Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Number 3, July 2025
DOI : https://doi.org/10.33395/sinkron.v9i3.14841

e-ISSN : 2541-2019
p-ISSN : 2541-044X

Convolutional Neural Network Algorithm Implementation for Classifying Traditional Wood Carving Motifs of Patra Bali

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Submitted : May 21, 2025 | **Accepted** : Jun 27, 2025 | **Published** : Jul 12, 2025

Abstract: This research develops an automatic classification system to recognize Balinese *Patra* carving motifs using a deep learning method based on Convolutional Neural Network (CNN). The dataset used consists of a total of 2000 images, with 500 images for each motif class: *Cina Patra*, *Mesir Patra*, *Punggel Patra*, and *Sari Patra*. These images have gone through preprocessing stages such as cropping, resizing, and augmentation in the form of flipping and rotation to increase data variation. Three pre-trained CNN models were used in testing, namely DenseNet169, InceptionResNetV2, and MobileNetV2. The training process was performed with Adam optimization, a batch size of 32, and 100 epochs. Model performance evaluation was carried out using accuracy and confusion matrix metrics. The results show that all three models achieved high accuracy on the test data. DenseNet169 reached an accuracy of 97.66% with the lowest loss value of 9.73%. InceptionResNetV2 followed with an accuracy of 95.18% and a loss of 15.12%. Meanwhile, MobileNetV2 achieved the highest accuracy of 97.91% with a loss value of 10.65%. Based on the confusion matrix, DenseNet169 and MobileNetV2 successfully classified all motif classes correctly, while InceptionResNetV2 showed a slight misclassification in the Patra Sari class. These findings prove that CNN is effectively used in the recognition of traditional carving motifs and has the potential to support cultural preservation through interactive visual technology.

Keywords: Patra Bali, Deep Learning, Convolutional Neural Network (CNN), Image Processing, Image Classification.

INTRODUCTION

Bali is an area rich in culture, one of which is reflected in traditional architecture such as temples and traditional houses. In such architecture, there are typical carved ornaments known as Patra. These carvings not only serve as decoration, but also contain deep symbolic and philosophical values for the Balinese people. Each type of Patra has its own visual characteristics and meanings. For example, the Sari Patra depicts beauty, while the Chinese Patra reflects outside cultural influences(Kadyanan et al., 2025). However, along with the times and the rise of modern design, the understanding of Patra forms among the younger generation has begun to fade.

This problem can be seen from the results of distributing questionnaires to 54 respondents aged 19-25 years, where as many as 74.1% did not know or could not distinguish the types of Patra. The most difficult types of Patra to recognize are Patra Sari (18.5%), Patra Cina (20.4%), Patra Punggel (31.5%), and Patra Mesir (31.5%). This indicates a gap in understanding of Bali's visual cultural heritage that needs to be addressed immediately.

To answer this problem, the study uses a quantitative approach and deep learning-based technology. The main method used is Convolutional Neural Network (CNN), a deep learning architecture that has proven effective in image classification tasks. CNN is used to train an image recognition model to automatically identify Patra types based on visual features of the input image data (Sandhopi et al., 2020). The training process includes collecting Patra image datasets, annotation, data augmentation, and evaluating model performance using accuracy metrics. With this approach, the system is expected to be able to recognize complex carving patterns and resemble the way humans distinguish visual ornaments. The purpose of this study was to determine the level of understanding of adolescents towards Balinese Patra carvings, as well as to build an automatic classification system based on CNN

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p-ISSN : 2541-044X

that can be used as an educational tool in reintroducing Patra varieties to the younger generation visually and interactively (I Gusti Ngurah et al., 2023).

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METHOD

This methodology section explains in detail the datasets used in developing the Patra Bali motif classification model, including architectural details of each implemented Convolutional Neural Network (CNN) model. In addition, the data preprocessing stages and the overall research workflow are described, starting from data preparation to the model performance evaluation process. Figure 1 presents the research flow starting from the data collection stage in the form of Patra Bali carving images that reflect various types of motifs. After the data is collected, the preprocessing stage is carried out which includes the crop and resize process to ensure uniform image sizes. The next step is image augmentation to increase data diversity by applying techniques such as flip and rotation. The dataset that has gone through this process is then used to develop three Convolutional Neural Network-based classification models, namely DenseNet169, MobileNetV2, and InceptionResNetV2(Nugraha et al., 2024). Each model is trained using training data and evaluated using test data. The model training process uses the Adam optimization algorithm to accelerate convergence and improve training accuracy. The final stage of this study is the evaluation of model performance using classification metrics such as accuracy and confusion matrix to measure the effectiveness and accuracy of each architecture in classifying Patra Bali motifs accurately (Reyad et al., 2023). The flowchart diagram referred to in this paragraph is presented in Figure 1 below.

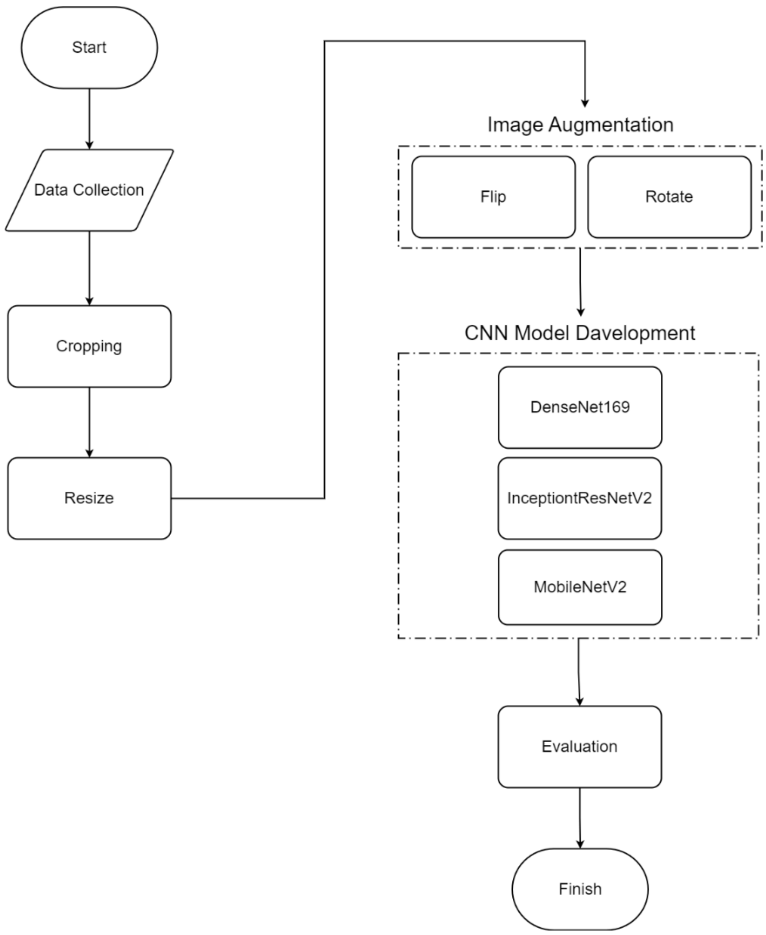

Fig. 1. Research Flow Stages

*name of corresponding author

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Data Description

This research was conducted in Banjar Mulung, Sumita Village, Gianyar District, Gianyar Regency, Bali Province, with a focus on collecting data in the form of images of Balinese *Patra* carvings. The data collection process took place from September to December 2024. During this period, researchers routinely visited the documentation center to obtain and document images of carvings that were relevant to the focus of the research. The carving motifs collected were motifs from traditional Balinese wood carvings, which reflect the richness of local art and culture. The data that was successfully collected included various types of Balinese *Patra* motifs, including *Cina Patra*, *Punggel Patra*, *Sari Patra*, and *Mesir Patra*, which were then used as the main material in the classification process using a machine learning model. The total dataset consists of 400 images, with 100 images for each of the four motif classes. These images were first processed through preprocessing and augmentation steps such as cropping, resizing, flipping, and rotation to enhance image quality and data diversity. After these steps, the dataset was split into training data (70%), validation data (20%), and testing data (10%) to support the model development and evaluation process effectively.

Table 1. Sample Dataset (Patra Bali)

Patra Cina	**Patra Punggel**	**Patra Mesir**	**Patra Sari**
			

Data Pre-processing

In the data preprocessing stage, an adjustment process is carried out on the Patra Bali carving images to ensure that the data used is in accordance with the analysis needs. The main steps taken include cropping and resizing each image. The goal is to emphasize the most relevant areas of the carving motif and to equalize the image size to be consistent for the next process. With this preprocessing, the images used become more focused, uniform, and ready to be included in the model training stage, so that it is expected to increase the accuracy and performance of the system in recognizing Patra Bali carving patterns(Fan et al., 2021).

A. Cropping Data

Cropping data is the process of cutting certain parts of an image to highlight or extract areas that are considered most important or relevant to the purpose of the analysis. The images of Patra Bali wood carvings obtained from the documentation process were then further processed to ensure that the image focus was on the part of the carving motif that was the object of study. The initial step taken was to carry out the cropping process, which is to cut parts of the image to extract the main object that is relevant to the research objective. This process is carried out to remove background elements or other unnecessary parts, so that the model can be more effective in recognizing and learning the patterns and characteristics of each Patra motif. By emphasizing important carving areas, the data used in model training becomes more accurate and relevant, thus supporting improved performance in the classification process (Liu et al., 2021; Sudipa et al., 2024; Udayana et al., 2022).

B. Resizing Data

Data resizing is a step to change the dimensions of a digital object such as an image without changing its content or visual meaning. In this case, what is meant is the Patra Bali carving image. The purpose of resize is to adjust the image size to suit the needs of the data processing process, visual display, or storage efficiency. The resize stage begins by setting a new size, either in pixels or a certain scale compared to the original size. In this study, the image size was changed to a scale of 224x224 pixels. Once the size is determined, the system will adjust the image dimensions while maintaining the aspect ratio so that the image shape is not distorted. Then, an interpolation algorithm will be used to add or subtract pixels so that the final result remains clear and proportional. Resizing the Patra Bali image is an important step to ensure that the data used is more optimal in the analysis process and further application (Semma et al., 2021).

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Data Augmentation

To enrich the variety of training data and improve the quality of the model, an image augmentation process was carried out on the Patra Bali carving images. This augmentation serves to increase the diversity of data without having to add new images manually. At this stage, flip and rotation techniques are applied to the existing images. Through this approach, the model is expected to be able to recognize carving motifs from various directions and angles, so that it can improve the model's ability to classify data more accurately and efficiently (Kusnadi & Atmaja, 2025; Xu et al., 2023).

A. Flip Augmentation

Flip augmentation is a technique in image processing that is used to increase the variety of data by flipping the image horizontally, vertically, or both. This technique is useful in improving the model's ability to recognize objects from various orientations, as well as preventing overfitting by expanding the amount and diversity of training data. In this research, the researchers applied only horizontal and vertical flip techniques to augment the dataset. The flip augmentation process begins by selecting the type of flip to be applied for example, a horizontal flip to flip the image from left to right, or a vertical flip to flip from top to bottom. Once the type of flip is determined, the original image is processed with a flip algorithm in the desired direction. The result of this process is a new image that is an inverted version of the original image but still retains the same visual information. In the context of the *Patra Bali* carving image, flip augmentation helps the model learn motifs from various perspectives, thereby increasing accuracy in the classification process.

B. Rotational Augmentation

Rotation augmentation is a technique in image processing that is used to increase data diversity by rotating the image at a certain angle. This method is useful for training the model to be able to recognize objects from various directions, thereby increasing the accuracy and generalization ability of the model. In this research, the images were rotated by 10 degrees to the right and 10 degrees to the left using a rotation method that adjusts the pixel positions according to those angles. The rotated images still retain important visual information from the original images but have different orientations. The application of this technique to the *Patra Bali* carving images allows the model to recognize motifs from a wider range of angles, which ultimately helps improve performance in the classification process.

Development of Convolutional Neural Network (CNN) Model

Model development was carried out by utilizing the Convolutional Neural Network (CNN) architecture using three types of pre-trained models, namely DenseNet169, InceptionResNetV2, and MobileNetV2. These three models were chosen because they have proven effective in feature extraction and image classification on various visual pattern recognition tasks. The selection of these architectures was based on several considerations, including model complexity, number of parameters, classification performance, and suitability for recognizing intricate and small-scale patterns such as those found in *Patra Bali* carvings. DenseNet169, with its dense connectivity and relatively deeper structure, is capable of capturing detailed texture information, making it suitable for distinguishing subtle motif variations. InceptionResNetV2 combines the strengths of Inception modules and residual connections, enabling it to process multi-scale features efficiently—ideal for complex ornamental designs. Meanwhile, MobileNetV2, known for its lightweight architecture and reduced computational load, offers a balance between accuracy and efficiency, making it particularly appropriate for real-time or resource-constrained applications without sacrificing performance. These considerations align with the nature of the dataset, which consists of 2,000 images evenly distributed among four motif classes (500 images per class) with intricate carving details, requiring models capable of precise and robust classification.

A. Densenet169

DenseNet169 is one of the Convolutional Neural Network (CNN) architectures designed to improve efficiency and accuracy in the feature extraction process in images. The main advantage of DenseNet169 lies in the dense connections between layers, where each layer receives input from all previous layers. This allows for better information flow and gradients during training, as well as reducing the risk of losing important information. With an efficient structure, DenseNet169 is able to produce rich and deep feature representations, making it suitable for use in image classification tasks, including in recognizing carving motifs such as in the *Patra Bali* data. In this study, the DenseNet169 model was implemented using the TensorFlow and Keras frameworks, which provide built-in access to pre-trained models and tools for customization and training. These libraries offer flexibility and scalability, allowing researchers to efficiently apply transfer learning on the *Patra Bali* dataset and optimize the model performance through fine-tuning and evaluation (Akbar et al., 2025).

B. Inceptionresnetv2

InceptionResNetV2 InceptionResNetV2 is a Convolutional Neural Network (CNN) architecture that integrates the strengths of two well-known models, namely Inception and ResNet. This model is designed to provide high performance in image recognition tasks by combining Inception's ability to capture features of various sizes and the residual connection approach of ResNet that maintains the stability of the gradient flow in deep networks. With

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this structure, InceptionResNetV2 is able to perform deeper and more accurate feature extraction without losing important information. This advantage makes it very suitable for use in image classification, including in recognizing carving motifs in *Patra Bali* data. In this study, the InceptionResNetV2 model was implemented using the TensorFlow and Keras libraries, which offer built-in support for loading pre-trained models and applying transfer learning. These frameworks simplify the process of adapting the model to specific datasets and provide essential tools for training, evaluation, and visualization of results (Gabriela Winarto & Lawi, 2021).

C. Mobilenetv2

MobileNetV2 is a Convolutional Neural Network (CNN) architecture designed to work efficiently while maintaining a good level of accuracy in image classification. This model adopts the depthwise separable convolution technique and linear bottleneck blocks to reduce network complexity and the number of parameters, making it ideal for use on devices with limited resources such as mobile devices or real-time systems. Although lightweight, MobileNetV2 is still able to perform feature extraction optimally. In this study, MobileNetV2 was implemented using the TensorFlow and Keras frameworks, which provide pre-trained model access and practical tools for applying transfer learning and model fine-tuning. In its application to the *Patra Bali* carving image, this model can perform classification quickly and efficiently without reducing the quality of the pattern recognition results. (Gulzar, 2023).

Evaluation

Model performance evaluation is done using accuracy and Confusion Matrix. Accuracy shows the percentage of correct predictions from the entire data, while Confusion Matrix provides detailed information about the number of correct and incorrect predictions for each class. These two metrics help assess how well the model recognizes and distinguishes carving motifs in the Patra Bali image.

Accuracy

Accuracy is the ratio of the number of correct predictions to the total amount of data tested. The higher the accuracy value, the better the model's performance in classifying compared to other models with lower accuracy. Here is the accuracy formula:

$$\text{Accuration} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \times 100\%$$

Precision

Precision is one of the evaluation metrics in machine learning, particularly in classification tasks, used to determine the proportion of positive predictions that are truly correct based on the actual labels.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Recall

Recall measures the percentage of correct predictions compared to the total number of actual cases in a specific class. The formula is:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

F1 Score

The F1-Score is the harmonic mean of Precision and Recall, and it is used to evaluate the balance between the two. It is especially useful when dealing with imbalanced datasets, where accuracy alone might be misleading.

$$\text{F1 Score} = 2 \times \frac{\text{Precision } \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Confusion Matrix

Confusion matrix is an evaluation method used to assess the performance of an image classification system by comparing the results of the system's classification to the actual labels. In this study, Patra Bali carving image data were classified into four classes based on different types of motifs. The confusion matrix will show the number of images that were successfully classified correctly or incorrectly in each class, which are divided into four main components: true positive (TP), false positive (FP), true negative (TN), and false negative (FN). Before the evaluation was carried out, all images were first manually labeled according to the visual characteristics of the four Patra Bali motif classes. After the classification process was run by the model, the confusion matrix was used to assess how accurate the model was in recognizing and distinguishing the carving motifs.

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JURNAL & PENELITIAN TEKNIK INFORMATIKA
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RESULT

Training Model

In the Patra Bali image classification model training, the adam optimization algorithm is used to adjust the learning rate. The model is trained with a batch size of 32 and run for 100 epochs to allow for optimal learning from the available data.

Table 2. Performance comparison on three pre-trained CNN models

No	Model	Accuracy	Loss
1	Densenet169	97.66%	9.73%
2	InceptiontResnetV2	95.18%	15.12%
3	MobileNetV2	97.91%	10.65%

A. DenseNet169

The results of model training using the DenseNet169 architecture show excellent performance, with an accuracy of 97.66% and a loss value of 9.73%. This indicates that the model was able to learn the patterns in the training data effectively while maintaining generalization to validation data. The relatively low loss value also reflects that the predictions made by the model are close to the actual target values. The training result graph, which illustrates the trend of increasing accuracy and decreasing loss across epochs, can be seen in the image below. This graph further supports the model's stability and effectiveness during the learning process.

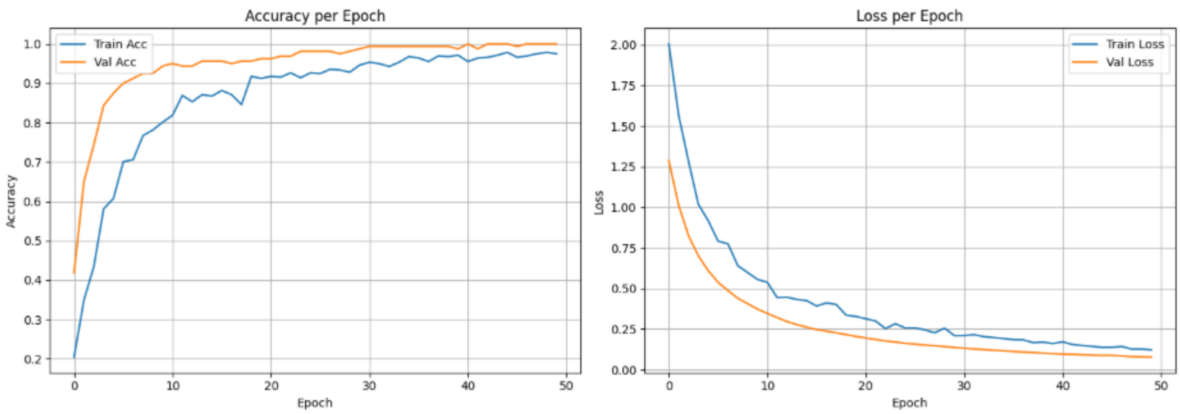

Fig. 2. DenseNet169 model training results

B. InceptionResnetV2

Model training using the InceptionResNetV2 architecture resulted in an accuracy of 95.18% with a loss value of 15.12 %. These results indicate that the model is able to recognize all Patra Bali motif images accurately on the data used, both in the training and testing processes. High accuracy and low loss values indicate that the model has succeeded in learning visual patterns effectively without experiencing significant overfitting. A graph depicting the development of accuracy and loss during the training process is shown in the figure below as visual evidence of the model's performance.

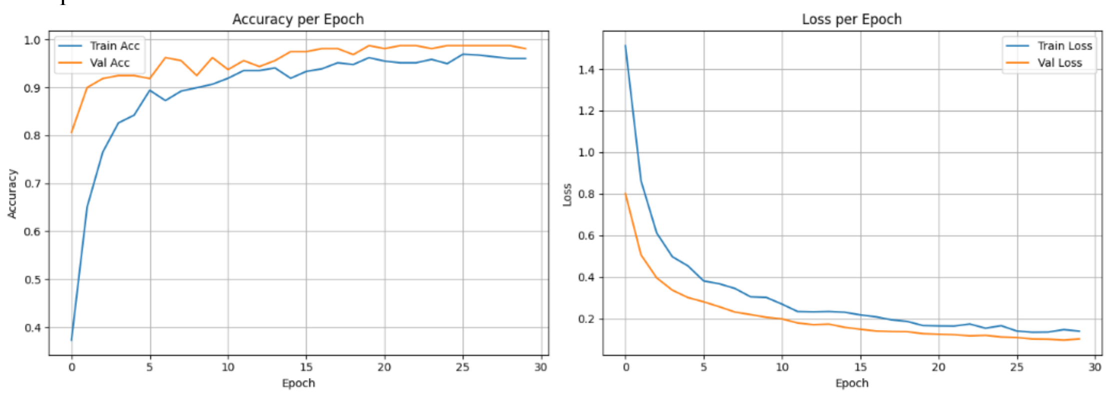

Fig. 3. Results of InceptionResNetV2 model training

*name of corresponding author

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C. MobileNetV2

The model trained using the MobileNetV2 architecture successfully achieved 97.91% accuracy with a loss value of 10.65%. This shows that the model is able to classify Patra Bali motif images very accurately. As a lightweight and efficient model, MobileNetV2 shows optimal performance even though the amount of data is limited. Perfect accuracy and very low loss values indicate that the learning process is running well without significant errors. The graph showing the development of accuracy and loss during training can be seen in the figure below.

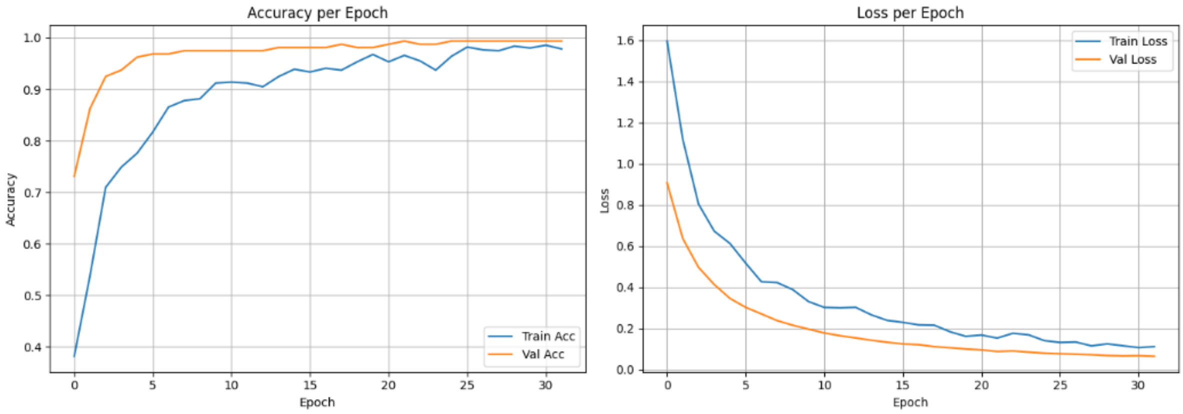


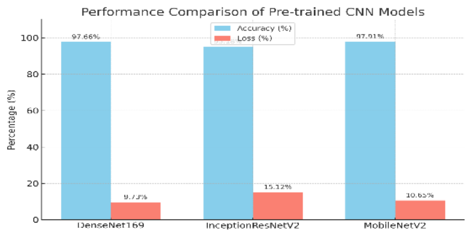
Fig. 4. MobileNetV2 model training results

D. Model Performance Evaluation

The performance evaluation of the models was conducted using three main metrics: accuracy, precision, and recall. The results for each model, which summarize the values of these evaluation metrics, are also supported by a bar chart that provides a visual comparison of model performance. These results are presented in Table 3 below.

Table 3. Performance Evaluation Model

Model	Accuracy	Precision	Recall	F1-Score
DenseNet169	97.66%	98.00%	97.50%	97.75%
InceptionResNetV2	95.18%	95.00%	94.00%	94.49%
MobileNetV2	97.91%	98.10%	97.80%	97.95%



E. Confusion Matrix DenseNet169

The confusion matrix image below shows the results of the DenseNet169 model evaluation on four classes of Balinese Patra motifs: Patra Cina, Patra Mesir, Patra Punggel, and Patra Sari. Each class contains 21 test samples, resulting in a total of 84 test samples (4 classes × 21 images). All samples were correctly classified, as indicated by the number 21 appearing on each cell along the main diagonal and zero values outside the diagonal. This means that there were no misclassifications. With these results, the model achieved an accuracy of 97.66%, and the confusion matrix clearly demonstrates the model's ability to recognize each motif type with high precision and consistency.

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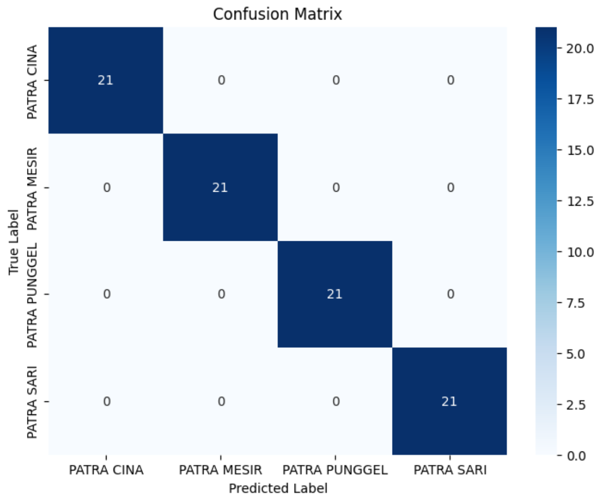

Fig. 5. Confusion Matrix Model DenseNet169

F. Confusion Matrix InceptionResNetV2

The confusion matrix in the image below shows the results of the InceptionResNetV2 model evaluation on four categories of Balinese Patra motifs, namely Cina Patra, Mesir Patra, Punggel Patra, and Sari Patra. Each class was tested with 21 images, resulting in a total of 84 test samples (4 classes × 21 images). The model successfully classified all images from the Cina Patra, Mesir Patra, and Punggel Patra categories, as indicated by the number 21 appearing along the main diagonal with no errors. However, in the Sari Patra category, three images were misclassified as Punggel Patra, resulting in only 18 correct predictions for that class. While the overall accuracy of the model remains high, this misclassification suggests that there may be visual similarities between certain motifs. This issue could potentially be addressed by refining the training process or further optimizing the model architecture.

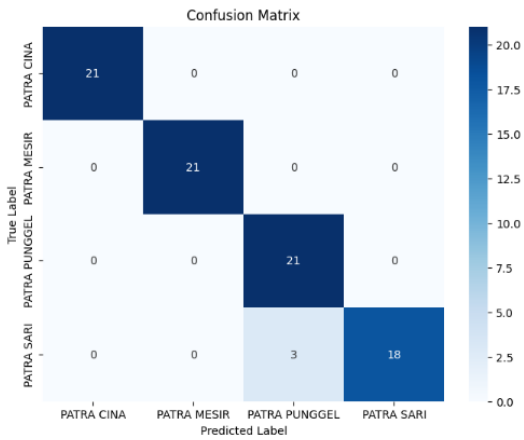

Fig. 6. Confusion Matrix Model InceptiontResnetV2

G. Confusion Matrix MobileNetV2

The confusion matrix image below shows the results of the MobileNetV2 model evaluation on four types of Balinese Patra motifs: Cina Patra, Mesir Patra, Punggel Patra, and Sari Patra. Each class was tested with 21 images, resulting in a total of 84 test samples (4 classes × 21 images). All test images were successfully classified correctly, as indicated by the number 21 along the main diagonal for each class, with no values appearing outside the diagonal. This indicates that there were no misclassifications. These results demonstrate that the MobileNetV2 model is highly accurate in recognizing each motif type and achieved an excellent overall accuracy of 97.91%.

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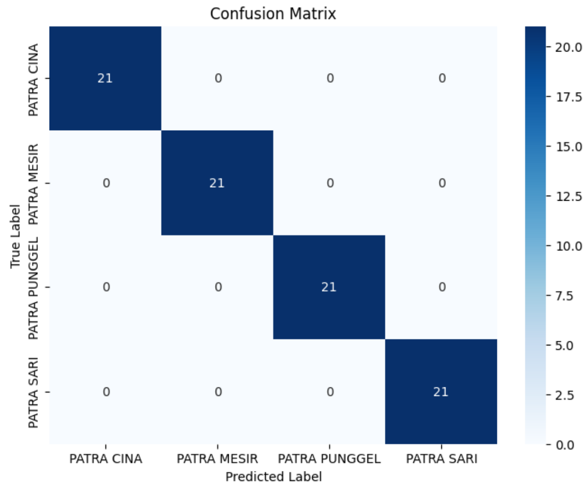

Fig. 7. Confusion Matrix Model MobileNetV2

DISCUSSIONS

The results of the study indicate that three pre-trained CNN architectures, namely DenseNet169, InceptionResNetV2, and MobileNetV2, were able to deliver excellent performance in classifying Balinese Patra carving motif images that had undergone preprocessing and augmentation stages. All three models demonstrated high accuracy on the test data, particularly in correctly classifying the Cina Patra, Mesir Patra, and Punggel Patra motifs. Among these models, DenseNet169 and MobileNetV2 successfully classified all test images correctly across all classes, reflecting stable performance and good generalization capability toward data variations. This stability is a result of their architectural characteristics: DenseNet169 utilizes dense connections that ensure effective feature reuse and gradient flow across layers, while MobileNetV2 employs depthwise separable convolutions and inverted residual blocks, which make the model lightweight and efficient, preventing overfitting and enhancing performance on limited yet diverse datasets.

Meanwhile, InceptionResNetV2 also achieved a high accuracy rate but encountered minor classification errors in the Patra Sari class, where three images were misclassified as Patra Punggel. This misclassification occurred due to the visual similarities between certain motifs, particularly between Patra Sari and Patra Punggel. Similar carving details and shape patterns directly influenced the model's ability to separate class-specific features. Although the overall performance of all models remained strong, the presence of high visual similarity among classes posed a clear challenge in achieving perfect classification.

Performance evaluation using a confusion matrix illustrates the distribution of predictions relative to the actual labels. The majority of classification results showed very high accuracy, supported by preprocessing stages such as cropping, resizing, and augmentation through flipping and rotation. These strategies played a crucial role in enriching data variation and enabling the model to learn from different visual perspectives.

From a technical standpoint, the use of the Adam optimization algorithm with a batch size of 32 and 100 training epochs proved effective during the model training process. This combination resulted in stable and accurate performance, supported by balanced data distribution and an augmentation strategy aligned with the visual characteristics of the Patra Bali motifs.

CONCLUSION

Based on the evaluation results of the deep learning models in classifying Balinese Patra motif images, the three pre-trained CNN architectures DenseNet169, InceptionResNetV2, and MobileNetV2 exhibited strong classification performance. Among them, MobileNetV2 achieved the highest accuracy of 97.91% with a relatively low loss of 10.65%, followed closely by DenseNet169 with 97.66% accuracy and 9.73% loss. InceptionResNetV2, while still performing well, recorded a lower accuracy of 95.18% and a loss of 15.12%, with three misclassified images in the Patra Sari class. These results confirm the effectiveness of CNN-based models in recognizing traditional patterns, particularly when supported by preprocessing and augmentation techniques.

Despite the promising performance, several limitations were identified. The relatively small dataset may have impacted the model's ability to generalize, especially for motifs with visually similar features such as Patra Sari and Patra Punggel. The current models also operate in an offline inference setting, without consideration for real-time deployment or mobile optimization. Moreover, the study did not yet explore advanced training techniques such as transfer learning fine-tuning or deeper hyperparameter tuning.

*name of corresponding author

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For future research, expanding the dataset and ensuring better representation of each motif class will be essential to increase robustness. Further performance gains may be achieved through hybrid model approaches or ensemble methods that combine the strengths of different CNN architectures. Additionally, real-time implementation using lightweight models like MobileNetV2 could enable practical applications in cultural preservation, such as mobile-based recognition tools for educational or tourism purposes. Visionary developments may also include integration with AR/VR systems, and exploration of attention mechanisms or transformer-based models to enhance the focus on intricate motif details.

ACKNOWLEDGMENT

This research can be carried out well thanks to the help of various parties. Therefore, the researcher would like to thank Mr. I Gede Iwan Sudipa, S.Kom., M.Cs., Mrs. Yuri Prima Fittryani, S.T, M.T. As lecturers who have guided in the implementation of this research. In addition, I would also like to thank my fellow students who always support the implementation of this research.

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