Classification Of Ulos Fabric Motifs Using MobileNetV3-Small Architecture

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Abstract: *Ulos fabric is an important cultural heritage of the Batak people in North Sumatra, characterized by diverse motifs and philosophical meanings that support social and ritual life. Public knowledge of Ulos motifs is declining due to lifestyle changes and limited use of digital technology for cultural education, so accurate image-based motif classification is needed for preservation and wider utilization. This study evaluates the performance of the lightweight MobileNetV3-Small architecture with a transfer learning approach for classifying Ulos motif images, positioning it as one of the earliest uses of MobileNetV3-Small for Ulos motif classification compared to previous Ulos studies that relied on heavier CNN or earlier MobileNet variants. The dataset consists of 906 images split into 80% training, 10% validation, and 10% testing, and the model is trained using the Adam optimizer with a batch size of 32 and learning rates of 0.001 and 0.0001. On the test data, the model achieves accuracies of 98.96% and 97.92%, with consistently high precision, recall, and F1-scores, demonstrating the effectiveness of MobileNetV3-Small for Ulos motif classification as a digital educational medium to support Batak cultural heritage preservation.*

Keywords: *Classification, Ulos Fabric, MobileNetV3-Small*

1. Introduction

Indonesia is known as an archipelago with extraordinary cultural wealth, and for the Batak Toba people in North Sumatra, Ulos is a traditional woven fabric that serves as both a work of art and a symbol of social and spiritual unity. Varieties of Ulos such as Ragi Hidup, Ragi Hotang, and Sibolang symbolize prayers, hopes, and prosperity and are used in various traditional ceremonies. However, modernization has led to a decline in understanding among the younger generation, a weakening of the weaving tradition, and limited digital documentation of the motifs and their meanings, making the preservation of Ulos an urgent need [1]. Ulos motifs also exhibit fine weaving textures, complex color compositions, and detailed geometric patterns that are often similar across motifs, influenced by variations in lighting, rotation, and fabric texture, making manual classification difficult and requiring an image processing approach that can reliably extract complex texture and pattern features [2]-[4].

Convolutional Neural Networks (CNN) have been widely used to recognize complex visual patterns in textile images and have proven to be superior to traditional methods such as Support Vector Machines (SVM) and K-Nearest Neighbors (KNN) [5]. CNN models such as FabricNet, which utilize Near-Infrared (NIR) images, achieve high accuracy and surpass the VGG and GoogleNet architectures, confirming the effectiveness of CNN for textile pattern recognition [6]. For implementation on resource-constrained devices, lightweight architectures such as

MobileNetV3, which uses inverted residual blocks, Squeeze-and-Excitation, and hard-swish activation functions, offer a combination of accuracy and computational efficiency, and several studies have shown that both MobileNetV3-Small and Large variants perform very well on textile image and complex object classification tasks [7]-[10].

Various studies on traditional Indonesian textiles report the success of CNN in recognizing distinctive regional motifs with accuracy above 98%, such as the Manggarai, Nage-Keo, and Ngada ikat weaving motifs, as well as batik and Sasirangan fabric motifs, which confirms CNN's ability to distinguish traditional fabric texture patterns with precision [11], [12]. However, in the specific case of Batak Toba Ulos, previous studies still rely on conventional CNN architectures and only report accuracies of 94% and 98.13% without exploring the more efficient and mobile-oriented MobileNetV3-Small architecture [13], [14]. This indicates a clear research gap in applying a modern lightweight CNN architecture that is both accurate and computationally efficient for Batak Toba Ulos motif classification.

Based on this gap, this study proposes a lightweight CNN approach based on MobileNetV3-Small that is optimized for the classification of Batak Toba Ulos motifs, explicitly positioning it as one of the earliest applications of MobileNetV3-Small to this cultural heritage context. This research aims to rigorously evaluate the ability of MobileNetV3-Small to produce high accuracy in Ulos motif classification with a lower computational load than conventional CNN, making it more suitable for deployment on edge or mobile devices while simultaneously supporting the preservation of Batak Toba culture through Ulos motif digitization and the development of digital educational media.

2. Methods

This study applies a CNN model using the MobileNetV3-Small architecture [15] for the classification of Ulos fabric motifs. The specifications of the MobileNetV3-Small architecture can be seen in Figure 1.

Input	Operator	exp size	#out	SE	NL	s
$224^2 \times 3$	conv2d, 3x3	-	16	-	HS	2
$112^2 \times 16$	bneck, 3x3	16	16	✓	RE	2
$56^2 \times 16$	bneck, 3x3	72	24	-	RE	2
$28^2 \times 24$	bneck, 3x3	88	24	-	RE	1
$28^2 \times 24$	bneck, 5x5	96	40	✓	HS	2
$14^2 \times 40$	bneck, 5x5	240	40	✓	HS	1
$14^2 \times 40$	bneck, 5x5	240	40	✓	HS	1
$14^2 \times 40$	bneck, 5x5	120	48	✓	HS	1
$14^2 \times 48$	bneck, 5x5	144	48	✓	HS	1
$14^2 \times 48$	bneck, 5x5	288	96	✓	HS	2
$7^2 \times 96$	bneck, 5x5	576	96	✓	HS	1
$7^2 \times 96$	bneck, 5x5	576	96	✓	HS	1
$7^2 \times 96$	conv2d, 1x1	-	576	✓	HS	1
$7^2 \times 576$	pool, 7x7	-	-	-	-	1
$1^2 \times 576$	conv2d 1x1, NBN	-	1280	-	HS	1
$1^2 \times 1280$	conv2d 1x1, NBN	-	k	-	-	1

Figure 1. MobileNetV3-Small Architecture Specification

The design stage in this study for the classification of Ulos cloth motifs using the MobileNetV3-Small Architecture was carried out in stages including dataset preparation, preprocessing, dataset division, image augmentation and noise addition, feature extraction, and model evaluation. The design stage can be seen in Figure 2.
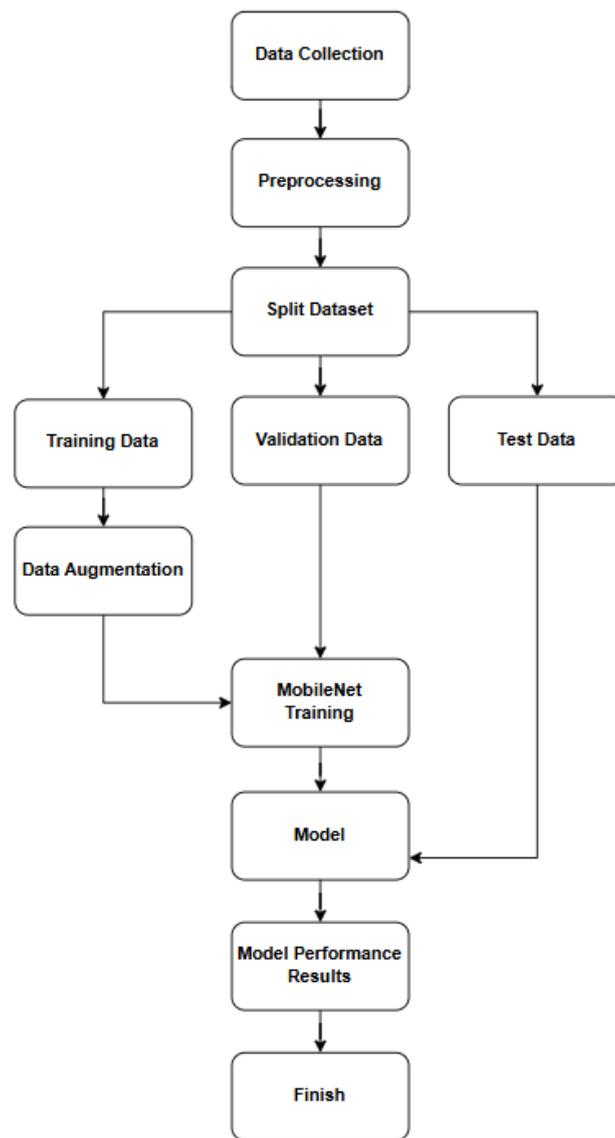
Figure 2. Research Flow

A. Data Collection

The initial dataset of Ulos fabric images was obtained from the Roboflow platform (https://universe.roboflow.com/usu-ukmth/ulos/dataset/4), which contained 962 images from six classes: Bintang Maratur, Mangiring, Ragi Hidup, Ragi Hotang, Sadum, and Sibolang. Although the original dataset is available in annotated form with bounding boxes, this study only uses the raw images without annotations. Each image was reviewed individually to ensure that only samples clearly and completely displaying the Ulos motif were used. Images dominated by background elements such as tables, chairs, or other non-Ulos objects were considered unrepresentative and removed. After this cleaning process, 56 images were discarded and 906 images remained, with a balanced distribution of 151 images per class. All images are in .jpg format, have an original resolution of 600×600 pixels, and are stored in class-specific folders with numeric file names used consistently to facilitate subsequent processing. The dataset description is summarized in Table 1.

Table 1. Ulos Fabric Dataset

Class	Images	Number of Samples
Bintang Maratur		151
Mangiring		151
Ragi Hidup		151
Ragi Hotang		151
Sadum		151
Sibolang		151
Total		906

B. Preprocessing

Once the dataset was prepared, each image was verified to be in three-channel RGB format. The images were then resized to 224 × 224 pixels to match the input size required by MobileNetV3-Small. After resizing, pixel values were converted to the float32 data type and normalized to the range 0–1 by dividing each pixel value by 255. This normalization step ensures a consistent scale and more stable distribution of pixel values, which facilitates effective learning of Ulos motif patterns during model training.

C. Split Dataset

After preprocessing, the 906 images were divided into three subsets: training, validation, and test data. The splitting proportions were 80% for training, 10% for validation, and 10% for testing, resulting in 725 training images, 91 validation images, and 90 test images. A stratified splitting strategy was employed so that each subset preserved the class distribution of the original dataset. This proportional division helps keep the training process balanced across classes, allows more accurate monitoring of model performance on the validation set, and provides an objective evaluation on the test set without bias toward particular classes.

D. Data Augmentation

Data augmentation was applied only to the training set to increase image diversity and improve the model's ability to generalize Ulos fabric patterns from a limited amount of data. The augmentation pipeline included horizontal and vertical flips, small random rotations (about $\pm10°$), and random zooming (about $\pm10\%$) so that the model becomes robust to changes in orientation and scale. In addition, random contrast and brightness adjustments (both within about $\pm10–12\%$) were used to simulate different lighting conditions, while random cropping was applied to mimic partial views of the fabric. To further simulate real-world visual disturbances such as illumination variations and subtle camera noise, Gaussian noise with a probability of 20% and a standard deviation of 0.01 was added to the training images. These augmentation and noise strategies were designed to enhance robustness; however, this study does not perform a separate ablation or comparison experiment between models trained with and without augmentation/noise, and this limitation is noted as a direction for future work. The validation and test sets were kept in their original form to ensure an objective evaluation.

E. MobileNet Training

MobileNetV3-Small was chosen as the backbone because it is an efficient, lightweight CNN capable of extracting salient visual features with low computational complexity. The model was initialized using ImageNet pre-trained weights so that generic visual features could be reused for Ulos motif recognition. The original classification head was removed using the include_top =False setting and replaced with a Global Average Pooling layer, a Dropout layer, and a Dense layer with Softmax activation for six-class classification. Global Average Pooling summarizes spatial feature maps into a compact representation, Dropout reduces overfitting by randomly deactivating neurons, and the Softmax layer outputs class probabilities for each Ulos motif.

F. Model

Model training was carried out using the augmented training set and the unmodified validation set for up to 50 epochs with a batch size of 32. The Adam optimizer was used with two learning-rate configurations, 0.001 and 0.0001, to compare their effect on convergence and classification performance. A fine-tuning strategy was applied by freezing the early layers of MobileNetV3-Small and only training the higher-level layers and new classification head so that generic features from ImageNet were preserved while the model adapted to Ulos-specific patterns. Early stopping was employed with a patience of several epochs, automatically terminating training when the validation loss stopped improving, thereby limiting overfitting and unnecessary computation without requiring a detailed epoch-by-epoch description.

G. Model Performance Results

After training, the final model was evaluated on the held-out test set, which did not undergo any augmentation or noise addition. Evaluation metrics included accuracy, precision, recall, F1-score, and the confusion matrix to assess the reliability of the model in recognizing Ulos fabric motifs on unseen data. These results form the basis for assessing the effectiveness of the MobileNetV3-Small architecture for Ulos motif classification.

3. Results and Discussion

The results of the implementation and evaluation of the CNN model were analyzed in depth through a series of experiments designed to obtain the most optimal hyperparameter configuration in the MobileNetV3-Small architecture. At this stage, testing was carried out by varying the learning rate values, namely 0.001 and 0.0001, using the Adam optimizer and a batch size of 32 as the main training settings. The complete results of the MobileNetV3-Small model testing can be seen in Table 2.

Table 2. Model Test Results

Learning Rate	Accuracy	Precision	Recall	F1-Score
0.001	*0.9896*	0.9902	0.9806	0.9896
0.0001	0.9792	0.9815	0.9792	0.9791

Table 2 shows the test results of the MobileNetV3-Small classification model using the Adam optimizer, a batch size of 32, and two learning rates, 0.001 and 0.0001. With a learning rate of 0.001, the model attains an accuracy of 0.9896, precision of 0.9902, recall of 0.9806, and an F1-score of 0.9896, most test samples are correctly classified with an excellent balance between precision and recall.

For a learning rate of 0.0001, the accuracy (0.9792), precision (0.9815), recall (0.9792), and F1-score (0.9791) are slightly lower but still high. These differences suggest that a learning rate of 0.001 enables larger weight updates, allowing Adam to escape shallow minima and find more discriminative weight configurations, whereas the very small step at 0.0001 slows convergence and may lead to less optimal solutions within the same number of epochs. Overall, under the training scheme used in this study, the configuration with a learning rate of 0.001 provides the best performance. However, no statistical significance tests or confidence interval analyses were conducted, so the superiority of the 0.001 configuration remains indicative and should be corroborated in future work through repeated runs or k-fold cross-validation with confidence interval calculations.
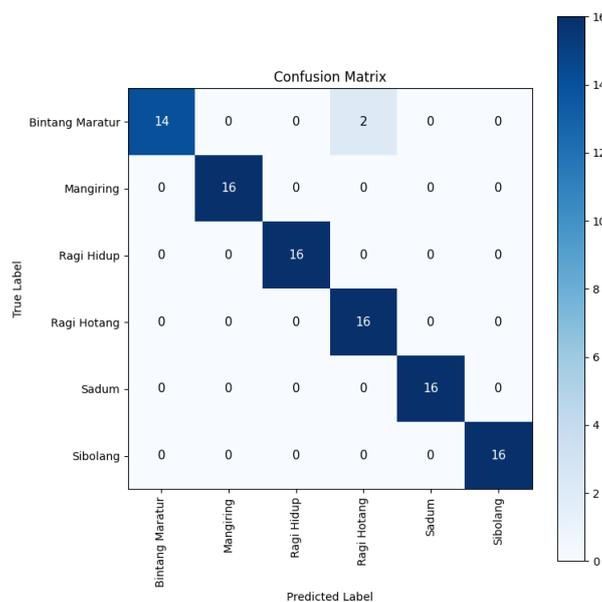

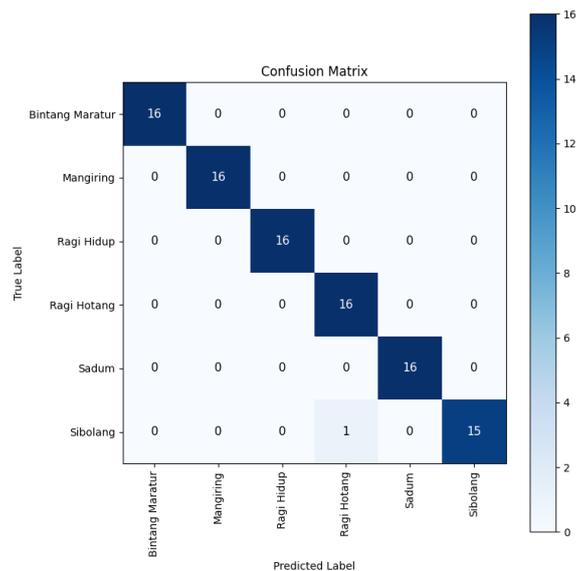**Figure 3.** Confusion Matrix learning rate 0.0001

Figure 4. Confusion Matrix learning rate 0.001

Figure 3 shows the confusion matrix of the MobileNetV3-Small model with a learning rate of 0.0001. Each Ulos motif class has 16 test images, with the vertical axis representing true labels and the horizontal axis model predictions. Most classes are perfectly recognized, while the only misclassifications occur in the Bintang Maratur class, where 14 images are correctly classified and 2 are predicted as Ragi Hotang, indicating a remaining difficulty in distinguishing these two visually similar motifs despite overall high performance.

Figure 4 presents the confusion matrix for the same configuration using a learning rate of 0.001. Here, all images from the Bintang Maratur, Mangiring, Ragi Hidup, Ragi Hotang, and Sadum classes are correctly classified (16 on the diagonal), while only one Sibolang image is misclassified as Ragi Hotang. This produces a prediction distribution that is more concentrated along the main diagonal with fewer off-diagonal errors, suggesting that the larger update step at 0.001 helps the model better separate motif patterns. Overall, the confusion matrices show that a learning rate of 0.001 yields fewer misclassifications and more cells with the maximum value on the main diagonal than 0.0001. In contrast, the 0.0001 configuration still produces some errors, particularly for classes with similar patterns. These visual results are consistent with the higher accuracy, precision, recall, and F1-scores obtained at 0.001, empirically indicating that this setting provides more accurate and reliable Ulos motif recognition with MobileNetV3-Small under the same experimental conditions.
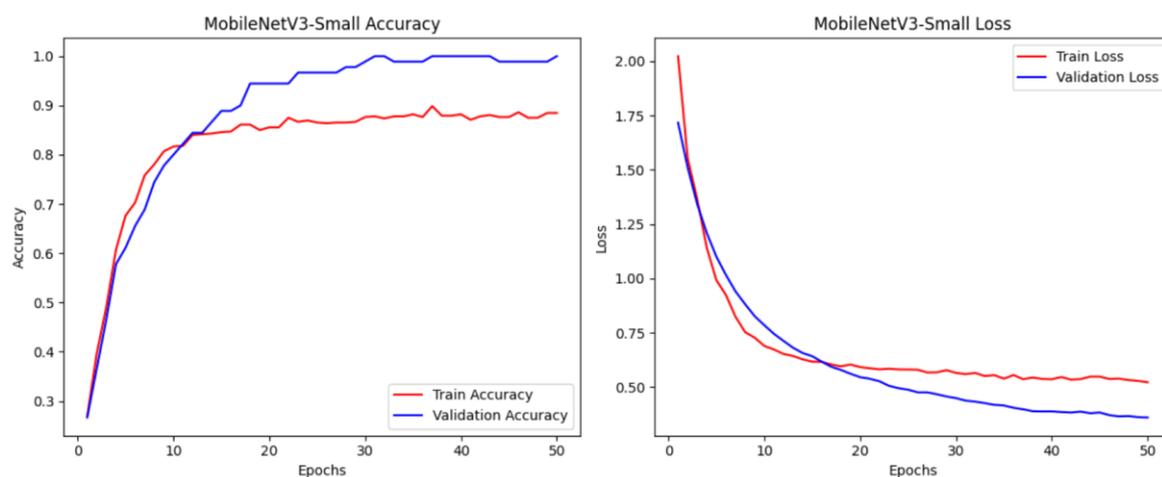

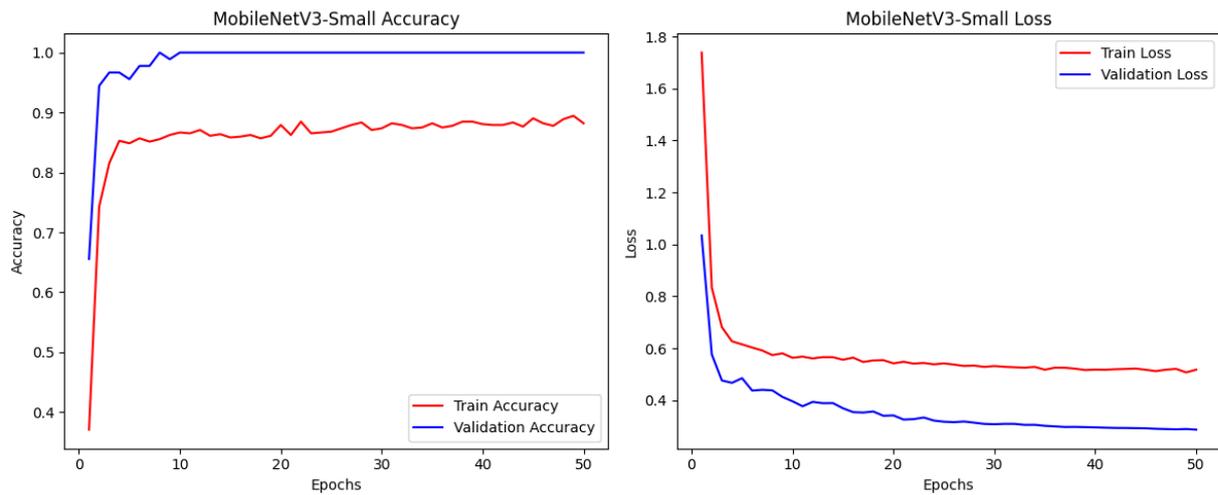**Figure 5.** Accuracy graph and learning rate 0.0001

Figure 6. Accuracy graph and learning rate 0.001

Figure 5 shows the accuracy and loss curves of the MobileNetV3-Small model trained with a learning rate of 0.0001 for 50 epochs. Training and validation accuracy rise sharply in the early epochs and then stabilize at high values, with validation accuracy reaching around 0.98–0.99 and training accuracy around 0.87–0.90. The loss curves start above 2.0, then drop steeply in the first 10 epochs and flatten, with validation loss slightly lower than training loss and decreasing to about 0.35–0.40, indicating steadily reduced prediction error and stable learning without clear overfitting at this learning rate.

Figure 6 shows the accuracy and loss curves for a learning rate of 0.001 over 50 epochs. Both training and validation accuracy quickly exceed 0.80 within the first 3–5 epochs, and validation accuracy reaches around 0.98–0.99 at the end, while training accuracy remains around 0.84–0.88, yielding a somewhat larger gap than in Figure 5. The loss values fall from above 1.2 to about 0.55–0.60 (training) and 0.35–0.40 (validation), with validation loss decreasing faster, indicating a more aggressive and efficient learning process that attains lower validation loss and high accuracy in fewer epochs compared to the 0.0001 configuration.

Although the configuration with a learning rate of 0.001, Adam, and batch size 32 produces very high accuracy, precision, recall, and F1-scores close to 99%, these results must be interpreted cautiously because such extreme performance can signal data bias or data leakage. To mitigate this risk, the dataset was split into three mutually exclusive subsets (training, validation, and test) so that each image appears in only one subset; however, further evaluation on truly independent data and with more rigorous partitioning schemes is still needed to ensure that the high performance truly reflects the model's generalization ability rather than artifacts of the dataset.

4. Conclusions

This study demonstrates that the MobileNetV3-Small architecture successfully classifies six Ulos fabric motifs with very high performance, achieving a best test accuracy of 98.96% at a learning rate of 0.001 and consistently high precision, recall, and F1-scores across almost all classes. However, the experiments are limited to six motif categories, a single curated dataset, and relatively controlled image conditions, so the extent to which the model generalizes to other Ulos motifs, more diverse lighting and background settings, different camera devices, and truly independent datasets remains uncertain and should be examined in future work through broader data collection and cross-dataset evaluations. From a practical deployment perspective, especially on mobile or edge devices, the current model still needs to be adapted to real-world constraints such as limited computation, memory, storage, and battery life; therefore, additional steps such as

model pruning or quantization, latency and energy-consumption measurements on various smartphone specifications, and usability testing in actual Ulos identification scenarios are required before the system can be reliably adopted as a large-scale digital tool for Batak cultural preservation.

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