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Songket Motif Classification using MobileNet Architecture for Cultural Heritage Preservation

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Abstract

Cultural heritage is a nation's identity that must be preserved. In Bali, Indonesia, Songket is a very valuable cultural heritage. There are several famous Songket motifs, such as Bunga Pucuk, Naga, Cangkir, Bintang, and Wayang. Unfortunately, many people have difficulty distinguishing the existing motifs. In this case, the use of CNN is one of the most proven effective ways to overcome this problem. In this study, we utilized MobileNetV2 to train the detection model with K-Fold Cross Validation to validate the model's performance. According to the experimental result, we can obtain the best performance with accuracy=99.98%. In addition, we conducted usability testing with the System Usability Scale (SUS) that showed an average score of 86.33 as the "Best Imaginable" category. This research is expected to support cultural preservation and support the digital promotion of local Songket.

Keywords:
Songket, Motif, Classification, MobileNet, CNN

1. Introduction

Culture is a very valuable and priceless heritage that has been passed down from generation to generation by ancestors, and this reflects the identity, character, and richness of a nation [1]. Indonesia is known as a country rich in cultural heritage, one of which is traditional fabrics that have high aesthetic and philosophical value. Among the various traditional Balinese fabrics, Songket is one of the cultural heritages that is full of artistic and symbolic value. Jinengdalem Village, Buleleng, is one of the villages that produces Songket with distinctive motifs. Songket motifs (decorative motifs) in Buleleng are generally grouped into five categories, namely, geometric decorative motifs, floral decorative motifs (plants), fauna decorative motifs (animals), human decorative motifs, and mixed decorative motifs (prembon) [2]. Of the five categories, in this study, only one motif was taken from each category. The motifs used are *cangkir* motifs (prembon), bunga pucuk motifs (flora), bintang motifs (geometric), wayang motifs (humans), and naga motifs (fauna) [3].

Although they have different motif themes, as time goes by, manual recognition of these motifs is becoming increasingly difficult, especially because there are visual similarities between motifs that can confuse the general public. This problem can be overcome using methods such as a Convolutional Neural Network (CNN). CNN has been proven to be able to recognize visual patterns effectively in various fields, such as in the case of cultural inheritance using the CNN method to distinguish Solo batik motifs with 7 motif classes, namely Parang, Semenrante, Sidomukti, Ceplok, Kawung, Truntum, and Buketan motifs,

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which achieve an accuracy of 95% [4]. One of the architectures developed from this CNN method, which is very suitable for application in mobile, is MobileNetV2. MobileNetV2 is a CNN architecture specifically designed for mobile devices because of its light weight and memory efficiency, such as its application in a case study of melanoma skin cancer detection represented in an Android-based system with 93% accuracy and Black Box Testing [5]. Then there is also a classification of 3 types of brain tumors, namely Glioma, Pituitary, and Meningioma, which have similar characteristics. However, MobileNetV2 can operate even with a limited data set of approximately 186 images. The performance achieved was quite good, yielding 83% accuracy on the validation data and 78% on the testing data [6].

This research focuses on the development of a MobileNetV2-based classification model. The research was limited to only six Songket motifs, using the MobileNetV2 architecture as the sole model. Due to the limited number of original images, the data used was enhanced through augmentation techniques to produce a more robust model. The results are expected to contribute to cultural preservation through technological approaches and help the public recognize Songket motifs quickly and accurately. This paper is structured as follows: Section 2 discusses related research, Section 3 explains the methods used, Section 4 presents the experimental process, Section 5 presents the results, and Section 6 provides conclusions.

2. Related Works

Culture is a valuable heritage that reflects the identity of a nation. It is important to ensure that the younger generation knows about it to maintain its sustainability. There are many ways to do this, such as building artificial intelligence that can distinguish fabric motifs, as in [7], using the CNN method for the classification of Sabu Raijua Woven Fabric Motifs, which obtained an overall accuracy of 85%. CNN was also used for the classification of West Sumatran clay batik with an accuracy of 98.75% on training data and 62.5% on test data [8]. [9] obtained an accuracy of 73.33% on validation data for batik classification using Efficient Net-B0. [10] used MobileNetV2 to classify Semarang batik motifs with 3,020 images and produced an accuracy of 100% on validation data. The classification of Rote Ndao Woven motifs was carried out by building a MobileNetV2 plus Dropout architecture model and using a Learning Rate of 0.0003, which was trained and evaluated using K-Fold Cross Validation with a value of K = 5, obtaining an accuracy of 93% [11]. [12] classified 4 types of Pandai Sikek Songket cloth motifs with the classes Balah Kacang, Salapah, Cukia Barantai, and Sirangkak, with each motif consisting of 50 images using MobileNetV2. In the test, a comparison of training data and test data was carried out by means of data splitting, such as 70%: 30%, 80% : 20%, and 90% : 10%. The results of the model accuracy for each data splitting were 100%, 100%, and 72.22%. The best model was at a ratio of 90%: 10%, and there was no overfitting. In addition, MobileNetV2 also had many successes, such as research that utilized MobileNetV2 with transfer learning for the task of identifying moving cargo [13]. Complementing this achievement, other research used MobileNetV2 with transfer learning to detect fruit freshness [14]. In addition, MobileNetV2 with transfer learning was also used to recognize vehicle license plate colors in small data sets from CCPD and PKU vehicle data sets [15]. MobileNetV2 was used to classify chili pepper quality and outperformed other models [16].

In conclusion, many methods have been used to classify fabric motifs, such as songket, woven fabrics, and batik. MobileNetV2 is one of them and is most suitable because it is designed to run on mobile devices. Furthermore, MobileNetV2 also performs well even when the fabric motif data is not included. This study aims to recognize the *cangkir* motif (prembon), the *bunga pucuk* motif (flora), the *bintang* motif (geometric), the *wayang* motif (human), the *naga* motif (fauna), and motifs from outside Jineng Dalem village.

3. Proposed Method

In this study, a series of systematic steps was carried out to ensure the effectiveness and reliability of the research process. These steps included the collection of Songket motif data, obtained from local sources in Jinengdalem Village, particularly Poni Songket, and from other areas outside Jinengdalem to ensure a wider representation of motif variations. This was followed by motif categorization based on their distinctive visual characteristics. The next step involved data preprocessing, which aimed to improve the quality and consistency of the input data through techniques such as resizing, normalization, and noise reduction. After that, an appropriate architectural model was designed according to the research objectives. The model was then trained using the prepared dataset, allowing it to learn relevant patterns and features. After that, the model underwent a comprehensive evaluation to assess its performance and generalization capabilities based on predetermined metrics. This study also used the Research and Development (R&D) method with a Prototype method approach to develop the mobile application. The Research and Development (R&D) method is a research methodology that has a primary focus on developing and testing new products or improving existing products [17]. Finally, the model will be implemented into a mobile application called ISongket, which will also be evaluated using blackbox, whitebox, and usability testing methods with the System Usability Scale.

In this study, we conduct data collection to ensure the quality of input in the training and evaluation stages of the classification model. The dataset used consists of images of Songket cloth motifs taken directly from the production site, namely Poni Songket, located in Jinengdalem Village. Images were taken using a digital camera to obtain high-quality images. Each image was taken in good lighting conditions so that the details of the motifs can be clearly recorded. In addition, images were also taken from various angles to increase diversity in the dataset. The standard size of each image is 1200 x 1600 pixels with a horizontal and vertical resolution of 96 dpi and a color depth of 24 bits. The images were then grouped into five categories based on the type of Songket motif. *Cangkir* motif, a motif featuring floral patterns with a predominance of dark red and pink, consisting of 33 images. *Bunga Pucuk* motif, a motif dominated by dark purple and gold, featuring floral patterns that blend with leaves, consisting of 21 images.

The *Bintang* motif combines purple, pink, and brown with geometric shapes such as flowers and petals. It consists of 21 images. The *Wayang* motif features a silhouette of a figure with outstretched arms and legs, using geometric patterns in pink and gold as the base colors. It consists of 32 images. The *Naga* motif features a dragon with white heads, yellow eyes, and mouths emitting fire. It consists of 10 images. Furthermore, this study added a class, Unknown. This class consists of 7 images of Songket motifs originating from outside Jinengdalem Village. This aims to test the model's ability to recognize motifs originating from Jinengdalem Village and classify non-Jinengdalem motifs into the previously created Unknown class.

After the images were collected and categorized, a preprocessing stage was carried out to ensure that the data used in model training was of adequate quality and diversity. The preprocessing stage began by removing images with noise, blurriness, or low quality to maintain classification accuracy. The next step is to select the images so that only high-quality images will proceed to the next stage. The images are then resized to 224 x 224 pixels and then normalized. The next important step is data augmentation to increase and enrich the dataset's variety. Augmentation techniques help the model recognize motifs from various angles and lighting conditions. The augmentation techniques used in this study include rotation, zoom, position shifting, and flipping. The result of this process is 100 images for each motif class. An example of the data used in this study can be seen in Fig 1.

Fig. 1. Sample of Dataset

MobileNetV2 is used in this study to classify Jinengdalem Songket motifs. The procedure begins with an Input Layer, which receives a 224x224 pixel image. Next, Depthwise Separable Convolution is used, which divides the convolution process into two parts, namely, depthwise convolution and pointwise convolution. This method significantly reduces the number of parameters, making it more suitable for mobile devices. Furthermore, the ReLU activation function is used to introduce nonlinearity, allowing the model to learn complex patterns from images [18]. Each convolutional layer is also equipped with Batch Normalization, which speeds up training and reduces the risk of vanishing gradients. A fully connected layer then connects the extracted features to the final components of the model, and the Output layer generates classification probabilities for each class using the Softmax activation function. This approach allows the model to classify patterns based on the confidence level of the prediction results, which are then displayed to the user through the application [19]. The MobileNetV2 architecture can be seen in Fig. 2.

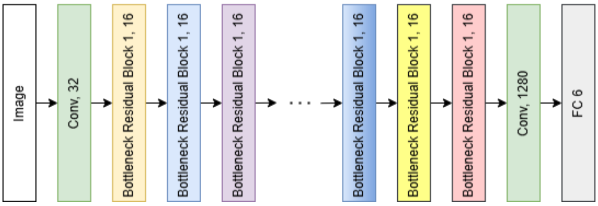

Fig. 2. MobileNetV2 Architecture

In this study, we construct a mathematical formulation for Jinengdalem Songket Classification using MobileNet Architecture as follows:
Let an input Songket image be denoted as

$$\mathbf{X} \in \mathbb{R}^{H \times W \times C},$$

where H, W, and C represent the image height, width, and number of channels, respectively.
MobileNet employs depthwise separable convolution, which factorizes standard convolution into two operations: depthwise convolution and pointwise convolution. The depthwise convolution is defined as

$$\mathbf{Y}_d(i,j,k) = \sum_{m,n} \mathbf{X}(i+m, j+n, k) \cdot \mathbf{K}_d(m,n,k), \tag{1}$$

where $\mathbf{K}_d$ is a depthwise filter applied independently to each channel k.

The pointwise convolution then combines channel-wise features using a 1×1 convolution:

$$\mathbf{Y}_p(i,j,l) = \sum_{k} \mathbf{Y}_d(i,j,k) \cdot \mathbf{K}_p(k,l), \tag{2}$$

where $\mathbf{K}_p$ is the pointwise kernel mapping features to the output channel l.
After several stacked MobileNet blocks, global average pooling produces a feature vector $\mathbf{f}$. The final classification layer uses a Softmax function to predict the Songket motif class:

$$\hat{y}_c = \frac{e^{\mathbf{w}_c^\top \mathbf{f}}}{\sum_{k=1}^{K} e^{\mathbf{w}_k^\top \mathbf{f}}} \tag{3}$$

where K is the number of Jinengdalem Songket motif classes.
Model training minimizes the categorical cross-entropy loss:

$$\mathcal{L} = -\sum_{c=1}^{K} y_c \log(\hat{y}_c) \tag{4}$$

ensuring efficient and accurate classification while preserving computational efficiency, making MobileNet suitable for cultural heritage image recognition and deployment on resource-constrained devices.

In this study, we adopt MobileNetV2 to build a classification model due to its efficiency and suitability for mobile devices. TensorFlow was used to train the model, which included the Adam optimizer and ReLU and Softmax activation functions for the output. The dataset was split using a K-Fold Cross Validation approach with a K value of 5 to prevent overfitting and allow for thorough model testing [20][21][22]. The main parameters used were a learning rate of 0.0001, a batch size of 32, and 55 training epochs. Accuracy, precision, recall, and F1-score measures were used to evaluate the model. A 6x6 confusion matrix was also used, as there are 6 classes. For more robust results, all model training sessions used a k-fold validation technique with 5 folds. To avoid overfitting, a dropout approach was also employed. Dropout(0.4) was used to randomly remove neurons during training. Furthermore, there are two testing scenarios used, namely, (1) testing with internal data from Jinengdalem and (2) testing with external data outside the Songket motifs used in training.

4. Result and Analysis

A. This *Model Performance Evaluation*

At this stage, the model is evaluated using accuracy, precision, recall, and F1-score. Table 1 below shows the combined results from five folds, while Fig. 3 shows an example of a confusion matrix from one-fold.

TABLE 1. MOBILENETV2 PERFORMANCE

Motif	Precision	Recall	F1-Score	Support
Star	1.00	1.00	1.00	500
Flower Bud	1.00	1.00	1.00	500
Cup	1.00	1.00	1.00	500
Dragon	1.00	1.00	1.00	500
Unknown	1.00	1.00	1.00	500
Wayang	1.00	1.00	1.00	500
Accuracy			1.00	3000
Macro avg	1.00	1.00	1.00	3000
Weighted avg	1.00	1.00	1.00	3000

The evaluation results show that each class achieved 100% accuracy, precision, recall, and F1-score. As can be seen in Table 1 and Figure 2, all predictions fall on the main diagonal, indicating no misclassification errors in the internal data. This demonstrates that the model is highly capable of recognizing patterns in training scenarios using augmented data. The evaluation results demonstrate that the use of K-Fold Cross Validation reduces bias, although even with small and random datasets, the results can still be optimal [23]. To improve the objectivity of the model's generalization, external dataset testing will also be conducted.

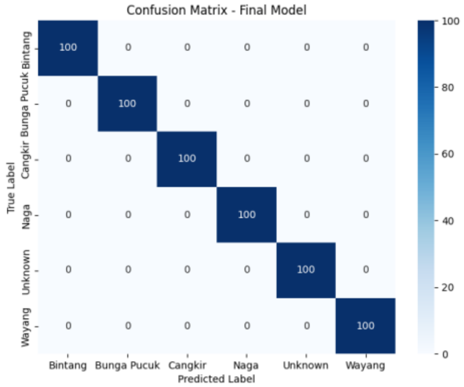

Fig 3. Confusion Matrix

B. Testing Model

After training was completed, testing was conducted on the previously used training dataset and an external dataset, which was new data, to evaluate the algorithm's ability to generalize to previously unseen data. Detailed results from the two test scenarios can be seen in Tables 2 and 3.

TABLE 2. PERFORMANCE ON TRAINING DATA

No	Motif Name	Motif Recognition Rate (%)
1	Star	99.99
2	Flower Bud	100.0
3	Cup	100.0
4	Dragon	100.0
5	Unknown	99.90
6	Wayang	99.99
Mean		99.98

TABLE 3. PERFORMANCE ON EXTERNAL DATA

No	Motif Name	Recognized Motifs	Motif Recognition Rate (%)
1	Star	Star	98.00
2	Flower Bud	Star	43.00
3	Cup	Flower Bud	33.00
4	Dragon	Wayang	53.00
5	Unknown	Unknown	77.00
6	Wayang	Dragon	86.00
Mean			65.00

The test results in Tables 2 and 3 show that the model performed very well in recognizing the training data with an average accuracy of 99.98%. However, when tested on external data, the results fluctuated significantly. For example, the Bintang motif was recognized with 98.00% accuracy, but decreased for other motifs, particularly the *cangkir* motif, which was recognized by only 33.00%. This indicates that the model still struggled to distinguish between motifs with underrepresented data in terms of shape variation during the training process.

Furthermore, changes in weaving quality between weavers can also impact accuracy by producing uneven visual detail even when the motif is identical. The average accuracy for all motifs in this test was 65.00%, indicating that the model's generalization is still limited. Therefore, supplementing the training data with a wider variety of photographs, including different shooting angles and weaving styles, is crucial to enhance the model's resilience to visual changes and improve classification accuracy on new and more varied data.

C. Application Development

At this stage, MobileNetV2 was implemented in an Android-based mobile application called iSongket to classify pre-trained motifs, ensuring its practical use in everyday life. The programming language used was Kotlin, and Android Studio was the IDE, with the integration of a classification model in TensorFlow Lite (TFLite) format. The iSongket application was also tested for functionality and user experience. Functional testing was conducted using two methods: black box and white box [24]. The purpose of black box testing is to determine whether every aspect of the application operates according to the designed functional specifications [25].

The black box testing results showed that all key application functions, such as image selection, classification, and displaying motif prediction results, functioned properly and without errors or failures. Every test scenario was completed, including responding to incorrect input and testing functional limits. This indicates that the iSongket application meets basic functional requirements and is ready for use by end users in real-world scenarios. A screenshot of the iSongket application can be seen in Fig 4.

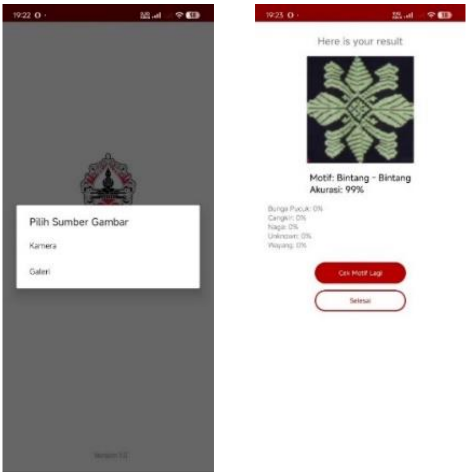

Fig 4. Black box testing

Meanwhile, white box testing involves tracing the code logic and program execution flow in critical areas of the application, such as the loadModelFile(), classifyImage(), and convertBitmapToByteBuffer() functions. This testing ensures that the image processing and classification workflows align with the model design. The results showed no logical errors or technical challenges in integrating the MobileNetV2 model into the Kotlin-based Android application.

To evaluate the quality of the user experience (usability), the System Usability Scale (SUS) questionnaire was used. Fifteen general users responded to the questionnaire. Detailed SUS results can be seen in Table 4.

TABLE 4. SUS INITIAL SCORE

No	Responden	Skor Asli									
		Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
1	Responden 1	4	1	5	1	5	1	5	1	5	1
2	Responden 2	5	1	5	2	5	2	4	1	4	1
3	Responden 3	5	1	5	1	5	1	5	1	4	2
4	Responden 4	4	1	5	1	5	2	5	1	5	1
5	Responden 5	3	1	5	2	4	2	4	1	3	1
6	Responden 6	3	1	5	2	5	1	4	1	4	1
7	Responden 7	3	1	5	1	4	1	3	2	4	1
8	Responden 8	4	2	4	1	4	1	4	2	3	2
9	Responden 9	2	4	5	2	5	1	3	1	4	4
10	Responden 10	3	1	5	2	4	2	3	2	3	2
11	Responden 11	4	1	5	1	5	1	5	1	5	1
12	Responden 12	3	1	5	1	5	2	5	2	4	1
13	Responden 13	5	1	4	2	4	1	5	2	4	2
14	Responden 14	5	1	5	1	5	1	5	1	5	1
15	Responden 15	2	1	5	1	5	1	4	2	4	3

The average SUS score was 86.33, which is in the "Best Imaginable" category. This indicates that the iSongket program is not only accurate in its classification but also easy to use and comfortable for general users. This assessment demonstrates that the application of deep learning technology in the form of a smartphone application is well-received and effectively supports the digital preservation of the Songket tradition.

5. Conclusion

This study successfully developed an image classification system for Jinengdalem Songket motifs using the MobileNetV2 architecture, focusing on five distinctive patterns: Bunga Pucuk, Naga, Cangkir, Bintang, and Wayang. To address the challenge of limited dataset availability, K-Fold Cross Validation and data augmentation techniques were applied, ensuring robust training and improved generalization performance. The experimental results demonstrate that the proposed model achieved an outstanding classification accuracy of 99.98%, validated through both black-box and white-box testing approaches, indicating high reliability and consistency in motif recognition.

In addition to technical performance, this research also evaluated the system from a user perspective. Usability testing using the System Usability Scale (SUS) yielded an average score of 86.33, which falls into the “Best Imaginable” category. This result confirms that the developed system is not only accurate but also user-friendly and suitable for practical deployment, particularly for artisans, cultural practitioners, and educational institutions. Overall, the findings highlight the strong potential of lightweight deep learning models such as MobileNetV2 in supporting digital documentation, preservation, and promotion of traditional cultural heritage. For future work, the integration of object detection methods such as YOLO is recommended to enable real-time motif localization and classification, thereby enhancing the robustness and applicability of the system in more complex and dynamic environments.

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