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Culturally Adaptive AI System for Wayang Character Visualization and Recognition for Children

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ABSTRACT The study created an artificial intelligence-based drawing and classification system, which could help children visualize wayang characters and preserve their cultural identity at the same time. The paper aimed to find a solution to the lack of interest of the younger generation towards cultural heritage, which required an innovation in terms of culturally adaptive visualization of cultural heritage in a visually appealing way. As a result, a generative model based on StyleGAN-3 was trained to create child-friendly visualizations of ten wayang characters, whereas the ResNet-18 classification model was used to classify character images.For this paper, the image dataset consisted of 400 training images and 60 test images, including some children's drawings as a part of the evaluation of the generalization capability of the proposed models. The images were preprocessed and augmented to make the models more robust. The classification model showed an accuracy of 87% which indicated its high capability to classify wayang characters even under different styles of visual representation. Moreover, the evaluation of visual preferences of children indicated that some of the produced characters received positive feedback from children because of their good proportion and expressiveness.

KEYWORDS: Artificial Intelligence; StyleGAN-3; ResNet-18; Wayang Characters; Cultural Identity

I.INTRODUCTION

Indonesia has many cultural treasures, including wayang (traditional puppet theater), which has been proclaimed by UNESCO as Masterpiece of the Oral and Intangible Heritage of Humanity. Aside from providing entertainment, wayang is also used as a vehicle to pass moral values, philosophical ideas, and character education in Javanese society [1] .

Yet nowadays, wayang is less appealing to children because in this digital age kids seem to lose interest in Indonesia's culture [2]. This is also due to the influence of foreign cultures such as Western culture and Asian aesthetics like J-Pop, K-Pop, and anime that children are drawn to [3]. Aside from that, media and children's interests are now focused on modern images that tend to flash brightly on screens [4].

Children Children tend to easily absorb new culture changes because they spend more time interacting with electronic devices [5], [6]. This increases their likelihood of experiencing drastic changes in behavior as influenced by foreign cultures [7]. As a result, cultural heritage may become less prevalent within the current generation and less likely to be passed down to future generations.

Recent advancements in Artificial Intelligence (AI) allow for cultural aspects to be conveyed through interactive media in a child-friendly visual form [8]. AI drawing engines are able to automatically produce artwork given proper input such as prompts or datasets [9]. Using these engines, wayang characters can be reconstructed to look more interesting and appealing to children without losing their identity [10], [11].

Artificial intelligence has increasingly been used in cultural preservation and educational media development. Several recent studies suggest that AI-generated images can[12] support cultural heritage preservation by creating digital representations of cultural artifacts . The use of AI-generated visual content has also been associated with higher levels of learner engagement in educational environments [13]. In addition, digital cultural platforms have provided new opportunities for younger generations to interact with and learn about cultural heritage [14].

In spite of these advancements, limited research has focused on developing culturally adaptive visualization systems specifically designed for children. Most existing studies emphasize cultural heritage preservation, tourism, or general educational applications, while the integration of AI-based image generation and character recognition for traditional cultural learning remains relatively underexplored. In addition, children's responses to AI-generated cultural visualizations have received limited attention in previous studies. These gaps highlight the need for an AI-based system that can preserve cultural identity while presenting wayang characters in a visually engaging and child-friendly manner.

TABEL 1. Comparison with Previous Studies

Study	Focus	Method	Evaluation
Liang et al. [15]	Cultural preservation	AI-generated visualization	Visual quality
Bian et al. [16]	Educational visualization	AI-generated media	Student engagement
Pesce et al. [17]	Cultural awareness	Digital platform	User participation
Proposed Study	Wayang education	StyleGAN-3 + ResNet-18	Classification and children's preference

Table 1 shows that previous studies have mainly focused on cultural preservation, educational visualization, or cultural engagement as separate areas of research. While AI-generated visual content has been applied in cultural and educational contexts, the integration of image generation and character recognition for traditional cultural learning remains limited. Furthermore, children's responses to AI-generated cultural visualizations have rarely been evaluated. Therefore, this study combines culturally adaptive wayang visualization, automated character recognition, and children's visual preference evaluation within a single framework for cultural education.

For this reason, this research aims to create a culturally sensitive AI based drawing implementation for wayang character visual reinterpretation for children.

Specifically, this study aims to:

(1) develop culturally adaptive visual representations of wayang characters for children,

(2) implement an AI-based image generation and character recognition system

(3) evaluate the classification performance of the proposed system.

(4) assess children's responses toward the generated visualizations.

The novelty of this study lies in the integration of AI-based image generation and character recognition within a single framework for wayang learning [18]. Unlike previous studies that primarily focus on cultural preservation or AI-generated visual content independently, this research combines culturally adaptive wayang visualization, automated character recognition, and children's visual preference evaluation to support cultural education through interactive digital media. This study will advance research on adaptive culture-based educational media as well as help Indonesian children maintain their cultural identity in the digital age [19].

II.METHOD

Methodology using generative machine learning together with image classification was applied as the experimental and design research methodology in this study to visualize wayang characters that are child-friendly [20], [21]. Figure 1 represents the stages of research.

2.1 Research Workflow

Stage 1 – Literature review and dataset collection about GAN, transfer learning technique and children's visual aesthetic principles in Visual Communication Design [22]. A collection of wayang characters dataset were gathered from digital archival sources, illustration artwork and documented visual resources as training dataset.

Stage 2 – Data curation and preprocessing technique. Dataset images were evaluated based on visual quality assessment, character legibility and according to wayang characteristics [23]. Image preprocessing such as resizing into 512 × 512 pixels, data augmentation (rotation, horizontal flip, and color jitter) and dividing training dataset with testing dataset were applied [24]. Training dataset images were ensured balanced in every class and differed in amount with testing dataset since the testing dataset was comprised from children drawings [25].

Stage 3 – Train generative model using StyleGAN-3 which produced synthetic output images that look similar to original wayang character images but targeted to children's visual preferences. Training implementation with ADA to prevent overfitting problem [26]. Qualitative evaluation through visual examination by Visual Communication Design expert ensuring generation preserves aesthetics and identity of the characters [27].

Stage 4 – Train classification model using ResNet-18 implementing transfer learning approach [28]. Fine-tuning was done on the model that was pre-trained using ImageNet data to classify our ten wayang character classes which are Abimanyu, Anoman, Arjuna, Bagong, Bima, Gareng, Gatotkaca, Kresna, Petruk, and Semar. We used Adam optimizer with the learning rate of 5×10^{-4}.

The data we fed to train our model contained both original and generated images [29].

Fifth stage was classification performances evaluation which we visualized using confusion matrix and calculated (1)

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

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

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

$$F_{\text{1-score}} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

A classification model was incorporated into a Python interface, enabling users to upload wayang images and receive immediate classification results [30]. This application showcases the real-world application of artificial intelligence in Visual Communication Design as an engaging platform for cultural education for children [31].

The last phase included the documentation and sharing of research results, such as trained models, source code repositories, and scholarly articles. Ethical concerns regarding data utilization and visual copyright were carefully upheld.

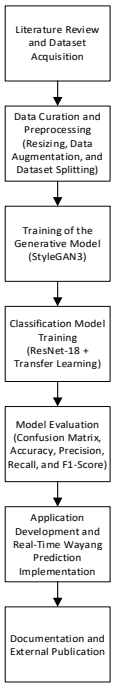

Figure 1. Research Flowchart

2.2 Research Dataset

The The dataset utilized in this research includes 400 training images and 60 testing images. The training dataset was used to train both the StyleGAN-3 and ResNet-18 models, while the testing dataset was used to evaluate classification performance on unseen data.

The dataset includes ten wayang character classes: Abimanyu, Anoman, Arjuna, Bagong, Bima, Gareng, Gatotkaca, Kresna, Petruk, and Semar. The training dataset was balanced, with 40 images per class (total 400 images).

The testing dataset consists of children's drawings, resulting in an imbalanced class distribution. The detailed distribution is shown in Table 2.

Table 2. Dataset Distribution per Wayang Character

No	Character	Training	Testing
1	Abimanyu	40	4
2	Anoman	40	3
3	Arjuna	40	8
4	Bagong	40	4
5	Bima	40	6
6	Gareng	40	10
7	Gatotkaca	40	4
8	Kresna	40	6
9	Petruk	40	9
10	Semar	40	6
	Total	**400**	**60**

2.3 Training Dataset Structure

The training dataset consists of ten folders representing each wayang character class. Each folder contains digital documentation images, illustrations, and generative images representing the distinctive visual characteristics of each character.

The total number of training images is 400, which were used to train both the StyleGAN-3 model for generative learning and the ResNet-18 model for classification.

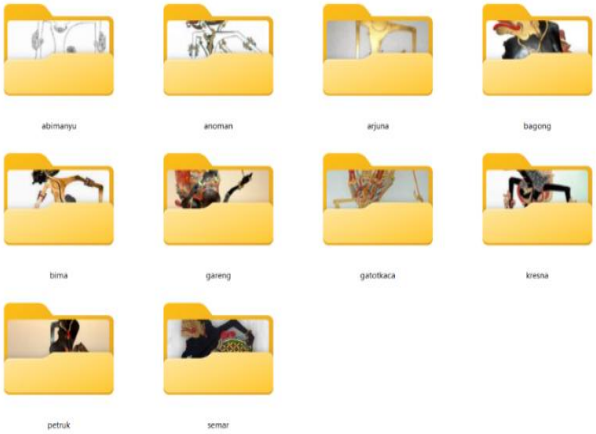

Figure 2. Training Dataset Structure of Wayang Characters

2.4 Testing Dataset

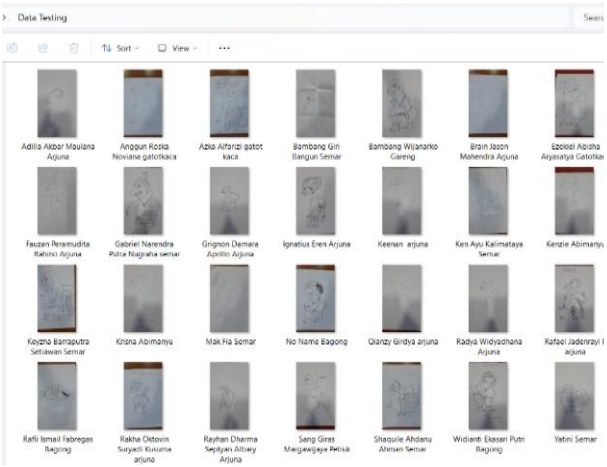

Figure 3. Testing Dataset (Children's Drawings of Wayang Characters)

The testing dataset consists of 60 images created by children. These images were used to evaluate the model's ability to recognize *wayang* characters based on more expressive and non-conventional visual styles.

Using testing data from a different visual domain aims to assess the generalization capability and robustness of the classification model when dealing with stylistic variations outside the training distribution.

2.5 Structure of the StyleGAN-3 Model and Model Selection

The StyleGAN-3 model is used to create culturally adaptable images of the wayang characters. The model includes two parts, namely Generator and Discriminator. Generator creates the image from the latent vector, whereas the Discriminator checks if the synthesized image looks like real images of the training set. With the help of the adversarial learning, both parts of the model are trained together in order to create believable wayang character images.

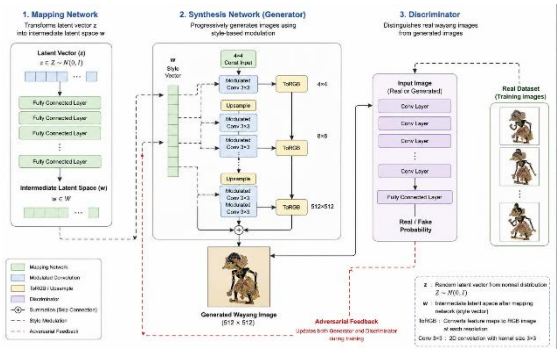

Figure 4. StyleGAN-3 Architecture for Wayang Image Generation

Figure 4 describes the architecture of the StyleGAN-3 model used in the research. Firstly, the process starts by taking a randomly initialized latent vector (z) and using the mapping network to convert it to an intermediate latent vector (w). After that, the synthesis network creates the images of wayang characters based on style modulation and progressive image generation. The created images are compared with the training dataset of wayang characters by the discriminator, which is able to differentiate between the two images.

The training process is improved through Adaptive Discriminator Augmentation (ADA). All images are resized to 512x512 pixels before training. Generated images are evaluated by such criteria as visual quality, wayang character recognition, and appropriateness for children.

StyleGAN-3 was chosen as the best model due to its ability to preserve unique style of wayang characters and create visually appealing images. It consumes less computational resources compared to diffusion models; moreover, it works well even with a small dataset. Contrarily, images generated by Variational Autoencoders have lower quality and details.

Table 3. Comparison of Generative Models

Criteria	StyleGAN-3	Diffusion Model	Variational Autoencoder (VAE)
Image Quality	High	High	Moderate
Visual Detail	High	Very High	Moderate
Preservation of Wayang Characteristics	High	High	Moderate
Computational Resources	Moderate	High	Low
Training Efficiency	High	Moderate	High
Performance on Small Datasets	Good	Moderate	Good
Suitability for This Study	✓ Selected	–	–

Comparison Table 3 is used to compare the StyleGAN-3 with other commonly used generative methods. The StyleGAN-3 algorithm was chosen due to its ability to generate images efficiently while being computationally cost-effective and able to perform well on smaller datasets. This combination is necessary for generating distinct wayang characters.

2.6 Evaluation of Visual Preference of Children

In conducting an evaluation for visual preference, 60 children from 7 to 12 years old from an elementary school were selected as participants.

The participants were exposed to a series of images of wayang characters that were generated via the StyleGAN-3 model. The method used in conducting this evaluation is a visual preference questionnaire wherein the participants were asked to choose the image of wayang character that they found to be most visually appealing.

There were 60 responses obtained during the study. In terms of data analysis, only 58 of the responses were considered as valid responses and thus, were included in the analysis while the other two responses were omitted due to incompleteness and inconsistencies. The purpose of conducting this evaluation was to determine children's visual preferences towards the images of wayang characters generated.

III.RESULTS AND ANALYSIS

This section presents the results and analysis of the proposed AI framework for wayang visualization and character classification. The performance of the StyleGAN-3 image generation model, the ResNet-18 classification model, and the children's visual preference evaluation are discussed through quantitative and qualitative analyses.

3.1 Classification Performance Evaluation

The model's performance was evaluated using parameters such as precision, recall, F1-score, and support. Precision determines the correctness of the prediction of an instance in every category, recall measures the ability of the model to predict all the relevant instances correctly, whereas F1 score is a measure of the harmonic mean of precision and recall. Support refers to the number of test samples in each category..

The experiment was carried out using 60 test images that belonged to ten categories of wayang characters. The performance results are displayed in Table 4 below.

Table 4. Classification Performance

Class	Precision	Recall	F1-Score	Support
Abimanyu	1	0.75	0.86	4
Anoman	0.75	1	0.86	3
Arjuna	0.88	0.88	0.88	8
Bagong	0.43	0.75	0.55	4
Bima	1	0.83	0.91	6
Gareng	0.91	1	0.95	10
Gatotkaca	1	1	1	4
Kresna	1	1	1	6
Petruk	1	0.78	0.88	9
Semar	0.8	0.67	0.73	6
Accuracy			**0.87**	60
Macro Avg	0.88	0.87	0.86	60
Weighted Avg	0.9	0.87	0.87	60

The proposed model achieved a classification accuracy of 87%. The macro-average precision, recall, and F1-score of 0.88, 0.87, and 0.86, respectively, indicated a relatively uniform accuracy across all ten classes of wayang characters.

Among wayang characters, Gatotkaca and Kresna achieved the highest F1-score of 1.00, while Gareng had an F1-score of 0.95. This might be attributed to these characters' distinctive visual features. Recognizing Bagong, however, proved much more difficult as he had the lowest F1-score of 0.55, as there were much more cases of him being confused with other Punakawan characters. This is likely due to visual similarity to Punakawan characters.

Reliable classification performance of the model is concluded to be confirmed due to the achieved classification accuracy value of 87% and weighted F1-score of 0.87.

3.2 Confusion Matrix Analysis

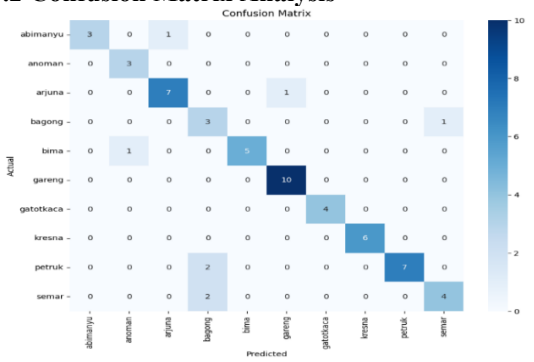

Figure 5. Confusion Matrix

Predictions Classification results occur more often in the primary diagonal which means that classification is accurate. The perfectly classified characters are Gatotkaca (4/4), Kresna (6/6), and Gareng (10/10). This result confirms the idea that characters with distinct physical features will be easily classified using the model.

The mistakes in classification occurred because of similar characters. It happened, for example, when Abimanyu was mistakenly identified as Arjuna and Bagong as Semar. There were also mistakes when Petruk was confused with Bagong. This result indicates that there are similarities between the proportions of faces and heads of certain classes of characters.

Overall, the confusion matrix confirms the findings obtained during the analysis of quantitative data in Table 2.

3.3 System Implementation Testing

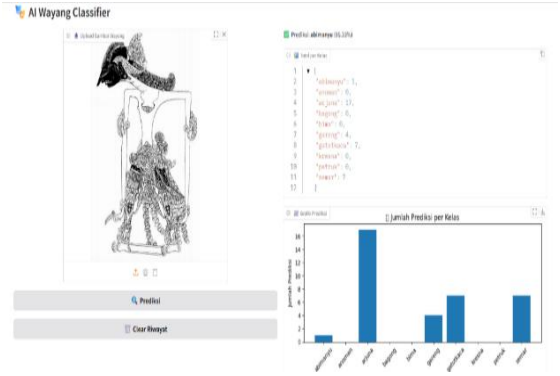

Figure 6. Classification System Interface

Once the image is uploaded, the model automatically predicts the character class together with the confidence score for the same. As seen from the example below, the model predicted the input image as Abimanyu with 95.33% confidence level showing that it can indeed predict reliably based on the extracted visual features.

Apart from predicting individually, the system also shows the prediction in terms of summary in numerical form as well as graphically. As can be observed from the bar chart visualization above, characters such as Arjuna, Semar, and Gatotkaca occur more often in the prediction frequency.

3.4 Visual Preference Analysis of Generated Images

Figure 7 depicts the results of visual preference evaluation carried out by children in relation to 400 StyleGAN-3 generated images.

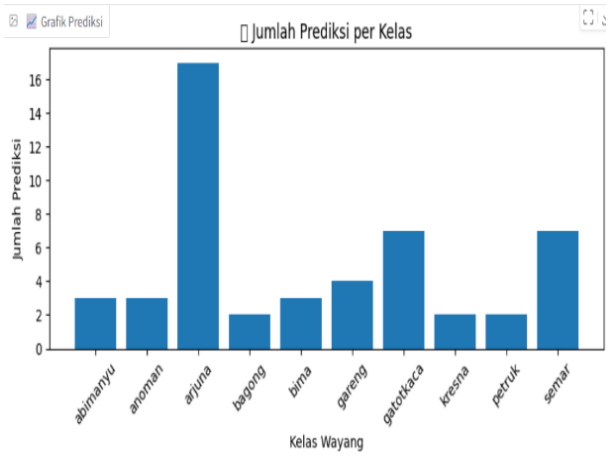

Figure 7. Distribution of Children's Visual Preferences

A total of 58 valid data samples were collected in the children's preference evaluation test concerning the wayang characters through ten categories. Arjuna got the most selections (16 choices), followed by Semar and Gatotkaca with 7 choices each. Gareng was chosen 4 times, whereas Bima, Abimanyu, and Anoman were all selected 3 times. Bagong, Kresna, and Petruk were only chosen twice.

It can be concluded that the generated visual representation of Arjuna was preferred by the most respondents. Bagong, Kresna, and Petruk, on the other hand, received fewer votes than the rest. Some variations in preferences show that some generated representations of wayang characters are more attractive to the participants. However, more research needs to be done to identify those characteristics that made children choose one generated representation over another..

The generated wayang representations were generally welcomed by the target users. Alongside the classification results, it is proven that the proposed AI framework has the potential to create culturally adaptive digital learning media in teaching children about wayang characters.

3.5 Comparison with Previous Studies

For a better understanding of how the framework contributes, the following table provides comparisons to prior work conducted on AI generated visual systems, applications in cultural heritage, and educational media.

Table 5. Comparison of the Proposed Framework with Previous Studies.

Study	Image Generation	Cultural Heritage	Child Evaluation	Character Recognition
Liang et al. [15]	✓	✓	✗	✗
Bian et al. [16]	✓	✗	✓	✗
Pesce et al. [17]	✗	✓	✓	✗
Proposed Study	✓	✓	✓	✓

As shown in Table 5, previous studies have addressed different aspects of AI-assisted visual systems and cultural heritage applications. Bian et al. employed Stable Diffusion-generated images to support visual art education and evaluated students' engagement, but did not incorporate cultural heritage content or automated recognition capabilities. Liang et al. focused on AI-generated cultural heritage visualizations using diffusion-based models and ControlNet, emphasizing visual quality and cultural consistency. However, their work did not include user evaluation involving children or character classification functionality. Pesce and Franzè investigated digital technologies for cultural heritage dissemination and user

engagement, but image generation and recognition mechanisms were not part of the proposed framework.

In contrast, the present study integrates four important components within a single framework: AI-based image generation, cultural heritage preservation, children's visual preference evaluation, and automated character recognition. Using StyleGAN-3, the framework generates culturally adaptive wayang character visualizations, while ResNet-18 enables automatic classification with an accuracy of 87%. Furthermore, the evaluation involving children demonstrates the educational relevance of the generated visualizations. Therefore, the proposed framework extends previous studies by combining cultural preservation, educational interaction, and intelligent recognition into a unified AI-based learning system.

IV.CONCLUSION

The study successfully met all four research objectives. To start with, culturally adaptive visual representations of wayang characters have been produced with the use of StyleGAN-3 while ensuring that the fundamental cultural features of the traditional wayang were retained in these visuals. Furthermore, the implementation of the proposed image generation and character recognition framework based on AI was successful through the combination of StyleGAN-3 and ResNet-18. As for the classification performance evaluation, it was confirmed that the proposed framework ensured a satisfactory level of classification efficiency since its accuracy was equal to 87%. The macro-average precision, recall, and F1-score of the proposed framework was measured to be 0.88, 0.87, and 0.86, respectively. In this way, reliable performance of recognition of ten wayang characters was provided. As for the visual preference evaluation, which was conducted among the children, positive results regarding the visual appeal of the images were received, with Arjuna being the preferred character. Thus, the study has shown that the integration of image generation, character recognition, and user-centered evaluation techniques is possible and beneficial within a single framework. The findings indicate that the proposed solution could serve as a basis for designing culturally adaptive digital learning media.

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