



INTRODUCTION OF PAPUAN AND PAPUA NEW GUINEAN FACE PAINTING USING A CONVOLUTIONAL NEURAL NETWORK

Happy Alyzhya Haay^{1*}, Suryasatriya Trihandaru², Bambang Susanto³

^{1,2,3}Master of Data Science Study Program, Department of Mathematics and Data Science, Faculty of Science and Mathematics, Satya Wacana Christian University

Jl. Diponegoro No.52-60, Salatiga, Kec. Sidorejo, Kota Salatiga, Jawa Tengah 50711, Indonesia

Corresponding author's e-mail: * 632020002@student.uksw.edu

ABSTRACT

Article History:

Received: 21st September 2022

Revised: 14th December 2022

Accepted: 25th January 2023

Keywords:

Convolutional Neural Network;

ResNet-50;

VGG-16;

VGG-19;

In this research, the face painting recognition of Papua and Papua New Guinea was identified using the Convolutional Neural Network (CNN). This CNN method is one of the deep learning that is very well known and widely used in face recognition. The best training process model is obtained using the CNN architecture, namely ResNet-50, VGG-16, and VGG-19. The results obtained from the training model obtained an accuracy of 80.57% for the ResNet-50 model, 100% for the VGG-16 model, and 99.57% for the VGG-19 model. After the training process, predictions were continued using architectural models with test data. The prediction results obtained show that the accuracy of the ResNet-50 model is 0.70, the VGG-16 model is 0.82, and the VGG-19 model is 0.83. It means that the CNN architectural model that has the best performance in making predictions in identifying the recognition of Papua and Papua New Guinea's face painting is the VGG-19 model because the accuracy value obtained is 0.83.



This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution-ShareAlike 4.0 International License](https://creativecommons.org/licenses/by-sa/4.0/).

How to cite this article:

H. A. Haay, S. Trihandaru and B. Susanto., "INTRODUCTION OF PAPUAN AND PAPUA NEW GUINEAN FACE PAINTING USING A CONVOLUTIONAL NEURAL NETWORK," *BAREKENG: J. Math. & App.*, vol. 17, iss. 1, pp. 0211-0224, March 2023.

Copyright © 2023 Author(s)

Journal homepage: <https://ojs3.unpatti.ac.id/index.php/barekeng/>

Journal e-mail: barekeng.math@yahoo.com; barekeng.journal@mail.unpatti.ac.id

Research Article • **Open Access**

1. INTRODUCTION

Face painting is an essential part of traditional processions in Papua. When traditional events, such as wearing traditional clothes, face painting complements traditional makeup [1]. Face painting is found in Papua and other areas such as Papua New Guinea (PNG), where face painting is also an essential part of traditional processions. The close geographical location of Papua and Papua New Guinea means there are similarities in customs and culture as well as face painting.

Face Painting is a painting that is used only on the face as a medium or place to be painted [2]. The liquid or paint used in this face painting uses essential ingredients that come from nature. For example, to get black, one can use liquid squid ink or charcoal. Apart from that, to get a white color, one can also use lime mixed with water [1].

Along with the rapid development of technology, one computer vision technology can identify images which will then be categorized into several predetermined classes called image recognition. This image recognition can determine what is contained in the image, and then it will be classified based on a difference between one image and another. In this study, the introduction of facial painting images will be carried out.

After reviewing several studies, several studies have relevance to the research carried out. The first research is a study by [3] to identify seven primary human emotions: anger, disgust, fear, happiness, sadness, surprise, and neutrality. The architecture used for CNN is VGG-16 and ResNet-50. The second research that has been reviewed is conducted by [4] using the Convolutional Neural Network (CNN), which aims to classify traditional food images along with the development of the era. In this digital era, taking photos before eating and uploading them to social media is a lifestyle today. Subsequent research was carried out by [5] using the CNN model based on Transfer Learning which was developed to compare different approaches between VGG-16 and ResNet-50 to see if there are diseases in plants where plant diseases are one of the biggest threats in agriculture.

Another related study was conducted by [6] using three CNN architectures, namely VGG 16, ResNet-50, and SE-ResNet50. A comparison was made of the three architectures to detect seven human facial expressions, namely: anger, disgust, contempt, fear, happiness, and sad. Another related study was conducted by [7] using the CNN architecture to show that tattooing and face painting affected all modules tested, especially for images with large face areas covered with tattoos or painting. In addition, there was also research conducted using the Convolutional Neural Network (CNN) architecture, designed a system capable of detecting microscopic images of blood containing malaria parasites, carried out by [8]. Thus, even though there are similarities in the methods used by previous researchers with the research that will be carried out, given the different subjects, objects, and places of research, the research on the Identification of the Recognition of Papuan and Papua New Guinean Face Paintings used a Convolutional Neural Network with architectures of ResNet-50, VGG-16, and VGG-19 needs to be done.

2. RESEARCH METHODS

In this research, an introduction to Papua and Papua New Guinea (PNG) face painting was carried out using a deep learning method, namely the Convolutional Neural Network (CNN). CNN is used because this method is the best in terms of accuracy in image recognition. The data was obtained from Google and social media, which were collected with the keywords "Papuan customs" and "ethnic Papua New Guinea." The data used were photos with a focus on the face in the painting. The data included photos from two places: Papua and Papua New Guinea (PNG). The data collected were 155 for Papua and 155 for Papua New Guinea. Then, the data obtained were processed into 75% training data and 25% test data for each of the two classes, namely Papua and Papua New Guinea. **Figure 1**, which is shown below, is one of the data or photos used in the study.



Figure 1. An example of data (a) Photographs of Papua Face Paintings, (b) Photographs of Papua New Guinean Face Paintings

This research was conducted using the Python programming language on Google Colaboratory, or what is often known as Google Colab. In this research, Google Colab provides free GPU (Graphics Processing Unit) access to speed up the process with deep learning libraries.

2.1 Convolutional Neural Network

One of the most well-known and often-used neural network methods is the Convolutional Neural Network or CNN. In processing high-dimensional data such as images or videos, CNN is very capable of processing them. Similar to neural networks, in general, the way CNN works has the most crucial difference: using a 2-dimensional or high-dimensional kernel for each unit in the CNN layer to be convolved [9]. CNN is one of the deep learning algorithms that utilize local spatial coherence in the input image, which allows it to have less weight because several parameters are used together [10]. Images being objects used in CNN in mathematical terms are referred to as tensors. The more familiar terms related to tensors are vector and matrix. For example, $x \in R^{H \times W \times D}$ is a 3rd order tensor with an HWD element, where H is height, W is width, and D is depth and each is indexable (i, j, d) , with $0 \leq i < H$, $0 \leq j < W$ and $0 \leq d < D$. Convolutional Neural Network consists of several layers as follows:

Convolution Layer

This convolution layer is a special kind of linear operation. Convolution is a mathematical operation used in image processing. The mathematical operation in question is by shifting the Kernel matrix over the input matrix and applying the output function as a feature map of the input image. The convolution operation is written with the following formula:

$$s(t) = (x * w)(t) \quad (1)$$

The function $s(t)$ returns one output which is a feature map. The first argument is input (x) and the second argument is kernel or filter (w). Considering the input as a 2D image, we can treat t as pixels and replace them with i and j [9]. Therefore, operations involving input from one or more dimensions can be written as:

$$S_{(i,j)} = (I * K)_{(i,j)} = \sum_m \sum_n I_{(i-m,j-n)} K_{(m,n)} \quad (2)$$

The following shows **Figure 2** which is the convolution process carried out in **Equation (2)**.

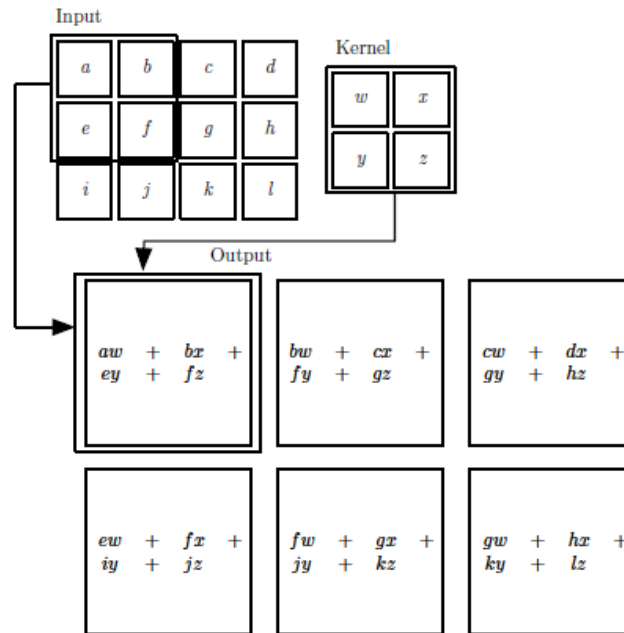


Figure 2. Convolution Process [11]

Kernels with a certain length and height (pixels) are formed from neurons in the convolution layer. The filter or kernel will be shifted in all parts of the image. The multiplication operation will be performed between the input and the kernel or filter.

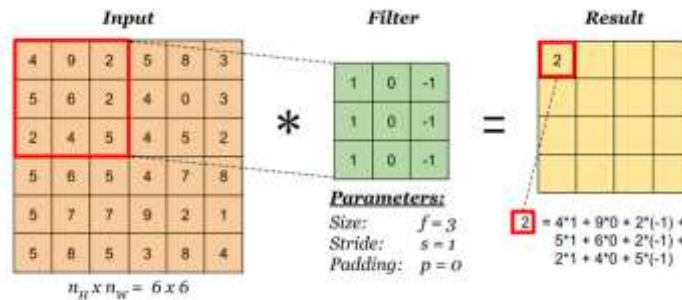


Figure 3. Input matrix multiplication and filter or kernel operation

This convolution process aims to extract features from the input image and produce a linear transformation of the input data that matches the information in the data. The output dimensions of the feature maps were calculated using the following formula:

$$\text{output } f.\text{maps} = \frac{W - N + 2P}{S} + 1 \quad (3)$$

note:

W = input size

N = filter size

P = zero padding

S = stride

Rectified Linear Unit (ReLU) Activation

There is also a non-linear activation function called Rectified linear unit or ReLU. ReLU is often known as a non-linearity function in neural networks [4]. The ReLU activation function serves to replace the output result from the convolution layer, which has a negative value to zero, and if it is positive, the output will be equal to the value of the activation function [12].

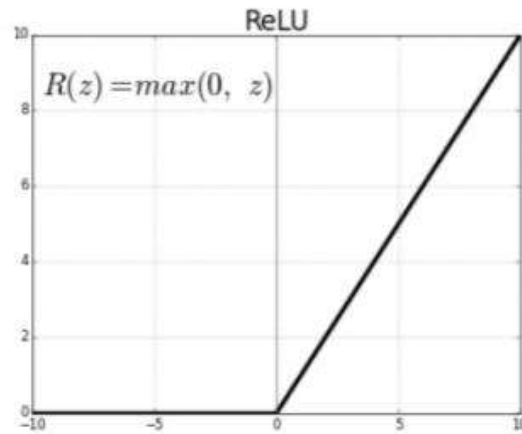


Figure 4. Graph of the ReLU activation function [9]

Compared to other activation functions, such as sigmoid and tanh, ReLU has advantages. Namely, it can speed up the configuration process carried out with Stochastic Gradient Descent (SGD),

Pooling Layer

The function of this pooling layer is to reduce the number of parameters with down-sampling operations [5]. Therefore, it can speed up the computing process. It aims to reduce the occurrence of overfitting. The pooling layer consists of two types, namely Average Pooling and Max Pooling. Kernels with size $n \times n$ (2×2), in which the maximum value is taken, are referred to as max-pooling, and kernels with size $n \times n$ whose average value is taken are referred to as average pooling.

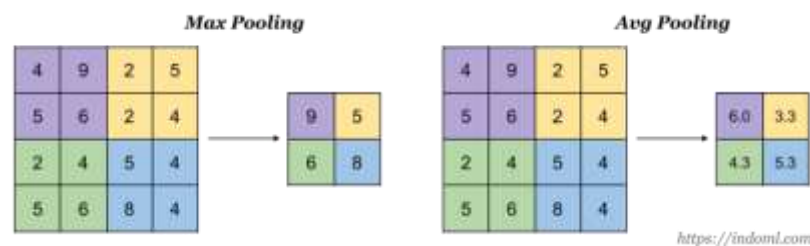


Figure 5. Differences between Max Pooling and Average Pooling operations

Fully Connected Layer

The layer formed due to the convolution process is called the fully connected layer. The fully connected layer is used to perform transformations on data so that data can be classified linearly [13]. The fully connected layer consists of several layers: the hidden layer, activation function, output layer, and loss function. This layer is generally located at the end of the CNN architecture, which is represented as a matrix multiplication with vector addition and implementing a non-linear function as follows:

$$y = f(W^T x + b) \quad (4)$$

where y is defined as an output vector that has a function of W which is a simple matrix that has weights connected to each other between units and then multiplied by x as the input vector [9].

2.2 Convolutional Neural Network Architecture Models

There are three CNN architectures used in this study, namely VGG-16, ResNet-50 and VGG-19.

Residual Network (ResNet-50)

Residual Networks stands for ResNet-50, a smaller version of ResNet-152. ResNet-50 is often used as a starting point for transfer learning. One of the reasons for using ResNet-50 is that it won first place in the 2015 ILSVRC classification competition with a top-5 error rate of 3.57%, won first place in the 2015 COCO and ILSVRC competitions in ImageNet Detection, ImageNet localization, Coco detection, and Coco segmentation [14]. It replaced the position of VGG-16, which was previously the best model.

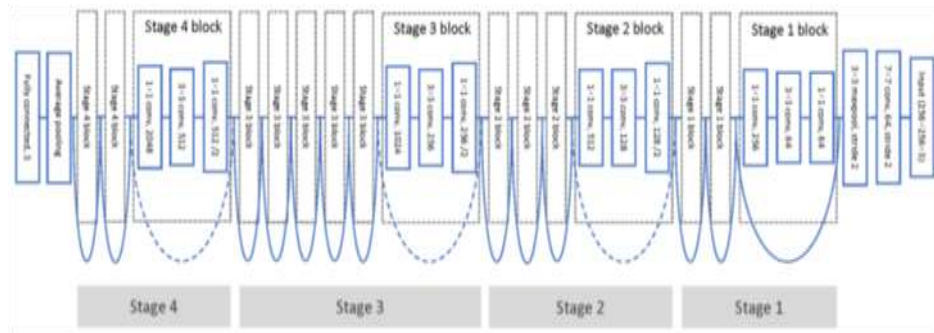


Figure 6. Architecture of ResNet-50

Visual Geometry Group

In the Visual Geometry Group, the VGG-16 and the VGG-19 models are the most frequently used model. These models are the best-performing models in the VGG-Net family. The VGG-16 model, for example, won 1st and 2nd place in the above categories at the 2014 ILSVRC challenge, where the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is an annual computer vision competition. The VGG-Verydeep-16 CNN model is a pre-trained CNN model released by the Oxford VGG group. The architecture of the VGG-16 model is shown in Figure 7 below. VGG-16 consists of 16 layers [3].

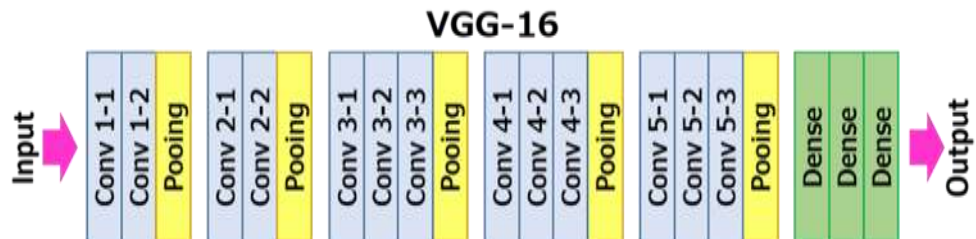


Figure 7. Architecture of VGG-16

Apart from VGG-16, the Visual Geometry Group also has another architectural model called VGG-19. The VGG-19 architectural arrangement is shown in Figure 8 below.

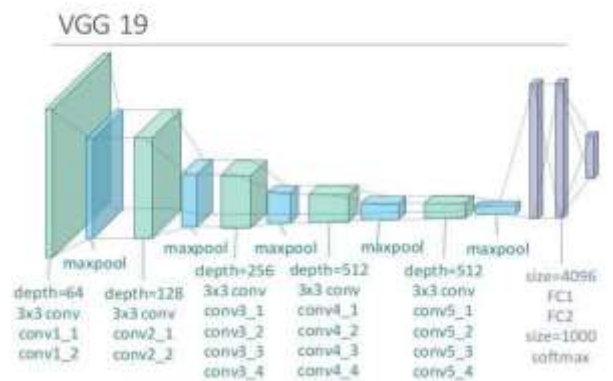


Figure 8. Architecture of VGG-19

2.3 Loss Binary Cross Entropy Function

The loss function often measures how well the prediction model predicts the expected results. In Machine Learning, the loss function consists of three parts. The first is the loss function for binary classification and the loss function for multi-class. In this research, we used the loss function for binary classification, or what is known as the binary cross entropy loss function. Mathematically, the cross entropy loss function is formulated as follows:

$$loss = -\frac{1}{N} \sum_{i=1}^N y_i \cdot \log \hat{y}_i + (1 - y_i) \cdot \log (1 - \hat{y}_i) \quad (5)$$

where \hat{y}_i is the predicted value, y_i is the corresponding target value and N is the amount of data.

2.4 Confusion Matrix

A confusion Matrix is a table used in measuring performance in classification. **Table 1** is a confusion matrix table consisting of four terms representing the classification process results. These terms are True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN). TP means positive data that has a truth value or is detected correctly. FP means data that is classified as wrong but detected positive. TN means that the detected negative data is correct. FN means that all predicted and actual data values are wrong.

Table 1. Confusion Matrix

		Actual Values	
		Positive	Negative
Predicted Values	Positive	TP	FP
	Negative	FN	TN

Accuracy

Accuracy shows the accuracy of a model in carrying out the classification correctly or, in other words, the closeness of the prediction with the model to its original state or actual value. Calculating accuracy is dividing the total number of correct prediction results by the total predicted data. The equation can be seen in **Equation (6)** [15].

$$Accuracy = \frac{TP}{TP+FP+TN+FN} \times 100\% \quad (6)$$

Precision

Precision means the comparison between the TP (True Positive) value and the total amount of data. Therefore, it is formulated as follows:

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

Recall

Recall means the predicted precision value which is relevant to the original data. Recall is calculated by comparing TP to the number of TP and FN. It is formulated as the following equation.

$$Recall = \frac{TP}{TP+FN} \quad (8)$$

F-Measure

F-Measure uses precision and recall values. The calculation to find the F-Measure or f1-score can be seen in the following equation

$$f1 - Score = 2 \times \frac{Precision \times Recall}{TP+FP+TN+FN} \quad (9)$$

3. RESULTS AND DISCUSSION

3.1. The Results of Data Training Process

Model ResNet-50

This analysis shows the results of the data training process by training the CNN model used to distinguish between Papuan and Papua New Guinean face paintings easily. The models were compiled using the Adam optimizer, binary cross entropy loss function, and 200 epochs or iterations. The early stopping function was used, which means the model stopped training after the 100th iteration. In the ResNet-50 model training process, the training process stopped at the 102nd iteration. The following table shows the accuracy and loss values of the ResNet-50 model from the train and validation data. The table is a table of accuracy and loss for the ResNet-50 model.

Table 2. The Results of Accuracy and Loss from the ResNet-50 Data Train Model

Epochs	Train Data		Validation Data	
	Accuracy	Loss	Accuracy	Loss
10	0.6838	0.6099	0.6316	0.6434
20	0.5769	0.7203	0.5263	0.6966
30	0.6880	0.6002	0.6316	0.6237
40	0.6795	0.6221	0.6579	0.6441
50	0.7308	0.5283	0.6711	0.6181
60	0.7607	0.5022	0.6974	0.6037
70	0.7778	0.4986	0.6842	0.6272
80	0.7222	0.5570	0.5789	0.7560
90	0.4973	0.7735	0.6711	0.6261
100	0.7393	0.4961	0.6579	0.7044

Based on the **Table 2** above, the accuracy of the data train from the ResNet-50 model is around 70%. Next, a graph of the accuracy and loss results with the CNN ResNet-50 model is shown in **Figure 9**, with 100 epochs for the train data and validation data.

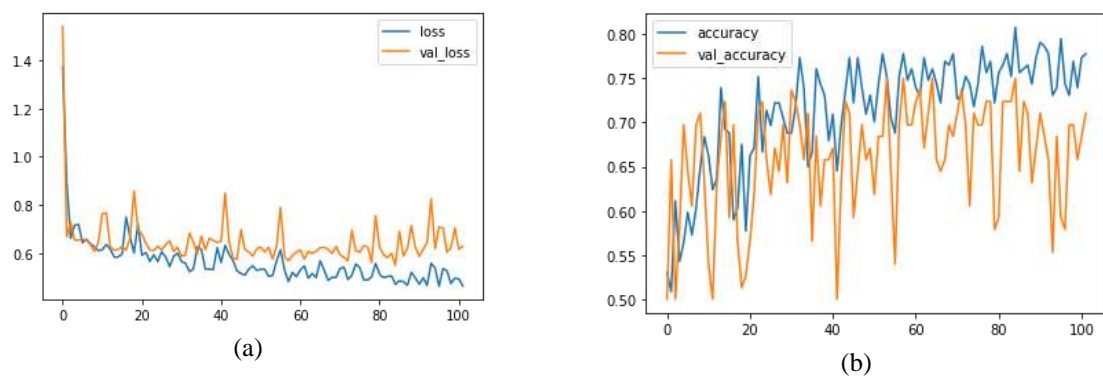


Figure 9. (a) The Graph of ResNet-50 Model Loss Value, (b) The Graph of ResNet-50 Model Accuracy Value

Figure 9 shows the loss and accuracy plots for the train and validation data in figures (a) and (b), respectively. In **Figure 9** (a), the loss value for the training data tends to decrease from the first epoch and is not constant. It is similar to the loss value for validation data. **Figure 9** (b) shows the accuracy value for the training and validation data. The graph shows that the accuracy value for the up and down train data is the same as the accuracy of the validation data.

In this training process, Early Stopping was also used as a strategy to stop the training process when the difference in performance between training and validation has exceeded the specified limits. Early stopping is also used to prevent overfitting. The training data results use early stopping. The training process stops at the 102nd epoch or iteration after passing 100 of the 200 epochs used during the model training process. The higher the epoch or iteration used in the training process, the better the accuracy value of the architectural model.

Model VGG-16

The training process with the VGG-16 model used the Adam optimizer, loss binary cross entropy function, and 200 epochs or iterations were carried out. The early stopping function was used, which means the model would stop training after the 100th iteration. In the ResNet-50 model training process, the training process stops at the 102nd iteration. The following table shows the accuracy and loss values of the VGG-16 model from the train and validation data. The table is a table of accuracy and loss for 100 epochs.

Table 3. Accuracy and loss results from the VGG-16 model train data

Epochs	Train Data		Validation Data	
	Accuracy	Loss	Accuracy	Loss
10	0.9359	0.1775	0.8158	1.0128
20	0.9915	0.0248	0.8421	1.0940
30	0.9701	0.0790	0.8026	1.3387
40	0.9915	0.0086	0.8289	1.4302
50	0.9915	0.0259	0.8026	1.3599
60	0.9957	0.0102	0.8158	1.6557
70	1	0.0081	0.8421	1.1865
80	0.9957	0.0061	0.8421	1.3910
90	0.9872	0.0314	0.8421	1.7319
100	1	0.0063	0.8158	1.8956

The training process obtained accuracy and loss values on the training and validation data for the VGG-16 model. It can be seen that the accuracy of the VGG-16 model is already high for the train data. After getting the accuracy of this training process, the VGG-16 model was evaluated to obtain the accuracy shown in **Table 3**. In the following, one can see the accuracy and loss graphs for the training and validation data with 100 epochs or iterations

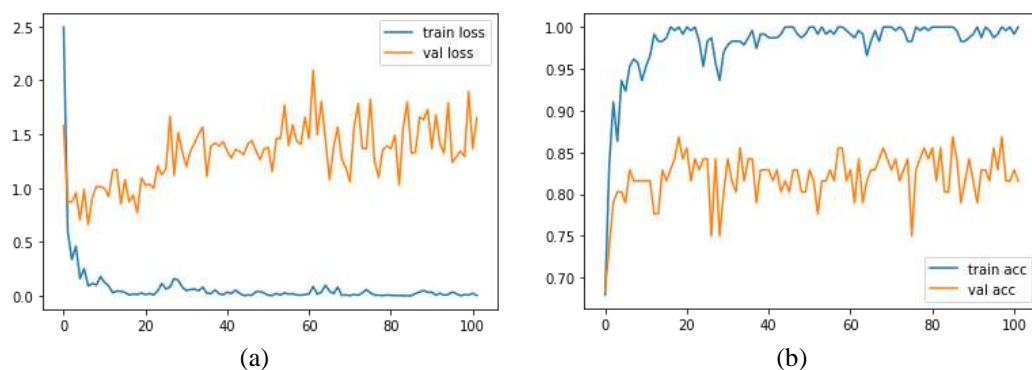


Figure 10. (a) The Graph of VGG-16 Model Loss Value, (b) The Graph of VGG-16 Model Accuracy Value

Figure 10 shows the accuracy and loss for the VGG-16 model training process. **Figure 10** (a) shows the train and validation data loss. The loss for the train data tends to decrease from the first to one hundred epochs. On the contrary, the loss of validation data increases from the first epoch. Whereas in **Figure 10** (b), the accuracy of the train data is seen to reach 100%, compared to the accuracy for the validation data, which fluctuates and tends to be constant. In the training process of the VGG-16 model, early stopping was used as a benchmark that the training process would stop when the training process had passed the 100th epoch or iteration of the 200 epochs or iterations that had been carried out.

Model VGG-19

Furthermore, in the training process, the VGG-19 model uses the Adam Optimizer, binary cross entropy loss function, and epochs or iterations of 200 epochs were carried out. The following table shows the accuracy and loss values of the VGG-19 model from the train and validation data. The table below is a table of accuracy and loss for 100 epochs.

Table 4. The results of Accuracy and loss from the VGG-19 model train data

Epochs	Train Data		Validation Data	
	Accuracy	Loss	Accuracy	Loss
10	0.9744	0.0649	0.8553	0.7251
20	0.9786	0.0367	0.8158	0.8102
30	0.9701	0.0940	0.8421	0.8644
40	0.9915	0.0180	0.8421	0.7600
50	0.9957	0.0128	0.8421	0.7412
60	0.9829	0.0839	0.7895	1.5057
70	0.9701	0.0700	0.8553	0.8615
80	1	0.0041	0.8684	0.7850
90	1	0.0066	0.8026	0.8186
100	0.9915	0.0232	0.7368	1.8979

Based on **Table 4**, the accuracy of the train data is higher than the accuracy of the validation data. The accuracy and loss that had been obtained are displayed in graphical form according to **Figure 11** below.

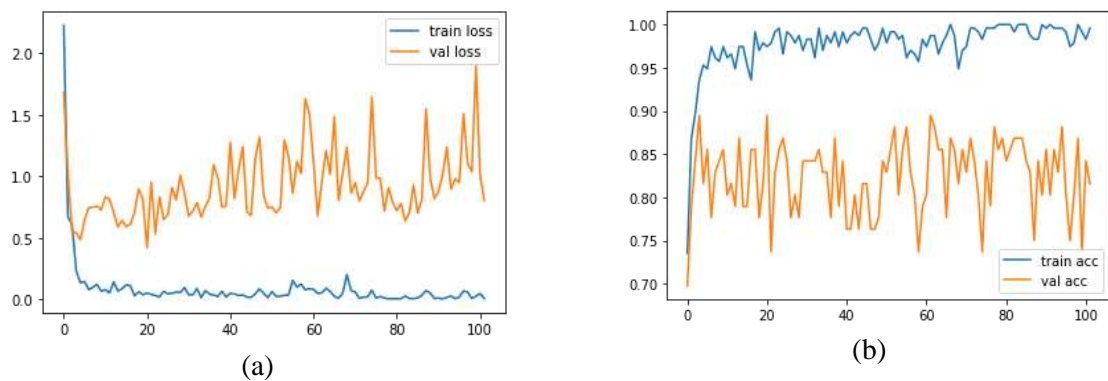


Figure 11. (a) The Graph of VGG-19 Model Loss Value, (b) The Graph of VGG-19 Model Accuracy Values

Figure 11 shows a graph of the accuracy and loss of the VGG-19 architecture. The graph shows that the VGG-19 model has almost the same graphical results as VGG-16. **Figure 11** (a) shows the loss for train data that goes down from the first epoch, but validation data tends to go up. Then, the accuracy of the train data that has increased from the first epoch was compared to the accuracy of the validation data, which tends to fluctuate. Early stopping is also used in the training process for the VGG-19 model, which means the training process will stop to prevent overfitting.

After the training process had been carried out for each CNN architectural model, it was followed by a model evaluation to obtain the best model. The evaluation model used the "model.evaluate()" function to obtain an accuracy value from the train data. **Table 5** shows the accuracy and loss values of the CNN model training process using the train data from the evaluation results of the CNN architectural model.

Table 5. The Results of Accuracy and loss train data from the evaluation model

	Accuracy	Loss
ResNet-50	0.8077	0.4654
VGG-16	1	6.5573e-04
VGG-19	0.9957	0.0088

Table 5 shows the accuracy and loss values from the model evaluation results using train data. The training data and model evaluation results show that the VGG-16 architectural model has a better level of accuracy than the ResNet-50 and VGG-19 models. It means that the VGG-16 model has better accuracy in distinguishing between Papuan and Papua New Guinean (PNG) face paintings in the training process. In addition to the results of accuracy in the training and evaluation process, predictions were made to obtain accuracy values in order to see the performance of each model, which can be shown in **Table 6**.

3.2 Prediction Results

After carrying out the training process using the train data, the model was then predicted with the "model.predict()" function using test data. Each architectural model was predicted. Then, the confusion matrix was obtained in **Figure 12**, **Figure 13**, and **Figure 14** for each CNN architectural model.

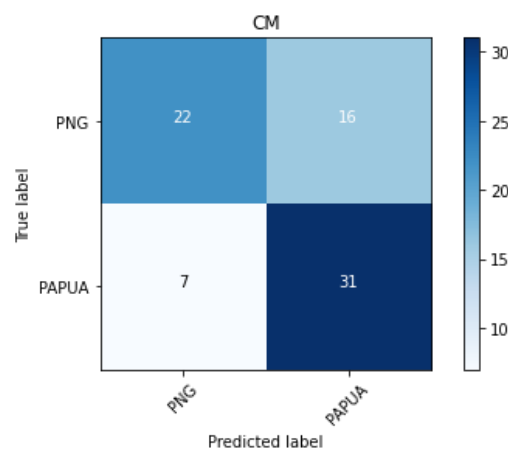


Figure 12. Confusion matrix from Model ResNet-50

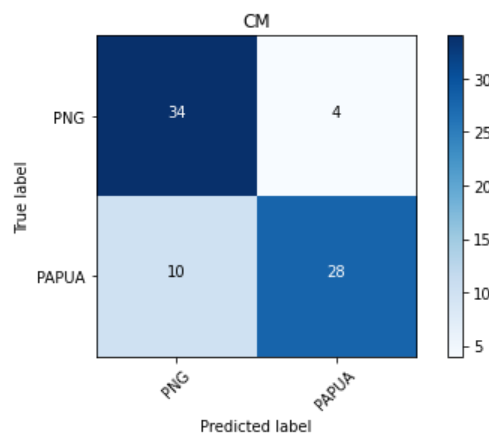


Figure 13. The confusion matrix of the VGG-16 model

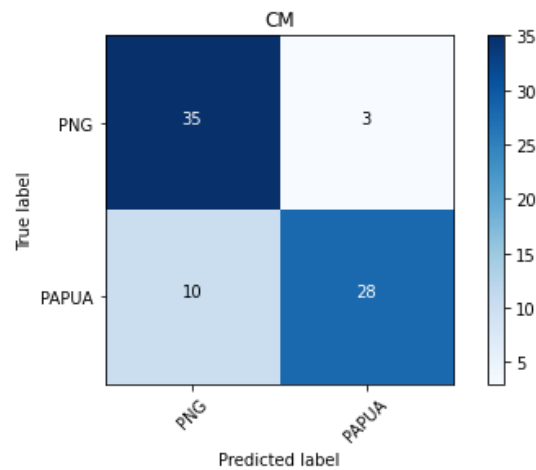


Figure 14. Confusion matrix from Model VGG-19

Figure 12, Figure 13, and Figure 14, which are the confusion matrix of each CNN architectural model, were continued by analyzing the prediction results to see the performance of each of these models. The performance of a good architectural model is shown in Table 6 for the predicted performance of each model of the CNN architecture.

Table 6. Model performance based on prediction results with Papua and PNG test data

Model	Category	Precision	Recall	<i>f1-score</i>	Accuracy
ResNet-50	PNG	0.76	0.58	0.66	0.70
	Papua	0.66	0.82	0.73	
VGG-16	PNG	0.77	0.89	0.83	0.82
	Papua	0.88	0.74	0.80	
VGG-19	PNG	0.78	0.92	0.84	0.83
	Papua	0.90	0.74	0.81	

Table 6 is a prediction result to see the performance of each CNN architectural model. The table compares the precision, recall, and *f1-score* values of the two categories in the CNN architectural model. The accuracy value of the ResNet-50 model is 70%, VGG-16 is 82%, and VGG-19 is 83%. According to the accuracy results obtained, the performance of the CNN architectural model that can distinguish between Papuan and Papua New Guinean (PNG) face paintings is the VGG-19 model, with an accuracy of 83%. The VGG-19 model can better predict between Papuan and PNG face paintings.

This painting of the faces of Papua and Papua New Guinea is a characteristic of the indigenous people when they wear traditional clothes in traditional events and traditional festivals. Papua New Guinea has a variety of unique cultures and rituals called "Sing Sing," where every tribe in Papua New Guinea gathers together to dance and play traditional musical instruments. Each tribe will paint their faces and bodies in bright colors and wear traditional clothing to showcase each other's culture, dance, and music. Similar to Papua, painting on the body is one of the cultural heritage. Apart from painting their faces for traditional events and cultural festivals, people also paint their bodies to unite with nature, such as using physical disguises for hunting in the wilderness. In particular, Papua has several indigenous tribes with various kinds of face-painting motifs that are often painted on faces. The motifs of the paintings also have their meaning.

Face painting is a characteristic of customs and culture. For this reason, it is essential to maintain and preserve the customs and culture of each tribe in their respective areas because, as time goes by, cultural heritage is almost extinct. Therefore, this study uses the Convolutional Neural Network Architecture to identify Papuan face painting, a regional culture.

Based on the results of this study, the best model results were obtained in recognition of Papuan and Papua New Guinean face painting after the training process and prediction results were carried out. The best model in the training process is the VGG-16 architectural model, and the best model in prediction is the VGG-19 model. Based on the results obtained, previous research has been carried out by [16] that study conducted a comparison of the Convolutional Neural Network architecture for fundus classification. In this study, two trials were carried out using CNN without gradient descent optimization. The results obtained from the two

trials obtained the VGG-16 and VGG-19 models as the best models in the study, with an accuracy of 89.3% in the first trial and 92.31% in the second stage trial. The same research was also carried out by [17]. In that study, an analysis of the performance of the Deep Learning VGG-19 model was carried out to detect COVID-19. By using medical image data, it is obtained that the VGG-19 model has a better performance compared to other models such as VGG-16, InceptionV3, and DensNet121 because the VGG-19 model can classify COVID-19 cases and healthy cases.

4. CONCLUSIONS

By looking at the results of this study, it was concluded that it is possible to identify the recognition of the Face Paintings of Papua and Papua New Guinea using the ResNet-50, VGG-16, and VGG-19 architectural models. The VGG-19 model was obtained as the model that has the best performance in recognizing the face painting of Papua and Papua New Guinea, with a prediction accuracy of 0.83 which is higher than the ResNet-50 and VGG-16 models.

REFERENCES

- [1] I. Peradantha and M. Murda, "Kajian Bentuk, Sumber Inspirasi dan Makna Simbolis Motif Body Painting Etnis Padaido di Papua," *J. Arkeol. Papua*, vol. Vol. 12 Ed, no. Juni, pp. 43–59, 2020.
- [2] Syamsiar, "EKSPLOKASI TEKNIK FACE AND BODY PAINTING UNTUK MENAMBAH ARTISTIK PAGELARAN BATIK FASHION ART WEAR," *Brikolase*, vol. 10, no. 1, 2018.
- [3] A. Savoie and J. Wong, "Recognizing Facial Expressions Using Deep Learning," p. 67, 2017, [Online]. Available: <http://cs231n.stanford.edu/reports/2017/pdfs/224.pdf>.
- [4] A. Rohim, Y. A. Sari, and Tibyani, "Convolution neural network (cnn) untuk pengklasifikasian citra makanan tradisional," *J. Pengemb. Teknol. Inf. dan Ilmu Komput.*, vol. 3, no. 7, pp. 7038–7042, 2019, [Online]. Available: <http://j-ptiik.ub.ac.id/index.php/j-ptiik/article/view/5851/2789>.
- [5] D. R. Talwekar, R. K. Jaiswal, N. Sharma, and D. S. Jain, "Evolutional of Vgg16 and Resnet50 Using Transfer Learning with Classification Plant Disease," *Gedrag Organ. Rev.*, vol. 33, no. 04, pp. 327–334, 2020, doi: 10.37896/gor33.04/031.
- [6] D. Theckedath and R. R. Sedamkar, "Detecting Affect States Using VGG16, ResNet50 and SE-ResNet50 Networks," *SN Comput. Sci.*, vol. 1, no. 2, pp. 1–7, 2020, doi: 10.1007/s42979-020-0114-9.
- [7] M. Ibsen, C. Rathgeb, T. Fink, P. Drozdowski, and C. Busch, "Impact of facial tattoos and paintings on face recognition systems," *IET Biometrics*, Apr. 2021, doi: 10.1049/bme2.12032.
- [8] N. K. C. PRATIWI, N. IBRAHIM, Y. N. FU'ADAH, and S. RIZAL, "Deteksi Parasit Plasmodium pada Citra Mikroskopis Hapusan Darah dengan Metode Deep Learning," *ELKOMIKA J. Tek. Energi Elektr. Tek. Telekomun. Tek. Elektron.*, vol. 9, no. 2, p. 306, 2021, doi: 10.26760/elkomika.v9i2.306.
- [9] O. Nurima Putri, "Implementasi Metode Cnn dalam Klasifikasi Gambar Jamur pada Analisis Image Processing (Studi Kasus: Gambar Jamur dengan Genus Agaricus dan Amanita)," 2020.
- [10] S. Tammina, "Transfer learning using VGG-16 with Deep Convolutional Neural Network for Classifying Images," *Int. J. Sci. Res. Publ.*, vol. 9, no. 10, p. p9420, 2019, doi: 10.29322/ijsrp.9.10.2019.p9420.
- [11] A. Goodfellow, Ian; Bengio, Yosua; Courville, *Deep Learning*, vol. 8, no. 9. 2017.
- [12] A. Victor Ikechukwu, S. Murali, R. Deepu, and R. C. Shivamurthy, "ResNet-50 vs VGG-19 vs training from scratch: A comparative analysis of the segmentation and classification of Pneumonia from chest X-ray images," *Glob. Transitions Proc.*, vol. 2, no. 2, pp. 375–381, 2021, doi: 10.1016/j.glt.2021.08.027.
- [13] M. R. Alwanda, R. P. K. Ramadhan, and D. Alamsyah, "Implementasi Metode Convolutional Neural Network Menggunakan Arsitektur LeNet-5 untuk Pengenalan Doodle," *J. Algoritma.*, vol. 1, no. 1, pp. 45–56, 2020, doi: 10.35957/algoritme.v1i1.434.
- [14] K. H. Mahmud, Adiwijaya, and S. Al Faraby, "Klasifikasi Citra Multi-Kelas Menggunakan Convolutional Neural Network," *e-Proceeding Eng.*, vol. 6, no. 1, pp. 2127–2136, 2019.
- [15] M. Hasnain, M. F. Pasha, I. Ghani, M. Imran, M. Y. Alzahrani, and R. Budiarto, "Evaluating Trust Prediction and Confusion Matrix Measures for Web Services Ranking," *IEEE Access*, vol. 8, no. July, pp. 90847–90861, 2020, doi: 10.1109/ACCESS.2020.2994222.
- [16] W. Setiawan, "Perbandingan Arsitektur Convolutional Neural Network untuk Klasifikasi Fundus," *J. Simantec*, vol. 7, no. 2, pp. 48–53, 2020, doi: 10.21107/simantec.v7i2.6551.
- [17] S. Namani, L. S. Akkapeddi, and S. Bantu, "Performance Analysis of VGG-19 Deep Learning Model for COVID-19 Detection," 2022 *9th Int. Conf. Comput. Sustain. Glob. Dev.*, pp. 781–787, 2022, doi: 10.23919/INDIACom54597.2022.9763177.

