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Utilizing Machine Learning for Pattern Recognition of Wayang Kamasan in Efforts to Digitize Traditional Balinese Art

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Abstrak

Kepunahan identitas budaya lokal memunculkan pertanyaan mendalam mengenai pendekatan konservatif yang dapat diadopsi oleh berbagai pemangku kepentingan. Proses globalisasi yang sedang berlangsung terus mendorong inovasi teknologi, sementara pengetahuan budaya lokal semakin terpinggirkan. Sebaliknya, sikap afirmatif terhadap pelestarian budaya lokal berkorelasi positif dengan pengetahuan budaya lokal. Penelitian ini berfokus pada budaya Wayang Kamasan dan menggunakan pendekatan berbasis pembelajaran mesin untuk memperkenalkan kembali Wayang Kamasan dalam konteks komunitas global. Penelitian ini menggunakan kombinasi metode kualitatif dan kuantitatif eksperimental. Yang pertama digunakan untuk mendapatkan pemahaman mendalam tentang aspek sosial budaya Wayang Kamasan, sedangkan yang terakhir digunakan untuk menilai efektivitas metode pembelajaran mesin.Hasil prediksi dengan menggunakan model CNN, dengan menggunakan gambar wayang yang baru menghasilkan tingkat akurasi sebesar 100%. Pendekatan pembelajaran mesin untuk mengklasifikasikan Wayang Kamasan merupakan metode yang efektif untuk melestarikan budaya Bali. Dengan mengklasifikasikan identitas visual Wayang Kamasan secara akurat, maka dimungkinkan untuk mendokumentasikannya secara digital, sehingga memfasilitasi pelestarian budaya lokal Bali. Pengenalan pola melalui klasifikasi memungkinkan pelestarian warisan budaya ini dalam bentuk digital sekaligus mendukung pengenalan wayang Bali.

Kata kunci— *Wayang Kamasan, Machine Learning, pelestarian budaya*

Abstract

The extinction of local cultural identities gives rise to profound inquiries concerning the conservative approach that may be adopted by a range of stakeholders. The ongoing process of globalization continues to drive technological innovation, while local cultural knowledge is increasingly marginalized. Conversely, an affirmative attitude towards the preservation of local culture is positively correlated with knowledge of local culture. This study focuses on Wayang Kamasan culture and employs a machine learning-based approach to reintroduce Wayang Kamasan in the context of a global community. The research employs a combination of qualitative and experimental quantitative methods. The former is used to gain an in-depth understanding of the socio-cultural aspects of Wayang Kamasan, while the latter are employed to assess the effectiveness of machine learning methods. The prediction results of CNN testing with new wayang images, can predict with confidence level 100%. The application of machine learning methods for the classification of wayang, especially Wayang Kamasan, has significant effectiveness in efforts to preserve Balinese culture.The findings demonstrate that the machine learning approach to classifying Wayang Kamasan is an effective method for preserving Balinese

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culture. By accurately classifying the visual identity of Wayang Kamasan, it is possible to digitally document it, thereby facilitating the preservation of Balinese local culture. Pattern recognition through classification enables the preservation of this cultural heritage in digital form while also supporting the recognition of Balinese wayang.

Keywords— *Wayang Kamasan, Machine Learning, preserving culture*

1. INTRODUCTION

The extinction of local cultures is a concern in global sustainability discourse. Local culture is a form of early human civilization thinking about shared social welfare. Local culture is an innovation from society to realize mutual survival between humans and other aspects outside themselves. Many studies [1][2][3][4][5][6][7] show that local culture is a protective circle for local communities. The local context in local culture refers to a set of values, rules, principles, beliefs, and other expressions of a particular community in a limited geographic area [8]. Local communities use values and rules as a guide to realizing their common goals in their social system. This broadly illustrates the deep need to recognize and re-explore local cultural identities to build networks from below for human sustainability in the future.

Wayang art has various forms and types that are spread across various regions of the archipelago. The distribution of types of wayang in various regions of the archipelago enriches the treasury of wayang culture but, at the same time, tends to create identity bias, both geographically, historically, and culturally. Wayang classification through technology has been widely developed. Mapping of several existing studies [9][10][11][12][13][14] shows the adaptation of Artificial Intelligence (AI)-based technology to introduce or promote local culture. Mahathir et al. [9], in their study on the use of AI for wayang image classification, stated that the use of AI needs to be considered in preserving and introducing wayang to the community in a broader context. From the study that stated the potential of AI as a catalyst for recognizing local culture, the adaptation of AI in recognizing patterns to identify Wayang Kamasan has yet to be carried out.

This study aims to expand the scope of previous study objects that do not specifically analyze the implementation of AI on cultural objects of painted puppets from Kamasan Village, Bali (Wayang Kamasan). Through machine learning, the Wayang Kamasan Recognition Pattern reinterprets the identity of the cultural heritage of the Kamasan Village community, Bali, facilitating tradition-based innovation. This study proposes the following questions: 1) How can Wayang Kamasan be identified using a machine learning approach using the Convolutional Neural Network (CNN) method in mapping the Wayang Kamasan recognition pattern? The answers to these questions provide an in-depth understanding of tradition-based innovation to recognize and understand the local identity inherent in Wayang Kamasan. Through the CNN approach, this study identifies patterns of Wayang Kamasan so that they can reintroduce local cultural identities to a broader audience. It is expected to foster cultural appreciation, revive interest, and ensure cultural preservation for future generations. The research involves five main stages: data collection, preprocessing, model development, testing, and analysis. Data collection was conducted through observations, interviews, literature reviews, and documentation, resulting in a dataset. Preprocessing included resizing images, normalizing colors, augmenting data for variability, and labeling each image. The Convolutional Neural Network (CNN) model was then developed and trained to identify the unique patterns of Wayang Kamasan with high accuracy. Testing and validation followed to evaluate the model's performance, achieving 100% accuracy in classifying the images. Finally, the results were analyzed to highlight the model's effectiveness and documented digitally to support cultural preservation efforts. The dataset consists of 25 images of Wayang Kamasan, a traditional Balinese art form, categorized into 70% training data and 30% testing data. The images represent various Wayang Kamasan characters with distinctive visual patterns, textures, and colors that were used for training and testing the CNN model in this research.

CNN compared to other methods is its ability to extract features automatically without the need for manual feature design, making it more efficient and able to handle variations in scale, rotation, and lighting in images [15][16][17][18][19][20]. This study contributes to preserving Wayang Kamasan, a traditional Balinese art form, by integrating machine learning techniques, specifically CNN. By applying modern technology to cultural heritage, the research offers a systematic approach to identifying and classifying unique patterns in Wayang Kamasan, and this facilitates the creation of a digitized repository that safeguards and promotes Balinese culture globally. The primary contributions of this research include developing a high-accuracy machine learning model (achieving 100% classification accuracy), providing a validated process for digital documentation, and demonstrating the potential of technology in preserving and reintroducing traditional art forms to a broader audience. These findings underline the synergy between innovation and tradition, ensuring cultural heritage remains relevant in the digital era.

2. METHODS

The methodology in this study includes problem analysis and architectural or design approaches applied to solve the problems. In the context of this study, the topic raised is "Utilizing Machine Learning for Pattern Recognition of Wayang Kamasan in Efforts to Digitize Traditional Balinese Art", so a mix of qualitative research methods and quantitative experiments are used to integrate modern technology with traditional art in order to preserve cultural heritage through digitization. Qualitative data focuses on data exploration about Wayang Kamasan, while quantitative experiments focus on Wayang Kamasan recognition patterns. The research involves several key stages that integrate cultural exploration and technological application:

1. **Data Collection**: Observations were conducted in Kamasan Village, accompanied by interviews with traditional artists and a review of literature to gather images and contextual information about Wayang Kamasan.
2. **Data Preprocessing**: The collected images were processed to ensure consistency and quality. This included resizing to 224x224 pixels, normalizing color values, and applying data augmentation techniques (rotation, flipping, zooming) to enhance dataset variability. Each image was labeled based on its pattern or character.
3. **Model Development and Training**: A CNN model was designed to extract and recognize intricate patterns, textures, and colors unique to Wayang Kamasan. The model was trained using 70% of the dataset to identify these patterns accurately.
4. **Testing and Validation**: The trained model was evaluated using the remaining 30% of the dataset, achieving 100% accuracy in identifying and classifying Wayang Kamasan patterns, demonstrating its reliability and effectiveness.
5. **Analysis and Documentation**: The results were analyzed to assess the performance of the CNN model and its implications for cultural preservation.

Classified Wayang Kamasan images were documented digitally, contributing to a repository that supports cultural heritage preservation. This systematic process demonstrates how modern machine learning techniques can be applied to preserve and promote traditional art forms effectively.

2.1 Dataset Collection

Developing relevant and accurate datasets requires a strong and relevant data foundation. Data was collected through observation, interviews, literature studies, and documentation. Observations were conducted in Kamasan Village, a communal village of Wayang Kamasan painting. The objects observed included making Wayang Kamasan, details of the shapes of figures and characters, ornaments, and coloring patterns used. In-depth interviews were conducted with informants (painters) who were determined by purposive sampling. Literature studies were conducted to obtain supporting data from scientific and popular articles about Wayang and other sources relevant to the research objectives. Documentation includes photos, videos, and field notes. Overall, qualitative data is used to determine important variables in the dataset, resulting in a relevant dataset. The resulting dataset consists of 25 Wayang Kamasan images, which are then used as the primary material for the training and testing process of the machine learning model.

Figure 1. The image displays most of the dataset utilized for testing and training purposes.

2.2 Pre-processing Dataset Wayang Kamasan

The preprocessing process for the Wayang Kamasan dataset was carried out to ensure the data had appropriate and consistent quality before being used in model training. The preprocessing stages include resizing images to uniform dimensions of 224x224 pixels to be compatible with the standard input of the CNN model and color normalization by changing the pixel values to the range 0-1 to speed up the training process. Furthermore, the data augmentation process is carried out through rotation, flipping, zooming, and shifting to increase the variation of the dataset without increasing the amount of original data so that the model is more robust to pattern variations. In some cases, images are also converted to grayscale to highlight specific texture and contour features to simplify the data. Finally, each image is labeled according to the pattern or characteristic of the Kamasan Wayang it represents so the dataset is ready to train the model effectively.

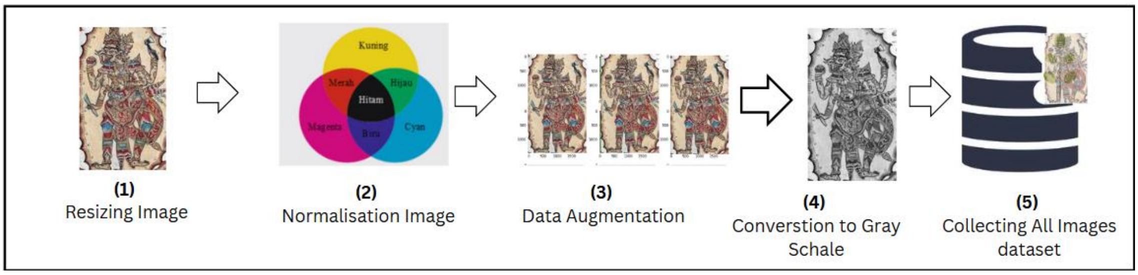

Figure 2. Image preprocessing

Figure 2. shows the image data preprocessing process, which consists of five main steps: (1) Image Resizing to equalize the size of all images to be consistent, (2) Color Normalization to align color values and reduce differences due to lighting conditions, (3) Data Augmentation by applying transformations such as rotation, flipping, or scaling to increase and enrich the variety of the dataset, (4) Conversion to Gray Scale to simplify the data by removing the color dimension, and (5) Image Dataset Collection which stores all preprocessed images into one dataset ready to be used for training or further analysis.

The normalization technique applied in this research, as illustrated in Figure 2, does not involve changing the color space. Instead, it normalizes the color values within the existing RGB color space by scaling pixel values to a range between 0 and 1. This step ensures consistency in color representation across the dataset and accelerates the training process of the CNN model by standardizing input data. The technique retains the original RGB color space, emphasizing color fidelity to maintain the visual characteristics of Wayang Kamasan, which are critical for accurate pattern recognition and classification.

2.3 Identify Wayang Kamasan with CNN

Identification of Wayang Kamasan patterns using a Convolutional Neural Network (CNN) focuses on utilizing a model architecture designed to recognize complex visual features in traditional paintings. CNN has superior capabilities in visual data processing because its architecture is designed to extract features hierarchically from simple to complex patterns [18]. The Convolutional Neural Network (CNN) architecture used in this study is designed to effectively process and classify the intricate patterns and textures of Wayang Kamasan. The architecture consists of the following layers and components:

1. Input Layer: The input images are resized to 224x224 pixels to standardize dimensions across the dataset and ensure compatibility with the CNN architecture.
2. Convolutional Layers: These layers apply filters (kernels) to the input images to extract local features, such as edges, lines, and textures. The initial layers capture simple patterns, while deeper layers detect more complex features unique to Wayang Kamasan.
3. Activation Function (ReLU): After each convolution operation, the ReLU (Rectified Linear Unit) activation function is applied to introduce non-linearity, enabling the model to handle complex patterns in the images.
4. Pooling Layers (Max Pooling): Pooling layers reduce the spatial dimensions of the feature maps, retaining the most significant information while making the model computationally efficient. Max pooling selects the maximum value from a defined region, preserving critical features.
5. Dropout Layers: Dropout is used during training to deactivate a fraction of neurons, preventing overfitting and improving the model's ability to generalize across diverse data.
6. Fully Connected (Dense) Layers: After feature extraction, the fully connected layers integrate these features to make predictions. These layers connect all neurons to produce a classification output.

7. Softmax Output Layer: The final layer applies the Softmax function to generate probability distributions for each class, determining the category (e.g., Wayang Kamasan patterns) with the highest likelihood.

The CNN is trained using the Adam optimization algorithm and categorical cross-entropy as the loss function. This architecture ensures that the model effectively learns the distinctive visual features of Wayang Kamasan while maintaining accuracy and robustness during classification tasks. The evaluation method used in this study to assess the performance of the Convolutional Neural Network (CNN) model involved multiple steps to ensure reliability and accuracy:

1. Accuracy Assessment
2. Confusion Matrix
3. Training and Evaluation Times
4. Error Rate
5. Cross-Validation

These evaluation methods collectively validated the CNN model's ability to accurately classify and preserve Wayang Kamasan art while ensuring computational efficiency and robustness. The data analysis process connects the research object (Wayang Kamasan) with the research variable (preservation of Wayang Kamasan culture). Through literature studies [6][7][8][9][10], the socio-technological perspective is used to explore the connection between technology and the local culture of the local community. The socio-technological perspective provides a comprehensive perspective on the construction of technology in Balinese society's social and cultural context and how the implications of technology, such as machine learning, can support and promote the preservation of Wayang Kamasan.

3. RESULTS AND DISCUSSION

In this discussion, Wayang Kamasan's identification describes the results of applying the Convolutional Neural Network (CNN) method in identifying Wayang Kamasan images. The results obtained from this experiment will be analyzed to evaluate the model's effectiveness in recognizing the unique characteristics of Wayang Kamasan. During the initial data collection of the study in Kamasan Village (observation and interviews), this research collected 25 dataset in the form of Wayang Kamasan images. The Wayang Kamasan images will then undergo a processing process. This processing process includes activities in the form of labeling or naming each puppet image that is successfully collected. Labeling is also carried out in a separate labeling activity on puppets (outside Wayang Kamasan) with the same structure, material, or character, such as Balinese, Javanese, and Sundanese wayang. Through the machine learning model, the computer can recognize the unique patterns possessed by Wayang Kamasan compared to puppets with Balinese, Javanese, or Sundanese characteristics. In addition, various factors affecting model performance, such as data quality, CNN architecture parameters, and the influence of variations in wayang images, will also be discussed to provide further insight into the potential and challenges of using machine learning to preserve this traditional culture.

To convert an image of Wayang Kamasan (a traditional Balinese puppet art) into a CSV file containing color features for image classification using CNN. Wayang Kamasan, known for its distinctive color patterns and intricate designs, often relies on specific color intensities and combinations that are critical in distinguishing different characters and scenes in traditional Javanese performances. The first step is to load the image and convert it to the RGB format (if it’s not already), using an image processing library like PIL or OpenCV. Once in RGB format, the next step is to extract the color features from the image. This involves computing average values for each of the three primary color channels—red (R), green (G), and blue (B)—across the entire image or specific regions of interest, such as the face or costume of a puppet. Alternatively, color histograms can be calculated to capture the distribution of colors within the image, which can provide insight into the dominant color themes typical of Wayang Kamasan, such as earthy tones for background elements or bright, saturated colors for the puppet's features.

These extracted features are essential for the classification task, as the distinctive color patterns in Wayang Kamasan serve as important identifiers for recognizing different characters, scenes, or themes. For example, the skin tones of the puppets, the bright reds and yellows of their costumes, and the contrasting backgrounds are all crucial for distinguishing between characters. The extracted features, such as average RGB values or histograms, are then organized into a table format, where each row corresponds to an image of a Wayang Kamasan puppet, and the columns represent the calculated color features. This data is stored in a CSV file, which can serve as input to a CNN model. The CNN model can then use these color features to learn the unique color signatures of each puppet or scene, helping to classify and recognize different elements in the Wayang Kamasan art based on their color patterns. Ultimately, this approach leverages the rich and symbolic use of color in Wayang Kamasan to improve the accuracy of image classification, especially when distinguishing between the various characters and elements that make up this traditional art form.

Table 1. Values for color and texture features

File Name	Description
File Name	NaName of the image file
Label	Label given to the image, whether Wayang Kamasan or not
average_red	Average value of Red color
average_green	Green Average value of Green color
average_blue	blue Average value of Blue color
hist_r_mean	Average histogram of color R
hist_g_mean	Average histogram of color G
hist_b_mean	Average histogram of color B
hist_r_std	Standard deviation of histogram of color R
Hist_g_std	Standard deviation of histogram of color G
hist_b_std	Standard deviation of histogram of color B

Training and testing with the CNN model and using image data of 80 percent training data and 20 percent testing data produced an accuracy rate of 100%, meaning that the Kamasan puppet image can be identified using the CNN algorithm. The following are the test results with the CNN algorithm, shown in Table 2.

Table 2. Test results with CNN model

Test variables	Value
Training Time	33.32 Second
Evaluation Time	0.10 Second
Test Accuracy	100 %
Eror Rate	0 %

The study's results showed that the CNN model for identifying Kamasan puppet images performed very well. The training time was only 33 seconds, with a training time per iteration of 0.10 seconds, indicating the model's efficiency in the computational process. This model achieved

100% accuracy in testing, meaning that all images were correctly classified without error, reflected in the 0% error. These results indicate that the model is accurate, efficient, and reliable in classifying Kamasan puppet images. However, testing with a more extensive and more diverse dataset needs to be done to ensure consistency.

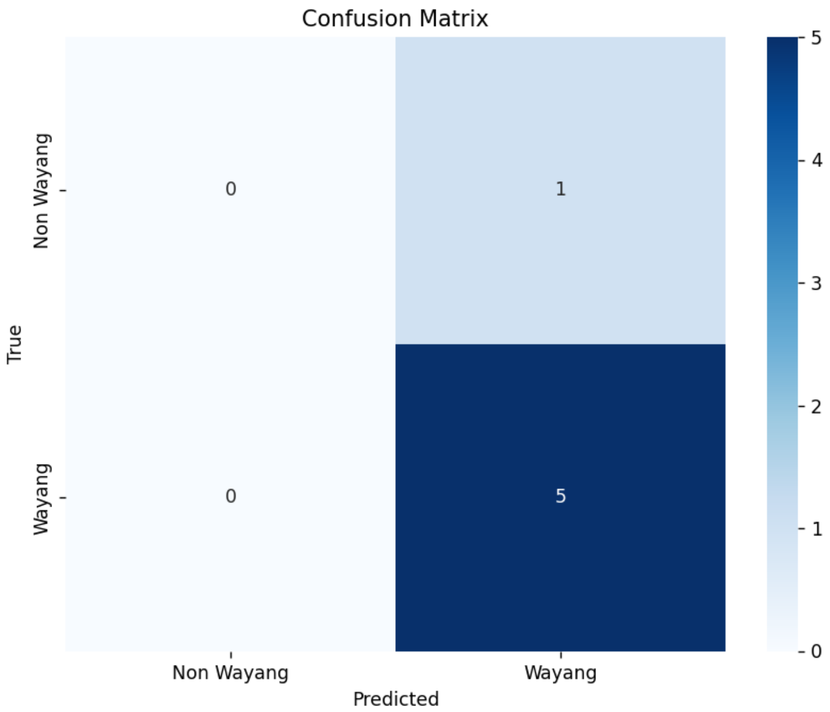

Figure 3. Confusion matrix identification results with CNN

Figure 3 explains the given confusion matrix, with True Positives (TP) = 0, False Positives (FP) = 0, False Negatives (FN) = 1, and True Negatives (TN) = 5; the model has an accuracy of 83.33%, which means the model correctly classifies about 83% of the total images tested. However, the model cannot correctly identify the Wayang Kamasan image because TP = 0, and there is one misclassification where the Wayang Kamasan image is incorrectly categorized as not Wayang Kamasan (FN = 1). On the other hand, no non-Wayang Kamasan images are incorrectly classified as Wayang Kamasan (FP = 0), and the model correctly classifies 5 Wayang Kamasan images as not Wayang Kamasan (TN = 5). Although the model shows promising results in identifying non-Wayang Kamasan images, its performance must be improved to identify Wayang Kamasan accurately.

The test results of CNN testing with new wayang images, where the first image is a Javanese wayang motif and the second image is a wayang with a Kamasan motif, show that both images can be identified correctly. The prediction for the right image is non-wayang with a Confidence level of 100%, while the left image is a Wayang Kamasan motif with a confidence level of 100%. The application of machine learning methods for the classification of wayang, especially Wayang Kamasan, has significant effectiveness in efforts to preserve Balinese culture. Through accurate classification, the visual identity of puppets can be digitally documented, which helps preserve local Balinese culture. Pattern recognition through classification allows for digital preservation and supports the recognition of Balinese wayang. With the help of machine learning, cultural heritage can be widely introduced, and its relevance is maintained in today's digital era, making it one of the practical solutions to support the preservation of Balinese culture through a technological approach, its show in picture 4.

The ability demonstrated by machine learning to identify the unique pattern of Wayang

Kamasan with other wayang only represents a significant technological development. Furthermore, the compatibility of machine learning allows for in-depth observation and identification of Wayang Kamasan. The unique pattern found in Wayang Kamasan shows the expertise of local communities in the past in forming their cultural identity. The identification of the unique pattern of Wayang Kamasan that distinguishes it from other types of wayang confirms that Wayang Kamasan is a cultural entity with exclusive local values. Wayang Kamasan, although part of the wayang art form, has an original identity that is entirely different from other types of wayang in the archipelago. Thus, the ability of machine learning to identify Wayang Kamasan shows that local communities have also developed innovations in their arts and culture.

Prediction: Non-Wayang

Prediction: Wayang

The application of machine learning methods for the classification of wayang, especially Wayang Kamasan, has significant effectiveness in efforts to preserve Balinese culture. Through accurate classification, the visual identity of puppets can be digitally documented, which helps preserve local Balinese culture. Pattern recognition through classification allows for digital preservation and supports the recognition of Balinese wayang. With the help of machine learning, cultural heritage can be widely introduced, and its relevance is maintained in today's digital era, making it one of the practical solutions to support the preservation of Balinese culture through a technological approach.

Applying machine learning technology can inject new vitality into the Wayang Kamasan culture. Image identification technology allows image recognition that is no longer limited to identification but includes recording and collection tools. Machine learning methods, such as CNN, have proven effective in image classification because of their ability to automatically extract visual features, such as shape and texture [20]. In addition to CNN, many machine learning methods can be combined to optimize the identification of certain local cultures in a broader context. Support Vector Machine (SVM), for example, is also often used for classification based on specific visual features, such as texture and color, and can provide accurate results with lower computational costs than deep learning models [24]. Random Forest and Extreme Gradient Boosting (XGBoost) are also popular choices for wayang classification, especially after visual features are extracted because these ensemble models can handle high dimensions and have reasonable control over overfitting [25]. Transfer Learning methods using pre-trained models such as VGG or ResNet often improve classification accuracy, especially on limited datasets, by fine-tuning specific patterns, such as Wayang Kamasan. Using a combination of these methods, wayang classification can be done with high accuracy, thus helping preserve Balinese art and culture through digitalization.

The CNN model was trained over 100 epochs using the Adam optimization algorithm, which combines adaptive learning rates and momentum for faster and more stable convergence. A learning rate of 0.001 was employed, balancing convergence speed and training stability, with a batch size of 32 to optimize memory usage and ensure stable gradient updates. The categorical cross-entropy loss function was utilized, as it is well-suited for multi-class classification tasks such as identifying different Wayang Kamasan patterns. These parameters collectively ensured efficient training, resulting in a highly accurate and robust model for classifying Wayang Kamasan art.

4. CONCLUSIONS

The machine learning approach in identifying Wayang Kamasan is an integral part of the construction of technology in cultural heritage. The interaction between humans and computers allows computer systems to be used in broader schemes and functions. The complex machine learning model applied in identifying Wayang Kamasan presents a new experience regarding the conservative role of technology in local culture. AI-enhanced visual data processing improves the readability of the unique patterns of Wayang Kamasan. Thus, identifying Wayang Kamasan through CNN provides an excellent opportunity to optimize the contextual understanding of the iconographic composition or other forms contained in Wayang Kamasan.

The trend of machine learning adaptation impacts not only the accuracy but also the usability of computer systems. The development of machine learning can benefit more types of local cultural artifacts. In the context of cultural heritage, computer technology is used when the design of artificial intelligence systems is intended to respect cultural values. Thus, the responsibility of implementation and collaboration between technology and culture has a crucial role in the preservation and authenticity of traditional cultural heritage.

By utilizing Convolutional Neural Networks (CNN), the identification of Wayang Kamasan has demonstrated an impressive classification accuracy ranging from 86% to 100%. This high level of accuracy showcases the model's capability in distinguishing the intricate color patterns and unique artistic elements characteristic of Wayang Kamasan. Additionally, the confusion matrix for the classification task reveals a notable performance with True Negatives (TN) = 5, indicating that the model effectively identified and correctly classified images that were not part of the target category. Such performance highlights the robustness of CNN in recognizing and classifying cultural icons, making it a valuable tool in preserving and understanding traditional cultural heritage.Certain factors, such as image resolution, relative angle of the image, and the number of datasets, also influence the system's performance in this study. The rapid and ongoing progress of machine learning technology will certainly play a big role in signaling the development of this research in the future.

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