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# Detection of Diabetic Retinopathy Using Convolutional Neural Network (CNN)

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## ABSTRACT

One of the complications of Diabetes Mellitus, namely Diabetic Retinopathy (DR) damages the retina of the eye and has five levels of severity: Normal, Mild, Medium, Severe and Proliferate. If not detected and treated, this complication can lead to blindness. Detection and classification of this disease is still done manually by an ophthalmologist using an image of the patient's eye fundus. Manual detection has the disadvantage that it requires an expert in the field and the process is difficult. This research was conducted by detecting and classifying DR disease using Convolutional Neural Network (CNN). The CNN model was built based on the VGG-16 architecture to study the characteristics of the eye fundus images of DR patients. The model was trained using 4750 images which were rescaled to 256 X 256 size and converted to grayscale using the BT-709 (HDTV) method. The CNN-based software with VGG-16 architecture developed resulted in an accuracy of 62% for the detection and classification of 100 test images based on five DR severity classes. This software produces the highest Sensitivity value in the Normal class at 90% and the largest Specificity value in the Mild class at 97.5%.

**Keywords**: Diabetic Retinopathy, Eye Fundus Image, Deep Learning, CNN, VGG-16

## 1. INTRODUCTION

Diabetes is a lifestyle disorder that incidence is increasing worldwide, where more than 60% of the world's diabetes population is from Asian countries [1]. Diabetic Retinopathy (DR) is a complication of Diabetes Mellitus that causes vision loss experienced by middle-aged people or the elderly [2]. This disease will attack the retina of the patient's eye causing damage to the blood vessels and swelling of the eye and if continues it can cause bleeding and blindness. The method usually used to detect DR is by observing the retinal fundus image manually by ophthalmologist. To reduce the risk of blindness, the detection of DR on patients must be easy, fast, and accurate. One of the best methods that can be used is the Convolutional Neural Network (CNN). CNN is consisted of several component layers such as Convolutional Layer, Non-linear Layer, Pooling Layer, and Fully-Connected Layer. Therefore, CNN has an outstanding performance in dealing with machine learning problems including its application to data in the form of image [3]. The VGG-16 architecture is an architecture with 13 Convolutional Layers, 2 Fully Connected Layers and 1 SoftMax Classifier which was introduced by Karen Simonyan and Andrew Zisserman in 2014. They created 16 network layers using only 3X3 Convolutional Layers stacked on top of each other for simplicity [4]. In addition, VGG is known as an architecture with good generative capacity so that the Convolutional Layer with the VGG-16 architecture is used as a good feature extractor [5].

Based on national criteria, there are five stages of DR, starting with normal eyes, mild DR, moderate DR, severe DR, and DR proliferate. Classification of DR should be able to distinguish the stages where an approach using CNN can be carried out [6]. Various methods have been used to detect and classify DR with good results, including a study by [7] which used SVM and High Order Spectra (HOS) on 300 DR images divided into 5 classes. They used Histogram Equalization to increase the contrast and used HOS to obtain the bispectral invariant. The results obtained are 82% classification accuracy and 88% specificity level. Another research by [8], which uses CNN to detect DR by using 80,000. The classification results obtained are 75%, with a specificity of 95% and a sensitivity of 30%.

In addition, research by [9], where they obtained an accuracy of 94.5% of the CNN model with their own architecture combined with 5 image augmentations. The 1000 images used were performed with 5 types of augmentation, namely rotation, flipping, shearing, rescaling, and translation. Furthermore, research by [10], where they classified 5 DR classes with a total data of 35,216. Unfortunately, the data they use has an imbalance where the data in the normal class is 36 times more than the data in the proliferative class. The augmentation used is Non-Local Means Denoising (NLMD), and training is carried out using several architectures such as AlexNet, VGGNet, GoogleNet and ResNet which are combined using transfer learning methods. The highest classification results obtained at 95.68% on the VGGNet architecture, followed by GoogleNet at 93.36%, ResNet at 90.40%, and AlexNet at 89.75%. The last research by [11], they used data from EyePacs where researchers faced difficulties because of the data was not balanced with 73% of the data included in the negative class. The results obtained accuracy of 88% for the classification of 5 classes and an accuracy of 95% for the classification of 2 classes (DR, and Non-DR).

Accuracy, specificity, and high sensitivity are important and needed in the DR classification process. So, in this paper a study was conducted to classify the severity of DR on eye fundus images using CNN. In addition, this study was to determine the level of CNN’s accuracy with the used of VGG-16 architecture in recognizing the DR stages. With the completion of this research, researchers have developed software using the CNN method with the VGG-16 architecture to classify DR disease on eye fundus images and obtain the level of accuracy in the process of classifying the severity of DR.

## 2. MATERIAL AND METHODS

### 2.1 MATERIAL

DR is a complication of Diabetes Mellitus (DM) which causes microvascular complications in the eye which if allowed to continue can cause blindness. Based on the results of research conducted by [12] in 3.983.541 samples from 288 countries stated that DR sufferers increased from 2.6 million in 2015 to 3.2 million in 2020 with DR more common in women than men with an odds ratio of 2:52 for all ages. Based on research by [13] in the United States in 1990, adults under the age of 65 years who have diabetic blindness require medical expenses of 12,769 dollars per year and for those aged over 65 years need 823 dollars per year.

Based on data from the World Health Organization (WHO), Indonesia is ranked fifth for adults with diabetes worldwide with an estimated increase of 6.5 million to


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more than 20 million in 2030, excluding the number of people who are not identified as having diabetes. where it can continue to increase [14]. Patients with DR will continue to increase along with the number of people with DM, where the blindness caused by DR causes a social burden for the community so that this disease becomes a disease with a high level of alertness throughout the world [15].

DR patient at RSUD Dr. Soetomo Indonesia has increased. From the results of the study, data obtained that DM patients took 8 years to suffer from DR with a delay in handling 10-15 years, and the most DR stages were proliferative DR (worst) around 74% or 219 of 295 patients [16]. The DR assessment is done by taking pictures of the infected eye followed by an assessment procedure This assessment can determine and classify the level of DR into mild, moderate, severe (non-proliferative) and proliferative. Therefore, early detection and diagnosis to reduce damage to the eye needs to be done and regular medical examinations are highly recommended [17].

The data used in this study is secondary data. The data is taken from several Kaggle website in the form of an image of the eye fundus with various stages of Diabetic Retinopathy (DR) starting from normal, mild, moderate, severe, and proliferative. The images obtained from different website then combined. In the end, the number of data obtained were 4850 eye fundus images which were divided based on 5 levels of severity of DR.

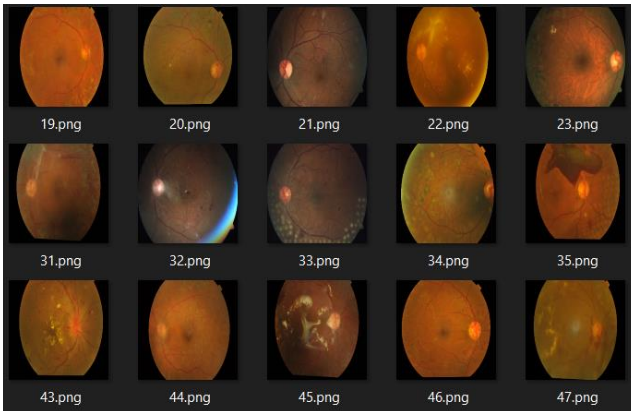


FIGURE 1. Dataset

## 2.2 METHODS

### 2.2.1 CONVOLUTIONAL NEURAL NETWORK

CNN is one of the best forms of Artificial Neural Network (ANN) which is commonly used to solve a pattern recognition problem in an image based on its simple but precise architecture. CNN has differences with ANN because CNN is more often used for pattern recognition in images where we can include image-specific features in the architecture so that the architecture is more focused on its task and reduces the parameters needed to build the model [18]. The CNN architecture consists of a combination of 3 layers, namely Convolutional, Max-Pooling, and Classification where all three work together to produce Feature Maps which function to extract features from the input image [19].

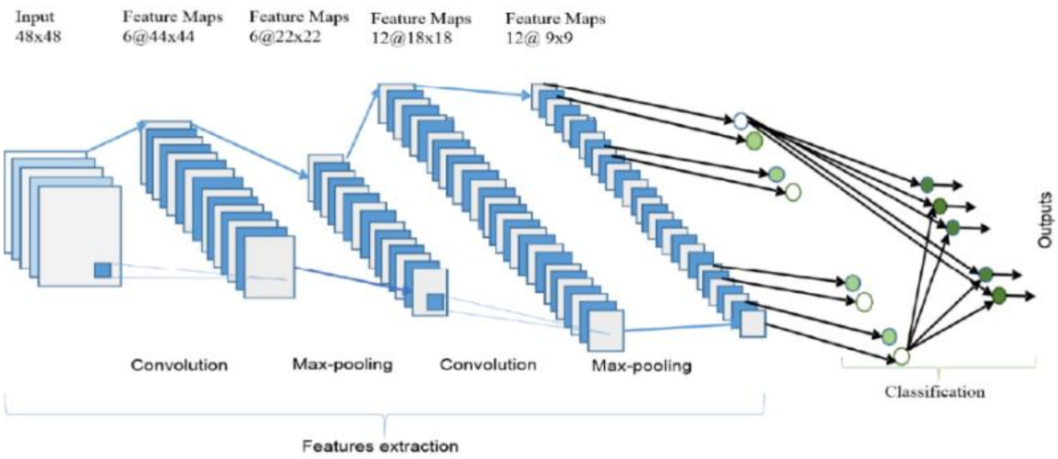


FIGURE 2. CNN Process

CNN works by extracting features that are the important keys in this algorithm and get as much as information by extracting a small number of features from a pixel value in the image, so that the differences in the objects then obtained to be continued in the categorization process [20]. The implementation of CNN with its extraordinary performance is the reason why this method is more widely used in various domains such as object detection, image classification, speech recognition, facial expression recognition, vehicle recognition, diabetic retinopathy detection and many more [21]. CNN is a method constructed from mathematics which consists of three types of layers, namely convolutional, pooling and fully connected layers where the convolutional and pooling layers will extract features from an image which is then followed by a fully connected layer that will map the extracted features into final output such as classification [22,23].

What distinguishes CNN from other methods is that firstly, CNN does not require a hand-made extraction feature (determined by the researcher), secondly it does not require image segmentation carried out by an expert in the field. Finally, CNN requires a lot of data because of its parameters that can be learned to estimate so that computation is expensive, and requires a Graphical Processing Unit (GPU) to conduct model training [24].

### 2.2.2 VGG-16

VGG 16 is an architecture developed in 2014 by K. Smonyan and A. Zisserman from Ofxord University. The model they built with this architecture achieved 92.7% accuracy on ImageNet, a dataset of 14 million images with 1000 classes [25]. This architecture has 16 layers of which 13 layers are convolutional layers with a 3x3 kernel. Each convolutional block will be followed by a max-pooling layer which is useful for downsampling. The last 3 layers are fully-sonnected layers which are used for classification [26].


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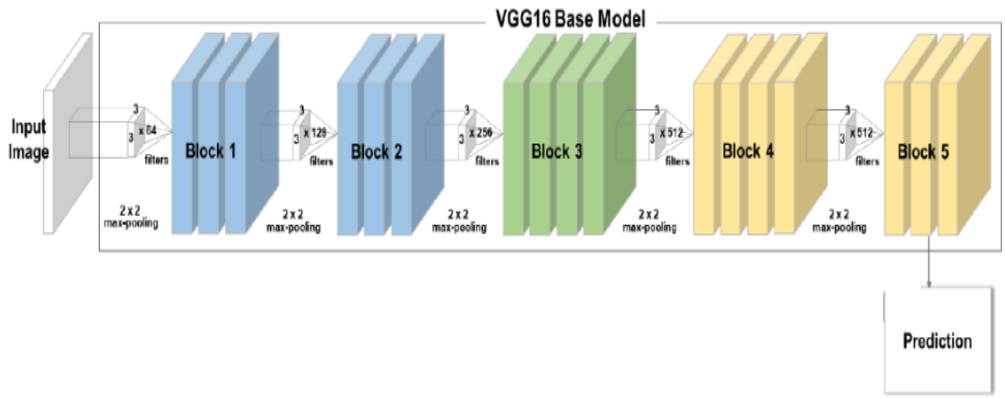


FIGURE 3. VGG-16 Architecture [27]

### 2.2.3 DATA PRE-PROCESSING

The data obtained consists of different pixel sizes and data types, so the first image pre-processing is carried out to equalize the size, image format, and image color format. The image is resized to 512 X 512 pixels using the Jpeg image format and the image color format is converted to grayscale using the BT-709 (HDTV) method. BT-709 is a format developed by ITU-R [28] for Image Encoding and signal characteristics owned by High-Definition Television (HDTV). In the process of changing the eye fundus image data into grayscale format, the BT-709 method is used where the Red value is 0.21, the Green value is 0.72 and the Blue value is 0.07. Images that are already in grayscale format will be given two types of augmentation, namely Vertical Flip and Horizontal Flip. The data is divided into 5 classes and then made into 4 scenarios with different amounts of training data and test data. The first scenario will have a ratio of training data and test data of 50:50, the second scenario with a ratio of 60:40, the third scenario with a ratio of 70:30, and the fourth scenario with training data of 4750 and test data of 100 images. The purpose of this data division is to know the best ratio of data train and data test that give the best result.

### 2.2.4 PERFORMANCE METRIC

Performance metric is used to determine whether model CNN that been made has succeeded in achieving the best result to get the best target. The performance

Truth

| Test Result | Disease (number) | Non Disease (number) | Total (number) |
|---|---|---|---|
| Positive (number) | A (True Positive) | B (False Positive) | $T_{Test\ Positive}$ |
| Negative (number) | C (False Negative) | D (True Negative) | $T_{Test\ Negative}$ |
| | $T_{Disease}$ | $T_{Non\ Disease}$ | Total |

FIGURE 4. Confusion matrix

measure used in this study is sensitivity(1), specificity(2) and accuracy(3). The performance measure is based on Confusion matrix.

Sensitivity or True Positive Rate shown the number of data that is predicted to be positive from all data that are truly positive where A would be True Positive and C would be False Negative

$$\textit{Sensitivity} = \frac{A}{A+C} \times 100 \quad (1)$$

Specificity or True Negative Rate shown the number of data that is predicted to be negative from all the data that are truly negative where D would be True Negative and B would be False Positive based on the confusion matrix.

$$\text{Specificity} = \frac{D}{D+B} \times 100 \quad (2)$$

Accuracy shown the value of how near the predicted data with the value of actual data.

$$\text{Accuracy} = \frac{A+D}{A+B+C+D} \times 100 \quad (3)$$

## 3. RESULT AND DISCUSSION

### 3.1. MODEL VALIDATION AND EVALUATION ACCURACY RESULTS

In Tables 1, 2, 3 and 4 are the validation and evaluation accuracy values results obtained for each scenario that has been made. Validation accuracy is the value obtained during the training process where the CNN model will check whether it has successfully predicted well. Evaluation accuracy is the value obtained when the CNN model is tested using test data. It can be seen that the combination of the highest and closest validation and evaluation accuracy values is shown in Table 4 of 68% for validation and 66% for evaluation.

TABLE 1.
Scenario with 50% Data *Train* 50% Data *Test*

| Process | Accuracy Result (%) |
|---|---|
| Model Validation | 74.6% |
| Model Evaluation | 50.68% |

TABLE 2.
Scenario with 60% Data *Train* 40% Data *Test*

| Process | Accuracy Result (%) |
|---|---|
| Model Validation | 66.4% |
| Model Evaluation | 59.18% |


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TABLE 3.
Scenario with 70% Data *Train* 30% Data *Test*

| Process | Accuracy Result (%) |
|---|---|
| Model Validation | 55.9% |
| Model Evaluation | 57.11% |

TABLE 4.
Scenario with 4750 Data *Train* dan 100 Data *Test*

| Process | Accuracy Result (%) |
|---|---|
| Validasi Model | 68% |
| Evaluasi Model | 66% |

### 3.2. RESULTS OF SENSITIVITY, SPECIFICITY, AND ACCURACY CALCULATIONS USING CONFUSION MATRIX

Table 5 shows the results of data classification based on five predetermined classes, namely normal, mild, medium, severe, and proliferate.

TABLE 5.
Classification Result With 5 Class

| Class | Normal | Mild | Medium | Severe | Proliferate | Total |
|---|---|---|---|---|---|---|
| Normal | 18 | 1 | 2 | 1 | 0 | |
| Mild | 2 | 12 | 0 | 0 | 0 | |
| Medium | 0 | 3 | 12 | 13 | 2 | |
| Severe | 0 | 3 | 2 | 2 | 0 | |
| Proliferate | 0 | 1 | 4 | 4 | 18 | |
| Total | 20 | 20 | 20 | 20 | 20 | 100 |

The classification results in Table 5 are used to obtain True Positive, False Positive, False Negative, and True Negative, with the confusion matrix method which can be seen in the table 6. True Positive is the value obtained where the model can predict a positive class as positive, False Positive where the model predicts a negative value as positive, False Negative where the model predicts a positive value as negative, and True Negative where the model predicts a negative class as negative.

TABLE 6.
Confusion Matrix Calculation

| Class | True Positive | True Negative | False Positive | False Negative |
|---|---|---|---|---|
| Normal | 18 | 76 | 4 | 2 |
| Mild | 12 | 78 | 2 | 8 |
| Medium | 12 | 62 | 18 | 8 |
| Severe | 2 | 75 | 5 | 18 |
| Proliferate | 18 | 71 | 2 | 9 |

The resulting data in Table 6 is then used to calculate the value of sensitivity, specificity. Table 7. Sensitivity or called the true positive rate is the accuracy of the data that has been predicted correctly and specificity or called the true negative rate is the accuracy of the data that has been predicted to be wrong.

TABLE 7.
Result of Sensitivity and Specificity Calculation

| Class | Sensitivity | Specificity |
|---|---|---|
| Normal | 90% | 95% |
| Mild | 60% | 97.5% |
| Medium | 60% | 77.5% |
| Severe | 10% | 93.8% |
| Proliferate | 66.7% | 97.3% |

Sensitivity = True Positive Rate
Specificity = True Negative Rate

Table V-8 shows the accuracy results of CNN-based software with VGG-16 architecture where the accuracy is 62%. This value states that from 100 test data the software can predict 62 images correctly.

TABLE 8.
Result of Model's Accuracy on Software

| | |
|---|---|
| Model's Accuracy on Software | 62% |

### 3.3. ANALYSIS OF MODEL VALIDATION AND EVALUATION ACCURACY

The results of testing the accuracy of the validation and evaluation of the model show that the amount of train data used can affect the value of the validation and evaluation accuracy obtained. It can be seen in Figure 1 that the combination of values between evaluation and validation that are close to each other is found in the fourth scenario. It can be said that the large amount of train data has an effect on getting good evaluation and validation values and is also consistent/convergent (the distance between validation and evaluation values is not far apart).

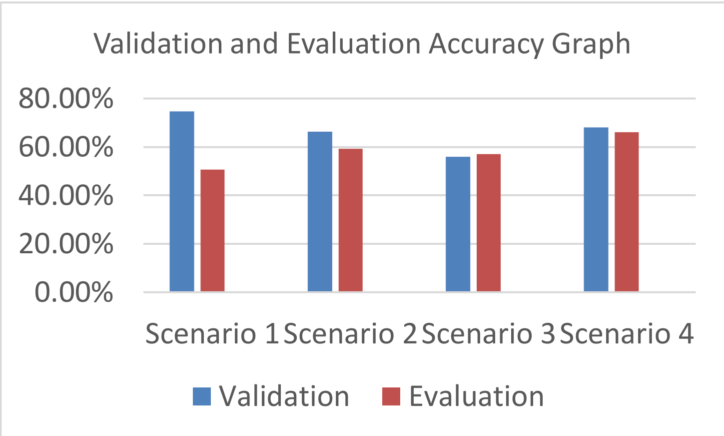


FIGURE 5. Model's Validation and Evaluation Accuracy


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### 3.4. ANALYSIS OF SENSITIVITY, SPECIFICITY, AND ACCURACY CALCULATIONS RESULTS USING CONFUSION MATRIX

Based on the test results to determine the best scenario, the fourth scenario is used to be converted to TF Lite and deployed into software to be continued in the second test. In the second test, the results of calculations using the confusion matrix show that the software can perform the best classification for normal and proliferative classes. However, if seen in Table 6, the model has difficulties when classifying the Severe class. This means that from all images in the severe class, the model can only predict two images correctly. In Table 6, it can be seen that the value of sensitivity or called the true positive rate where the positive data that is predicted to be the largest positive is in the Normal class, so it is said that the model makes the best predictions if an image belongs to the Normal class. For the specificity value or called the true negative rate where the negative data that is predicted to be the largest negative is in the Mild class, then the model is said to predict well if an image does not belong to the Mild class.

Finally, for the accuracy of the software, it can be seen that there is a decrease of 4% from the evaluation results where the decrease occurs in the process of converting from ordinary Tensorflow to TF Lite. This is because there is an optimization process in the model size, the model which was originally 1.9GB in size was reduced to 161MB or there was a size reduction of 1,199%. This is done because the Android Studio framework only accepts TF Lite format models with sizes under 250MB. Even so, the accuracy obtained by the software is 62%, meaning that the software can correctly predict 62 images from 100 images in the test data.

## 4. CONCLUSION

Based on the research that has been done, it is concluded that the amount of data affects the accuracy of the CNN model with the VGG-16 architecture. The best scenario with the most training data (4750 data) results in an evaluation value of 68% and a validation value of 66%. Furthermore, CNN-based software with VGG-16 architecture can predict and classify Diabetic Retinopathy with a prediction accuracy of 62%. Then, the prediction and classification of Diabetic Retinopathy resulted in the best sensitivity value in the Normal class of 90%, showing the CNN model with the VGG-16 architecture accurately predicts the normal (no pain) eye image. Finally, the prediction and classification of Diabetic Retinopathy resulted in the best specificity value in the Mild class of 97.5%, indicating that the CNN model with the VGG-16 architecture accurately predicts images of eyes that do not belong to the Mild class.

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