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Detecting the Same Pattern in Choreography Balinese Dance Using Convolutional Neural Network and Analysis Suffix Tree

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ABSTRACT

The Balinese dances that are popular today were created by maestros who have existed since time immemorial. To develop the dances made by the existing maestro, one must know the characteristics of each dance based on the motion used. The help of digital image processing and string algorithm analysis methods will help to determine the characteristics of a dance. The algorithm used for dance analysis is the Suffix Tree, where the suffix tree is one of the algorithms that can be used to find patterns from input strings. The string to be analyzed is a series of codes performed by the classifier. The classifier used is Convolutional Neural Network. This method uses an image as its input, which will later perform convolution operations and perform a full-connected layer. The results were obtained using the Convolutional Neural Network method with Alexnet architecture as the classification and confusion matrix to calculate the level of accuracy of the test set, the best accuracy for the head is by using parameter learning rate 0.001, epoch 150, and RGB color space obtained 95% accuracy, 88% precision, 78% recall, and 82% f1-score. For the full body, using a learning rate of 0.01, epoch 150, and RGB color space, the accuracy is 85%, precision is 79%, recall is 64%, and f1-score is 69%. For the legs, using a learning rate of 0.001, epoch 150, and RGB color space, the accuracy is 92%, precision is 84%, recall is 59%, and f1-score is 65%. The results of the suffix tree analysis between codes that use ground truth and classification results have similar values, although the results of the movement patterns obtained by the suffix tree algorithm have not varied, which is dominated by class A because class A is the dominant class in each dance.

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1. INTRODUCTION

Dances in each region have different purposes and objectives [1][2]. One way to find out the meaning of a dance is to know what movement patterns are often used in a dance [3]. Balinese dance is not only done as a hobby for the Balinese people but becomes one of the livelihoods that can be done by people in the Bali area [4]. Although Balinese dance is something that is favored by young Balinese people, not a few do not know the meaning of a dance from the maestro who creates the dance. To find out the characteristics of the dance can be known based on the dress and make-up. If the make-up and clothes fit, then only by looking at that aspect can we understand the theme of the dance and, at the same time, determine the characteristics of the dance [2]. In addition to these two aspects, the characteristics of the dance can be known through the movement pattern. Even with the movement pattern, it is possible to know the characteristics of a maestro who creates the dance, which in previous research conducted by Kesiman et al. [5] proposed a quantitative calculation of each dance with the aim of obtaining the characteristics of the dance maestro. Several popular Balinese dances have been developed by maestros who have been around for quite a long time [5].

Knowing the characteristics based on the movement patterns of the maestro in each dance makes it possible to add the duration of a dance and combine several dances based on characteristics. It is even possible to create a new dance based on the characteristics of a particular maestro [6]. The process that must exist before the computer can add duration, merge, dance, or create is that the computer must be able to know both the characteristics of each dance and the characteristics of a particular maestro. At the time this research was carried out, there was no ground truth for the basic movements of Balinese dance, so the ground truth construction was the initial stage to be carried out.

Research related to characteristic search based on Balinese dance movement patterns has been carried out by Kesiman et al. [5][6]. Both studies used the clustering method, which is to group large amounts of data into smaller groups in such a way that the data objects in one group have similar characteristics while those in the same group have similar characteristics. Other characteristics of the object are different [7]. The clustering carried out in the study conducted by Kesiman et al. [5] was carried out both for grouping the features of dance frames and analyzing the patterns that have been obtained. The results obtained from the pattern analysis were made in 7 profiles, and later on, from this profile, conclusions would be drawn from both the characteristics of the dance and the maestro. There are several methods that can be used to classify images, and the methods used are very influential on the prediction results of an image. K-Nearest Neighbor is one of the image classification methods that can be used, in a study conducted by Rahmadianto et al. [8] got good accuracy for classifying egg quality. The way the k-nearest neighbor works is to find the closest data from 2 objects with the provision that k is the parameter. In addition to the K-nearest neighbor method, there is a convolutional neural network method. Unlike the K-nearest neighbor which requires feature extraction for its image, the Convolutional Neural Network (CNN) can process the image as input without having to perform feature extraction. The Convolutional Neural Network (CNN) method has been used in research conducted by Nurfita & Ariyanto [9], and the results obtained with the Convolutional Neural Network (CNN) method are very good. There are several working processes from CNN, in the first step is to calculate the resulting image with the appropriate filter which will later produce an activation map or feature map; the second process in the pooling layer, where the activation map will search for certain values according to the specified filter and shift, the value sought is usually the maximum value. The purpose of the pooling layer is to reduce the number of parameters to be processed at a later stage; The last stage is the fully connected layer, which is changing the activation map dimensions into vectors as many as the number of classes you want to predict.

In this research, the classification of Balinese dance image frames will be carried out, and the results will be pattern analysis. The Balinese dance image frames are classified to determine which class a particular image frame belongs to. The image of the Balinese dance frame that will be carried out only focuses on the dances that are danced by female dancers and the movements that have been determined according to the dancers' body parts, namely the face 2 basic Balinese dance movements for the full-body 11 basic Balinese dance movements and the legs 4 basic movements Balinese dance, plus 1 movement in each part which is considered not to be included in the predetermined basic Balinese dance movements, such as frames during transition movements or frames that are considered unclear or blurry. If the classification in dance for each frame has been obtained, then the result of the classification will be a series of class codes which will later be analyzed using a string-matching algorithm and look for similarities with other dances, both with the same or different masters. The method that will be used for classification, namely Convolutional Neural Network (CNN). There are several reasons why this method is used. The first reason is that this method is very popular and is often used to classify images in various studies. Another reason is that the accuracy produced is relatively high. Research conducted by Nurfita & Ariyanto [9] obtained 100% results in the training process. In research conducted by Jain et al. [10], where the performance of the Deep Convolutional Neural Network is very good for classifying the test dataset. In the process of analyzing the classification results, researchers use the suffix tree method. The suffix tree functions as a complete index of the string which also gives access to each segment of all strings and provides the position of each occurrence of the string [11][12][7][13]. Based on these problems, the authors use digital image processing techniques and pattern analysis algorithms.

The results were obtained using the Convolutional Neural Network method with Alexnet architecture as the classification and confusion matrix to calculate the level of accuracy of the test set, the best accuracy for the head is by using parameter learning rate 0.001, epoch 150, and RGB color space obtained 95% accuracy, 88% precision, 78% recall, and 82% f1-score. For the full body, using a learning rate of 0.01, epoch 150, and RGB color space, the accuracy is 85%, precision is 79%, recall is 64%, and f1-score is 69%. For the legs, using a learning rate of 0.001, epoch 150, and RGB color space, the accuracy is 92%, precision is 84%, recall is 59%, and f1-score is 65%. The results of the suffix tree analysis between codes that use ground truth and classification results have similar values, although the results of the movement patterns obtained by the suffix tree algorithm have not varied, which is dominated by class A because class A is the dominant class in each dance.

2. METHODS

In this research (Fig. 1), there will be several stages to get the results of the equation of movement patterns between dances, the steps to be carried out are doing ground truth on the dataset, preprocessing the image, classifying to make a model of each body part, evaluating with a confusion matrix to get the level of accuracy of each body part and perform pattern analysis to obtain the characteristics of the dance.

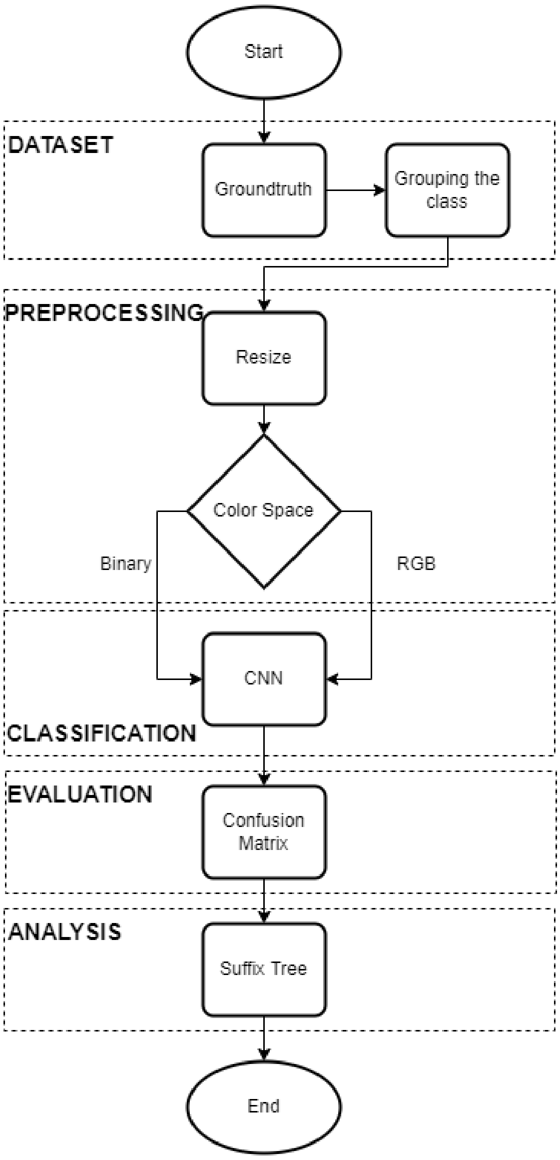

Fig. 1. Research Flow

2.1. Dataset

The Balinese dance dataset used was obtained from research conducted by Kesiman et al. [5] with the title Profiling Balinese Dances with Silhouette Sequence Pattern Analysis. Each frame in each dance will identify basic movements, where the basic movements used are divided according to body parts [14][15]. Each dance will have a crane code for basic Balinese dance movements [16][17][18]. The ground Truth that is done in this research is done manually. The steps taken by the expert are looking at each dance frame that has been received, then identifying each frame, and classifying the frame according to the right motion. In this research, each dance is divided into 3 parts of the movement, namely 2 basic movements of the face, 11 basic movements of the full body, and 4 basic movements of the legs, wherein each part of the movement in the basic dance there is 1 uncategorized motion where the movement is considered not included in the basic movements in each category of Balinese dance that have been determined, such as frames during transition movements or frames that are considered unclear or blurry. Ground truth will be validated by means of each expert matching the results from the previous categorization and if there is a difference then the difference will be discussed by the two validators to get 1 final result that is appropriate. After the categorization and validation are complete, the data is processed to form ground truth. There will be 2 ground truth files in txt format. The first file is the name of the movement and its code, an example of writing it:

Agemkanan:B;
agemKiri:C;
.....
seledetKiri:V;

While the second file is a series of codes contained in the first file where each frame, there will be 3 codes, namely 1 code for the face, 1 code for the full body, and 1 code for the legs, an example of writing:

AAAAAAAAAAAAAADAADAADAADAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAG ABAAAAAAAVCA.

2.2. Data Preprocessing

The preprocessing stage in digital image processing is a stage that aims to improve the quality of the image, eliminate noise contained in the image, and look for certain parts that will be used in the next process [19]. In this research, preprocessing will be carried out, namely image cutting and image quality improvement. The first preprocessing is cropping images. There are several stages in cutting Balinese dance images, with the aim of getting the parts needed to conduct training on the CNN (Convolutional Neural Network) classifier later. The first cut is done to get the full-body part by performing the operation:

$$\text{CfullBadan} = \text{C}[25\%: 75\%][:] \tag{1}$$

$$\text{Ckaki} = \text{C}[:][50\%:] \tag{2}$$

As for the head section, it uses a function found in the dlib library in python, namely dlib.get_frontal_face_detector(), which accepts image input with gray color space [20]. The second process in data preprocessing is binarization in which the image of the Balinese dance frame, which was originally RGB, will be converted first to the grayscale color space [21]. After the image has a Grayscale color space, then the image binarization process is carried out, namely the process of changing the image value into 2 groups of black and white or foreground and background. Image binarization is generally calculated by:

$$G(x,y) = \{1\ if\ f(x,y) \geq T\ 0\ if\ f(x,y) < T \tag{3}$$

In this research, the method used for image binary is local adaptive thresholding which aims to find the local image threshold value. The following is the formula for calculating local threshold values for the locally adaptive thresholding method:

$$T = median\ \{f(x,y), (x,y)\ \epsilon\ W\} \tag{4}$$

Where W is the processed block, NW is the number of pixels in each block W, C is a flexibly determined constant value

2.3. Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is one of the methods used to classify input files in the form of images [22][23], Fig. 2. Unlike other image processing classification methods, Convolutional Neural Network (CNN) does not require feature extraction as input, which this method creates itself in the process [24][25][26]. The CNN method is made to lighten the computational load, minimize memory usage, and speed up the training process when using a multilayer perceptron (MLP) classification with a fully connected layer, but CNN no longer uses a full connection but uses a local connection [27][28][29]. What is meant by this local connection is a kernel or filter used for images by performing convolution operations. Before classifying using an artificial neural network, feature maps must be vectors. This stage is called flattening in convolutional neural networks. Flattening is the process of converting the pooled feature into a 1-dimensional vector which will be the input of the artificial neural network process. The last stage in the convolutional neural network to perform the classification is using the Artificial Neural Network (ANN) [30][31][32]. In this process, there are 3 layers, namely the input layer, the fully-connected layer, and the output layer.

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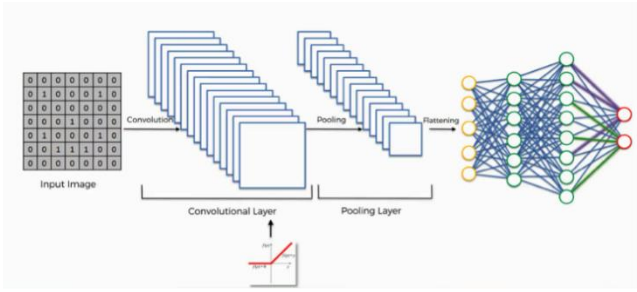


Fig. 2. Element Interaction on CNN

This research will use Alexnet as the architecture for Convolutional Neural Network (CNN), Fig. 3. The output layer will be adjusted to the number of classes in each part. The learning rate and epoch parameters used are 50 and 150 epochs, while the learning rates are 0.01 and 0.001. The distribution of data as training, valid, and test is 70% for the training set, 15% for the valid set, and 15% for the test set.

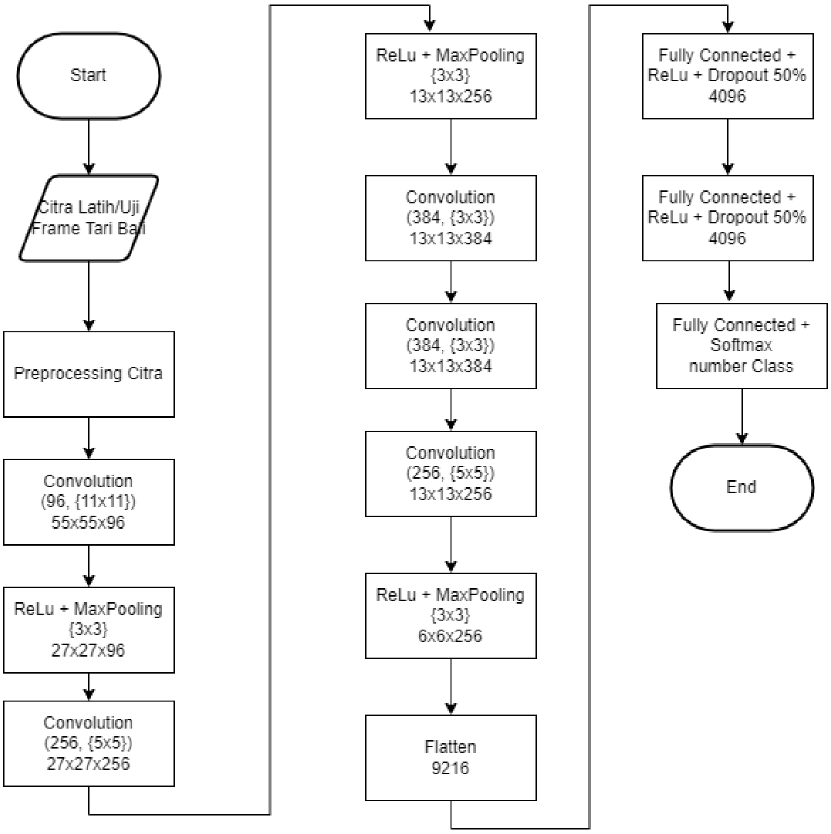


Fig. 3. Architecture Alexnet

2.4. Confusion Matrix

In testing the performance of the classifier, there are several ways to test it or calculate it [33]. One way to calculate classifier performance is to use a confusion matrix (Table 1) [34]. The confusion matrix is one method that can be used to calculate the accuracy of the data mining concept [35][36][37].

Table 1. Confusion Matrix

Actual	**Predicted**	
	Positive	**Negative**
Positive	True Positives (A)	False Negatives (C)
Negative	False Positives (B)	True Negatives (D)

To calculate accuracy, precision, and recall, is found in Equation (5), Equation (6), and Equation (7).

$$\text{Accuracy} = (A + B) / (A + B + C + D) \tag{5}$$

$$\text{Precision} = A / (A + B) \tag{6}$$

$$\text{Recall} = A / (A + D) \tag{7}$$

2.5. Suffix Tree

A suffix Tree is an algorithm that can be used to find patterns from a string [13]. A suffix tree of string (sequence of character codes) is a tree containing the path to each end of each string [5]. In addition to looking for patterns from a string, it can also be used to search for the longest repeated substring, look for the longest substring that often appears, and look for the longest palindrome string. The way the suffix tree algorithm works is to search for the same character or pattern as desired. That is, it is carried out at each existing node and then traces to the edge. If there is a suitable pattern to the edge, the corresponding number increases. If not, then the number of conformity will remain [38][39][40]. In this research, the pattern that will be used is several profile criteria that have been previously proposed by Kesiman et al. [5]. However, there are some changes in the definition of movement patterns where the movement has a total number of codes of at least 15 codes with the assumption that there are at least 5 rows of images because every 1 image has 3 movement codes which are divided into facial parts, full body parts, and legs. The following criteria will be used in this research:

- Number of Patterns:
  - a) Very Low: 0 – 29
  - b) Low: 30-59
  - c) Normal: 60-89
  - d) High: 90-119
  - e) Very High: More than 119
- Longest Pattern:
  - a) Very Low: 0 – 18
  - b) Low: 19-29
  - c) Normal: 30-60
  - d) High: 61-81
  - e) Very High: More than 81
- Average Patterns:
  - a) Very Low: 0 – 3
  - b) Low: 4-12
  - c) Normal: 13-15
  - d) High: 16-21
  - e) Very High: More than 21
- Shortest Distance:
  - a) Very Low: 0 – 1
  - b) Low: 2-3
  - c) Normal: 4-5
  - d) High: 6-7
  - e) Very High: More than 7
- Longest Distance:
  - a) Very Low: 0 – 93
  - b) Low: 94-188
  - c) Normal: 189-282
  - d) High: 283-376
  - e) Very High: More than 376
- Avarage Distance:
  - a) Very Low: 0 – 21
  - b) Low: 22-44
  - c) Normal: 45-66
  - d) High: 67-88
  - e) Very High: More than 88

3. RESULTS AND DISCUSSION

3.1. Final Dataset

The data used in this study amounted to 3797 Balinese dance frames. The 3797 frames are a combination of 8 Balinese dances, namely the Cendrawasih Dance, Margapati Dance, Nelayan Dance, Panji Semirang Dance, Puspanjali Dance, Sekar Jagat Dance, Wiranata Dance, Wiranjaya Dance, of which the Cendrawasih Dance is 297 and other dances are 500 frames. Each frame will be categorized into 3 parts, namely the full body, the face, and the legs. The total image to be processed is 11391. The distribution of data in the classification process is 70% for training, 15% for data validation, and 15% for test data. Table 2, Table 3, and Table 4 are details for the distribution of data in each class.

Table 2. Distribution of Face Frames

No	Basic Movement	Total
1	*Seledet Kanan*	261
2	*Seledet Kiri*	132
3	Uncategorized	3404

Table 3. Full Body Part Frame Distribution

No	Basic Movement	Total
1	*Agem Kanan*	405
2	*Agem Kiri*	208
3	*Mentang Laras*	45
4	*Gandang Arep*	144
5	*Gandang Uri*	73
6	*Luk Nerutdut*	88
7	*Luk Ngelimat*	26
8	*Mukah Lawang*	26
9	*Nyalud*	69
10	*Ulap Ulap*	93
11	*Nabdab Gelung*	64
12	Uncategorized	2579

Table 4. Distribution of Face Frames

No	Basic Movement	Total
1	*Tampak Sirang Pada*	54
2	*Piles*	99
3	*Malpal*	72
4	*Tanjek*	190
5	Uncategorized	3382

3.2. Convolutional Neural Network (CNN)

All models have similarities where the model is more likely to predict class A, which is caused by the dataset owned by class A being very large, and there are some similarities in the shape of the image in classes other than A. From several experiments carried out in each section (Table 5, Table 6, and Table 7), the best values for the head section were found, namely a learning rate of 0,001, an RGB color space, and an epoch of 150; for the full-body, the learning rate is 0,01, the color space is RGB, and the epoch is 150; and for the legs of the learning rate 0,001, the RGB color space, and the 150 epochs. For the results for each section, see Fig. 4.

Table 5. The Result of Model Face

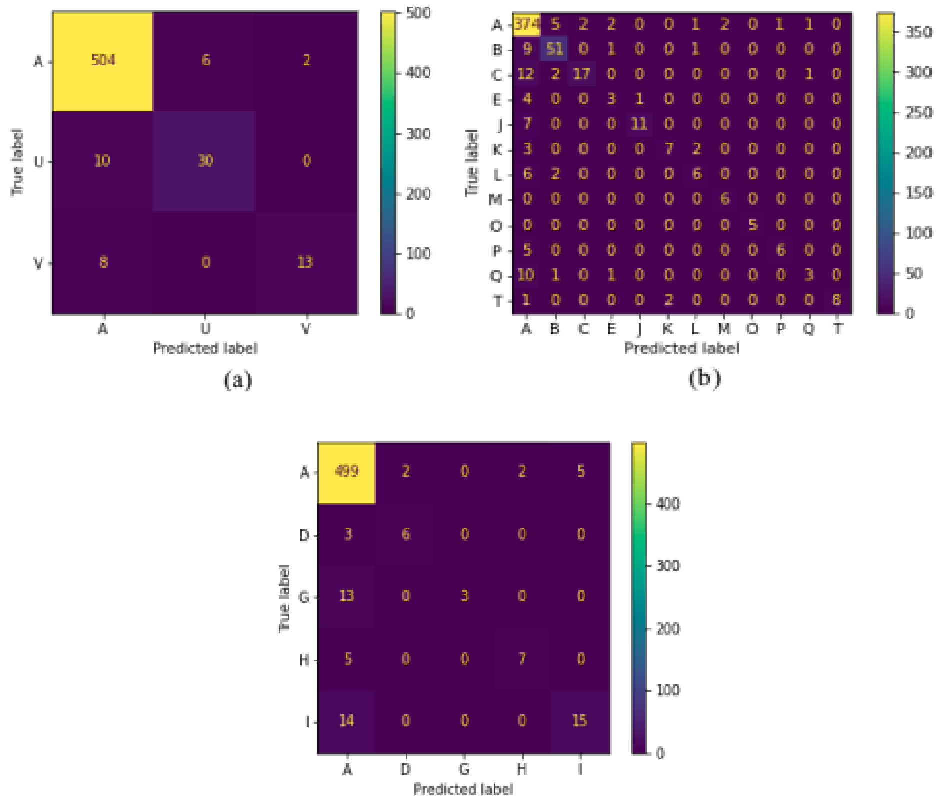
Epoch	Learning Rate	Color Depth	Training Accuracy	Testing Accuracy
50	0.001	RGB	100%	94%
50	0.01	RGB	100%	95%
50	0.001	Biner	100%	93%
50	0.01	Biner	100%	94%
150	0.001	RGB	100%	95%
150	0.01	RGB	100%	95%
150	0.001	Biner	100%	94%
150	0.01	Biner	100%	94%

Table 6. The Result of Model Full Body

Epoch	Learning Rate	Color Depth	Training Accuracy	Testing Accuracy
50	0.001	RGB	95%	85%
50	0.01	RGB	98%	84%
50	0.001	Biner	100%	80%
50	0.01	Biner	100%	72%
150	0.001	RGB	100%	85%
150	0.01	RGB	100%	85%
150	0.001	Biner	100%	80%
150	0.01	Biner	100%	82%

Table 7. The Result of Model Leg

Epoch	Learning Rate	Color Depth	Training Accuracy	Testing Accuracy
50	0.001	RGB	96%	92%
50	0.01	RGB	98%	92%
50	0.001	Biner	100%	89%
50	0.01	Biner	100%	90%
150	0.001	RGB	100%	92%
150	0.01	RGB	100%	92%
150	0.001	Biner	100%	90%
150	0.01	Biner	100%	90%



(c)

Fig. 4. Result from confusion matrix (a) Face Part (b) Full-Body Part (c) Legs Part

3.3. Suffix Tree Result

In Table 8, it can be seen the results of the analysis using the ground truth code suffix tree method, and the classification results code. For categorization using the Linkert scale, almost all dances have the same value. For the decimal value between the ground truth code and the code using the classification results, there is also not much difference. However, if you look at each pattern, the movement code A or unknown is the code that dominates in each movement pattern.

Table 8. Result Profiling Dances

Dance Name	Ground truth Code Analysis Results	CNN Classification Analysis Results
Tari Cendrawa-sih	1. Number of Patterns: 11 (Very Low) 2. Longest Patterns: 66 (High) 3. Average Patterns: 30.545454545454547 (Very High) 4. Longest Distance: 78 (Very Low) 5. Shortest Distance: 0 (Very Low) 6. Average Distance: 8.5 (Very Low)	1. Number of Patterns: 11 (Very Low) 2. Longest Patterns: 66 (High) 3. Average Patterns: 30.0 (Very High) 4. Longest Distance: 69 (Very Low) 5. Shortest Distance: 0 (Very Low) 6. Average Distance: 7.351851 (Very Low)
Tari Wiranata	1. Number of Patterns: 4 (Very Low) 2. Longest Patterns: 78 (High) 3. Average Patterns: 42.0 (Very High) 4. Longest Distance: 292 (High) 5. Shortest Distance: 0 (Very Low) 6. Average Distance: 54.1 (Normal)	1. Number of Patterns: 7 (Very Low) 2. Longest Patterns: 78 (High) 3. Average Patterns: 31.7142857 (Very High) 4. Longest Distance: 292 (High) 5. Shortest Distance: 0 (Very Low) 6. Average Distance: 34.3333 (Low)
Tari Nelayan	1. Number of Patterns: 10 (Very Low) 2. Longest Patterns: 90 (Very High) 3. Average Patterns: 36.0 (Very High) 4. Longest Distance: 143 (Low) 5. Shortest Distance: 0 (Very Low) 6. Average Distance: 15.916666666666666 (Very Low)	1. Number of Patterns: 10 (Very Low) 2. Longest Patterns: 96 (Very High) 3. Average Patterns: 44.1 (Very High) 4. Longest Distance: 136 (Low) 5. Shortest Distance: 0 (Very Low) 6. Average Distance: 18.4 (Very Low)
Tari Panji Semirang	1. Number of Patterns: 9 (Very Low) 2. Longest Patterns: 51 (Normal) 3. Average Patterns: 27.33 (Very High) 4. Longest Distance: 261 (Normal) 5. Shortest Distance: 0 (Very Low) 6. Average Distance: 21.82 (Low)	1. Number of Patterns: 8 (Very Low) 2. Longest Patterns: 51 (Normal) 3. Average Patterns: 26,25 (Very High) 4. Longest Distance: 510 (Normal) 5. Shortest Distance: 0 (Very Low) 6. Average Distance: 26.81 (Low)
Tari Puspanjali	1. Number of Patterns: 8 (Very Low) 2. Longest Patterns: 93 (Very High) 3. Average Patterns: 50.62 (Very High) 4. Longest Distance: 111 (Low) 5. Shortest Distance: 0 (Very Low) 6. Average Distance: 10.63 (Very Low)	1. Number of Patterns: 8 (Very Low) 2. Longest Patterns: 93 (Very High) 3. Average Patterns: 48,37 (Very High) 4. Longest Distance: 111 (Low) 5. Shortest Distance: 0 (Very Low) 6. Average Distance: 11.5 (Very Low)
Tari Sekar Jagat	1. Number of Patterns: 10 (Very Low) 2. Longest Patterns: 120 (Very High) 3. Average Patterns: 52.5 (Very High) 4. Longest Distance: 67 (Very Low) 5. Shortest Distance: 0 (Very Low) 6. Average Distance: 8.71 (Very Low)	1. Number of Patterns: 10 (Very Low) 2. Longest Patterns: 120 (Very High) 3. Average Patterns: 52.5 (Very High) 4. Longest Distance: 67 (Very Low) 5. Shortest Distance: 0 (Very Low) 6. Average Distance: 8.71 (Very Low)
Tari Wiranata	1. Number of Patterns: 9 (Very Low) 2. Longest Patterns: 54 (Normal) 3. Average Patterns: 23 (Very High) 4. Longest Distance: 375 (High) 5. Shortest Distance: 0 (Very Low) 6. Average Distance: 26.7 (Low)	1. Number of Patterns: 9 (Very Low) 2. Longest Patterns: 54 (Normal) 3. Average Patterns: 22.66 (Very High) 4. Longest Distance: 348 (High) 5. Shortest Distance: 0 (Very Low) 6. Average Distance: 23.59 (Low)
Tari Wiranjaya	1. Number of Patterns: 11 (Very Low) 2. Longest Patterns: 147 (Very High) 3. Average Patterns: 34.09 (Very High) 4. Longest Distance: 117 (Low) 5. Shortest Distance: 0 (Very Low) 6. Average Distance: 10.43 (Very Low)	1. Number of Patterns: 11 (Very Low) 2. Longest Patterns: 147 (Very High) 3. Average Patterns: 34.09 (Very High) 4. Longest Distance: 117 (Low) 5. Shortest Distance: 0 (Very Low) 6. Average Distance:10.43 (Very Low)

4. CONCLUSION

Based on the results of research and discussion research on the development of the Balinese Dance Movement Pattern Analysis System, it can be concluded that the results obtained using the Convolutional Neural Network (CNN) method with Alexnet architecture as the classification and confusion matrix to calculate the level of accuracy of the test set, the best accuracy for the head is by using parameter learning rate 0.001, epoch 150, and RGB color space obtained 95% accuracy, 88% precision, 78% recall, and 82% f1 -score. For the full body, using a learning rate of 0.01, epoch 150, and RGB color space, the accuracy is 85%, precision is 79%, recall is 64%, and f1-score is 69%. For the legs, using a learning rate of 0.001, epoch 150, and RGB color space, the accuracy is 92%, precision is 84%, recall is 59%, and f1-score is 65%. The results of the suffix tree analysis between codes that use ground truth and classification results have similar values, although the results of the movement patterns obtained by the suffix tree algorithm have not varied, which is dominated by class A because class A is the dominant class in each dance. There are several suggestions that can be used for further research that will be carried out by other researchers; adding the number of datasets in the class that has a small amount of data in order to make the model learn more and get better accuracy in later testing; using an automatic method to detect the dancer's body, which aims if the system is tested using other datasets the system can still detect the dancer's body; using other methods to detect the shape of the dancer so that the classification model has a better accuracy value; detect more detailed body parts such as the eyes or the lower legs so that the accuracy of the model has a better level of accuracy; adding movements other than the basic movements of Balinese dance on the grounds that there are several movements that should be able to be categorized into a Balinese dance movement, but in this study, these movements are included in the uncategorized class; focusing on making a classification model for each part of the dancer's body, with the aim of getting the best level of accuracy in each part of the dancer's body by testing more classification methods and preprocessing stages.

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