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# Diabetic Retinopathy Parameters Detection Using Convolutional Neural Network

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**Abstract.** Diabetic Retinopathy is a disorder of the retinal blood vessels that occurs as a complication of diabetes mellitus. It can be caused the risk of decreased vision function to permanent blindness if the patient can not recognize it earlier. Basic Health Research conducted by the Ministry of Health stated that in almost all provinces in Indonesia, diabetic retinopathy had increased. Therefore, an analysis is needed to recognize diabetic retinopathy according to its severity. In this study, Convolutional Neural Network engineering was used to measure the accuracy of diabetic retinopathy detection. The parameters used are stride filter and zero padding. The stride parameter is three, and zero padding is the same. Three images were taken on the testing data, and the results obtained were 33.16% accuracy with Mild severity, 30.11% accuracy with Moderate severity, and 39.79% accuracy with Normal severity.

**Keywords:** Convolutional Neural Network, diabetic retinopathy, stride, zero padding.

## INTRODUCTION

*Diabetic Retinopathy* is a disorder of the retinal blood vessels that occurs as a complication of diabetes mellitus. It can be caused the risk of decreased vision function to permanent blindness if the patient can not detect it in the long term [1]. Blindness caused by diabetes mellitus should be watched out for because it can reduce patients' quality of life and productivity, which creates a social burden on society [2]. Basic Health Research conducted by the Ministry of Health in 2013-2018 stated that in almost all provinces in Indonesia, diabetic retinopathy increased. Therefore, a detection system is needed to determine someone who is suffering from diabetic retinopathy according to its severity.

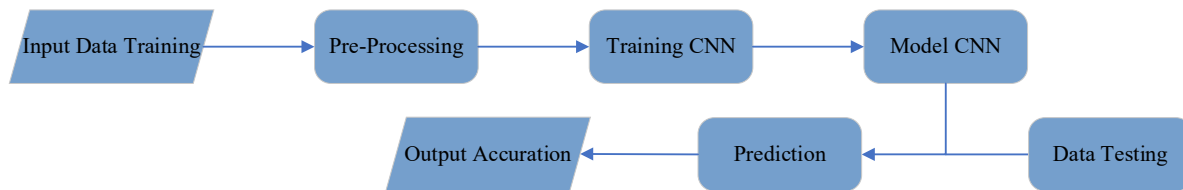
Diabetic Retinopathy is divided into two types, namely Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR) [3]. Non-Proliferative Diabetic Retinopathy (NPDR) early symptoms are characterized by aneurysms, which occurring swellings in blood vessels [4]. Swelling blood vessels in the eye can cause blockage and trigger the occurrence of rheum that come out of the back of the eye. Exudates are yellow or white patches caused by injury to the capillaries in the retinal area [5]. Proliferative Diabetic Retinopathy (PDR), the most severe type of diabetic retinopathy, which people with diabetes mellitus suffer, is characterized by the appearance of abnormal blood vessels caused by damage to the retinal blood vessels [6]. It causes patients with advanced retinopathy to complain about their decreased vision.

Several previous studies are using the Convolution Neural Network for Diabetic Retinopathy detection. The study shows that with the implementation of CNN, the accuracy results are 57%. Another classification of Diabetic Retinopathy based on fundus photos uses DenseNet Convolutional Neural Network. This study uses DenseNet Convolutional Neural Network (CNN) with an accuracy of 64.81%. Another study is the Classification of Diabetic Retinopathy using the Convolutional Neural Network (CNN) Deep Residual Network Model. This research uses the Convolutional Neural Network of Resnet type and gets a high accuracy result of 90.18%.

This study uses the Convolution Neural Network method, a variation of an artificial neural network with weights and several hidden layers arranged into an architecture [7]. Convolution Neural Network is a deep learning class that can take input images, assigns weights, and traces various aspects of the image so that it is different from the others. So the *Convolutional Neural Network* is better than *neural networks*. Therefore, this study aims to predict the accuracy of *diabetic retinopathy* and to engineer the *Convolutional Neural Network* for accuracy parameters so that the results produced are more accurate by using *filter stride* and *zero padding*. Therefore the author conducted a study entitled Architectural Engineering *Convolutional Neural Network Accuracy Parameters Diabetic Retinopathy*.

## METHODS

This study was built to classify eye fundus images based on the severity level: normal, *mild*, *moderate*, *severe*, and *proliferative*. This study uses the *Convolutional Neural Network (CNN) method*. The model in this study is shown in **FIGURE 1**.



**FIGURE 1.** Block Diagram of Convolution Neural Network Method

CNN or Convolutional Neural Network is included in the development of the multilayer perceptron (MLP) used to process two dimensions data [8]. Ordinary CNN is used for data in the form of working images for detecting and recognizing objects on an image. CNN includes in type network nerve imitation used in processing images. CNN mimics methods like man cells nerves communicate with inner neurons connected and have the same architecture [9]. Architecture in CNN can be trained and have several stages. This Stages in the form of input or output from some of the usual arrays called *feature maps*. The main component of a CNN consists of Convolution Layer, Pooling Layer, Fully Connected Layer, and Dropout.

## SOURCE OF DATA

The dataset used in this study is an image taken from MESSIDOR (Methods for Evaluating Segmentation and Indexing techniques Dedicated to Retinal Ophthalmology). Messidor is a research program funded by the French Ministry of Research and Defense in the TECHNO-VISION 2004 program. At the time of testing, it used images that will be divided into two datasets, namely training and testing data, with a total of 3912 images.

## PRE-PROCESSING

Image data is input to be processed and enters the pre-processing stage, which consists of three processes: image resizing, image conversion, and image enhancement. In the early stages of pre-processing, an image will be resized, which aims to change the size of the image by reducing the scale on the horizontal and vertical sides [10]. RandomFlip is flipping the image horizontally or vertically, which is the process of rotating the image based on the angle. Image enhancement is an improvement in reducing the contrast of the image by expanding the range of values of the pixel intensity of the image quality using the contrast stretching method, which aims to increase or decrease the contrast of the image by expanding or narrowing the range of values of the image pixel intensity [11].

## TRAINING AND TESTING

At the training stage, the data used for the training process is the image of the training dataset. This training, namely epochs, is carried out 25 times with 46 iterations. The training stage for epochs in classification is intended so that machines can learn with predetermined algorithms [12]. In the process, the machine learns iteratively to get maximum results.

The testing phase is carried out based on the model architecture that has been trained. At this stage, the data testing predicts the class classification of Diabetic Retinopathy. Diabetic Retinopathy classes are divided into five predictions, which are used to predict the possible value of the fundus image based on the class of Diabetic Retinopathy.

## RESULTS AND DISCUSSION

The architecture used in this study uses CNN for the accuracy parameters of Diabetic Retinopathy. The parameters used in the CNN are stride filter and zero padding. The CNN is used in testing data to be processed, resulting in the accuracy and severity of Diabetic Retinopathy. The engineering used in the CNN is shown in **FIGURE 2**.

```

num_classes = len(class_names)
model = Sequential([
    img_augmentation,
    layers.Rescaling(1./255, input_shape=(img_height, img_width, 3)),
    layers.Conv2D(16, 3, padding='same'),
    layers.BatchNormalization(),
    layers.Activation('relu'),
    layers.MaxPooling2D(),
    layers.Conv2D(32, 3, padding='same'),
    layers.BatchNormalization(),
    layers.Activation('relu'),
    layers.MaxPooling2D(),
    layers.Conv2D(64, 3, padding='same'),
    layers.BatchNormalization(),
    layers.Activation('relu'),
    layers.MaxPooling2D(),
    layers.Flatten(),
    layers.Dense(128, activation='relu'),
    layers.Dense(num_classes, activation='softmax')
])
optimizer = tf.keras.optimizers.Adam()
model.compile(optimizer=optimizer,
              loss=tf.keras.losses.SparseCategoricalCrossentropy(),
              metrics=['accuracy'])
model.summary()

```

**FIGURE 2.** Convolution Neural Network Method

In the picture above, there are strides and zero padding. Stride is worth three, which indicates the convolution filter shifted from horizontal to vertical by 3 pixels. Next, zero padding is the 'same'. The value of 'same' is the value of zero padding, which is equal to the stride value. When the stride value is three, zero padding is worth 3. Zero padding is worth the 'same' because the output size is the same as the input size. After engineering CNN, the next step is data training on the engineered model. The results of the movement are shown in **FIGURE 3**.



**FIGURE 3.** Training and Validation Accuracy

This training has two aspects: training and validation accuracy and training and validation loss. The training was conducted in 25 epochs of training and verification of accuracy. The picture above shows a graph on training and data validation that has increased. When the first iteration of training has an accuracy of 0.5304 and continues to grow until

the twenty-fifth iteration is 0.7420 while the validity of the first iteration is 0.6503 then in the second iteration it decreases with a value of 0.5560 after that validation shows the value continues to increase.

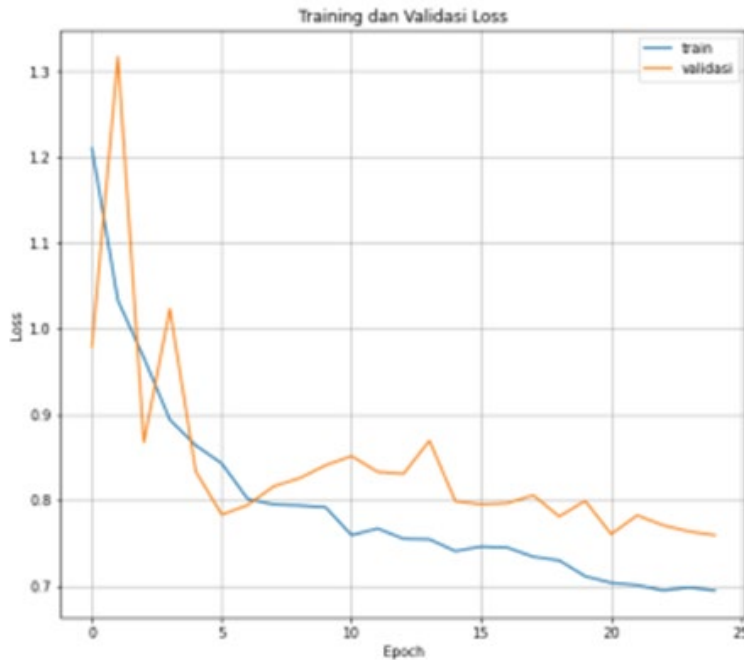


FIGURE 4 Training and Validation Loss

As shown in **FIGURE 4**, Training and Validation Loss has decreased. When the first iteration of training was worth 1.2102, then reduced to the twenty-fifth iteration with a value of 0.6948, and for validation, the first iteration was worth 0.9792 and increased in the second iteration with a value of 1.3166 then in the next iteration, it decreased to 0.7322.

After the training process, the testing data of 250 images will be processed to become predictive data and used to determine the accuracy and severity of Diabetic Retinopathy. The input image for accuracy is taken randomly from the total number of images. The following are the results of random image capture accuracy, as shown in **TABLE 1**.

In the results of this test, three images are taken at random. For the first image retrieval, the results obtained are 33.16% accuracy with Mild severity, the second image retrieval results in 30.11% accuracy with Moderate seriousness, and the third image retrieval results in 39.79% accuracy with Normal severity.

TABLE 1. Prediction Results From Random Images

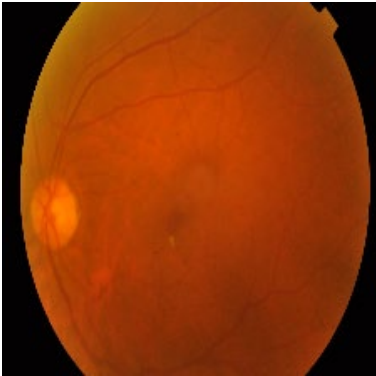

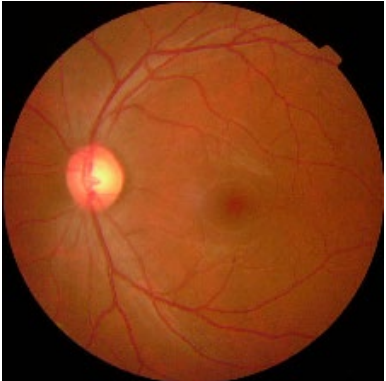
Image	Result Accuracy	Level Severity
	33.16 %	Mild

Image	Result Accuracy	Level Severity
<b>Continued</b>		
	30.11%	Moderate
	39.79%	Normal

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## CONCLUSION

Based on the research that has been done, it can be concluded that engineering using a Convolutional Neural Network for Diabetic Retinopathy has been successful. Determination of the accuracy and severity of diabetic retinopathy was successfully carried out. Applying stride and zero padding filter parameters to accuracy using the Convolutional Neural Network produces a different level of accuracy from other studies. In this study, the application of stride and zero padding parameters on the first image showed an accuracy of 33.16% with Mild severity, the second image showed 30.11% accuracy with Moderate seriousness, and the third image showed 39.79% accuracy with Normal severity.

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