 20 images. The dataset is designed to ensure that each class has a sufficiently balanced number of samples to prevent model bias toward any particular category. The exact number of images in the dataset is not explicitly stated in the code but can be retrieved using train_generator.samples and val_generator.samples, which reflect the total number of images in each subset. For the distribution of data, refer to Figure 1.



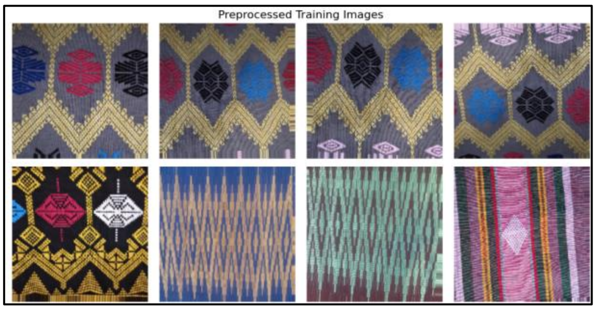
Source: (Research Results, 2025)
Figure 1. Distribution of Training and Validation Data

Source: (Research Results, 2025)
Figure 2. Sample Images from Each Songket Motif Class

Figure 2. The image above presents sample images from each songket motif class used in this study, namely Pringgasela, Sade, and Sukarara. Each motif represents a distinct traditional weaving pattern originating from Lombok, Indonesia. The dataset includes two sample images per class, showcasing variations in color, texture, and motif structure. These differences highlight the unique characteristics of each songket style, which are essential for the classification model to recognize and differentiate them effectively. The structured distribution of samples ensures that the model is exposed to a diverse range of patterns, improving its ability to generalize well to unseen data.

Preprocessing Result

The preprocessing step ensures the traditional Lombok songket fabric images are optimized for model training. Images are rescaled (dividing pixel values by 255) for numerical stability and resized to 224×224 pixels to match the ResNet50V2 input requirements. Augmentation is applied to the training set, including rotation (5°), width/height shifts (5%), shear (5%), zoom (5%), and horizontal flipping to enhance generalization and prevent overfitting. Validation images are only rescaled to maintain data integrity. Using ImageDataGenerator, images are processed dynamically in batches of 32, ensuring efficient memory usage. These preprocessing techniques help the model learn robust representations of songket patterns, improving classification performance.



Source: (Research Results, 2025)
Figure 3. Preprocessed Image Results

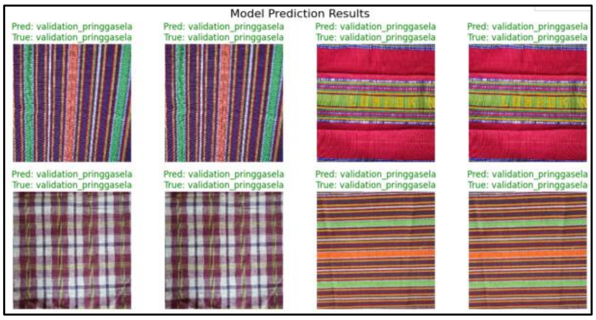
Figure 3. The image above showcases a set of preprocessed training images from the songket motif dataset. These images have undergone a series of augmentation techniques to enhance model generalization and improve classification performance. The applied preprocessing steps include rescaling, where pixel values are normalized to the range of [0, 1], and various geometric transformations such as rotation, width and height shifts, shear, zoom, and horizontal flipping. These augmentations help the model become more robust to variations in motif orientations and structural distortions. The diverse range of patterns and colors seen in the images indicates the presence of multiple motif categories, ensuring that the model learns to differentiate them effectively. The preprocessing also ensures that each image is resized to 224×224 pixels, which aligns with the input requirement of the ResNet50V2 model. By applying these techniques, the model is expected to better handle real-world variations in songket motifs, ultimately leading to improved classification accuracy.

Implementation of the ResNet50V2 Model

The implementation of the ResNet50V2 model for songket motif classification demonstratses promising performance in distinguishing motifs from various regions, namely Sade, Sukarara, and Pringgasela. The model underwent fine-tuning, where the last 50 layers were activated to train features specific to the dataset, while the remaining layers were frozen to retain the pretrained weights from ImageNet. Additionally, the use of the AdamW optimizer with a small learning rate (0.0001) helped stabilize the training process and prevent overfitting. Evaluation results showed that the model achieved a high level of accuracy, as indicated by the confusion matrix and classification report. From the visualization of prediction results, the model was able to classify most images correctly, although some classification errors still occurred, likely due to the similarities between motifs from different regions. Further analysis of training loss and validation accuracy suggests that this model's performance can be further improved through additional hyperparameter tuning or by increasing the amount of training data. The dataset used consisted of 150 images for training and 60 images for validation, ensuring a balanced distribution across different classes.

Performance of the Proposed Model

The performance of the proposed model was evaluated based on several key metrics, such as accuracy, confusion matrix, and classification report. From the testing results, the fine-tuned ResNet50V2 model demonstrated good performance in classifying songket motifs from three regions: Sade, Sukarara, and Pringgasela. The accuracy obtained indicates that the model was able to recognize patterns effectively, although some misclassifications were observed, as shown in the confusion matrix. Example classification results can be seen in Figure 4.



Source: (Research Results, 2025)
Figure 4. Model Prediction Results

Based on Figure 4, the classification results show that the ResNet50V2 model successfully identified the songket motifs from the Pringgasela region with good accuracy. Each image demonstrates the prediction result (Pred: validation_pringgasela), which matches the actual label (True: validation_pringgasela), highlighted in green. This indicates that the model can effectively recognize the songket patterns from Pringgasela with a high accuracy rate. However, to evaluate the model's overall performance, it is necessary to analyze the predictions for the other classes (Sade and Sukarara) and examine the confusion matrix to determine if the model shows any bias toward a particular class. Additionally, while the results are promising, the model could still be improved by strategies such as increasing the dataset size, adjusting hyperparameters, or exploring more complex model architectures.

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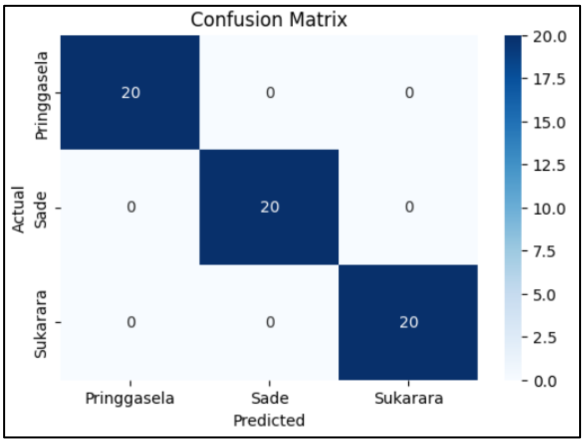


Source: (Research Results, 2025)
Figure 5. Confusion Matrix

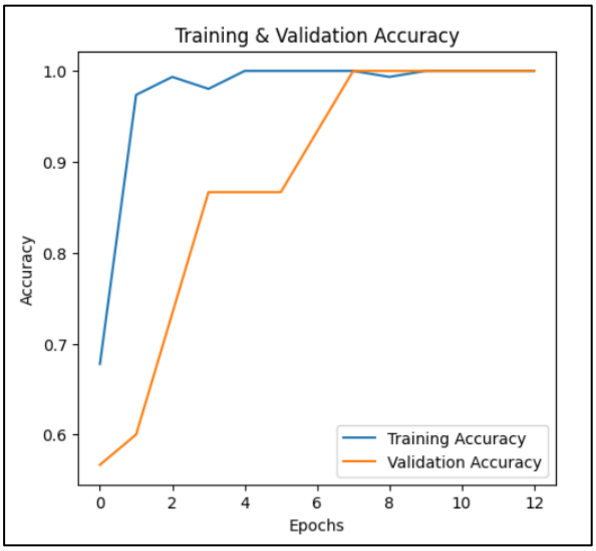
Based on the confusion matrix analysis in Figure 5, which reflects the best results obtained after 15 epochs of training, the ResNet50V2 model demonstrates excellent performance, achieving 100% accuracy on the validation dataset. This is evidenced by the absence of misclassifications across the three classes, Pringgasela, Sade, and Sukarara, with each class having 20 samples correctly classified without any erroneous predictions.

However, despite these excellent results, further analysis is required to ensure that the model does not suffer from overfitting, especially given the limited dataset used. One approach to improving the model's generalization capability is by exploring advanced optimization strategies, such as adjusting the learning rate, increasing the training data through augmentation or additional data collection, and experimenting with other, more complex or lightweight model architectures. Furthermore, selecting the optimal number of epochs is crucial, as each epoch can yield different results. Careful balancing between underfitting and overfitting is necessary, ensuring that the model not only performs well on training data but also generalizes effectively to unseen data.

Classification Results Evaluation

Figure 6 illustrates that the ResNet50V2-based model used in this experiment successfully captures the visual patterns of songket fabric. The implementation of Batch Normalization, Dropout (0.4), and the AdamW optimizer with a small learning rate (0.0001) contributes to maintaining training stability and preventing overly aggressive parameter exploration. Therefore, this model can be considered effective for classifying traditional Lombok songket fabrics. However, further optimization could be achieved through additional regularization techniques or more in-depth fine-tuning.

Source: (Research Results, 2025)
Figure 6. Training and Validation Loss



Source: (Research Results, 2025)
Figure 7. Training and Validation Accuracy

Figure 7 shows that training accuracy continues to increase and approaches 100%, while validation accuracy also exhibits a stable improvement, reaching 100% at the 15th epoch. There is no significant gap between training and validation accuracy in subsequent epochs, indicating that the model does not suffer from overfitting and generalizes well to new data. In other words, the model does not merely memorize patterns from the training data but can also recognize similar patterns in previously unseen validation data. From the results presented in the graph, it can be concluded that the 15th epoch is the optimal point where the model achieves maximum accuracy without signs of overfitting. This demonstrates that the fine-tuned ResNet50V2 architecture effectively captures the characteristics of songket fabric. With an accuracy reaching 100%, the model is ready for use in songket fabric classification systems with a high level of confidence. However, to ensure consistent performance under various conditions, further testing with a larger and more diverse dataset is necessary.

The overall classification results can be seen in detail in Table 1, which presents the model's accuracy in classifying Sade, Pringgasela, and Sukarara songket fabrics. This table provides an overview of the extent to which the model successfully recognizes patterns from each fabric category. The displayed accuracy reflects the model's performance based on the validation data used, making it a key indicator for assessing the model's effectiveness in distinguishing different types of songket fabrics.

Table 1. Overall Experiment Results

No	Epoch	Batch Size	Learning Rate	Accuracy
1	5	32	0.0001	96.67%
2	7	32	0.0001	86.67%
3	10	32	0.0001	80.00%
4	15	32	0.0001	100.00%
5	30	32	0.0001	83.33%
6	40	32	0.0001	96.67%

Source: (Research Results, 2025)

Table 1 presents the overall results of the songket fabric classification experiment using different combinations of epochs, batch sizes, and learning rates. The findings indicate that at epoch 5, with a batch size of 32 and a learning rate of 0.0001, the model achieved an accuracy of 96.67%, demonstrating high performance. However, at epoch 7, despite keeping other parameters constant, accuracy dropped to 86.67%, suggesting that reducing the number of epochs may affect the model's ability to learn complex patterns. At epoch 10, accuracy further declined to 80%, potentially indicating that the model had reached its learning capacity or was experiencing overfitting. The highest accuracy of 100% was achieved at epoch 15, marking the optimal performance point. However, accuracy decreased to 83.33% at epoch 30 and then increased again to 96.67% at epoch 40, though it did not surpass the peak performance at epoch 15.

The model's 100% accuracy demonstrates optimal learning of songket motifs without signs of underfitting or overfitting. This performance is supported by several key factors. First, the fine-tuning approach on ResNet50V2, where only the last 50 layers are trained, allows the model to retain general image features from ImageNet while effectively adapting to the intricate patterns of songket fabric. Second, the use of the AdamW optimizer with a small learning rate (0.0001) stabilizes training by preventing extreme weight updates, enabling gradual and effective learning.

Additionally, balanced data distribution ensures that the model can recognize patterns from all classes without bias, preventing over-reliance on any specific motif. The incorporation of Batch Normalization and Dropout (0.4) further enhances stability, reducing the risk of overfitting and improving generalization to unseen data.

While the high accuracy confirms strong model performance, further evaluation using a larger and more diverse dataset is essential. This step will validate the model's robustness in real-world applications and ensure its ability to generalize across a wider variety of songket patterns.

CONCLUSION

Based on the results of the songket motif classification experiment using the fine-tuned ResNet50V2 model, it can be concluded that the model demonstrates excellent performance in classifying songket fabrics from the three regions: Sade, Sukarara, and Pringgasela. The evaluation results indicate that at epoch 15, the model achieved 100% accuracy, signifying that it successfully identified songket fabric patterns with high precision. Furthermore, selecting the optimal number of epochs played a crucial role in achieving the best performance, as increasing the number of epochs did not always yield better results and, in some cases, led to a decline in accuracy. The fine-tuning process on ResNet50V2, where only the last 50 layers were trained, combined with the use of the AdamW optimizer with a low learning rate (0.0001), proved effective in preventing overfitting and ensuring stable training. However, despite the exceptional classification results, there is still room for improvement in terms of model generalization. Further experiments involving additional training data, hyperparameter adjustments, or the exploration of more complex model architectures could enhance the model's performance across diverse conditions and datasets. Overall, this model exhibits significant potential for implementation in a songket fabric classification system with a high level of reliability. Nevertheless, further testing with larger and more varied datasets is necessary to ensure its robustness in real-world applications.

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