BAB V
KESIMPULAN DAN SARAN

5.1 Kesimpulan

Dari penelitian ini diperoleh beberapa kesimpulan yaitu :

1. Proses klasifikasi Wayang kulit dengan menggunakan metode *deep learning* dengan arsitektur CNN yang telah disusun telah berhasil mengenali pola wayang dan melakukan klasifikasi selain itu telah dilakukan visualisasi dari masin-masing layer pada arsitektur CNN.
2. Proses pelatihan dilakukan dengan menggunakan beberapa nilai epoch yaitu *epoch* 10, *epoch* 20, *epoch* 50, *epoch* 100. Akurasi terbaik yang didapatkan saat pelatihan adalah 97.3% dan validasi 93.6%.

5.2 Saran

Adapun saran dari penulis untuk penelitian berikutnya adalah:

1. Penambahan lebih banyak dataset untuk mengurangi nilai overfitting.
2. Dalam penelitian ini, dapat dilakukaan perubahan optimisasi.
3. Penambahan kelas untuk dataset sehingga dapat dikenali pola wayang lebih dari kelas yang digunakan dalam penelitian ini.

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Lampiran 1. Source Code Pelatihan

```
import matplotlib
matplotlib.use("Agg")
from keras.preprocessing.image import ImageDataGenerator
from keras.optimizers import Adam
from keras.preprocessing.image import img_to_array
from sklearn.preprocessing import LabelBinarizer
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
from imutils import paths
import numpy as np
import argparse
import random
import pickle
import cv2
import os
epoch = 50
learn_rate = 1e-3
batch_size = 32
Dimensi = (96, 96, 3)
data = []
labels = []
direktori = sorted(list(paths.list_images(args["dataset"])))
random.seed(42)
random.shuffle(dir)
for imagePath in dir:
	image = cv2.imread(imagePath)
	image = cv2.resize(image, (Dimensi[1], Dimensi[0]))
	image = img_to_array(image)
	data.append(image)
	label = imagePath.split(os.path.sep)[-2]
	labels.append(label)
data = np.array(data, dtype="float") / 255.0
labels = np.array(labels)
lb = LabelBinarizer()
labels = lb.fit_transform(labels)
```

Lampiran 2. Source Code Pengujian

```
gambar = cv2.imread(args["image"])
output = gambar.copy()
image = cv2.resize(gambar, (96, 96))
image = image.astype("float") / 255.0
image = img_to_array(image)
image = np.expand_dims(image, axis=0)
model = load_model(args["model"])
lb = pickle.loads(open(args["labelbin"], "rb").read())
proba = model.predict(image)[0]
idx = np.argmax(proba)
print(proba)
label = lb.classes_[idx]
filename = args["image"][args["image"].rfind(os.path.sep) + 1:]
label = "{}: {:.2f}%".format(label, proba[idx] * 100)
output = imutils.resize(output, width=400)
cv2.putText(output, label, (10, 25),  cv2.FONT_HERSHEY_SIMPLEX,
        0.7, (255, 255, 0), 2)
print("[INFO] {}".format(label))
cv2.imshow("Output", output)
cv2.waitKey(0)
```

Indonesian Traditional Shadow Puppet Image Classification: A Deep Learning Approach

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Abstract— **Puppet is one of Indonesian traditional art which is an art performance performed by a puppeteer. The puppets have their own features and character according to the puppet character. So one way to preserve it, we do research to recognize and classify the type of puppets. So with this can be known the types of puppet based on shades and shapes. With the differences of these characteristics, the writer made the classification of puppets by using Deep Learning method which is currently popular on computer vision. In this study we used Deep Convolutional Neural Network architecture such as AlexNet and VGG-16. By using our own dataset, we classify the types of puppets based on the puppet feature with the number of databases that we have after going through the data augmentation is 5130. The best result we made is using architecture VGG-16.**

Keywords—Deep Learning, Deep Convolutional Neural Network, GPU, Image Classification

I. INTRODUCTION

Traditional Shadow Puppet is one art from Indonesia where each puppet has features and characteristics of different carvings according to the role it plays. Traditional shadow puppet is played by the puppeteer who is also the narrator of the puppet characters. Given the different shapes and characteristics of puppet , we do research to apply the effect of learning algorithm in doing image recognition, retrieval, and classification. In this case the we will use the method of deep learning that is currently popular in computer vision.

The concept of Deep Learning is based on the study of artificial neural network learning. Until now deep learning is growing and widespread which is applied in several fields such as language natural processing, computer vision, speech recognition etc. Y. LeCun et al.[1] proposed the concept of Convolutional Neural Network (CNN). In this research, Convolutional Neural Network will be used to identify with deep architecture [2]. Convolutional neural networks generally consist of convolutional layers, pooling layer and fully connected layer . This is a type of deep neural network with local connection and weight sharing and feature mapping architecture with activation function. Pooling Layer not only serves to reduce the calculation level of computational complexity of the data, this layer also at once in recognition has strong robustness to the input sample. So with this the CNN is very good in terms of feature extraction. In this case we apply learning from scratch training.

First , In this paper will be applied the use of some deep learning architecture such as AlexNet and VGG-16 in recognition of the pattern of the puppet dataset. Secondly we will do improvisation on CNN in training and pattern puppet recognition. The final result of this paper we will provide information on training and validation results based on accuracy and loss. We will describe the comparison of each architecture in the classification of puppet . By using GPU in training, we get faster time compared to CPU.

The research that has been done on Indonesia shadow puppet is aimed for preservation one of which is music emotion recognition of Indonesian puppet theater by Tito Pradhono Tomo et al. [3]. Arik Kurnianto et al. making puppets as characters in games. The reason is because shadow puppet in Indonesia has strong local identity [5].

In this research, we are aim to protect shadow puppet of Indonesia from extinction as well as to preserve it. We used deep learning to recognize a puppet through its style and type. The reason we are apply deep learning in this research is deep learning usually work better than traditional machine learning because deep learning also learned part of the feature extraction. Convolutional neural network Made from multi layer processing with better identification. Deep learning technique learn by making more abstract representation of data as the network grows deeper.

II. MATERIALS AND METHOD

A. Deep Learning

Deep learning provides computational models that are composed of multiple processing layers for learning from data representation with multiple levels of abstraction [7]. This method improves the state of the art in image identification, speech recognition, object detection and other domain. Deep learning has made great progress in solving problems in the world of artificial intelligent.

B. Deep Convolutional Neural Network Architecture

CNN is a neural network proposed by Yann LeCun [1] used for image recognition, which is excellent in image classification and retrieval [8] [9] [10], target detection [11] and so on [12]. CNN extract features automatically from domain specific image. In CNN there is a layer that has an important role as follows:

Input Layer. It is an input of a 224x224x3 image which is a dataset of Puppet.

Convolutional Layer. Is a layer consisting of a rectangular matrix of neurons. The convolutional weights indicate the convolutional channel [13]. Convolutional will count the neurons connected to the input layer, each connected with the weight and small region they are connected to in the input layer. The constraint that is obtained Convolutional layer is get better generalization on computer vision [3].

Pooling Layer. Is a layer used for reducing dimensionality, it take the greatest value of rectangular block from convolutional layer and subsample to produce single output from block [14]. Max pooling and average pooling are typical types.

Fully Connected Layer. Layer that is at the end of the CNN network. Fully connected layer take neuron from previous layer and then followed by the activation function [19].

Activation Function. Is applied after convolutional layer and fully connected layer. The activation function used in this research is ReLu and Softmax. ReLU function is define as:

$$f(x) = \begin{cases} x, if\ x > 0 \\ 0, otherwise \end{cases} \tag{1}$$

C. Hardware and Tools

In this study, we use hardware devices Intel(R) Core (TM) i7-3770K CPU@ 3.50 GHz, NVIDIA GTX980 8192MB, 16GB RAM. In doing our code stages use the Keras and Tensorflow python library. As well as in training we utilize parallel computing using GPU.

D. Dataset

In this study we collect the dataset itself. Our dataset is collected from several puppet museums in Bali. The type of puppets we will train in the dataset are Arjuna puppet, Yudistira Puppet , Rahwana Puppet , Sahadewa Puppet, Dewi Sinta Puppet and Gatot Kaca Puppet. The data we divide into two part for training and validation. In this research we use role dataset 80-20 (80% used for training, and 20% used for validation), An example of chunk dataset is shown in the following Figure:

Fig. 1. Example chunk of dataset shadow puppet

E. Data Augmentation

To increase performance of CNN and reduce overfitting, then we do augment data randomly generated on the dataset such as flip, rotate, and scale image during training to increase the number of datasets. We perform image transformations with low computing rates so that the image transformation does not have to be stored on the storage device. By doing image aumentation we decrease count of image dataset. Each image 200 randomly transformation. So, in our dataset include Arjuna Puppet (400), Yudistira Puppet (450), Rahwana Puppet (420), Sahadewa puppet (460), Gatot Kaca Puppet (400) and Dewi Sinta puppet (400).Total dataset after data augmentation is 2530 (6 classes) In the experiment we did, we perform data transformation by using Keras libraries in Python and using GPU. The success of doing augmentation data makes our dataset count increase. Figure 2 shows the image transformation of the same target with different method.

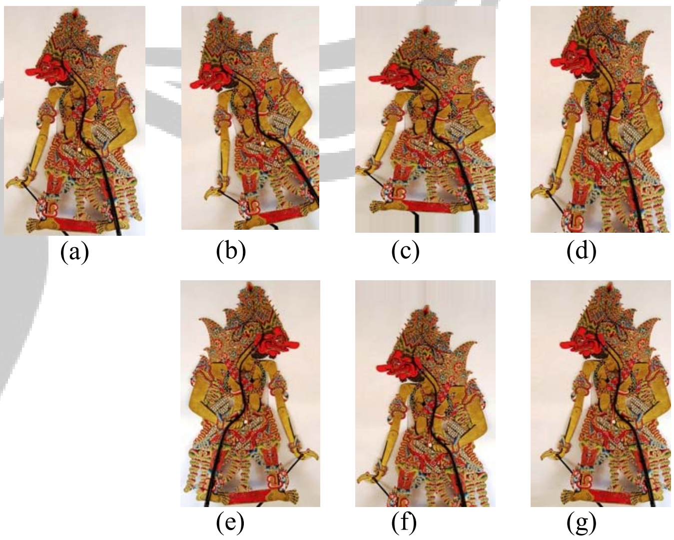

Fig. 2. Example data augmentation on dataset of puppet image (a) Original Image, (b) Rotation, (c) Shear, (d) Zoom, (e) Flip, (f) Height Shift, (g) Width Shift

F. Methodology

In this section, we will explain our evaluation of 2 Deep CNN model selected for analysis, then we will present the results of each architecture. Figure 3 shown our research process.

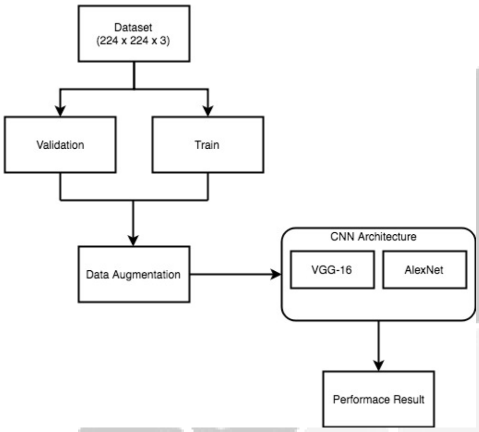

Fig. 3. Flowchart of shadow puppet classification

G. Deep CNN Models

1) AlexNet Architecture

Alexnet proposed by Alex Krizhevsky et al. for first time deep learning applied for image classification on a large scale [15]. Alexnet is composed of 8 layers, first layer with 5 convolutional layer and 3 layer the other is a full-connection layer. The first two convolutional layers (1,2) are followed by normalization and pooling layer respectively, and the last convolutional layer followed by a single pooling layer [16]. The final fully connection layer (fc-8) has 6 output in our adapted version of Alexnet (Total number of classes in our dataset). In the last fully connection using the activation softmax to categorize into a class in accordance with the training data. All the first layer of AlexNet have ReLu non-linearity activation. And the first two fully connected layer (fc-(6) and (fc-7).

2) VGG-16 Architecture

VGG model is typical CNN with high classification and recognition rate [20]. VGG is a deep neural network group. With input size 224x224x3 (RGB image), then the image will be processed by convolutional layer and max-pooling layer with kernel size 3x3 and stride 1 [17]. Max pooling layer has 2x2 window size with size of stride 2. In the fully connected layer, VGG has 4096 channels and 6 on the final layer. And final layer is softmax activation function. We apply the VGG network to categorize 6 types of puppets.

The ReLu non-linearity is used after the convolutional layer and fully connected layer. Stochastic Gradient Descent (SGD) is used to reduce the number of loss with learning rate parameter 1e-4. The results given by SGD are very good compared to other adaptive learning methods. The batch size we use is 32. The last layer output is 6 with the activation of softmax, value 6 is the number of classes in the puppet dataset.

We used image size 224x224x3 based on patches extraction from VGGNet [17] and AlexNet [15]. In this study we tried to test the ability VGG-16 with AlexNet. We chose VGGNet and AlexNet because this architecture frequently used in the computer vision field, not only used for full scratch fields but also used as feature generator.

Table 1 explain the layer of Alexnet architecture and VGG-16 that we use in this research:

TABLE I. ALEXNET VS VGG-16 ARCHITECTURE LAYER

AlexNet			**VGG-16**		
Layer Name	***Type***	***Output Shape***	***Layer Name***	***Type***	***Output Shape***
Input_1	Input Layer	(224,224,3)	Input_1	Input Layer	(224,224,3)
Conv2d_1	Conv2D	(128, 128, 96)	Block1_conv1	Conv2D	(224,224,64)
max_pooling2d_1	MaxPooling2D	(64, 64, 96)	Block1_conv2	Conv2D	(224,244,64)
conv2d_2	Conv2D	(64, 64, 96)	Block1_pool	MaxPooling2D	(112,112,64)
max_pooling2d_2	MaxPooling2D	(32, 32, 256)	Block2_conv1	Conv2D	(112,112,128)
conv2d_3	Conv2D	(32, 32, 384)	Block2_conv2	Conv2D	(112,112,128)
conv2d_4	Conv2D	(32, 32, 384)	Block2_pool	MaxPooling2d	(56,56,128)
conv2d_5	Conv2D	(32, 32, 384)	Block3_conv1	Conv2D	(56,56,256)
max_pooling2d_3	MaxPooling2D	(16, 16, 256)	Block3_conv2	Conv2D	(56,56,256)
conv2d_6	Conv2D	(16, 16, 256)	Block3_conv3	Conv2D	(56,56,256)
max_pooling2d_4	MaxPooling2D	(8, 8, 256)	Block3_pool	MaxPooling2d	(28,28,256)
fc	Fully Connected Layer	4096	Block4_conv1	Conv2d	(28,28,512)
fc	Fully Connected Layer	4096	Block4_conv2	Conv2d	(28,28,512)
fc	Fully Connected Layer	6	Block4_conv3	Conv2d	(28,28,512)

Block4_pool	MaxPooling2d	(14,14,512)
Block5_conv1	Conv2d	(14,14,512)
Block5_conv2	Conv2d	(14,14,512)
Block5_conv3	Conv2d	(14,14,512)
Block5_pool	MaxPooling2D	(7,7,512)
fc	Fully Connected Layer	4096
fc	Fully Connected Layer	6

III. Results and Discussion

A. Experimental Result

By using the existing architecture, the results we obtained by using the first architecture VGG-16. Our experiment was done using 50 iterations of epoch (show on Table 2). We tested by arranging the number of train-test data with Role VGG-16 (80% for training – 20% for validation) we get performance achieved on training 99% and validation accuracy is 98%. The time required for the GPU to do the computation is 316s. As for our Alexnet architecture accuracy is lower than VGG-16 ie 75% for training and 73% for validation. Results from experiments comparison for VGG-16 and Alexnet are shown as Figure 4 and 5.

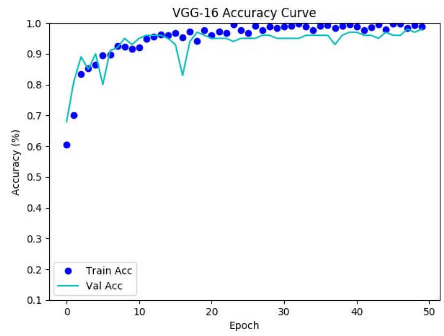

Fig. 4. Training vs validation accuracy AlexNet architecture from scratch

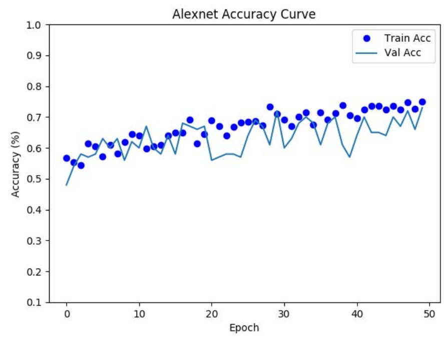

Fig. 5. Training vs validation loss VGG-16 architecture from scratch.

Table 2 explains the results we recorded in experiments using the Alexnet and VGG-16 architectures.

TABLE II. Experiment Result on each Deep Convolutional Neural Network

CNN Architecture	Train Accuracy Rate (%)	Validation Accuracy Rate (%)	Time Training (seconds)	Number Epoch
AlexNet	75%	73%	222s	50
VGG-16	99%	98%	316s	50

From the table above can be concluded that the VGG-16 architecture has better capability compared to AlexNet architecture. On Experiment, we also change the learning rate value. Tabel 3 shows the result of the changed of learning rate.

TABLE III. Experiment Result on each Deep Convolutional Neural Network With Different Learning Rate

CNN Architecture	Train Accuracy Rate (%)	Validation Accuracy Rate (%)	Time Training (seconds)	Number Epoch	Learning Rate
AlexNet	70%	69%	224s	50	1e-5
VGG-16	99%	98%	316s	50	1e-5
AlexNet	62%	57%	232s	50	1e-6
VGG-16	90%	89%	312s	50	1e-6

From experiment result based on Table 3, by changing the value of learning rate, the best results obtained with accuracy 98% with time training 316s by using learning rate value 1e-5.

B. ConvNet Layer Visualization

In this section, we focused on the visualization of space representations composed by different layers and visual information extracted on each layer of CNN. In this visualization we describe how images of puppet datasets are processed on each of Alexnet and VGG-16 layers.

Visualizing of Activations CovNet in initial layer of Alexnet and VGG-16 refers to feature map output by variation of convolutional layer and pooling layer on the network. This visualization shows how the input layer decomposes into the learning filter by the network. Figure 6 shows the visualization of the convolutional layer VGG-16 layer (block1_conv1) and Figure 7 show the visualization of AlexNet layer (conv2d_1)

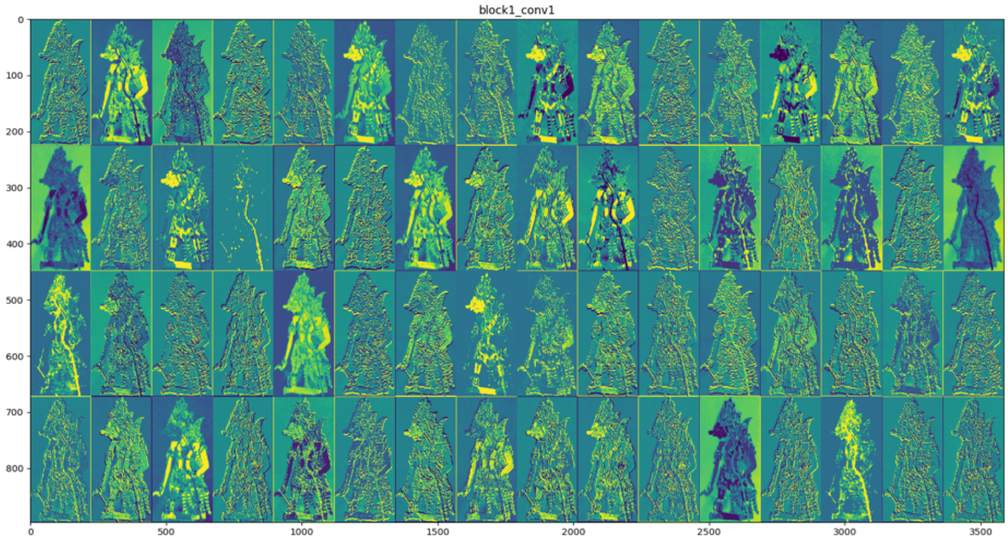

Fig. 6. Visualization of activation in initial layers of VGG-16 (Block1_conv1)

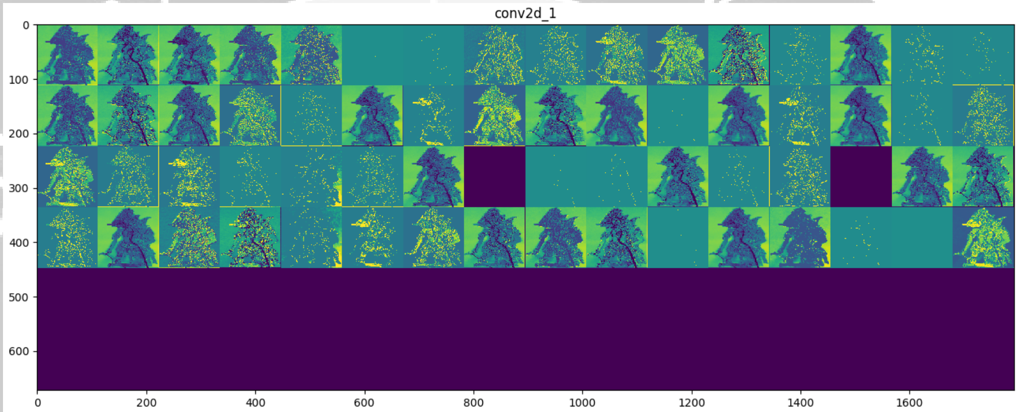

Fig. 7. Visualization of activation in initial layers of AlexNet Layer (conv2d_1)

IV. Conclusion

In this paper, to preserve Indonesia shadow puppet we are try to recognize a shadow puppet of its style and shape which has characteristics different from each other which applied to the computer system. A convolutional neural network has been applied to the puppet classification is one deep learning method deep learning. Using the Alexnet architecture and VGG-16 can automatically classify puppet images. We collect the puppet dataset by ourselves. We do augmentation Data to add our dataset at once to reduce overfitting. By leveraging our GPU acquire a very fast time compared to the CPU. From the experiment we get the result that the VGG16 architecture has better classification accuracy level than AlexNet in terms of puppet image classification. We get best validation accuracy 98% with VGG-16 architecture. Our next research will lead to applying some of the other Deep Convolutional Neural Network architectures and combining with some method also make minor changes to get the best results. Through this classification, the sustainability of shadow puppet is maintain to recognize by computer system.

Acknowledgement

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Lampiran 4. Rangkaian Surat Elektronik ICITEE

[ICITEE 2018] Your paper #1570443969 ('Indonesian Traditional Shadow Puppet Image Classification: A Deep Learning Approach') Inbox x

icitee2018-chairs@edas.info Apr 27
to me

Dear Mr. Ib. Sudiatmika:

Congratulations - your paper #1570443969 ('Indonesian Traditional Shadow Puppet Image Classification: A Deep Learning Approach') for 2018 10th International Conference on Information Technology and Electrical Engineering (ICITEE) has been **accepted**.

The reviews are below or can be found at https://edas.info/showPaper.php?m=1570443969.

======= ICITEE 2018 review 1 =======

> *** Relevance and timeliness: Rate the importance and timeliness of the topic addressed in the paper within its area of research. Acceptable (3)

> *** Technical content and scientific rigour: Rate the technical content of the paper (e.g.: completeness of the analysis or simulation study, thoroughness of the treatise, accuracy of the models, etc.), its soundness and scientific rigour. Valid work but limited contribution. (3)

> *** Novelty and originality: Rate the novelty and originality of the ideas or results presented in the paper. Some interesting ideas and results on a subject well investigated. (3)

> *** Quality of presentation: Rate the paper organization, the clearness of text and figures, the completeness and accuracy of references. Substantial revision work is needed. (2)

> *** Recommendation: How do you rate your recommendation? Possible Accept. (2)

> *** Detailed comments: Please justify your recommendation and suggest improvements in technical content or presentation.

The paper presents implementation of deep learning technique for puppet images classification. Although the idea is interesting, the usage of convolutional neural network (CNN) should be judged with appropriate scientific reasoning. The authors should explain: "Why deep learning was used for classification, albeit there are a lot of classifier? Are the other classifiers not appropriate for this case?"

In the Related Works section, the authors should explain other works that are related with the domain of "preservation of shadow puppet". That is, the goal of this research should be clear, "why do we need to classify shadow puppets with deep learning? What is the difference between this research and the other research works? Is it for preservation purpose? Or educational purpose?"

For example, please considers these papers:

https://dl.acm.org/citation.cfm?id=2502104 https://dl.acm.org/citation.cfm?id=1823825 https://ieeexplore.ieee.org/abstract/document/7418931/ https://www.inderscienceonline.com/doi/abs/10.1504/IJART.2017.084944 http://repository.unej.ac.id/handle/123456789/3415

Lampiran 5. Hasil Pengukuran Kesamaan dengan Turnitin

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