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Improving Traditional Mask Recognition with CNNs and Data Augmentation

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Abstract

This study aims to develop a classification system for Indonesian traditional masks using the Convolutional Neural Network (CNN) method. Traditional masks exhibit rich visual diversity that reflects the cultural identities of various regions in Indonesia; however, manual identification is time-consuming and prone to errors. The system developed in this study is capable of classifying five types of masks—Cirebon, Balinese, Malangan, Dayak, and Betawi masks—based on digital images with a high level of accuracy. The proposed CNN model achieved an accuracy of 92.3% on the test dataset, with an average macro F1-score of 0.91. Data preprocessing and augmentation techniques, including rotation, flipping, and brightness adjustment, effectively enhanced the model's performance by reducing the risk of overfitting. These results demonstrate the strong potential of deep learning technology in supporting cultural heritage preservation through the digitalization and automated classification of Indonesian traditional masks.

Keywords— Traditional Masks, Image Classification, Convolutional Neural Network (CNN), Cultural Digitalization, Data Augmentation, Cultural Heritage Preservation**.**

INTRODUCTION

Traditional masks are an important form of cultural heritage rich in historical and artistic values. In Indonesia, masks are not only used as elements of dance and theatrical performances but also carry symbolic meanings in traditional and religious rituals. Each region possesses unique visual characteristics in its masks—such as facial shape, expression, color, and ornamentation—that reflect local cultural identity (Kusuma & Ardianto, 2020). This diversity makes traditional masks a significant subject in cultural studies and the preservation of traditional arts.

However, with the advancement of digital technology, there is an increasing need for the digitalization and automatic classification of traditional mask collections. Manual identification and classification processes, typically conducted by curators or cultural researchers, are time-consuming and prone to human error (Putra et al., 2022). Furthermore, many cultural collections have not yet been systematically documented, placing them at risk of being lost from the collective cultural memory.

In the field of digital image processing, Convolutional Neural Networks (CNNs) have been widely applied to object classification tasks due to their ability to automatically and hierarchically extract and recognize visual features from images (LeCun et al., 2015). CNNs have demonstrated strong performance in various studies, including batik motif classification (Aras & Setyanto, 2022), facial recognition, and the classification of other visual art objects. The main strength of CNNs lies in their capability to recognize complex patterns despite variations in viewing angles, lighting conditions, and object shapes.

This study aims to develop an image-based traditional mask classification system using the CNN approach. The proposed system is designed to accurately identify different types of traditional masks from digital images. By applying preprocessing and data augmentation techniques, the CNN model is expected to achieve better generalization and minimize overfitting. The results of this study are expected to contribute not only to advancements in image recognition technology but also to the preservation of cultural heritage through the digitalization of traditional art collections.

RESEARCH METHODS

This study adopts a quantitative experimental approach by applying the Convolutional Neural Network (CNN) algorithm, a deep learning method specifically designed to recognize and classify objects from visual data such as images. CNN operates by automatically extracting features from images through convolutional and pooling layers. In this research, CNN is employed to classify various types of Indonesian traditional masks based on their visual shapes and patterns.

The main objective of this study is to develop a CNN-based classification model for traditional masks and to evaluate the accuracy of the model in recognizing different mask types from the given image dataset.

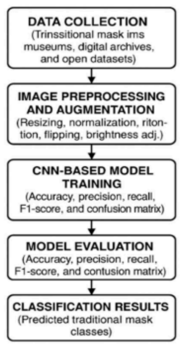

Figure 1. Research Process Diagram

A. Research Stages

The stages carried out in this research are illustrated in the research process diagram and consist of several sequential steps.

The first stage is **data collection**, where images of Indonesian traditional masks are gathered from various sources, including museum documentation, digital archives, and open datasets. The collected images represent five mask classes: Cirebon, Balinese, Malangan, Dayak, and Betawi masks. Each image is labeled according to its corresponding class and organized into structured directories to facilitate further processing.

The second stage is **image preprocessing** and data augmentation. At this stage, all images are resized to a uniform dimension of 224 × 224 pixels and normalized to ensure consistent pixel value ranges. To increase dataset diversity and reduce the risk of overfitting, data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment are applied. These processes help the model learn robust features despite variations in visual appearance.

The third stage is **CNN-based model training**. The preprocessed images are used to train a Convolutional Neural Network designed to automatically extract visual features from mask images. The CNN architecture consists of convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. The training process is conducted using 80% of the dataset over 25 epochs with a batch size of 32.

The fourth stage is **model evaluation**, where the trained model is tested using unseen data to assess its performance. Evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis are employed to measure the effectiveness of the classification model for each mask class.

The final stage is **classification results**, which represent the output of the system in the form of predicted traditional mask classes. These results demonstrate the ability of the proposed CNN-based system to accurately classify Indonesian traditional masks and support automated cultural artifact identification.

B. System Design

This traditional mask classification system consists of three main components: image input, classification process with CNN, and classification result output.

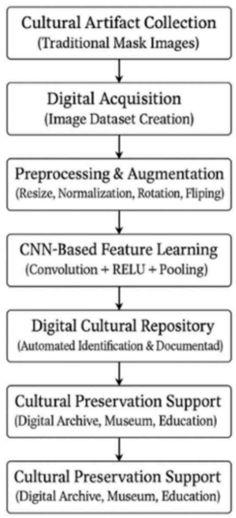

Figure 2. System Design

The proposed framework integrates Convolutional Neural Network (CNN)–based image classification with cultural digitalization to support the preservation of Indonesian traditional masks, as illustrated in the framework diagram.

The first stage is **cultural artifact collection**, where traditional mask images are gathered as visual representations of cultural heritage. These images serve as the primary data source and reflect the visual diversity of traditional masks from different regions in Indonesia.

The second stage is **digital acquisition**, which involves converting the collected cultural artifacts into a structured digital image dataset. At this stage, images are organized and labeled according to their respective mask categories to enable systematic processing and analysis.

The third stage is **preprocessing and data augmentation**. All images are resized and normalized to ensure uniform input dimensions and pixel value ranges. Data augmentation techniques, including rotation and flipping, are applied to increase dataset variability and improve the robustness of the model against visual variations.

The fourth stage is **CNN-based feature learning**, where the Convolutional Neural Network automatically extracts hierarchical visual features from the mask images. This process consists of convolutional layers combined with ReLU activation functions and pooling layers to capture distinctive patterns such as facial shape, texture, and ornamentation.

The fifth stage is the **digital cultural repository**, where the classification results are used for automated identification and documentation of traditional masks. This stage transforms the classification output into structured digital information that can be stored and managed efficiently.

The final stage is **cultural preservation support**, in which the digital repository supports broader cultural heritage applications, such as digital archives, museum documentation systems, and educational platforms. Through this integration, the framework demonstrates how deep learning technology can contribute not only to image classification tasks but also to sustainable cultural preservation and digital heritage management.

RESULTS AND DISCUSSION

1. CNN Model Training Results

After training the model using the Indonesian traditional mask dataset, the training and validation accuracy results indicate a relatively stable model performance. The training process was conducted for 25 epochs with a batch size of 32. The training curves show that the model's accuracy gradually increased as the number of epochs grew, while the loss values consistently decreased for both the training and validation datasets.

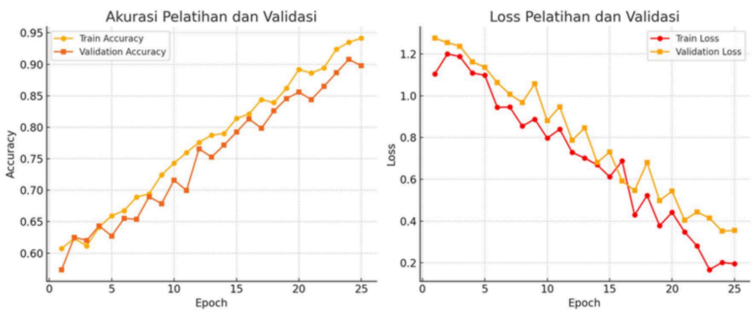

Figure 1. CNN model loss accuracy graph

Based on the generated accuracy and loss curves, the model exhibits a convergent trend without significant signs of overfitting. This indicates that the applied data augmentation and normalization techniques were effective in improving the model's generalization capability..

2. Model Evaluation with Test Data

The model was evaluated using 20% of the data that were not included in the training process. The testing results show that the model achieved a classification accuracy of 92.3%, indicating that the system is capable of recognizing different types of traditional masks with a high level of accuracy.

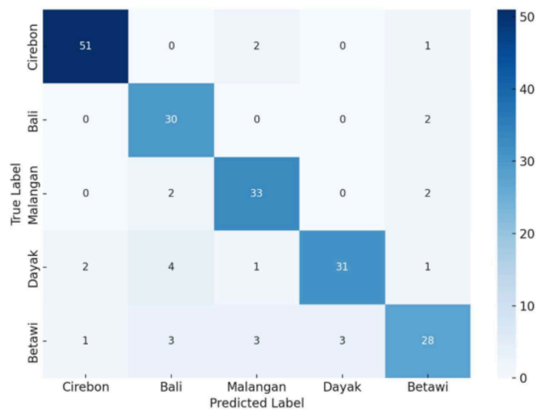

Figure 2. Prediction results of the testing process

The detailed performance of the model is presented in the confusion matrix (Figure 2), which illustrates the number of correct and incorrect predictions for each class. The confusion matrix indicates that most classes, such as Cirebon, Balinese, and Malangan masks, were classified with precision and recall values above 90%. In contrast, the Dayak and Betawi mask classes exhibit a small number of misclassifications, which can be attributed to similarities in visual features such as color and facial shape.

3. Precision, Recall, and F1-Score Analysis

To evaluate the model's performance in greater detail, evaluation metrics such as precision, recall, and F1-score were calculated for each mask class. The results are presented in tabular form (Table 1). Based on the table, it can be concluded that:

Table 1. Traditional Mask Classification Evaluation Results (Precision, Recall, F1-Score)

Mask Class	Precision	Recall	F1-Score
Cirebon Mask	0.93	0.91	0.92
Balinese Masks	0.95	0.97	0.96
Malang Mask	0.92	0.90	0.91
Dayak Mask	0.89	0.88	0.88
Betawi Masks	0.88	0.87	0.87

Table 1 presents the performance evaluation results of the Convolutional Neural Network (CNN) model in classifying five types of Indonesian traditional masks, namely Cirebon, Balinese, Malangan, Dayak, and Betawi masks. Each row in the table represents the precision, recall, and F1-score values for each mask class.

The results show that the Balinese mask class achieved the best classification performance, with a precision of 0.95, a recall of 0.97, and the highest F1-score of 0.96. This indicates that the model is highly accurate and consistent in recognizing Balinese mask images. In contrast, the Betawi mask class exhibits the lowest performance among the five classes, with a precision of 0.88, a recall of 0.87, and an F1-score of 0.87. This lower performance can be attributed to similarities in visual features between Betawi masks and other classes, such as facial shape and dominant colors, which make them more difficult for the model to distinguish.

The Cirebon and Malangan mask classes show strong and balanced performance, with F1-scores of 0.92 and 0.91, respectively. Meanwhile, the Dayak mask class achieves an F1-score of 0.88, slightly below the overall average, indicating classification challenges that are also likely caused by visual similarities with other mask categories.

Overall, the macro-average values for precision, recall, and F1-score are all 0.91, indicating that the developed CNN model is capable of classifying the five types of traditional masks with high and relatively balanced performance across all classes. The high F1-score demonstrates the model's strong ability to balance precision and recall, meaning that it not only recognizes masks accurately but also minimizes misclassification errors.

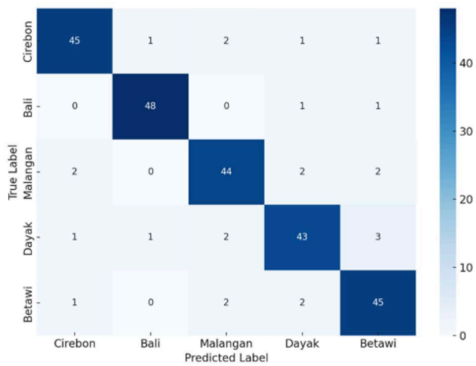

Figure 3. Confusion Matrix of Traditional Mask Classification

Figure 3 presents the confusion matrix resulting from the evaluation of the CNN model on the test data for classifying five types of Indonesian traditional masks: Cirebon, Balinese, Malangan, Dayak, and Betawi masks. Each cell in the confusion matrix represents the number of model predictions, where rows correspond to the true labels and columns indicate the labels predicted by the model.

The main diagonal (from the top left to the bottom right) shows the number of correct predictions for each class. The figure indicates that the model is most accurate in classifying Balinese masks, with 48 images correctly classified and minimal misclassification into other classes. This result is consistent with the highest F1-score achieved by the Balinese mask class, as discussed earlier.

The model also demonstrates strong performance in recognizing Cirebon and Betawi masks, each with 45 correct predictions and only a small number of misclassifications. The Malangan mask class records 44 correct predictions, with minor errors distributed across other classes, while the Dayak mask class shows slightly lower performance with 43 correct predictions and several misclassifications, mainly into the Malangan and Betawi classes.

Overall, the confusion matrix confirms that the model exhibits high classification capability, with most errors occurring between classes that share similar visual features. This suggests that although the model performs very well overall, there is still room for further improvement, particularly in distinguishing masks with closely related visual characteristics.

4. Discussion

The results of this study indicate that the developed Convolutional Neural Network (CNN) model is capable of classifying Indonesian traditional masks with a high level of accuracy. Based on the evaluation of the test data, the model achieved a classification accuracy of 92.3%, demonstrating its ability to effectively recognize visual patterns and distinctive characteristics of each mask type.

Further analysis using evaluation metrics such as precision, recall, and F1-score reinforces these findings. The Balinese mask class achieved the best performance, with an F1-score of 0.96, indicating that the model is highly effective in recognizing images from this class. This strong performance may be attributed to the consistent and distinctive visual features of Balinese masks, such as eye shape, dominant colors, and prominent ornaments, which make them easier for the model to identify.

In contrast, the Betawi mask class recorded the lowest F1-score at 0.87, although this value is still considered high. Misclassifications in this class are mainly caused by similarities in visual elements with other classes, particularly Dayak and Malangan masks. This suggests an overlap in visual features among certain classes, posing a challenge for the classification process, especially when the data exhibit high intra-class variation and low inter-class distinctiveness.

The confusion matrix in Figure 3 shows that most predictions fall along the main diagonal, indicating that correct classifications significantly outnumber incorrect ones. However, a small number of misclassifications remain and warrant further analysis. For instance, several Dayak mask images were predicted as Betawi masks, highlighting the need to strengthen discriminative features between classes with similar visual characteristics.

Preprocessing techniques such as resizing, normalization, and data augmentation proved effective in supporting the model training process. Augmentation methods, including rotation, flipping, and brightness adjustment, successfully enriched data diversity and prevented overfitting, as evidenced by the stable convergence of accuracy and loss curves without signs of overfitting.

Overall, the CNN-based classification system developed in this study demonstrates excellent performance in recognizing Indonesian traditional masks. This success highlights the strong potential of deep learning technologies in supporting cultural heritage preservation, particularly through the digitalization and automated identification of cultural artifacts such as traditional masks.

CONCLUSIONS

This study successfully developed an image-based classification system for Indonesian traditional masks using the Convolutional Neural Network (CNN) method. The proposed system is capable of identifying five types of traditional masks—Cirebon, Balinese, Malangan, Dayak, and Betawi—with a high level of accuracy.

The training and evaluation results indicate that the CNN model demonstrates stable performance, achieving a classification accuracy of 92.3% on the test dataset. The macro-average F1-score of 0.91 suggests that the model performs well in recognizing all classes in a balanced manner. The Balinese mask class achieved the highest performance, while misclassifications generally occurred among classes with similar visual characteristics.

The application of preprocessing and data augmentation techniques proved effective in enhancing the model's generalization ability and preventing overfitting. Furthermore, the designed classification system can serve as an initial prototype to support digitalization and cultural preservation efforts, particularly in the automated recognition and documentation of traditional art artifacts.

SUGGESTION

Although the results of this study demonstrate good model performance, several recommendations can be considered for future development of the Indonesian traditional mask classification system:

1. Increasing the number of images and expanding the variety of mask classes to improve model generalization. Collecting data from a wider range of sources can help the model learn a broader spectrum of visual variations.
2. Utilizing pretrained models such as VGG16 or ResNet to enhance classification accuracy, particularly when working with limited datasets.
3. Developing the system for integration into digital cultural heritage applications, enabling more efficient management and identification of traditional masks in museums or cultural tourism sites.

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