Preserving Cultural Heritage Through AI: Developing LeNet Architecture for Wayang Image Classification

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***Abstract*—Wayang, an ancient cultural tradition in Java, has been an integral part of Indonesian culture for 1500 years. Rooted in Hindu cultural influences, wayang has evolved into a highly esteemed and beloved performance art. In the form of wayang kulit, this tradition conveys profound philosophical messages and implicit meanings that resonate with Javanese society. This research aims to develop an artificial intelligence (AI) model using deep learning with the LeNet architecture to accurately classify wayang images. The model was tested with 2515 Punakawan wayang images, showing excellent performance with an accuracy of 80% to 85%. Although the model successfully recognizes and distinguishes wayang classes, it faces some challenges in classifying specific classes, particularly in scenarios 2 and 4. Nevertheless, this research has a positive impact on cultural preservation, as the developed AI model can be used for automatic wayang image recognition. These implications open opportunities to better understand and preserve this rich cultural heritage through AI technology. With further improvements, this model has the potential to become a valuable tool in the efforts to preserve and introduce wayang culture to future generations.**

***Keywords*—Wayang; LeNet; artificial intelligence; deep learning; cultural tradition**

I. INTRODUCTION

Wayang, a cultural tradition in Java, has been cherished and recognized by the Javanese people for around 1500 years. Its origins can be traced back to the influences of Hindu culture, particularly in the form of shadow puppetry, which eventually evolved into the renowned wayang performances [1], [2]. Indonesia is rich in folktales inherited from our ancestors, and among them, wayang kulit holds a special place as one of the most beloved and influential stories. Wayang kulit art is highly esteemed, primarily due to its profound philosophical values deeply rooted in the history of wayang kulit [3]. Wayang can be classified into two main types: wayang orang, performed live by human actors, and wayang boneka, controlled by a puppeteer called a dalang. Wayang kulit, a form of puppetry, features intricately crafted wooden puppets dressed in leather attire [4]–[8].

In Indonesia, the term "wayang" generally refers to puppetry [9]. The Javanese language defines "wayang" as shadow, while in Malay it denotes shadow, vagueness, or even transcendence [10], [11]. Wayang represents the embodiment of human qualities, encompassing virtues, greed, and more [12]–[15]. For over a thousand years, wayang has been cherished and embraced by the Javanese community, carrying implicit meanings that resonate with their local languages. It showcases classical stories and narratives, often derived from the Ramayana and Mahabharata, which have been adapted to Javanese culture while maintaining their Hindu-Indian origins [13], [16]. Wayang performances hold significant value as they go beyond mere entertainment, serving as a form of cultural art that imparts life lessons, education, and guiding principles for living [17].

Wayang holds a versatile nature that allows its application in various contexts [18], [19]. A wayang performance carries numerous valuable lessons and life principles. Notably, it serves as an educational and moral medium, particularly benefiting the younger generation [17]. Wayang encompasses a wide range of types and forms, each possessing its distinct characteristics, influenced by specific regions. In Javanese cultural traditions, wayang exhibits diverse variations and styles, including wayang Gareng, Batara Wisnu, Yudishtira, Werkudara, Arjuna, and others, exemplifying the richness of its cultural significance.

The rapid advancement of technology in Indonesia has had a detrimental impact on the preservation of cultural heritage [20]. Wayang, one of Indonesia's invaluable cultural treasures, has historically played a vital role in shaping character through its insightful advice and captivating stories. However, the visibility of wayang performances has significantly declined, primarily due to a waning interest among the audience [21], [22]. Consequently, younger generations are becoming increasingly unfamiliar with the names and significance of wayang characters.

This diminishing awareness of wayang and other cultural aspects poses a significant challenge in contemporary society. To address this issue, it is essential to explore innovative approaches and leverage technological advancements. Computerization emerges as a potential solution to educate and engage the community effectively. Utilizing techniques such as LeNet classification, computer-based methods can be employed to enhance the understanding and appreciation of various wayang types and other cultural elements. By leveraging technology, we can revive interest, foster cultural appreciation, and ensure the preservation of Indonesia's rich cultural heritage for future generations.

The study introduces a CNN-based approach for recognizing artificial tire-side pressure printing characters on tire surfaces. The method employs image pre-processing with an enhanced SSR algorithm, character localization and segmentation using template matching, and character recognition utilizing an improved LeNet-5 network structure. Experimental results showcase impressive recognition accuracy, with 95.9% accuracy on the training set, 99.5% accuracy on the validation set, and 95.6% accuracy on the testing set [23].

We propose a novel fault diagnosis model for rotating machinery that overcomes the limitation of directly feeding one-dimensional data into convolutional neural networks. Our model employs a rainbow recursive plot (RRP) to convert vibration signals into two-dimensional color images, allowing for the capture of important fault information. By utilizing a LeNet-5-based CNN, we extract features from the converted images, enabling accurate fault diagnosis recognition. Experimental results on public datasets show a significant improvement in recognition accuracy, reaching 97.86% [24].

Motivated by the strengths and uniqueness of the LeNet method in object classification, this research aims to create a new classification model applied to the case of wayang identification. The selection of wayang as the research case is based on its intricate shapes and the similarities among different types of wayang, posing a challenge in accurately detecting objects with high accuracy.

The explicit objectives of this research are as follows:

- Classify wayang types based on images using the LeNet architecture.
- Evaluate the performance of the classification approach based on the LeNet architecture with depthwise separable method.

II. Experiment

A. Research Architecture

The research architecture built in this study is presented in Fig. 1.

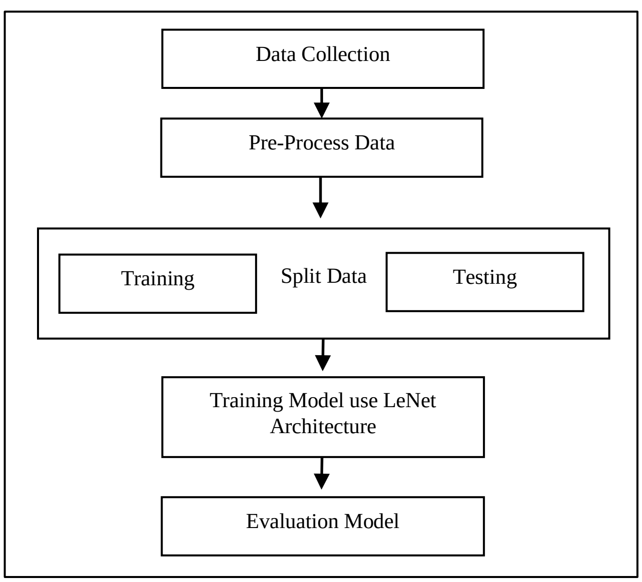

Fig. 1. Research architectural model utilized in this study for wayang classification.

Fig. 1 depicts the research architectural model utilized in this study for Wayang classification. The process begins with data collection, followed by pre-processing, where the dataset is curated to include suitable and unsuitable images as samples. Subsequently, the dataset is divided into three subsets: training, validation, and testing. The LeNet architecture is then employed to construct a deep learning model, utilizing the training set for model training. After the training phase, the model's performance and accuracy are evaluated using the validation set. The evaluation process involves the application of Eq. (1) to (4) to calculate relevant metrics such as accuracy, precision, recall, and F1-score. Finally, the model's effectiveness is assessed by testing it on the independent testing set. This comprehensive approach ensures the robustness and reliability of the developed Wayang classification model.

B. Data Collection and Pre-Processing Data

In this study, the technique of collecting wayang data was conducted using a smartphone camera at a distance of approximately 30cm. The data collection procedure began by preparing the necessary equipment, which included a high-quality smartphone with a camera. The lighting conditions around the wayang object were then adjusted to ensure adequate lighting. Next, the distance between the smartphone camera and the wayang object was set at around 30cm to ensure optimal focus and capture detailed images. The position of the smartphone camera was also considered to align with the wayang object, avoiding perspective distortion. The camera settings on the smartphone were adjusted according to the needs, including image resolution and appropriate modes. During the photo capture process, the smartphone camera was directed directly at the wayang object without obstructing the light or object with hands or fingers. The captured photos were then examined to ensure clarity and detailed depiction of the wayang images. If necessary, the photo capture process could be repeated to obtain the best results. Thus, the technique of collecting wayang data using a smartphone camera at a distance of 30cm can provide adequate data for further analysis.

After collecting the wayang image data using a smartphone camera, the next step is to preprocess the data to prepare it for further analysis. Wayang data preprocessing involves several important stages. Firstly, the image format and resolution are adjusted to meet the analysis requirements. This includes resizing the images, adjusting the file format, and enhancing image clarity. In this preprocessing stage, efforts are made to remove noise or disturbances that may appear in the images. If necessary, disruptive elements such as shadows or other artifacts are also removed. By carefully following the preprocessing steps, the wayang image data is ready to be used in the next stage of analysis, such as pattern recognition and character classification of wayang. Thorough and meticulous preprocessing ensures the reliability and quality of the data that will be used in this research.

C. Split Data

In the data analysis of this research, we used a sample of 2515 Punakawan wayang images, consisting of four different types of wayang. The sample was divided proportionally for training and testing purposes. The training data, which accounts for 80% or approximately 2000 images, was used to train the model for analysis. The testing data, comprising 20% or about 515 images, was used to assess the model's performance and evaluate its ability to classify wayang images. This division is crucial to ensure a good representation of various types of wayang in the dataset and minimize bias in the analysis. Therefore, this data analysis provides a strong foundation for this research and ensures the validity of the results obtained from the developed model.

D. LeNet Architecture

LeNet-5 is a convolutional neural network (CNN) architecture designed for image recognition tasks. It was developed by Yann LeCun et al. in 1998 and has become a foundational model in deep learning [25]–[27]. The architecture consists of convolutional layers, pooling layers, and fully connected layers. For LeNet-5, the input is typically a grayscale or color image with a size of 32x32 pixels. The convolutional layers apply learnable filters to extract features from the input image, generating feature maps that capture different aspects of the image. Pooling layers reduce the spatial dimensions of the feature maps, aiding in feature extraction and computational efficiency. Max pooling is commonly used, selecting the maximum value within a specified window. The resulting feature maps are then flattened and fed into fully connected layers for classification. The final fully connected layer produces the output, representing the predicted class probabilities. LeNet-5 has played a significant role in advancing CNNs and remains a widely studied architecture in image recognition. Fig. 2 illustrate the architectural design of LeNet, which was developed for the purpose of classifying wayang.

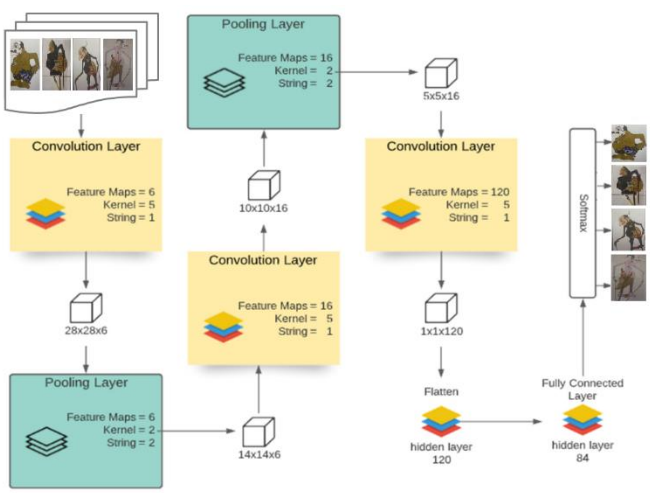

Fig. 2. LeNet architecture.

E. Hyperparameter Initialization

Learning parameters play a crucial role in the accuracy and performance of a model during training. This study explores several important learning parameters, namely Epoch, Batch size, Optimizer, and activation functions. Epoch determines the number of times the entire dataset is used during training. A higher epoch value increases the number of iterations but may lead to overfitting. Batch size refers to the number of data samples used in each iteration. A larger batch size enhances training speed but may impact generalization. Optimizer algorithms like SGD, Adam, and RMSprop optimize the model during training, each with its strengths and weaknesses. Activation functions introduce non-linearity, such as ReLU, Sigmoid, and Tanh, influencing convergence speed and feature representation. Selecting appropriate learning parameters is crucial for achieving optimal model performance. Careful experimentation and parameter tuning are necessary to find the most suitable combination for each specific task and dataset. The candidate hyperparameters utilized in this study are outlined in Table I.

TABLE I. HYPERPARAMETER MODEL

Parameter	Candidate
Epoch	(10, 50, and 100)
Batch Size	(10,20,40,60,80,and 100)
Optimizer	(SGD, RMSprop, Adagrad, Adam and Nadam)
Activation function	(Tanh, Relu, Linear, Sigmoid, Softmax)

F. Performa Measure

The confusion matrix is a valuable method for evaluating the accuracy of an object estimation model. It compares the predicted classification results with the actual classes and provides a detailed view of the model's performance [28]–[30]. The accuracy of the method reflects how well the predicted values align with the actual values. Precision, on the other hand, measures the repeatability of the measurements or the proportion of accurate predictions. Recall represents the number of correct positive responses identified by the model. Combining precision and recall yields the f1-score, which gives a balanced average assessment of the model's performance. These metrics can be calculated using the following formulas, where TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative, respectively [31]–[33].

Description

TP = True Positive

FP = False Positive

FN = False Negative

TN = True Negative

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

$$Precision = \frac{\text{TP}}{\text{TP+FP}} \quad (2)$$

$$Recall = \frac{\text{TP}}{\text{TP+FN}} \quad (3)$$

$$F1 = \frac{2*Presicion*Recall}{\text{Presicion+Recall}} \quad (4)$$

III. RESULT AND DISCUSSION

In this session, we present the research results on wayang classification using the deep learning architecture LeNet. Two scenarios were built to extract information from object images, namely using the default LeNet and implementing the depthwise separable method. Depthwise separable is a data processing technique in neural networks that combines two convolution stages: depthwise convolution and pointwise convolution. Depthwise convolution applies filters to each input channel separately to reduce the number of parameters [34], [35]. Furthermore, we conducted a search for the best hyperparameters to improve model performance using Grid search. This approach aims to achieve optimal model performance by selecting the right combination of hyperparameters, enabling the model to provide accurate and efficient results in the wayang classification training and testing process.

A. Samplel Wayang

Fig. 3 illustrate the unique characteristics of each wayang character. In this image, Bagong is seen with a cheerful face full of wit, while Gareng appears loyal and friendly with a heartwarming smile. Additionally, Petruk's image portrays a funny yet clumsy figure, bringing joy with his comical expressions. On the other hand, the image of Semar presents a wise and gentle character with a gaze full of understanding. Through these images, the distinctiveness and roles of each character in wayang performances can be clearly explained, enhancing the charm and allure of Indonesia's wayang art. The beauty and profound meaning depicted in Fig. 3 enables the audience to appreciate and understand the local wisdom and cultural richness of Indonesia that emanate from this traditional wayang art.

(a) (b) (c) (d)

Fig. 3. Indonesian wayang characters (a) Bagong, (b) Gareng, (c) Petruk, and (d) Semar.

B. Training LeNet

The deep learning architecture based on LeNet is designed for image classification, as depicted in Fig. 2. The input is a 32x32x1 image, with the last dimension representing the color channel. The network includes two convolutional layers with 28 and 10 filters, followed by 2x2 max pooling layers to reduce feature map size. Rectified Linear Unit (ReLU) activation functions are used in the convolutional layers. After the second pooling layer, the output feature maps are flattened into a 120-dimensional vector. Dropout is applied to prevent overfitting by randomly zeroing input units during training. The dropout output then goes through a fully connected layer with 84 neurons using the dense activation function. Batch normalization is employed to normalize activations and improve model stability. ReLU is a popular activation function for its efficiency and performance improvement. Max pooling down samples feature maps to extract essential characteristics and enhance the network's effectiveness. A flatten layer transforms the output of the last convolutional layer into a 1D vector, followed by a fully connected dense layer. The final classification is determined by this layer, using the softmax activation function to generate probability scores for each class. The output layer produces the final classification predictions.

Based on the results of training the LeNet model on the wayang classification task, as presented in Fig. 4, a total of 61,496 parameters were obtained. These parameters encompass all the weights and biases that are fine-tuned and optimized throughout the training process. The overall count of parameters serves as an indicator of the model's complexity and capacity to discern patterns and features from the data. A greater number of parameters empowers the model to acquire intricate data representations. However, this must be carefully balanced against the potential for overfitting and the increased computational demands.

```
Model: "sequential_7"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_14 (Conv2D)          (None, 28, 28, 6)         456

 max_pooling2d_14 (MaxPoolin  (None, 14, 14, 6)        0
 g2D)

 conv2d_15 (Conv2D)          (None, 10, 10, 16)        2416

 max_pooling2d_15 (MaxPoolin  (None, 5, 5, 16)         0
 g2D)

 flatten_7 (Flatten)         (None, 400)               0

 dense_21 (Dense)            (None, 120)               48120

 dense_22 (Dense)            (None, 84)                10164

 dense_23 (Dense)            (None, 4)                 340

=================================================================
Total params: 61,496
Trainable params: 61,496
Non-trainable params: 0
_________________________________________________________________
```

Fig. 4. Training model LeNet (scenario 1).

The evaluation of deep learning models during training is primarily based on two key metrics: training loss and validation loss. Training loss measures the discrepancy between the predicted and actual values on the training data, while validation loss measures the discrepancy on the validation data. It is crucial to analyze both training and validation loss to obtain a comprehensive understanding of the model's performance. For visualizing the performance of the proposed algorithm, Fig. 5 presents the performance visualization, which incorporates both training and validation loss.

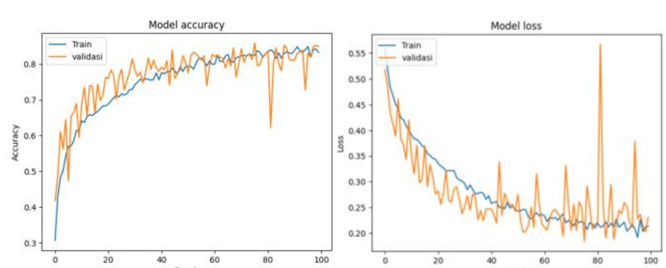

Fig. 5. Training and validation model LeNet (Scenario 1).

C. Training LeNet with Depthwise Separable

In this scenario, the deep learning model was constructed with the same architecture as the previous model, but with the integration of the depthwise separable approach to effectively diminish the total number of parameters. Following the application of the depthwise separable approach, the entire model comprises a total of 58,985 parameters. This represents a notable reduction in the parameter count compared to the previous model, all while maintaining the quality of the classification performance, as illustrated in Fig. 6.

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 separable_conv2d (Separable  (None, 28, 28, 6)        99
 Conv2D)

 max_pooling2d_2 (MaxPooling  (None, 14, 14, 6)        0
 2D)

 separable_conv2d_1 (Separab  (None, 10, 10, 16)       262
 leConv2D)

 max_pooling2d_3 (MaxPooling  (None, 5, 5, 16)         0
 2D)

 flatten_1 (Flatten)         (None, 400)               0

 dense_3 (Dense)             (None, 120)               48120

 dense_4 (Dense)             (None, 84)                10164

 dense_5 (Dense)             (None, 4)                 340

=================================================================
Total params: 58,985
Trainable params: 58,985
Non-trainable params: 0
```

Fig. 6. Training model LeNet with depthwise separable (scenario 2).

For visualizing the performance of the proposed algorithm, Fig. 7 presents the performance visualization, which incorporates both training and validation loss.

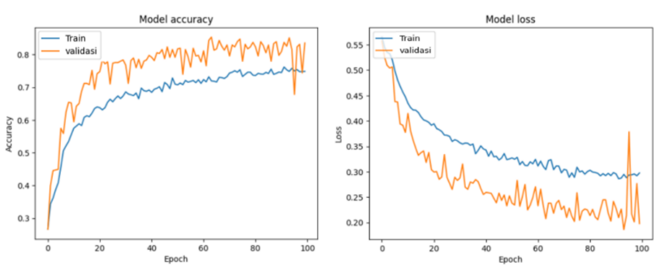

Fig. 7. Training and validation model LeNet with depthwise separable (Scenario 2).

D. Hyperparameter tuning

In this scenario, we used grid search to tune the hyperparameters of the LeNet model for both Scenario 1 and Scenario 2. Grid search is a systematic technique that allows us to explore various combinations of hyperparameter values. By experimenting with different combinations, we can find the best hyperparameter settings in terms of model performance and generalization for the wayang classification task. The results of tuning the hyperparameters for each scenario are presented in Table II. Additionally, to visualize the training and validation performance of the model, the training and validation curves for each scenario are shown in Fig. 8 and Fig. 9, respectively. These graphs provide a visual representation of how the model learns and adapts during the training process.

TABLE II. GRID SEARCH HYPERPARAMETER TUNING RESULTS

Parameter	**Candidate**	**Select Hyperparameter in Scenario 1**	**Select Hyperparameter in Scenario 2**
Epoch	(10, 50, dan 100)	100	100
Batch Size	(10,20,40,60,80,dan 100)	10	10
Optimizer	(SGD, RMSprop,Adagrad, Adam dan Nadam)	Adam	SGD
Fungsi Aktivasi	(Tanh, Relu, Linear, Sigmoid, Softmax)	Relu	Relu

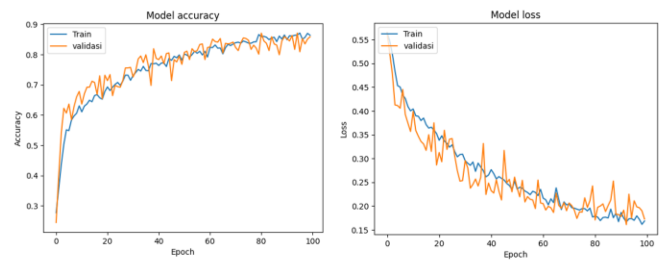

Fig. 8. Training model hyperparameter Scenario 1 (Scenario 3).

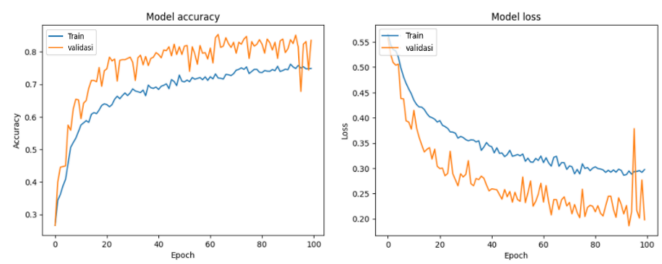

Fig. 9. Training model hyperparameter Scenario 2 (Scenario 4).

E. Evaluation

The findings of four scenarios utilizing the confusion matrix are depicted in Fig. 10, providing a valuable tool for evaluating model performance in classification tasks. The study employed the confusion matrix to assess four distinct scenarios' outcomes in data classification. By utilizing this matrix, we gauge the model's accuracy in classifying data accurately. Information from the confusion matrix aids in calculating essential performance evaluation metrics like precision, recall, accuracy, and F1-Score.

Furthermore, the performance metrics for the four scenarios are presented in Tables III-VI, offering a comprehensive evaluation of the model's classification performance. These tables present precision, recall, accuracy, and F1-Score for each scenario, crucial for assessing the model's effectiveness. Table III corresponds to Scenario 1, Table IV to Scenario 2, Table V to Scenario 3, and Table VI to Scenario 4. Analyzing these metrics allows us to determine the model's performance in various scenarios, facilitating comparisons to identify the most suitable approach for the classification task at hand. These tables play a pivotal role in comprehending the strengths and weaknesses of each scenario, guiding data-driven decisions to optimize and enhance the model's classification performance. The confusion matrix analysis and performance metrics' results provide valuable insights into the model's capabilities, enabling us to refine and fine-tune it for improved classification results.

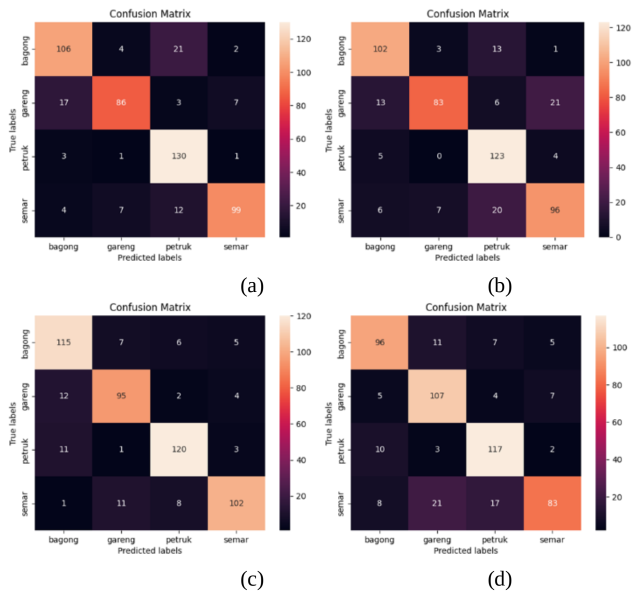

Fig. 10. Confusion Matrix Results (a) Scenario 1, (b) Scenario 2, (c) Scenario 3, and (d) Scenario 4.

TABLE III. LENET PERFORMANCE IN SCENARIO 1

	Precision	Recall	F1_score
Bagong	0.81	0.79	0.80
Gareng	0.87	0.76	0.81
Petruk	0.78	0.96	0.86
Semar	0.90	0.81	0.85
Accuracy	0.83		

TABLE IV. LENET PERFORMANCE IN SCENARIO 2

	Precision	Recall	F1_score
Bagong	0.80	0.85	0.83
Gareng	0.89	0.67	0.76
Petruk	0.75	0.93	0.83
Semar	0.78	0.74	0.76
Accuracy	0.80		

TABLE V. LENET PERFORMANCE IN SCENARIO 3

	Precision	Recall	F1_score
Bagong	0.83	0.87	0.85
Gareng	0.90	0.76	0.82
Petruk	0.90	0.93	0.92
Semar	0.81	0.87	0.84
Accuracy	0.85		

TABLE VI. LENET PERFORMANCE IN SCENARIO 4

	Precision	Recall	F1_score
Bagong	0.73	0.84	0.78
Gareng	0.77	0.74	0.76
Petruk	0.88	0.84	0.86
Semar	0.82	0.78	0.80
Accuracy	0.80		

In Scenario 1, the model achieved an accuracy of 83%. The evaluation results showed good performance in classifying all wayang classes. Petruk had the highest precision and recall values, indicating its excellent ability to identify the Petruk class. Bagong and Semar also had good F1_score values, indicating a balance between precision and recall. However, it should be noted that the precision for Petruk and Semar classes was slightly lower than recall, possibly due to some difficulty in classifying complex samples.

In Scenario 2, the model achieved an accuracy of 80%. There was variation in performance among the wayang classes. Gareng had a lower recall value, indicating some difficulty in accurately recognizing the Gareng class. Bagong and Petruk had good F1_score values, but the precision for the Petruk class was lower than recall. Semar had low F1-score values, suggesting challenges in classifying the Semar class accurately.

In Scenario 3, the model achieved an accuracy of 85%. The model showed consistent performance for all wayang classes with high F1_score values. The Petruk class had the highest precision and recall values, indicating an excellent ability to classify this class. The Gareng class also had a good F1_score. These results indicate that the model has a strong ability to recognize and distinguish between different wayang classes.

In Scenario 4, the model achieved an accuracy of 80%. Precision and recall for all wayang classes were relatively balanced, but the F1_score for the Gareng and Semar classes was slightly lower than other classes. It is important to note that the model showed some difficulty in accurately classifying the Gareng and Semar classes.

Overall, the evaluation results indicate that the model has good performance in classifying the wayang classes. However, there is some variation in performance among specific classes, which could be the focus of further model improvements. Careful evaluation of all performance metrics can help identify areas where the model can be enhanced to achieve better results in wayang classification tasks.

F. Discussion

The evaluation results of the four wayang classification scenarios show good performance in classifying wayang images. All scenarios achieve relatively high accuracy, ranging from 80% to 85%. Additionally, the precision, recall, and F1-Score values are balanced, indicating the model's ability to classify wayang images accurately and consistently. The best scenario is Scenario 3, which achieves an accuracy of 85% with a high precision of 86%, recall, and F1-Score of 85.75%. This demonstrates that the model in this scenario excels in classifying wayang images with great accuracy. On the other hand, the worst scenario is Scenario 2, with an accuracy of 80% and slightly lower precision, recall, and F1-Score compared to the other scenarios. Although it still performs well, this scenario can be improved to achieve higher accuracy and consistency. Overall, the evaluation results indicate that the developed model performs well in the wayang classification task and is reliable for further analysis. The best and worst scenarios can serve as a basis for further improvements and the development of more optimal models in wayang image recognition.

The AI models developed using the deep learning approach with LeNet (Scenarios 1, 2, 3, and 4) exhibited better performance compared to AI models using other methods such as KNN + GLCM [5] and MLP + GLCM [36]. The LeNet-based AI models achieved higher accuracy and more balanced precision, recall, and F1-Score, as shown in Table VII.

The results of this study provide insight into the effectiveness of using depthwise separable LeNet models in image-based puppet classification. This contributes to the development of better classification techniques in the domain of puppet recognition. Moreover, the use of depthwise separable is able to reduce the total number of model parameters, which indicates efficiency in the use of computational resources, although the addition of depthwise separable affects the level of accuracy gain.

In future research, there are several recommendations that can be considered. First, increasing the amount of puppet image data can help improve the performance of the model. Second, further exploration of hyperparameters and optimization techniques can be an important step in improving classification accuracy such as random search and Bayessian optimization. In addition, future research can consider the use of attention modules to improve the model's ability to deal with a larger variety of wayang images.

TABLE VII. COMPARISON WITH PREVIOUS STUDIES

Study (Ref)	AI Model	Accuracy	Precision	Recall	F1-Score
Sandy et all [5]	KNN + GLCM	0.775	-	-	-
Muhathir et all [30]	SVM + GLCM	0.834	-	-	-
Santoso el all [36]	MLP + GLCM	0.734	-	-	-
Scenario 1	Lenet	0.83	0.84	0.83	0.83
Scenario 2	Lenet	0.8	0.805	0.7975	0.795
Scenario 3	Lenet	0.85	0.86	0.8575	0.8575
Scenario 4	Lenet	0.8	0.8	0.8	0.8

IV. CONCLUSION

This research contributes to the development of AI models for wayang image classification using deep learning with the LeNet architecture. The AI models developed show superior performance in classifying wayang images compared to models using other methods such as KNN + GLCM and MLP + GLCM.

The evaluation results indicate that all wayang classification scenarios achieve relatively high accuracy, ranging from 80% to 85%. The precision, recall, and F1-Score values are well-balanced, demonstrating the model's ability to classify wayang images accurately and consistently. However, there is variation in performance among specific wayang classes, suggesting potential areas for further model improvements. Careful evaluation of all performance metrics can help identify these areas and enhance the model's performance in wayang classification tasks.

The research has the potential to benefit cultural recognition and preservation, as the developed AI model can be used for further analysis and automated recognition of wayang images. However, the study has some limitations, such as the size of the dataset and the complexity of wayang images, which may affect model performance. Therefore, future research should consider augmenting the data and exploring alternative deep learning approaches or combining different methods to further enhance the model's accuracy and robustness in wayang image recognition.

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