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Performance of Deep Learning Inception Model and MobileNet Model on Gender Prediction Through Eye Image

Syntia Widyayuningtias Putri Listio[1)*]
[1)] STIKI Malang, Indonesia
[1] syntia@stiki.ac.id

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Abstract: Convolutional neural network (CNN) is one of the neural networks used in image data. CNN has a good ability to detect objects in an image. This study discusses the comparison of two deep learning models based on convolutional neural network, namely the Inception-V3 method and the MobileNet method. Both algorithms are analyzed fairly on gender classification using eye images. There have been many research completions that have conducted studies on gender classification based on faces, but gender classification based on eyes has many challenges. This gender classification is grouped into two classes, namely male and female. This study aims to build a gender classification model from eye image. The processes in this research include selecting the dataset, preprocessing the data, dividing the data which is divided into training data and test data, modeling, and evaluating the performance of the model. This study uses a public dataset, where the data contains a total of 2,681 images consisting of 1251 male eyes and 1430 female eyes. This study concludes that gender classification using eye image using the Inception-V3 method is better than the MobileNet method. This is obtained based on the accuracy value generated by the Inception-V3 method which is higher than the MobileNet-V2 method which obtains an accuracy of 91.82%.

Keywords: Convolutional Neural Network, InceptionV3, MobileNetV2, Gender Classification

INTRODUCTION

The era of modern information technology development is currently growing rapidly following the times (Supriadi, Rachmawati, and Arifianto, 2021). Technological developments are constantly being updated to produce something new. One technology that has great potential is artificial intelligence technology. Artificial intelligence is a simulation of human intelligence applied to a program, so that the program can think or work like humans. Artificial intelligence is one of the fields of science in computer science which is shown in the manufacture of software and hardware (Darmatasia, 2020).

Machine learning is one of the applications in computer science. Maching learning has a mathematical algorithm, which requires a reference data so that it can produce a prediction or forecast in the future. The learning process in maching learning is related to how to build computer programs to be better. Based on research, maching learning is divided into three categories, the first is Supervised Learning, the second is Unsupervised Learning and the last is Reinforcement Learning.

Supervised Learning method is a popular method of maching learning, where there is a mapping between output and input. The supervised learning method is based on a sample data set that has labels. The collection of sample data is used to classify the size distribution of actors in each type of application so that a behavioral model is formed from the previous data. One application that uses the supervised learning method is face detection. Face detection is part of detecting objects, where face detection is based on the needs of the implementation fields. One of the face detection modeling is using Convolutional Neural Network (CNN) modeling. CNN is one of the neural networks used in image data (Torres, Granizo, and Hernandez-Alvarez, 2019). CNN has the ability to detect objects in an image. The dataset used by CNN has 40 notations to detect images of men and women. CNN uses the python application as a library machine.

Gender classification of faces has many challenges. Gender classification is grouped into two classes, namely male and female. It is easy for humans to distinguish them, not easy for machines to classify them. For gender classification, it can identify men or women based on additional information such as hairstyles, face

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shapes, accessories, and facial features. Gender classification is a topic that has often been discussed. In this study, gender will be classified using the image of the eye. The previous algorithm focused mainly on the use of texture features and not much research has been done on the application of Convolutional Neural Networks (CNN) for gender classification. (Savchenko, 2021).

LITERATURE REVIEW

Deep Learning

Face detection is part of detecting objects, where face detection is based on the needs of the implementation areas. One of the face detection modeling is using CNN (Convolutional Neural Network) modeling. CNN is a neural network used in image data. CNN has the ability to detect objects in an image. The dataset used by CNN has 40 notations to detect images of men and women. CNN uses the python application as a library machine. (Jeong et al., 2018). One of the fields of machine learning is deep learning. Deep Learning is motivated by the human cortex. This system implements an artificial neural network that has many hidden layers. Convolutional Neural Network (CNN) is one of the many deep learning methods created with the aim of covering the weaknesses of the previous methods. In this method a number of independent parameters can be reduced by deforming the input image with an adjustable scale. There is a lot of research and development on deep learning, as well as references that explain deep learning, so that currently researchers study a lot of artificial nerves, one of which is hard. Keras is part of the reference neural network where the programming language used is python. Keras can run on tensorflow or Theano. (Asriny et al., 2019).

Convolutional Neural Network

Convolutional Neural Network or abbreviated as (CNN) is one of the algorithms of Deep Learning. CNN is a development of Multi Layer Perceptron (MLP) which is designed to process data in grid form. CNN can be used on image data (Sultana, Sufian, and Dutta, 2018) (Alwanda, Ramadhan, and Alamsyah, 2020). Convolutional Neural Network (CNN) is one method of Deep Learning. The purpose of the training process is to train the artificial neural network model to minimize the error of the prediction results of the model with the original data. The input layer is a vector of the dataset images. Convolution layer is a convolution operation between 2 vectors. In equation 1, it is a convolution of two functions where g(x) is called the convolution kernel (filter) which will be operated in shifts on the vector F(x).

$$h(x) = F(x).g(x) = \int F(a).g(x-a)$$

The stages of CNN consist of two stages. The first stage is to group images using feedforward (Zein, 2020). Next, the second stage uses the backpropagation method. At this stage, before doing the classification, first do the wrapping and cropping methods to focus on the object to be classified. Then, training is carried out using feed forward and backpropagation methods. The architecture of CNN is divided into two major parts, namely the Feature Extraction Layer and the Fully-Connected Layer (MLP) (Setiawan, 2019). The following is an illustration of the CNN architecture which can be seen in Figure 1 below.

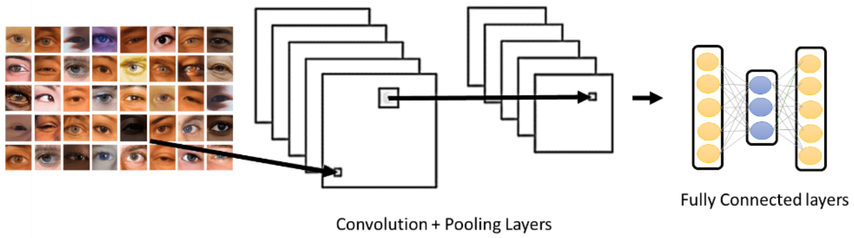

Fig. 1 Architecture Convolutional Neural Network

In the Feature Extraction Layer stage, the process that occurs is doing "encoding" of an image into features in the form of numbers which then present the image. At this stage the Feature Extraction Layer consists of two parts, namely the Convolutional Layer and the Pooling Layer. The convolutional layer consists of neurons arranged to form a filter with length and height (pixels). In this layer, a convolution operation will be performed between the input image matrix and the filter matrices. These filters will be shifted over the entire image surface so that it will produce a feature map matrix output. The Feature Map that will be generated is obtained from the following formula.

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$$n_{out} = \left(\frac{n_{in} - k + 2p}{s}\right) + 1$$

Where:
n_{out} = Feature map
n_{in} = Input matrix
k = Number of matrix filter
p = Padding
s = Stride

Furthermore, the convolution operation formula can be expressed in the following equation:

$$FM[i]_{j,k} = \left(\sum_{m}\sum_{n} N_{[j-m,k-n]}F_{[m,n]}\right) + bF$$

Where:
$FM[i]$ = Feature matrix number-*i* position
N = Input matrix
F = Matrix filter convolution
bF = Bias
j, k = Pixel position on matrix input
m, n = Pixel position on matrix convolution

Then the convolution process is carried out, then activate the activation function using the Rectified Linear Unit (ReLU) function. Each pixel in the feature map will be entered into the ReLU function, where pixels that have a value less than 0 will be converted to 0, with the formula f(x)=max(0,x). The filter from the polling layer has a certain stride size and can be shifted over the entire deadure map area. The pooling layer has a function to reduce the dimensions of the feature map (down sampling), this can speed up computations because the parameters are updated to a bit so as to overcome overfitting (Sikumbang, 2020).

Inception
Inception is one of the developments of the CNN (Convolutional Neural Network) method. Inception was first introduced by Szegedy, et al in 2014 in a journal entitled "Going Deeper with Convolutions". These very deep convolutional networks are central to image development. Inception has a very good performance architecture. Inception Inception network for the first version is Inception V1. Inception V1 is used to analyze a problem to be simple so that it can be solved or overcome. The following is an illustration of the architectural diagram of the Inception V1 which is presented in Figure 2 below.

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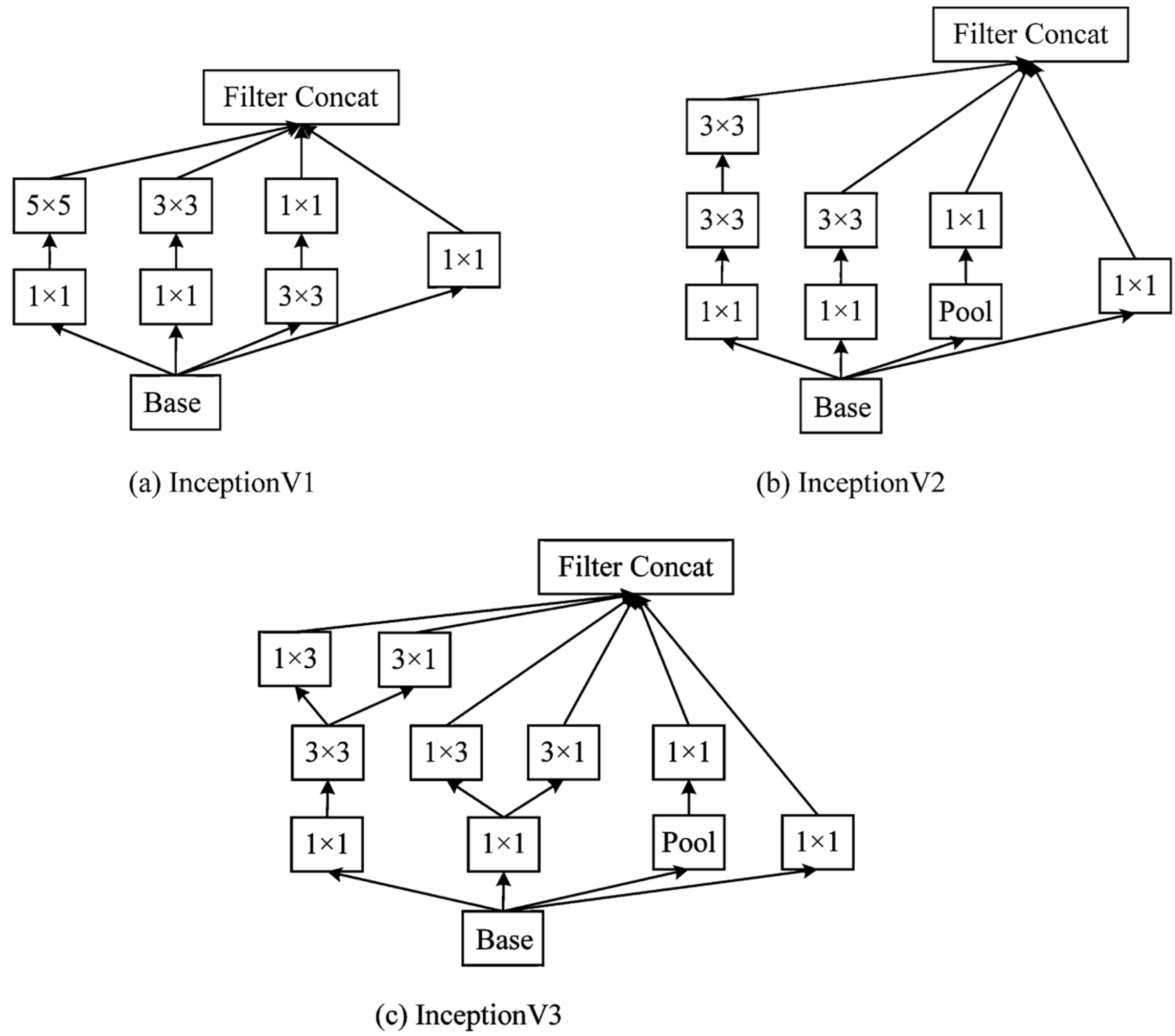

Fig. 2 Inception V1, V2 and V2 (Chen et al, 2021)

Inception V2 is designed to cover the shortcomings of the Inception V1, so the architecture of the Inception V2 is better than before. The way to cover the flaws and weaknesses of the previous inception is to structure the architecture to be broad rather than deep. Furthermore, the V3 inception is also the same as the V2 inception to cover the weakness of the previous inception. The Inception V3 model is an evolution of Googlenet which has a factored 7x7 convolution and is divided into 2 or 3, where 3x3 layers of convolution operations with the aim of increasing computations can receive images with a larger size of 299x299[16]. The following is an illustration of the Inception V2 and V3 architecture which is presented in Figure 2. (Abdurrohman, Dini, and Muharram, 2018).

Inception V2 and V3 have four modules which are as follows:

- Change the 5x5 convolution to 3x3.
- Convolution factoring is done on the module.
- The module is changed to become wider so that the complexity of the convolution network is reduced.
- Reduced the input grid size from 35x35 to 17x17.

Furthermore, the output size of each module can be seen in Table 1. The module output size is the size of the input in the next layer, using a variety of subtraction techniques, so that the initial grid size changes every time.

Table 1 Inception V2 and V3 Summary

Type	**Patch size/stride**	**Input Size**
Conv	3x3/2	299x299x3
Conv	3x3/1	149x149x32

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Conv Padded	3x3/1	147x147x32
Pool	3x3/2	147x147x64
Conv	3x3/1	73x73x64
Conv	3x3/2	71x71x80
Conv	3x3/1	35x35x192
3x inception A		35x35x288
5x inception B		17x17x768
2x inception C		8x8x1280
Pool	8x8	8x8x2048
Linear	Logits	1x1x2048
Softmax	Classifier	1x1x1000

MobileNet

MobileNet is a CNN (Convolutional Neural Network) architecture that has a function for accounting needs. MobileNet can be used on mobile phones. The general difference between the mobilNet architecture and the CNN architecture is in the convolution layer or layer with the filter thickness according to the input image. MobileNet V2 improves model performance for the better and is widely used in assignments and becomes the benchmark for different model size spectra. Mobilenet V2 is a feature extractor that is very effective for detecting an object, for example to detect it with a single shot detector lite. MobileNet V2 is more accurate than before, around 35% accuracy accuracy. (Feriawan and Swanjaya, 2020).

The bottleneck of MobileNet V2 encodes intermediate inputs and outputs while the inner layer encapsulates the power of a model to transform from lower level concepts like pixels to higher level descriptors like image categories. The use of traditional residual connection, makes training fast and accurate. MobileNet V2 still uses pointwise convolution and depthwise. MobileNet V2 uses depthwise and pointwise convolution. In addition, MobileNet V2 has also added two new features, namely the first linear bottleneck, then shortcut connections between bottlenecks.

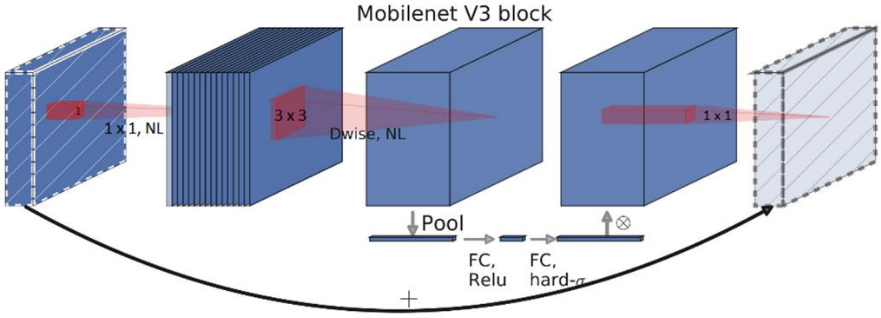

Fig. 3 Building blocks of MobileNet V3 architecture (Kabir et al, 2022)

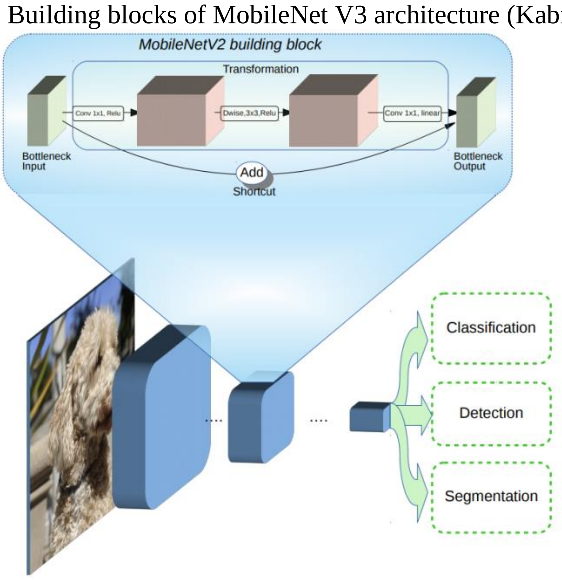

Fig. 4 Overview of MobileNetV2 Architecture (Nufus et al., 2021)

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Based on Figure 4, it can be seen that the blue box serves to show the formation block of the linear bottleneck convolution. In the bottleneck section, there are inputs and outputs between the models, where the inner layer or layer covers the model's ability to change the input from the pixel level so that the classification of the image can be known. Thus, shortcuts between bottlenecks result in faster training and better accuracy (Nufus et al., 2021).

Evaluation

In determining the best model performance in classifying CNN, it can be evaluated using accuracy performance. Each model will be searched for the accuracy value. Accuracy is a percentage of the data tested and classified into the correct group (Greco et al., 2020). In obtaining the accuracy performance can be calculated using the equation below.

$$acc = \frac{TP + TN}{TP + TN + FP + FN}$$

$$p = \frac{TP}{TP + FP}$$

$$R = \frac{TP}{TP + FN}$$

$$F1 - score = 2x\ \frac{PxR}{P + R}$$

In the equation above, there are various conditions in calculating the accuracy value of a model. There are two conditions, namely positive tupple and negative tupple. Positive tupples are tupples that are the focus of research, while negative tupples are tupples other than tupples that are the focus of research. Meanwhile, true positive (TP) is a positive tupple defined as true by the model. For True Negative (TN) is a tupple negative that is classified as true by the model. Furthermore, for False Positive (FP) is a condition of negative tupple which is classified as a positive group of the model, while False Negative (FN) is a condition of positive tupple which is classified as a negative group of the model. (Darmatasia, 2020) (Savchenko, 2019).

METHOD

The first thing that is needed in this research is to collect some data. The dataset used is obtained from http://mmlab.ie.cuhk.edu.hk/projects/CelebA.html which is a public dataset. The data obtained were 2,681 images consisting of 1251 male eyes and 1430 female eyes. The following is an image of the Sample Dataset presented in Figure 5.

Figure 5. Dataset

The next step is to preprocess the data. Data preprocessing is the treatment of objects prior to training and CNN classification experiments. The first stage in preprocessing is to change the color of the object from RGB

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(Red, Green, and Blue) which has three channels whose values range from 0-255 for each color in the image pixel to grayscale which consists of one channel (Munarto and Dharma, 2021). The next stage is to resize the object or change the pixel size in the image to be smaller so that the image recognition process is carried out faster by the computer so that the image size can be uniform according to the needs of the CNN classification.

Next is the training stage. The classification model is divided into two classes, namely 0 for female class, and 1 for male class. Next is the stage of testing the accuracy of the results. The accuracy value is used as a reference to determine the success rate of the model that has been made. Conversely, the loss value is an error value generated by the network with the aim of minimizing it. After preprocessing the data, the next step is to divide the data. The distribution of data is divided into two, namely training data and test data. The distribution of the data is divided into 80% for training data, while 20% is for test data. The distribution of the data refers to previous research (Darmatasia, 2020).

The process of training and testing data using the Convolutional Neural Network (CNN) model. For the training data, a training process is carried out, while for the test data a testing process is carried out. Then at the training stage in the training data, the results obtained from the accuracy and loss training values. However, if there is a condition that the desired accuracy value has not been obtained, then parameter adjustments are made to increase the desired accuracy value. After the desired accuracy value has been achieved, it can be continued with the testing phase. (Siqueira, Magg, and Wermter, 2020).

At the testing stage, the data used is image data that has not been trained using the CNN classification model that has been created. After the testing process is carried out, an analysis of the test performance is carried out. The evaluation of the model's performance in classifying test data is analyzed based on the values of accuracy, precision, and sensitivity.

RESULT

At this stage, a comparison table of the two models will be presented, namely the MobileNet V_2 and Inception V_3 models which can be seen in Table 2 below.

Table 2. Result accuracy both of IncetionV3 and MobileNet

Model	**Accuracy (%)**
InceptionV3	91,82
MobileNet	89,3

Based on Table 2, it can be seen that the level of accuracy generated by the Inception-V3 model is 91.20%. Furthermore, for the MobileNet V2 model, the resulting accuracy is 89.82 %. Based on this, it is found that the Inception-V3 model produces a higher level of accuracy than the MobileNet V2 model. Thus, it is found that the Inception-V3 model is better at predicting gender classification using eye images than the MobileNet V2 model. The graphs of training accuracy and validation on the Inception-V3 and MobileNet V2 models are presented in Figure 7.

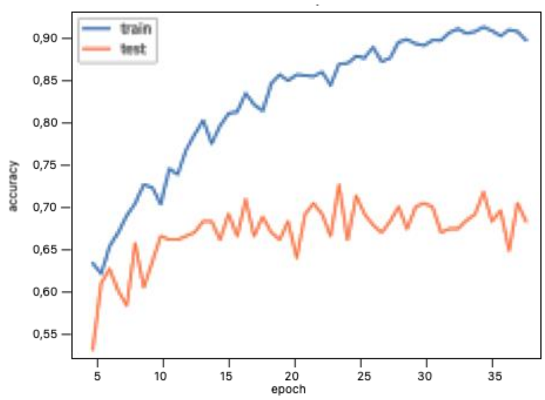

Fig. 6 Accuracy Graph for Inception-V3

Based on Figure 6, it can be seen that the training accuracy graph for the Inception-V3 model increases with the number of epochs and almost reaches convergence at epoch 30. It can be seen that the large number of epochs can increase accuracy. Furthermore, the training accuracy graph for the MobileNet model is presented in Figure 7.

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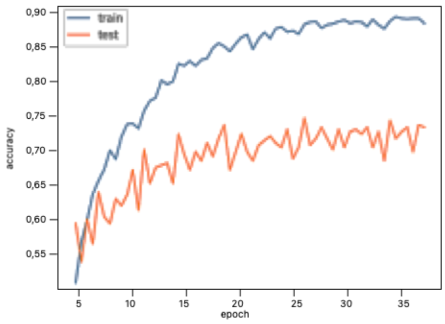

Fig. 7 Accuracy Graph for MobileNet

Furthermore, it can be seen that the training accuracy graph for the MobileNet V2 model is almost the same as the Inception-V3 model, which is increasing with the number of epochs and almost reaching convergence at epoch 30. However, it is known that the model that produces higher accuracy values is the Inception-V3 model.

CONCLUSION

The results show that the Inception V3 method and the MobileNet V2 method use transfer learning, three hidden layers where each hidden layer consists of a convolutional layer, ReLu activation and max polling can classify images that are male and female with good level of accuracy. The results of the testing and evaluation show that the accuracy value of the Inception V3 model is higher than the accuracy value of the MobileNet V2 model. This can be seen based on the accuracy value generated by the Inception V3 model which produces a value of 91.82%, while for the MobileNet V2 model it only produces an accuracy value of 89.1%. Therefore, it is concluded that the Inception V3 model is a good model in classifying gender based on eye image.

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*name of corresponding author