Implementation of Convolutional Neural Network (CNN) Approach for Classification of Lampung Textile (Tapis)

Putra Pribowo[1], Admi Syarif[2] and Favorisen R. Lumbanraja[3]

[1]Magister Program of Computer Science, Faculty of Mathematics and Sciences, Lampung University, Lampung, Indonesia, 35145
[2, 3]Department of Computer Science, Faculty of Mathematics and Sciences, Lampung University, Bandar Lampung, Indonesia, 35145
admi.syarif@fmipa.unila.ac.id

Abstract. Lampung is one of the provinces in Indonesia which is renowned for its rich cultural heritage. Among its internationally famous legacies is the Tapis Lampung. It is a woven fabric crafted using traditional weaving techniques and embellished with gold or silver threads. Within the Lampung community, Tapis serves as traditional attire, a symbol of social status, and a marker of cultural identity. There are at least ten types of Tapis Lampung, including Raja Tunggal, Raja Medal, Laut Linau, Laut Silung, Jung Sarat, Balak, Cucuk Andak, Pucuk Rebung, Pucuk Pinggir, and Tuho motifs. Each type typically features distinct patterns and colors, making the identification and classification of Tapis cloth very difficult tasks and usually only done by experts. Recently, as the use of Artificial Intelligence has gained popularity, there have been many reports on the success of AIs for image classification. Among them, Convolution Neural Network (CNN) has been reported as an approach that achieves a high accuracy. This research aims to evaluate the performance of CNN for the identification and classification of Tapis Lampung. The approach will distinguish different types of Tapis cloth by their motifs. Several numerical experiments have been done by using some images given and collectors of Tapis Lampung. The results by the approaches are evaluated by comparing to those given by experts.

Keywords: Machine Learning, Tapis Lampung, Classification, Convolution Neural Network (CNN), Lampung

1 Introduction

Indonesia has a rich and diverse textile heritage that reflects its cultural, ethnic, and historical diversity. Traditional Indonesian textiles, such as batik, songket, ikat, and woven fabrics, have long been recognized nationally and internationally, carrying strong cultural identities from various regions across the archipelago. Each region in Indonesia has its own distinctive characteristics in producing textiles, in terms of techniques, motifs, and materials used. For example, Batik from Java is recognized as a Cultural Heritage by UNESCO, while Songket from Sumatra, woven with gold threads,

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symbolizes luxury and social status in traditional societies. Indonesian traditional textiles are often used in various traditional ceremonies, showcasing the importance of textiles in the social and spiritual lives of the people. In addition, modern technology, such as Artificial Intelligence (AI), has begun to be applied to preserve and promote Indonesian textile heritage more efficiently, one of which is through digital image processing that facilitates the identification and classification of textile patterns. One traditional textile that is being explored using artificial intelligence technology is Tapis cloth from Lampung.

Lampung is known for its rich cultural heritage, particularly the Tapis fabric, which has gained national and international recognition. Tapis is a traditional textile distinguished by its weaving technique using gold or silver threads, symbolizing the cultural identity of the Lampung people. This fabric comes in various designs, such as Raja Tunggal, Raja Medal, Laut Linau, Laut Silung, Jung Sarat, Balak, Cucuk Andak, Pucuk Rebung, Pucuk Pinggir, and Tuho, each with distinct patterns and colors. Traditionally, the identification of various types of Tapis cloth has been carried out by experts based on their experience and understanding of the fabric's patterns and motifs. However, with the development of AI technology, a new approach now assists in the identification and classification of Tapis fabrics. AI has proven to be highly useful in processing digital images, offering innovative solutions for complex challenges like pattern recognition in traditional textiles. In recent years, AI has become increasingly popular for solving real-world problems, particularly in digital image processing. Previous research has shown promising results in applying AI to image recognition, including recognizing motifs in traditional fabrics [1], [2], [8].

The use of Convolutional Neural Networks (CNN), one of the most popular AI techniques for image recognition, achieved an accuracy of 93% in recognizing images of Wayang Golek [9]. Additionally, another study that classified motifs on Bumpak woven fabric using CNN reached 98% accuracy [10]. Other related research on fabric image classification using CNN architectures also reported high accuracy rates, above 92% [3], [4], [6], [11], [12], [13], [14], [18]. Over the past two decades, various AI techniques, including Genetic Algorithms for optimization [15], [16], [17], have been applied to real-world challenges. Research in various fields, from business solutions to medical problem-solving, has successfully achieved accuracy rates of over 90% [19]. This study aims to implement the identification of types of Tapis fabric from Lampung using machine learning techniques, particularly CNN. The data used in this study is taken from a collection of Tapis fabrics from Lampung with ten different motifs. Several experiments will be conducted to evaluate system performance using data validation methods and confusion matrices to ensure accuracy [5], [7], [20]. Thus, the application of AI in recognizing motifs of traditional textiles like Tapis Lampung not only helps preserve cultural heritage but also increases efficiency in the identification and classification process, supporting the preservation of Indonesian textiles in the modern era.

2 Method

The identification and classification process using machine learning techniques Convolutional Neural Network (CNN) was carried out in accordance with the research workflow outlined in **Figure 1**. The steps of the research can be described as follows:

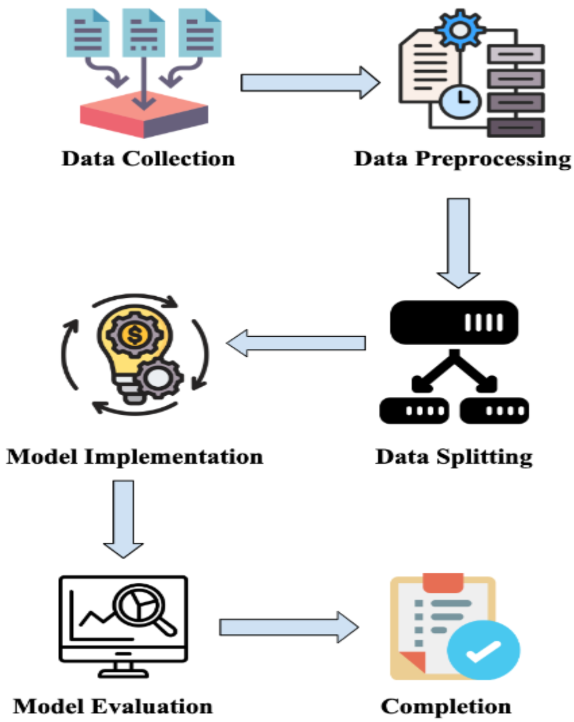


Fig. 1. Research Design.

2.1 Data Collection

This research utilized both primary and secondary data sources to gather the necessary information. Primary data were obtained through interviews with experienced collectors and owners of cloth Tapis Lampung, who have over 10 years of expertise in the field. These interviews provided valuable insights into the 10 specific types of Tapis used in the study, helping to formulate the research problem effectively. Secondary data were collected from document studies, including national and international journals focusing on machine learning techniques, such as Convolutional Neural Networks (CNN). A comprehensive literature review was conducted to ensure a thorough understanding of relevant methods and studies in the field. Additionally, Python 3's image generator library was employed to prepare and split the datasets, facilitating the evaluation of cloth Tapis Lampung using machine learning approaches.

2.2 Data Preprocessing

At this stage, the image generator library in Python 3 was employed to streamline the research process. This stage is crucial to ensure that the data used in the research is properly prepared before proceeding to the analysis or model training phase. The image data of cloth Tapis Lampung, which is the focus of this research, was processed and adjusted to meet the required format and structure for subsequent stages. The first step in this preprocessing involved resizing and normalizing the images, ensuring that each image had consistent dimensions and that its values fell within the desired range. Additionally, the Python library was utilized to perform data augmentation, such as rotation, lighting adjustments, and cropping, to increase the variety of images without losing significant information.

2.3 Data Splitting

In the data splitting stage, a representative dataset consisting of 10 types of cloth Tapis Lampung was selected to reflect the diversity in motif patterns and styles. The dataset was divided into three categories: training, validation, and testing, ensuring adequate samples for each stage of the model evaluation. This division was carried out automatically using the training and validation generator modules, allocating 70% of the data for training and 30% for testing. This careful segmentation aimed to enhance the model's ability to generalize effectively to unseen data, ultimately improving its classification accuracy for the different types of cloth Tapis Lampung.

2.4 Model Implementation

The model implementation stage involved various machine learning methods, encompassing several critical steps. Initially, suitable models were selected based on the data characteristics and research objectives, with Convolutional Neural Networks (CNN) chosen for their effectiveness in image classification tasks. Following the model selection, the corresponding code was developed using Python 3, utilizing platforms such as Google Colab for implementing the selected models. The training process utilized the prepared datasets, leveraging the image generator library to automate the training. After the training, the models underwent validation to assess their performance, which was also automated using the image generator library to evaluate the cloth Tapis Lampung classification models. Finally, the models were optimized through parameter adjustments, # feature selection, and data augmentation techniques to enhance overall performance. Examples of several cloth Tapis Lampung image models can be seen in **Figure 2**.

Fig. 2. Example of Cloth Tapis Lampung.

2.5 Evaluation

The model evaluation phase aimed to measure the performance of the implemented models. Data validation methods were utilized with a data generator, resulting in a validation accuracy of 92.11% and a training accuracy of 99.88%. Additionally, the confusion matrix from 100 tested samples yielded an accuracy of 97%. These results indicate that the implementation of Convolutional Neural Networks (CNN) on cloth Tapis Lampung with 10 motifs is highly effective.

3 Results and Discussion

This study evaluates the performance of the Convolutional Neural Network (CNN) method in identifying cloth Tapis Lampung, which encompasses ten distinct motifs: Raja Tunggal, Raja Medal, Laut Linau, Laut Silung, Jung Sarat, Balak, Cucuk Andak, Pucuk Rebung, Pucuk Pinggir, and Tuho. The results of this method are utilized to compare the effectiveness of identifying cloth Tapis Lampung based on specified labels.

Following the labeling of the dataset, which comprises ten distinct types of cloth Tapis Lampung, the researchers employed Google Colab with Python 3 for data processing. The objective was to assess the performance of the Convolutional Neural Network (CNN) algorithm in terms of accuracy.

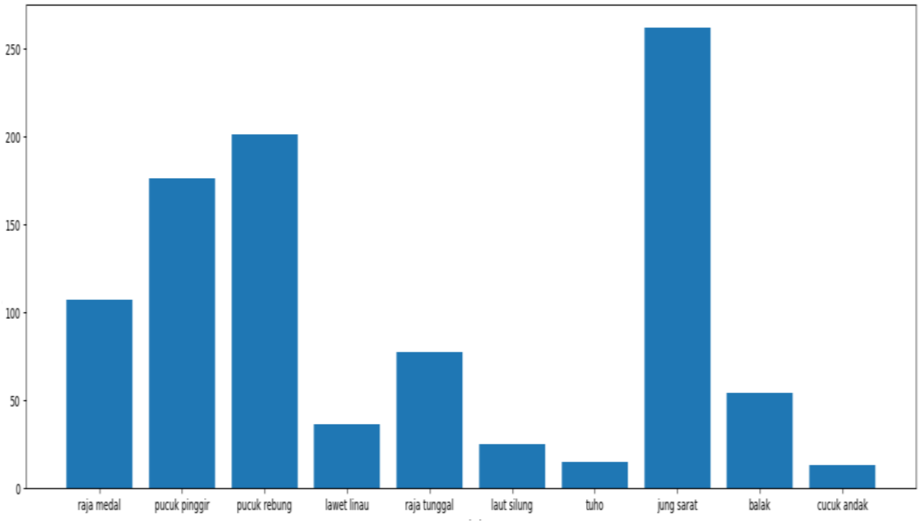
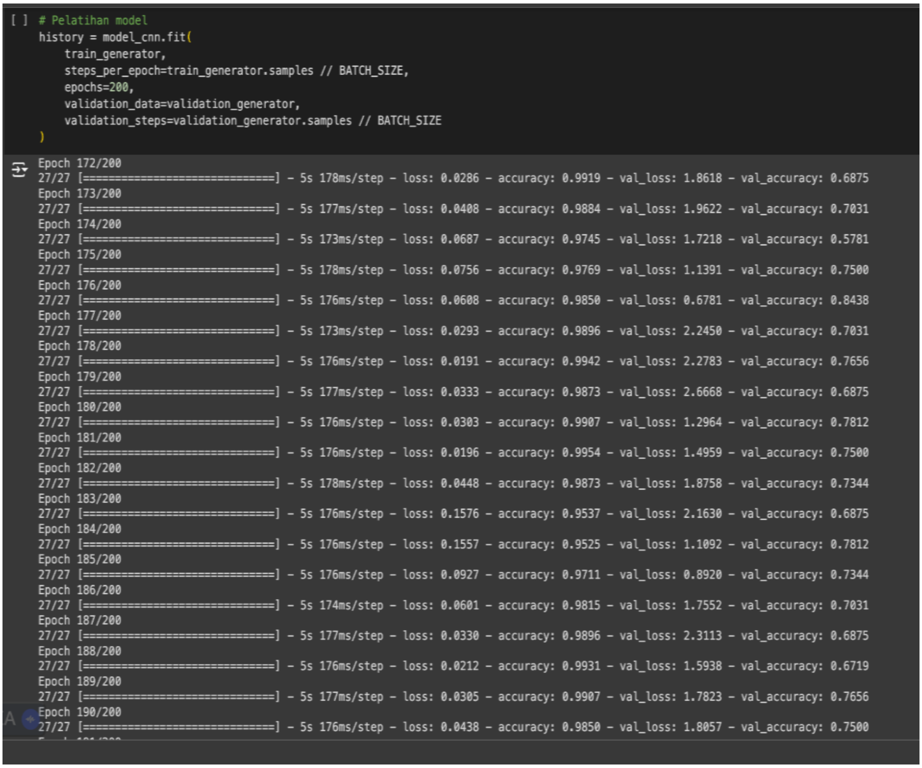


Fig. 3. Number of Images Per Label.

Figure 3 This dataset presents a comprehensive distribution of images across various labels, which is critical for training and evaluating machine learning models. The distribution includes 107 images for Raja Medal, 176 images for Pucuk Pinggir, 201 images for Pucuk Rebung, 36 images for Lawet Linau, 77 images for Raja Tunggal, 25 images for Laut Silung, 15 images for Tuho, 262 images for Jung Sarat, 54 images for Balak, and 13 images for Cucuk Andak, totaling 966 images. Each image is standardized to a resolution of 700x700 pixels, ensuring consistency and facilitating effective feature extraction during the model training process. The varied distribution across labels is essential for the robustness of the model, as it allows for the capture of a wide range of characteristics pertinent to each motif. The representation of different classes aids in preventing bias towards any particular category, ultimately enhancing the model's generalization capabilities.

The researchers conducted the machine learning process using 200 epochs, which resulted in a maximum accuracy of 99.88%. This high level of accuracy is particularly impressive given the relatively small size of the dataset. The model's performance demonstrates its strong ability to generalize from limited data, a challenge often encountered in machine learning tasks. Through multiple iterations of training, the model successfully learned the features and patterns present in the cloth Tapis Lampung dataset. **Figure 4** illustrates the learning process, showing how the model's accuracy steadily increased over time, eventually reaching near-perfect levels. These results confirm the efficiency of the chosen architecture and preprocessing techniques in handling cloth Tapis Lampung image data.



```
[ ] # Pelatihan model
    history = model_cnn.fit(
        train_generator,
        steps_per_epoch=train_generator.samples // BATCH_SIZE,
        epochs=200,
        validation_data=validation_generator,
        validation_steps=validation_generator.samples // BATCH_SIZE
    )

    Epoch 172/200
    27/27 [==============================] - 5s 178ms/step - loss: 0.0286 - accuracy: 0.9919 - val_loss: 1.8618 - val_accuracy: 0.6875
    Epoch 173/200
    27/27 [==============================] - 5s 177ms/step - loss: 0.0408 - accuracy: 0.9884 - val_loss: 1.9622 - val_accuracy: 0.7031
    Epoch 174/200
    27/27 [==============================] - 5s 173ms/step - loss: 0.0687 - accuracy: 0.9745 - val_loss: 1.7218 - val_accuracy: 0.5781
    Epoch 175/200
    27/27 [==============================] - 5s 178ms/step - loss: 0.0756 - accuracy: 0.9769 - val_loss: 1.1391 - val_accuracy: 0.7500
    Epoch 176/200
    27/27 [==============================] - 5s 176ms/step - loss: 0.0608 - accuracy: 0.9850 - val_loss: 0.6781 - val_accuracy: 0.8438
    Epoch 177/200
    27/27 [==============================] - 5s 173ms/step - loss: 0.0293 - accuracy: 0.9896 - val_loss: 2.2450 - val_accuracy: 0.7031
    Epoch 178/200
    27/27 [==============================] - 5s 176ms/step - loss: 0.0191 - accuracy: 0.9942 - val_loss: 2.2783 - val_accuracy: 0.7656
    Epoch 179/200
    27/27 [==============================] - 5s 177ms/step - loss: 0.0333 - accuracy: 0.9873 - val_loss: 2.6668 - val_accuracy: 0.6875
    Epoch 180/200
    27/27 [==============================] - 5s 176ms/step - loss: 0.0303 - accuracy: 0.9907 - val_loss: 1.2964 - val_accuracy: 0.7812
    Epoch 181/200
    27/27 [==============================] - 5s 176ms/step - loss: 0.0196 - accuracy: 0.9954 - val_loss: 1.4959 - val_accuracy: 0.7500
    Epoch 182/200
    27/27 [==============================] - 5s 178ms/step - loss: 0.0448 - accuracy: 0.9873 - val_loss: 1.8758 - val_accuracy: 0.7344
    Epoch 183/200
    27/27 [==============================] - 5s 176ms/step - loss: 0.1576 - accuracy: 0.9537 - val_loss: 2.1630 - val_accuracy: 0.6875
    Epoch 184/200
    27/27 [==============================] - 5s 176ms/step - loss: 0.1557 - accuracy: 0.9525 - val_loss: 1.1092 - val_accuracy: 0.7812
    Epoch 185/200
    27/27 [==============================] - 5s 176ms/step - loss: 0.0927 - accuracy: 0.9711 - val_loss: 0.8920 - val_accuracy: 0.7344
    Epoch 186/200
    27/27 [==============================] - 5s 174ms/step - loss: 0.0601 - accuracy: 0.9815 - val_loss: 1.7552 - val_accuracy: 0.7031
    Epoch 187/200
    27/27 [==============================] - 5s 177ms/step - loss: 0.0330 - accuracy: 0.9896 - val_loss: 2.3113 - val_accuracy: 0.6875
    Epoch 188/200
    27/27 [==============================] - 5s 176ms/step - loss: 0.0212 - accuracy: 0.9931 - val_loss: 1.5938 - val_accuracy: 0.6719
    Epoch 189/200
    27/27 [==============================] - 5s 177ms/step - loss: 0.0305 - accuracy: 0.9907 - val_loss: 1.7823 - val_accuracy: 0.7656
    Epoch 190/200
    27/27 [==============================] - 5s 176ms/step - loss: 0.0438 - accuracy: 0.9850 - val_loss: 1.8057 - val_accuracy: 0.7500
```

Fig. 4. Learning Process.

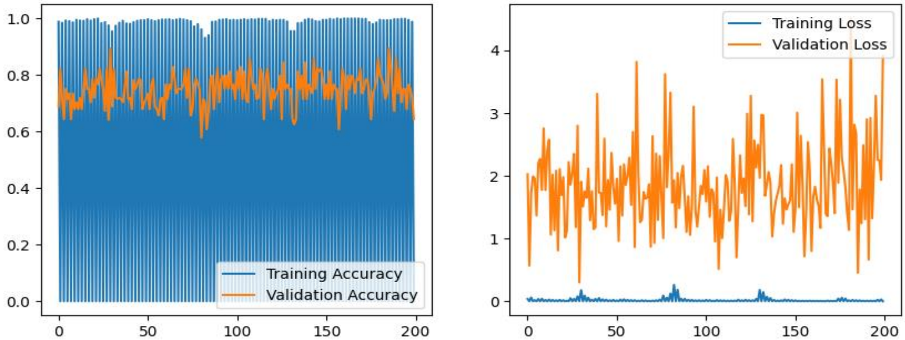


Fig. 5. Accuracy and Loss.

Figure 5 This study presents the training accuracy and loss achieved by a machine learning model while processing the cloth Tapis Lampung dataset. The highest training accuracy attained was 99.88%, with the lowest recorded loss at 0.12%. These results were achieved using the Convolutional Neural Network (CNN) method over 200 training epochs. Additionally, data validation yielded an accuracy of 92.29%, while the validation loss was recorded at 7.71%. These findings indicate that the evaluation metrics are satisfactory, demonstrating the effectiveness of the implemented model.

Table 1. Comparison of Image Pixel Sizes.

No	Pixel	Accuracy (Percent)
1	32x32	99,42%
2	64x64	99,77%
3	128x128	99,42%
4	150x150	99,88%
5	256x256	99,31%
	Average	99,56%

The Convolutional Neural Network (CNN) method was evaluated based on different image pixel sizes, as illustrated in **Table 1**. The evaluation results reflect the model's accuracy in classifying images across several pixel dimensions during training with 200 epochs. For the 32x32 pixel dimension, the model achieved an accuracy of 99.42%. Subsequently, with a pixel size of 64x64, accuracy increased to 99.77%, indicating a significant improvement in classification performance. However, as the pixel size increased to 128x128, the accuracy stabilized at 99.42%, suggesting that the model's performance began to plateau at this resolution. The best performance was achieved at a pixel size of 150x150, where the model recorded the highest accuracy of 99.88%. This demonstrates that at this dimension, the CNN model delivers optimal performance in image classification. For larger pixel sizes, such as 256x256, the accuracy slightly decreased to 99.31%. Nevertheless, this value still represents a high level of effectiveness, though slightly lower than the 150x150 size. The average accuracy across all tested pixel dimensions was 99.56%, indicating that the CNN method is highly effective in classifying images of cloth Tapis Lampung, which consist of 10 categories, regardless of pixel size variations. The results show that CNN can provide excellent performance in image classification tasks across various resolution sizes. In conclusion, the use of the CNN method for image recognition of cloth Tapis Lampung yields highly satisfactory results with high accuracy across different pixel dimensions. Its optimal performance is achieved at the 150x150 pixel size, but overall, CNN maintains excellent accuracy even with varying image pixel sizes.

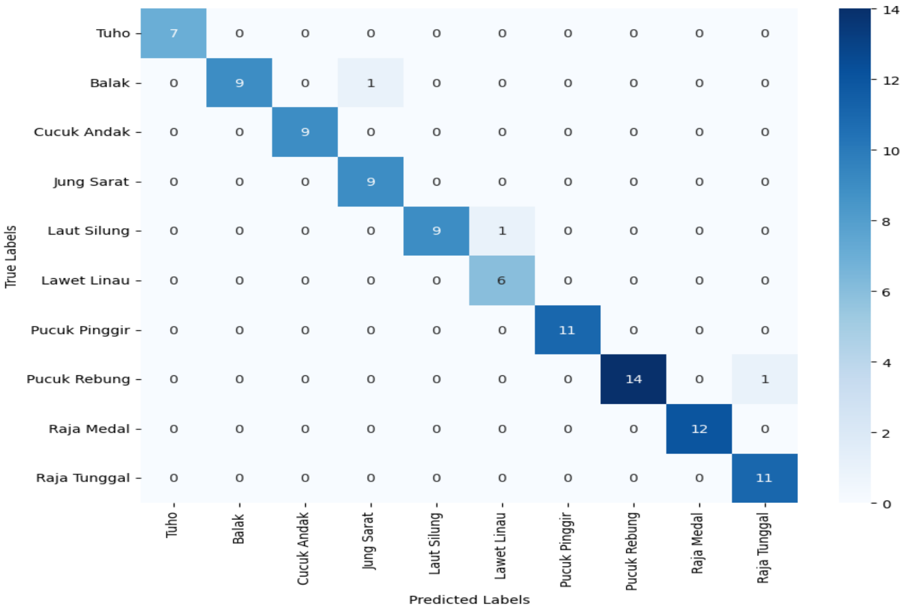


Fig. 6. Results of the Experiments.

Figure 6 presents the confusion matrix resulting from the classification using a Convolutional Neural Network (CNN) across multiple classes. This matrix visualizes the distribution of the model's predictions in relation to the actual classes. The classification involves the following classes: Tuho, Balak, Cucuk Andak, Jung Sarat, Laut Silung, Lawet Linau, Pucuk Pinggir, Pucuk Rebung, Raja Medal, and Raja Tunggal. The main diagonal of the matrix represents the correct predictions, where each element indicates the number of samples correctly classified for each class. For example, the model correctly classified 7 samples in the "Tuho" class. In another case, such as the "Balak" class, the model accurately classified 10 samples. However, some misclassifications occurred, such as in the "Laut Silung" class, where 1 sample was incorrectly classified. The test was conducted using 100 data points, and the model achieved an accuracy of 97%. The color scale in the confusion matrix ranges from light to dark, representing the intensity of the number of predictions in each position. Darker shades along the diagonal indicate a higher number of correct predictions compared to other elements. This suggests that the CNN model performs well in distinguishing between the different classes, although a few misclassifications still occurred in certain categories. The high accuracy rate indicates that the CNN was able to correctly predict the majority of the test data, demonstrating the model's effectiveness in multi class classification.

4 Conclusion

The results of this study indicate that the Convolutional Neural Network (CNN) method achieved a Training Accuracy of 99.88% and a Data Validation Accuracy of 92.29%

on the Tapis Lampung fabric dataset. Additionally, the confusion matrix demonstrated an accuracy of 97% tested on 100 data points using the CNN model, which consists of 10 motifs or classes. These findings highlight the effectiveness of the CNN method in classifying Tapis Lampung fabric motifs and its potential applications in textile pattern recognition.

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