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Classification of Traditional Balinese Kites Using CNN for Cultural Preservation

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Abstract: The digital preservation of cultural heritage has become increasingly important in sustaining local traditions amid rapid modernization. Balinese traditional kites represent a distinctive form of intangible cultural heritage with unique visual characteristics; however, their identification and classification are still largely based on subjective expertise. This research develops a Convolutional Neural Network (CNN)-based model for image classification to automatically recognize three primary types of Balinese traditional kites: Bebean, Janggan, and Pecukan. Beyond technical implementation, this research contributes to the development of a culturally specific visual dataset, addressing the limited representation of local heritage objects in mainstream computer vision research, which is predominantly based on global datasets of generic objects. A balanced dataset of 2,400 images was constructed and evaluated using 5-Fold Cross Validation to assess model stability and generalization capability. The proposed CNN model achieved an average validation accuracy of 91.5%, with balanced precision, recall, and F1-score across folds. Further evaluation on an independent test set of 282 images resulted in an accuracy of 87.94%, indicating a generalization gap of approximately 4%, which remains within an acceptable range. The results demonstrate that CNN-based classification can effectively support structured digital documentation of traditional kites. This study highlights the potential of computer vision not only as a technical tool, but also as a strategic approach to advancing data-driven cultural preservation and expanding AI applications within localized cultural contexts.

Keywords: Balinese Kites; Convolutional Neural Networks; Cross-Validation; Deep Learning; Image Classification

INTRODUCTION

Bali, as one of Indonesia's leading tourist destinations, is known not only for its natural beauty but also for its diverse arts, culture, and traditions that persist to this day (Bali, 2025). One tradition that forms a vital part of the Balinese cultural identity is the traditional kite. Unlike kites in general, Balinese kites serve not only as entertainment but also hold historical, philosophical, and religious significance, reflecting the community's social and spiritual life (Agus Eko Sattvika et al., 2025; Bali, 2025).

The tradition of flying kites, as the term for flying kites, is a cultural heritage of agrarian communities linked to the mythology of Sang Hyang Rare Angon, a symbol of the guardian of fertility and balance of nature (Sutana, 2022). Over time, this tradition has become not only a recreational activity but also a representation of harmony between humans and nature. The three main types of traditional Balinese kites—Bebean, Janggan, and Pecukan—have distinct visual characteristics, structures, and philosophies, making them important elements in cultural preservation (Agus Eko Sattvika et al., 2025; Pradipta, 2025; Sutana, 2022).

Despite their high cultural value, the documentation and classification of traditional Balinese kites have not been systematically conducted and tend to rely on individual subjective knowledge (Buragohain et al., 2024; Ye et al., 2025). This situation has the potential to lead to inconsistencies in identification and limitations in the development of digital cultural archives in the future. Furthermore, the limited use of technology in cultural documentation poses a challenge in attracting the interest of the younger generation amidst the tide of modernization (Febriansyah, 2024; Febrianto et al., 2025).

In this context, the application of computer vision based on digital image processing offers a more objective and measurable solution to the problem. Automatic image classification enables consistent identification and

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supports the development of structured data-based documentation systems (Sabha et al., 2024). However, most computer vision research still focuses on general objects and global datasets, leaving local cultural objects, particularly traditional Balinese kites, largely unexplored (Carvalho Ottoni & Cordeiro Ottoni, 2025; Harisanty et al., 2024; Monna et al., 2021).

Based on these challenges, the novelty of this research lies in the development of a CNN-based image classification system for traditional Balinese kites using a locally collected dataset comprising 2,400 augmented training images and 282 independent test images across three kite classes — Bebean, Janggan, and Pecukan. To the best of the authors' knowledge, no prior study has applied CNN to classify traditional Balinese kite types, nor has any structured dataset been developed for this object. Compared to previous CNN-based studies on Indonesian cultural object classification such as batik motif classification (Sinaga et al., 2024) and Javanese Keris classification (Sebatubun & Haryawan, 2024), the proposed model achieves a competitive average validation accuracy of 91.5%, demonstrating the feasibility of CNN for classifying underrepresented local cultural objects.

Furthermore, this study integrated a comprehensive evaluation approach using k-fold cross-validation to ensure the stability and generalizability of the model. Thus, this study not only provides technical contributions to the development of image classification models but also contributes to cultural preservation efforts through more objective, structured, and sustainable digitization.

LITERATURE REVIEW

This study contributes to the development of local culture-based visual datasets, which remains a challenge in computer vision research (Setiawardhana et al., 2025). Most existing research focuses on general objects and global datasets, making the study of regional cultural objects a significant opportunity for scientific contributions (Paymode & Malode, 2022).

In the context of Balinese cultural object classification, various previous studies have utilized the Convolutional Neural Network (CNN) approach, with results demonstrating strong performance. The study used the ResNet-152 architecture to classify Balinese Hindu ceremonial flowers and achieved 98% accuracy, demonstrating (Lumumba et al., 2024) the model's ability to extract complex visual features. Meanwhile, the study (Negara et al., 2024) compared CNN with AlexNet and ResNet in the image classification of Balinese god statues, where the CNN demonstrated competitive performance with an accuracy of 97.14%.

A "from-scratch" training approach was also explored in a study (Carvalho Ottoni & Cordeiro Ottoni, 2025) for Balinese inscription recognition using VGG16, MobileNetV1, and Simple CNN, with VGG16 demonstrating optimal performance. This indicates that the architecture depth can influence the model's ability to capture visual feature representations. Furthermore, a study in (Carvalho Ottoni & Cordeiro Ottoni, 2025) classifying Balinese Kekarangan carvings using a Gabor CNN achieved an accuracy of 89%, demonstrating that a combined approach of traditional feature extraction and CNN can yield good results for certain object types. Another study (Prasetyo Raharja et al., 2022) on pattern recognition of Kamasan Wayang showed an accuracy range between 86% and 100%, indicating that model performance is influenced by the complexity of the visual patterns as well as the quality of the dataset utilized.

Several prior studies have applied CNN to classify traditional Indonesian cultural objects. (Sinaga et al., 2024) proposed a multi-layer CNN with convolutional filters of sizes 3×3, 5×5, and 7×7 for batik motif classification, achieving an overall accuracy of 90.88%. (Widyantoko et al., 2021) employed transfer learning using InceptionV3 and MobileNetV2 to distinguish authentic batik from its imitation, with the best accuracy reaching 77.8%, highlighting the challenge of classifying visually similar cultural objects. (Sebatubun & Haryawan, 2024) implemented CNN for the classification of Javanese Keris types based on Dhapur, obtaining a training accuracy of 78.26%, and noted that limited dataset size remained a key constraint in achieving higher performance.

While these studies demonstrate the potential of CNN in preserving Indonesian cultural heritage through image classification, none have addressed the classification of traditional Balinese kites. To the best of the authors' knowledge, no publicly available dataset exists for this object, and no prior study has applied CNN to classify Balinese kite types. This study therefore contributes a novel locally collected dataset comprising 2,400 augmented images and 282 independent test images across three kite classes — Bebean, Janggan, and Pecukan — and proposes a CNN-based classification model that achieves an average validation accuracy of 91.5%, outperforming the aforementioned studies on comparable cultural object classification tasks.

Based on these studies, it can be observed that the CNN approach has strong potential for classifying Balinese cultural objects in images. However, several aspects still need to be developed. First, most research focuses on cultural objects such as flowers, statues, carvings, and paintings, while cultural objects in the form of visual artifacts, such as traditional kites, have not been widely explored. Second, previous research has tended to focus on model performance, while the systematic development of local culture-based datasets is still relatively limited. Third, the variation in the results indicates that the model performance is strongly influenced by the data characteristics and the complexity of the objects being classified.

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Therefore, this study aims to address this gap by developing a CNN-based image classification system for traditional Balinese kites, supported by a structured visual dataset. This study focuses not only on model performance but also emphasizes contributions to the development of local cultural datasets and the application of comprehensive evaluation to ensure the model's stability and generalizability.

METHOD

The research flow is illustrated in Fig. 1. This research started with image data collection, preprocessing, data augmentation, dividing the data into training and test data, building a CNN model and conducting training, then testing with k-fold cross validation, and model evaluation.

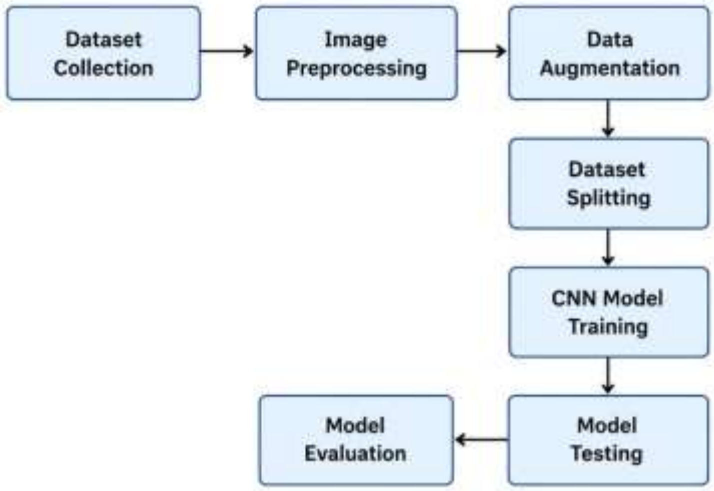

Fig. 1 Research Flow

This dataset consists of three classes: "Bebean," "Janggan," and "Pecukan." The "Bebean" class contains 800 images, the "Janggan" class contains 800 images, and the "Pecukan" classes contained 800 images each, for a total of 2,400 images. This study collected documentation and information related to traditional Balinese kites from Padang Galak and Mertasari beaches in September 2024. The three kites are illustrated in Fig. 2.

(a) (b) (c)

Fig. 1 (a) Bebean, (b) Janggan, (c) Pecukan

During data preprocessing, unstructured image data are transformed into a format that is suitable for model input. This process is carried out to reduce or remove irrelevant information, thereby increasing the efficiency and accuracy during the modeling stage. Image normalization was carried out by rescaling pixel intensity values from the range of 0–255 to the interval [0,1] through division by 255. This process is intended to enhance training stability, improve computational efficiency, and accelerate model convergence (Pei et al., 2023).

To improve the generalization ability and reduce the risk of overfitting, data augmentation techniques are used, namely the process of creating new variations from existing data without adding to the raw data (Hao et al., 2023). This method functions as a form of implicit regularization that helps the model become more robust to data variations and can be used to address data imbalances. Some of the augmentations used include the following:

1) Rotation: The image is rotated at a specific angle to expand the range of data orientations.

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2) Zoom: Zooming in or out of an image to introduce variations in scale.
3) Shift: Shifts the image horizontally and vertically to reflect variations in the object position.
4) Flipping: Horizontally flips the image to increase data diversity.

The dataset was subsequently divided into training and testing sets using an 80:20 ratio. This separation was performed so that the model could learn from representative and diverse data and be tested using previously unprocessed data. With this strategy, it is hoped that the model will be able to produce an accurate classification performance in recognizing kite types based on images (Bichri et al., 2024). In addition, a separate independent test set of 282 original (non-augmented) images that consisting of 94 images per class was collected to evaluate the final generalization performance of the best model under real-world image conditions. Subsequently, a classification model was built using a CNN architecture. The modeling process consists of two main stages: feature learning and classification. In the feature learning stage, the convolution process, as the core of the CNN architecture, is followed by max pooling and the use of the ReLU activation function. The extracted features were subsequently passed to the fully connected layer for classification. The detailed configuration of the CNN architecture is described as follows (Alzubaidi et al., 2021).

1) The input consists of grayscale images with a size of 224 × 224 × 1, where the single channel represents the grayscale format. The feature extraction stage is composed of three convolutional layers, three max-pooling layers, and one dropout layer.
2) The first convolutional layer employs 8 filters with a kernel size of 3 × 3 and utilizes the ReLU activation function, followed by a max-pooling operation with a pool size of 2 × 2.
3) The second convolutional layer uses 16 filters with a 3 × 3 kernel, applies the ReLU activation function, and is followed by a max-pooling layer with a 2 × 2 size.
4) The third convolutional layer consists of 32 filters with a 3 × 3 kernel, also using the ReLU activation function, and is followed by a max-pooling operation of 2 × 2.

During the classification stage, the output from the convolutional layers is transformed into a one-dimensional vector through a flattening process (Alzubaidi et al., 2021). This feature vector is then processed by a fully connected layer containing 256 neurons. A softmax activation function is applied at the final layer to classify the data into three categories. Additionally, a dropout layer is incorporated to reduce the risk of overfitting. The overall CNN architecture is illustrated in Fig. 3.

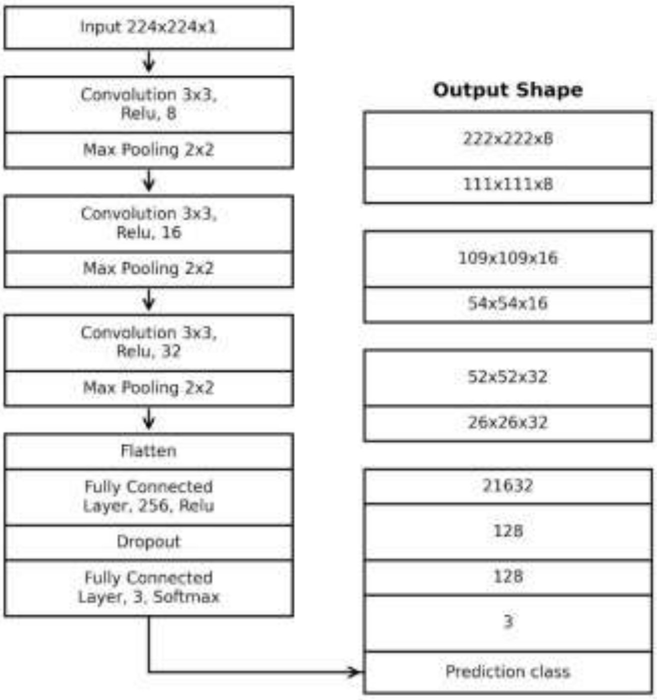

Fig. 2 Architecture of CNN

The CNN architecture implemented in this study can be summarized in the following algorithm:

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Table 1. CNN Architecture for Balinese Kite Classification

Algorithm: Three-Layer CNN

Initialization:

Input layer (image size 224×224×1)

Convolutional Layers:

a. Convolutional Layer 1:
- Convolution operation with 8 filters, 3×3 kernel
- ReLU activation with L2 regularization ($\lambda = 0.001$)
- Max-Pooling 2×2

b. Convolutional Layer 2:
- Convolution operation with 16 filters, 3×3 kernel
- ReLU activation with L2 regularization ($\lambda = 0.001$)
- Max-Pooling 2×2

c. Convolutional Layer 3:
- Convolution operation with 32 filters, 3×3 kernel
- ReLU activation with L2 regularization ($\lambda = 0.001$)
- Max-Pooling 2×2

Flatten Layer:

- Transform feature maps into a one-dimensional vector

Fully Connected Layers:

- Hidden layer with 256 neurons, ReLU activation
- Dropout layer (rate = 0.5)
- Output layer for classification: 3 classes, Softmax

Training configuration: Optimizer = Adam (lr = 0.00001), Loss = Categorical Cross-Entropy, Epochs = 50

The model architecture consists of an input layer with a shape of 224×224×1, followed by three convolutional layers with 8, 16, and 32 filters respectively, each using a 3×3 kernel size, ReLU activation, and L2 regularization (regularization factor of 0.001) to reduce overfitting. Each convolutional layer is followed by a max-pooling layer with a 2×2 pool size. After feature extraction, the resulting feature maps are flattened into a one-dimensional vector and passed to a fully connected layer with 256 neurons using ReLU activation, followed by a dropout layer with a rate of 0.5. The final output layer uses a softmax activation function to classify the input into three classes. The model is compiled using the Adam optimizer with a learning rate of 0.00001 and categorical cross-entropy as the loss function, and is trained for 50 epochs.

Model performance was evaluated using 5-fold cross-validation (K = 5), where the dataset was split into five subsets and each subset was used alternately for training and testing. The evaluation was based on results obtained from these iterations. A confusion matrix was applied to assess classification performance using metrics such as accuracy, precision, recall, and F1-score (Palanivinayagam et al., 2023). The error rate was also calculated to indicate the proportion of misclassified instances. The confusion matrix presents a comparison between predicted and actual labels, reflecting the model's ability to classify data correctly and incorrectly (Valero-Carreras et al., 2023). The confusion matrix consists of four components.

1. TP (True Positive) is the number of correctly predicted positive class.
2. FP (False Positive) is the number of incorrect predictions in the positive class.
3. TN (True Negative) is the number of correctly predicted negative class.
4. FN (False Negative) is the number of incorrect predictions in the negative class.

The formula for calculating the evaluation metrics is

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$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \times 100\% \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \times 100\% \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \times 100\% \quad (3)$$

$$F1\text{-}score = 2 \times \frac{Precision \times recall}{Precision + recall} \times 100\% \quad (4)$$

$$Error\ Rate = \frac{FP+FN}{TP+TN+FP+FN} \quad (5)$$

RESULT

This section presents the experimental results obtained from the training and testing of a Convolutional Neural Network model to classify three types of traditional Balinese kites: Bebean, Janggan, and Pecukan. A comprehensive evaluation was conducted using a 5-Fold Cross Validation approach to minimize bias caused by specific data splits, thus ensuring a more representative model performance. Furthermore, the loss and accuracy curves, confusion matrix, and performance on the final test data were analyzed to measure the model's generalizability to previously unseen data. The discussion in this section focuses not only on evaluation metrics, such as accuracy, precision, recall, and F1-score, but also on inter-fold performance stability, potential overfitting, and factors influencing classification errors. Thus, the results provide a comprehensive overview of the effectiveness of the proposed CNN architecture in supporting the automatic classification of traditional Balinese kite images.

A. K-Fold Cross Validation Results

Model performance evaluation was performed using 5-Fold Cross Validation to obtain a comprehensive assessment and avoid reliance on a single data distribution scheme. For each fold, 1,920 images were used as training data and 480 images were used as validation data. The training process lasted for 50 epochs using the Adam optimizer, a learning rate of 0.00001, and a categorical cross-entropy loss function. The training process also implemented image augmentation techniques to increase data variation and improve the model generalization ability.

Table 2. Results Of Model Performance Evaluation Based On Cross-Validation

Fold	Accuracy	Precision	Recall	F1-Score	Error Rate
1	90.42%	90.58%	90.42%	90.43%	9.58%
2	92.50%	92.45%	92.50%	92.47%	7.50%
3	91.67%	91.70%	91.67%	91.66%	8.33%
4	91.04%	91.00%	91.04%	91.01%	8.96%
5	91.87%	91.94%	91.88%	91.85%	8.13%

Based on Table 1, the accuracy values for each fold ranged between 90% and 92%. The performance variation between the folds was relatively small, indicating that the model had good stability against variations in the data distribution. The average validation accuracy was approximately 91.5%, indicating that the implemented CNN architecture had stable generalization capabilities on the traditional Balinese kite image dataset.

The relatively balanced precision, recall, and F1-score values for each fold indicate that the model was not biased toward any class. This is important considering the balanced dataset used, which has an equal number of images for each class.

B. Loss and Accuracy Curve Analysis

The training graph in the second fold (Figure 4) represents the model's learning process, as it yielded the best performance. The loss graph shows that the training and validation losses consistently decreased throughout the 50 epochs without any significant spikes. The distance between the two curves was relatively small, and the validation loss was slightly lower in the final epoch. This pattern indicates that the model did not experience

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overfitting and maintained a good generalization ability. In the accuracy graph (Figure 5), the performance increased significantly in the early epochs and began to stabilize after approximately the 30th epoch. The training and validation accuracy curves moved parallel until the end of training, with values above 90%, indicating that the model had reached convergence. The consistency between the training and validation curves confirmed that the CNN architecture used was capable of effectively extracting visual features without losing generalization ability.

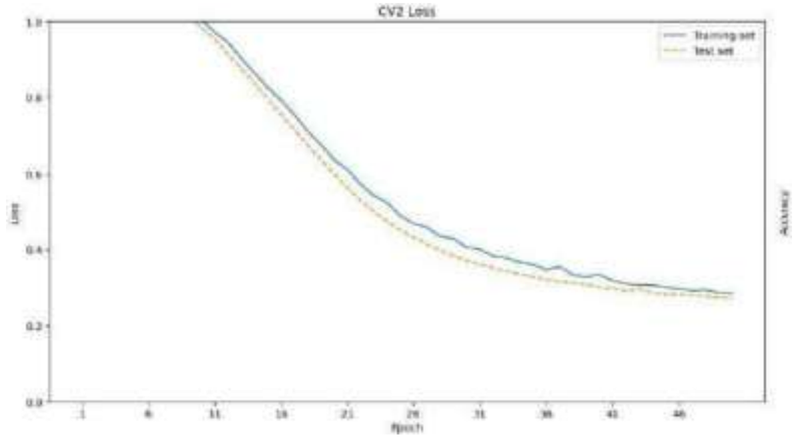

Fig. 3. Loss Fold Curve 2

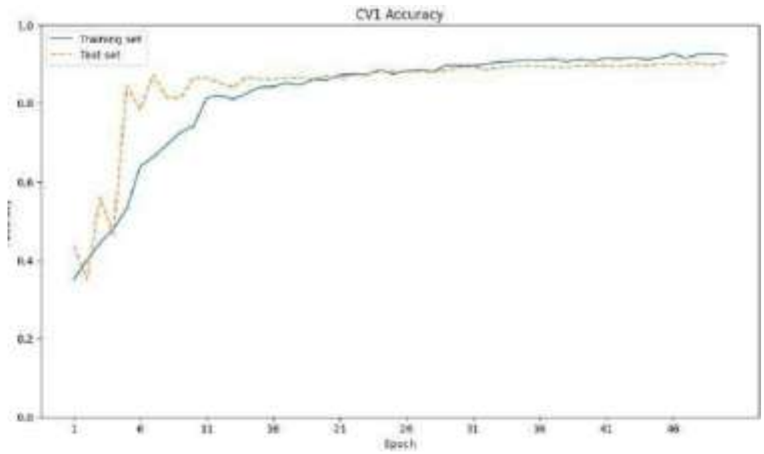

Fig. 4. Fold 2 Accuracy Chart

The 5-Fold Cross Validation results demonstrate that the proposed CNN model is capable of providing stable, accurate, and consistent classification performance in identifying the three types of traditional Balinese kites based on digital images.

C. Final Test Data Evaluation

The best model obtained from the 5-Fold Cross Validation process was then tested using a separate test dataset of 282 images (94 each for the Bebean, Janggan, and Pecukan classes). The evaluation was conducted using a confusion matrix with precision, recall, and F1-score metrics.

Table 3. Evaluation Results On Separate Test Data

Class	Precision	Recall	F1-Score
Bebean	74.59%	96.81%	84.26%
Janggan	97.92%	100%	98.95%
Pecukan	98.44%	67.02%	79.75%
Accuracy		**87.94%**	

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Testing on the independent test dataset showed that the model maintained high performance in the Janggan class, with a recall value of 1.0000 and an F1-score of 0.9895. In the Bebean class, the model was able to recognize almost all images with high recall (96.81%), although the precision was relatively lower (74.59%), indicating an overprediction for that class. Conversely, the Pecukan class demonstrated high precision (98.44%) but lower recall (67.02%), indicating that some images of this class were still misclassified.

Overall, the model achieved an accuracy of 87.94%, which was slightly lower than the average cross-validation accuracy of 91.5%, resulting in a generalization gap of approximately 4%. This difference is still within reasonable limits for an image classification scenario with incompletely controlled shooting conditions. Variations in lighting, shooting angle, and visual similarity, particularly between the Janggan and Pecukan classes, were the main factors influencing the classification errors.

Despite the variation in results, the evaluation showed that the model could still recognize the main visual characteristics of each kite type with a reasonable level of accuracy. These results demonstrate that the implemented CNN approach has sufficient generalization capacity and has the potential to support digitalization and cultural preservation efforts based on image-processing technology.

DISCUSSIONS

The results of this study indicate that the developed CNN model has good generalization capabilities in classifying images of traditional Balinese kites, achieving an average validation accuracy of 91.5% across five folds. This result is competitive when compared to previous CNN-based studies on Indonesian cultural object classification. (Sinaga et al., 2024) reported 90.88% accuracy using a multi-layer CNN for batik motif classification, while (Sebatubun & Haryawan, 2024) obtained only 78.26% training accuracy for Javanese Keris classification with a limited dataset. (Widyantoko et al., 2021) achieved a best accuracy of 77.8% using transfer learning for batik authenticity identification. The comparable performance of the proposed model, achieved using a custom CNN trained from scratch on a locally collected dataset, suggests that a well-designed lightweight CNN architecture can be effective for cultural object classification without relying on pre-trained models or complex multi-layer configurations.

The stable performance demonstrated in the validation process indicates that the model can consistently learn visual feature representations without relying on specific data splits. This demonstrates that the CNN approach is effective in capturing the key visual characteristics of each type of kite. From the training process perspective, the stable convergence pattern and the absence of any indication of overfitting indicate that the model achieved a balance between learning and generalization capabilities. This indicates that the combination of the CNN architecture and training strategy used is optimal for extracting visual features from image data with varying shapes and structures.

However, the difference in performance on independent test data (87.94%) compared to the cross-validation accuracy (91.5%) indicates that the model still faces challenges in handling variations under real-world image conditions. This generalization gap is consistent with findings in similar studies, where models trained on augmented datasets tend to show reduced performance when tested on original, non-augmented images (Widyantoko et al., 2021). Factors such as lighting, shooting angles, and non-uniform backgrounds can affect the model's ability to classify consistently. Furthermore, the similarities in the visual characteristics between the kite types also contributed to the misclassification.

These findings demonstrate that while the CNN approach has strong potential for image-based cultural object classification, model performance is still affected by the visual complexity of the objects and the quality of the dataset used. Future work could explore transfer learning architectures such as ResNet or MobileNet, which have demonstrated higher accuracy in Balinese cultural object classification tasks (Lumumba et al., 2024; Negara et al., 2024), to further improve classification performance. This study also emphasizes the importance of developing more diverse and representative datasets to improve model robustness, and this approach has broader implications for supporting technology-based cultural digitization and preservation.

CONCLUSION

This study demonstrates that a Convolutional Neural Network (CNN) can be effectively utilized to classify three types of traditional Balinese kites—Bebean, Janggan, and Pecukan—based on digital images. The experimental results answer the research objective by showing that the proposed model is capable of achieving stable performance, with an average accuracy of approximately 91.5% in 5-fold cross-validation and 87.94% on unseen test data, indicating good generalization ability.

The main contribution of this study lies in the development of a CNN-based classification approach supported by a culturally specific dataset of Balinese traditional kites, which remains underrepresented in computer vision research. These findings confirm that the model is able to capture the distinctive visual characteristics of each kite category.

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Although a slight decrease in accuracy was observed in the test phase, the performance remains acceptable and is likely affected by variations in image conditions. Future work may focus on improving performance through the use of pretrained architectures, expanding dataset diversity, and optimizing training parameters to obtain more robust results.

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