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Pneumonia Medical Image Classification Using Convolution Neural Network Model AlexNet & GoogleNet

Rio Subandi[1], Herman[2], and Anton Yudhana[3]

[1,2] Master of Informatics Engineering Study Program Ahmad Dahlan University, Yogyakarta, Indonesia*
[3]Department of Electrical Engineering University of Ahmad Dahlan, Yogyakarta, Indonesia

E-mail address: riosubandi9@gmail.com, hermankaha@mti.uad.ac.id, eyudhana@ee.uad.ac.id

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Abstract: *Pneumonia is one of the deadliest diseases in the world. Diagnosis of pneumonia is done with the help of CT-scan image analysis of the chest. This analysis is usually done by a pulmonary specialist. The availability of pulmonary specialists is still limited, especially in underdeveloped, outermost and frontier (3T) areas. In addition, manual analysis still faces the possibility of errors. The use of artificial intelligence technology is expected to overcome these problems. The purpose of this study is to obtain the results of pneumonia disease classification using the CNN algorithm using the AlexNet and GoogleNet models. The tools used in this research are python. The image dataset used amounted to 5856 images obtained from the Kaggle repository. The stages of this research consist of data preparation where this data has been preprocessed and split data. Furthermore, the CNN stage with the architecture used is AlexNet and GoogleNet. . The training data used is 90% of the data or 5270 images and the testing data is 10% or 586 images. Model training is carried out as many as 20 iterations so that the model used can recognize. The training model is done in as many as 20 iterations so that the model used can recognize the image more accurately. After the model has been trained the model will be tested by providing test data. The results of this research are displayed in the confusion matrix. The results of the research using the AlexNet and GoogleNet architectures get an accuracy value. This accuracy value is then compared between the two. The accuracy obtained from AlexNet architecture is 96% while that obtained from GoogleNet is 94%. From the results of the accuracy of the two models, it can be concluded that the AlexNet architecture has the highest accuracy of 96%.*

Keywords: AlexNet, GoogleNet, Pneumonia, Classification,

1. Introduction (Heading 1)

Pneumonia can pose a significant danger to health [1]. The process of diagnosing pneumonia involves various steps taken by the doctor to identify the infection in the lungs [2]. First, the doctor will gather information about the patient's symptoms and medical history. Next, a physical examination is performed to look for signs of infection in the lungs, such as abnormal breathing sounds. Radiological examinations, such as chest X-rays or CT scans, are used to see a clearer picture of the lungs. Doctors may also examine the patient's sputum samples to determine the cause of the infection, as well as conduct blood tests to measure the level of white blood cells that could indicate an infection. Once a diagnosis of pneumonia is established, appropriate treatment can be recommended by the doctor according to the cause and severity of the infection [3]. Prevention of pneumonia is also important, such as getting vaccinated and maintaining hand hygiene to reduce the risk of developing the disease. Early diagnosis and proper treatment are essential to effectively treat pneumonia. Doctors may perform a physical examination, blood analysis, chest X-ray, or other tests to identify a lung infection. Treatment usually involves antibiotics for bacterial pneumonia and symptomatic treatments to relieve symptoms [4].

Convolutional Neural Network (CNN) is a type of deep learning algorithm that has brought revolutionary changes in the world of healthcare, especially in diagnosing pneumonia [1]. The use of CNNs in the medical field, particularly for the analysis of medical images such as chest X-rays, has enabled early and accurate detection of this lung disease. One of the challenges in diagnosing pneumonia from X-ray images is the complexity of the structures and patterns that doctors must identify. CNNs can overcome this problem by repeatedly training using chest X-ray data that has been correctly classified by an expert. CNN will automatically extract important features from X-ray images to understand the important characteristics that indicate the

E-mail:author's email

presence of pneumonia infection. The trained CNN algorithm can analyze new chest X-ray images and accurately identify signs of pneumonia [5]. This allows for earlier detection and more timely intervention, thus speeding up the diagnosis and treatment of patients. In addition, the use of CNNs can help reduce the potential for human error in image interpretation, optimize the reliability of diagnosis, and reduce the risk of errors in medical treatment. The positive influence of CNN in diagnosing pneumonia means improved diagnostic efficiency and accuracy. Faster and more precise results from these algorithms can enable early treatment and reduce complications and mortality caused by pneumonia. Thus, the application of CNN in diagnosing pneumonia disease has opened up great opportunities in improving the quality of health care and reducing the burden of the disease in society [6].

In this research, the CNN model uses two architectures, namely GoogleNet and AlexNet. GoogleNet has 20 layers if we count only parameterized layers (or 27 layers if we also count pooling) [7]. This network in its native environment has been trained on over a million images and can classify images into 1000 object categories. The network architecture has learned a rich feature representation for various images. The network takes an image as input and outputs labels for objects in the image along with probabilities for each object category [8]. Eight layers make up the AlexNet architecture: three fully-connected layers and five convolutional layers, some of which are followed by max-pooling layers. With this network architecture, training performance is better than with ground and sigmoid networks because of the non-saturated ReLU activation function. [9].

2. LITERATURE REVIEW

There are several previous studies related to the objects and methods in this study.

Yopento et al [5] using the Sobel feature extraction-based Convolutional Neural Network approach to identify pneumonia in lung X-ray images. Lung image dataset objects are used in this study. The results were 91.54% accuracy, 91.8 % recall, and 91% precision. With an epoch value of 50, a learning rate of 0.0001, and a batch value of 20, this study's accuracy rate was 91.54%.

Abdillah et al [10] Using support vector machines and convolutional neural networks, classify viral pneumonia. The subjects of this study are two different types of images: lungs affected by bacterial pneumonia and lungs affected by viral pneumonia. The test results have an average accuracy of 0.85 according to the confusion matrix, so it can be concluded that the accuracy method is fairly high. The architecture and object methods are where this research differs from earlier studies. The CNN method and the subject of study are used in both prior research studies.

Nurkhasanah & Murinto [11] to classify facial skin diseases using the Convolutional Neural Network method. Objects used in facial image research. The results of the training process are 98% validation results with 325 image training data and 125 validation data. The accuracy result obtained when testing new data is 90% with 50 frames of test data. So it can be said that the results obtained in this research experiment are very good.

Gatc & Maspiyanti [12] Convolutional Neural Networks for the Prediction of Plasmodium Parasites in Microscopic Images of Red Blood Cells. The red blood cell image is the subject of this study. The test findings demonstrate good accuracy; specifically, the CNN algorithm model yields an accuracy score of 97.96 with a loss of 0.06 at roughly 121 seconds of computation time on average per epoch.

Gong & Kan [13] kidney tumors are divided and categorized using CNN. A 99.5% accuracy rate in the classification of benign and malignant tumors can be attained by combining 2D SCNet segmentation and classification. Dice coefficients of 0.946 and 0.846 were obtained in the three-label SCNet 2D segmentation results, respectively, suggesting that segmentation network learning benefits from the inclusion of a classification module.

Similarities from previous research both use the CNN method and some use the same object, namely pneumonia.

3. RESEARCH METHODS

The flow of research conducted from start to finish is shown in Figure 1.

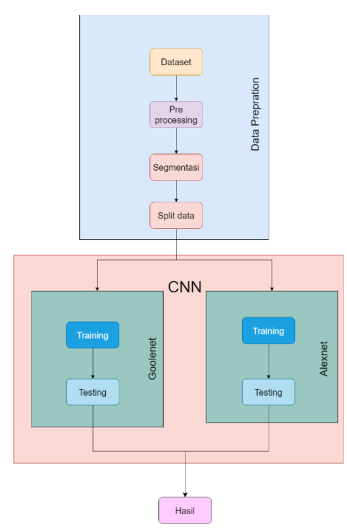


Figure 1. Research Flow

The research flow shown in Figure 1.1 shows the steps of the research flow in the initial stage, namely data preparation where at this stage the dataset will be preprocessed. preprocessing is done to transform the input image into a better image. split data where the data is divided into 90% training data and 10% testing data. Segmentation divides the image into certain regions. After this data preparation stage, enter the CNN stage. This CNN uses two architectures, namely AlexNet and GoogleNet.

A. Datasets

This study uses a dataset of CT-Scan generated pneumonia images. The dataset is used to train machine learning algorithms, such as Convolutional Neural Networks (CNN), in performing pattern recognition and classification of these images. The algorithms can learn important features of pneumonia CT-Scan images and accurately identify the location and size of the infection by utilizing deep learning technology. In addition, this dataset can also be used to develop decision support systems in the field of radiology, assisting doctors in diagnosing and planning patient treatment more precisely.

The use of pneumonia CT-Scan image datasets must consider the security and privacy aspects of the data. Since this medical data contains personal information of the patient, strict measures must be taken to protect the confidentiality and integrity of the data. Processing the dataset also requires trained radiologists to ensure the accuracy and reliability of the image annotations and diagnoses recorded in the dataset. Although pneumonia CT-Scan image datasets carry great potential in research and disease management, ethics and data security must remain a top priority to maintain trust and responsibility in their application. Based on this, this study uses a dataset from Kaggel that is freely used in research and has been labeled with images that have pneumonia and no disease. The dataset obtained is 5,856 which consists of two classes, namely normal and abnormal. With different image sizes 2090 x 2858, 1448 x 1056 and many other sizes. The format of the mind is jpeg, with a grayscale color model, 8 bit deep color. An example of the dataset used can be seen in Figure 2 (a)(b).

(a) (b)

Figure 2 (a)(b). Normal & Pneumonia Thorax Rotgen Image.

Figure 2 is a rotgen thorax image where this image will be used in this study. 2(a) is a normal image with an image size of 2090 x 2858, 2(b) is a pneumonia image with a size of 1448 x 1056.

B. PREPROCESSING

The datasets obtained have different sizes and types so that data preprocessing is needed. The purpose of image preprocessing is to perform a series of steps and transformations on digital images before further processing[14]. Image preprocessing aims to improve image quality, remove irrelevant or distracting information, and optimize the image so that it is more suitable for subsequent analysis and processing. Preprocessing, several important things are done, including resizing and image conversion.

C. RESIZING

Resizing is the process of changing the image size so that all images are the same size[15]. The image size used is 150x150. After all the data is resized to the same size, then the data is divided into 2, namely 90% training data and 10 testing data from the total dataset.

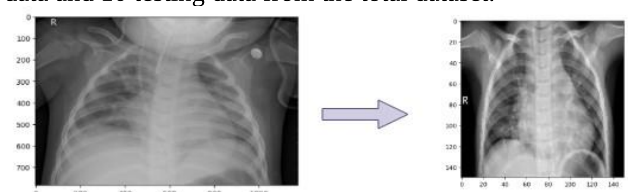


Figure 3 Resizing results

Figure 3 is the result of resizing, it can be seen that the image before preprocessing has a large size of 1576 x 787, this will make it difficult for the model to perform classification because the image size used is too large. It is necessary to do reesizing to reduce the size of the image by reducing its size to 150 x 150 the size used is very much different from the original size of the image. Image conversion is needed to change the image color to gray.

D. IMAGE CONVERSION

Image conversion is a process of changing the image from RGB to grayscale, the image used in this study is already in grayscale form but this conversion is still carried out to prepare the image data optimally so that it allows the classification algorithm to understand and identify relevant patterns or features in the image[16]. The results of the image conversion can be seen in Figure 4.

Figure 4 Image conversion results

Figure 4 is the result of image conversion, the initial image used is grayscale, this image conversion is still carried out for the efficiency of storage. The converted image will get a smaller size than the unconverted grayscale image. This conversion is done to improve the performance of machine learning algorithms.

E. SEGMENTATION

Segmentation is the process of separating the image between the desired object (foreground) and the background (background) contained in an image[17]. With the segmentation process, each object in the image can be taken individually so that it can be used as input for the next process. The results of the segmentation can be seen in Figure 5.

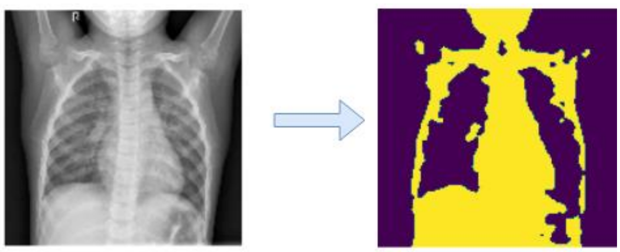


Figure 5. Segmentation Result

Figure 5 is the result of segmentation where after preprocessing consisting of resizing and image conversion, the segmentation stage is carried out. The results of the segmentation can be seen in the image above.

F. SPLIT DATA

The separation of datasets for use in the training and testing phases is known as split data. In this study, the data to be used in the training process is 90% while the data used in the testing process is 10% of the total data. 5856 data will be used in the research. 5270 for training data 586 for testing data.

G. CONVOLUTIONAL NEURAL NETWORK (CNN)

Convolutional Neural Network (CNN) is intended to process two-dimensional data with a high network depth. [18]. The network in question is an artificial neural network used to process images in this case classifying and recognizing objects. CNN works by mimicking the way nerve cells communicate with interrelated neurons. CNN uses convolutional operations that apply filters in each previous input section to extract patterns and this makes CNN unique compared to other artificial neural networks [19]. CNN uses a Graphics Processing Unit (GPU) for the computational process, in other words, when using the Nvidia Cuda platform, processing can be much faster than using a Central Processing Unit (CPU) the process in the CNN algorithm can be seen in Figure 6.

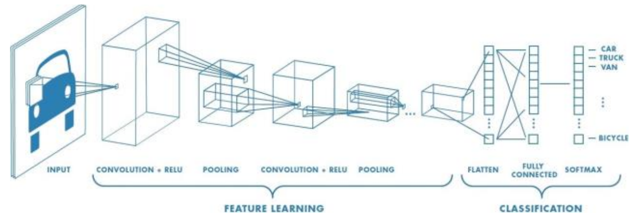


Figure 6 CNN Algorithm

Figure 6 is the CNN algorithm lag process, this process consists of two stages, namely feature learning, and classification. Input layer as matrix data from an image that is abstracted into a dual-dimensional feature map convolution layer. The output is a carnel that will be pooled. The result of pooling will be a new input layer, which will repeat the process. This is done several times to increase the number of neurons and various combinations of layer variations.

The convolutional layer is one of the core components of CNN. Its main function is to identify patterns and special features in the image data through convolution operations. The layer takes the image data and then applies a filter or kernel on top of the image, this kernel extracts the features by performing dot-product will be submitted to the next layer.

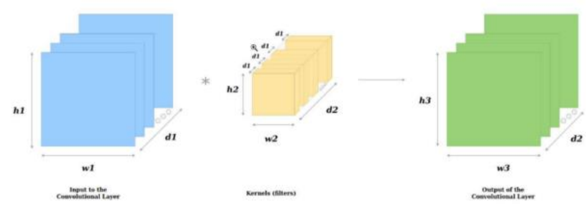


Figure 7. Convolutional layer

Figure 7 is an image of the convolutional scanning process that occurs in the input layer using a kernel or filter from the top left corner to the bottom right corner of the input layer. The kernel is a representation of the input layer value that is run through a computational process to place the resulting value on the output layer. The input and output layers have the same dimensions, namely width, height, and depth or the number of channels[19].

The purpose of the pooling layer, a downsampling layer, is to minimize the spatial extent of the parameter count. Generally, max pooling or average pooling techniques can be used for layer pooling. The max pooling operation is performed by selecting the maximum value of the region specified in the feature map. For example, if the pooling region has a size of 2x2 then the maximum value of 4 pixels within the region will be selected as the representative value. An example of max pooling can be seen in Figure 8.

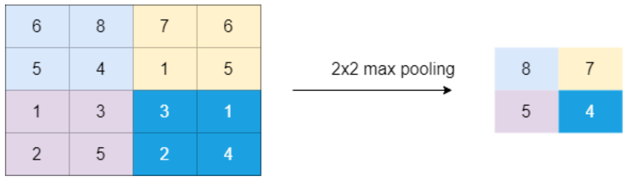


Figure 8 max pooling

Figure 8 is max pooling with a 4x4 layer size that is reduced to reduce the image to 2x2. There are several techniques used in max pooling, one of which is by finding the maximum value in the layer matrix.

The results of the convolution layer and final pooling in the form of a two-dimensional matrix are flattened and then entered into the full layer. Flatned is the process of converting all values into vectors [18]. An example of the flattened process can be seen in Figure 9.

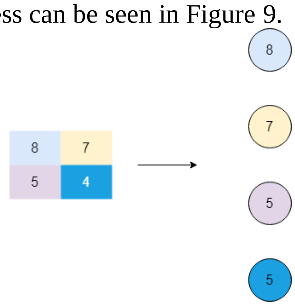
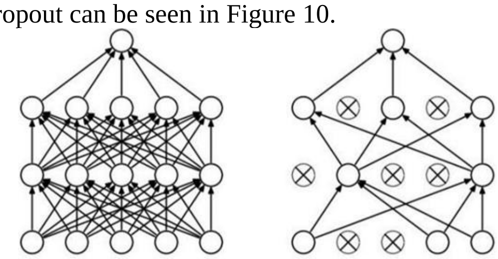


Figure 9 flattening process

Figure 9 is an image of the results of the flattening process where this process converts a two-dimensional layer into a one-dimensional vector value. At this stage, the value in the full layer will become a one-dimensional array sequence. In Figure 2.5 shows the matrix {8,7} and {5,4} are changed to {8,7,5,4}.

Dropout is a technique in artificial neural networks used to prevent overfitting and speed up the learning process[11]. Dropout temporarily removes or randomly discards neurons in the network. Each neuron is assigned a probability with values 0 and 1 [19]. The application of dropout can be seen in Figure 10.



(a) regular neural network (b) neural network after being subjected to the dropout technique

Figure 10 Application of dropouts

Figure 10 is an example of the application of dropout. Figure 10(a) is an image of a regular neural network where the number of neurons is too many, which can cause overfitting in the training process. Dropout is done to create a new layer and will discard neurons that are considered less probable. Figure 10(b) is an artificial neural network that has been subjected to the dropout technique so that the number of neurons is less.

H. ALEXNET ARCHITECTURE

AlexNet architecture is one type of architecture used in convolutional neural networks (CNN) to perform image recognition. In the framework of the 2012 ImageNet Large Scale Visual Recognition Challenge, Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton created the AlexNet architecture to create a more efficient model for crushing image recognition stages [20]. GPUs are used by AlexNet to accelerate modeling and generate fast, highly accurate class predictions. Figure 11 displays the AlexNet architecture.

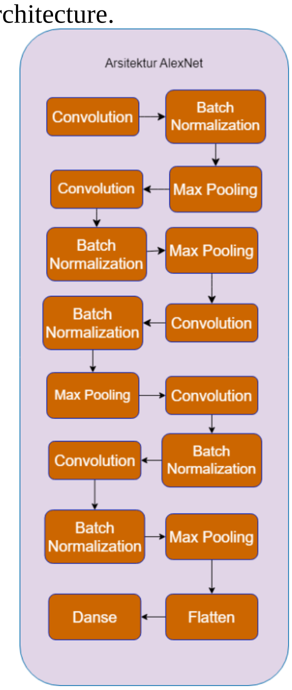


Figure 11 AlexNet Architecture

Figure 11 is the AlexNet architecture. The training process is carried out, After the preparation data has been processed, it will enter the input layer stage, this input layer uses an image size (of 150x150x3). BatchNormalization Layer This layer is used to normalize the input before the next Conv2D layer. MaxPool2D Layer This layer uses a 3x3 pooling size with 2x2 strides. Conv2D layer This layer uses 256 filters with a 5x5 kernel size and 1x1 strides. The activation function used is ReLU, and this layer is equipped with padding. BatchNormalization Layer This layer is used to normalize the input before the next Conv2D layer. MaxPool2D layer This layer uses a 3x3 pooling size with 2x2 strides. Flatten Layer This layer is used to generate multi-dimensional inputs into one-dimensional inputs for the fully connected layer. Dense Layer This layer uses 2 neurons and a softmax activation function to generate class predictions. This model uses Keras (TensorFlow) to perform image recognition by using several Conv2D, MaxPooling2D, BatchNormalization, and Dense layers. It also uses ReLU and Dropout activation functions to improve image recognition performance and accuracy.

The process of testing the AlexNet model can be seen in Figure 11 for the AlexNet architecture. After getting the output of the training iteration. At the testing stage, the evaluation model will be carried out, and the final stage in the testing process will get the results of the classification that gets the accuracy value.

I. GOOGLENET ARCHITECTURE

Google researchers created the deep convolutional neural network architecture known as GoogleNet. The Inception module, which is intended to expand the network's breadth and depth without appreciably raising its parameter count, is what distinguishes the GoogleNet architecture [21]. The Inception module consists of several convolutional filters of different sizes, which are applied in parallel to the same input. The outputs of these filters are then combined and passed on to the next layer. The GoogleNet architecture can be seen in Figure 12.

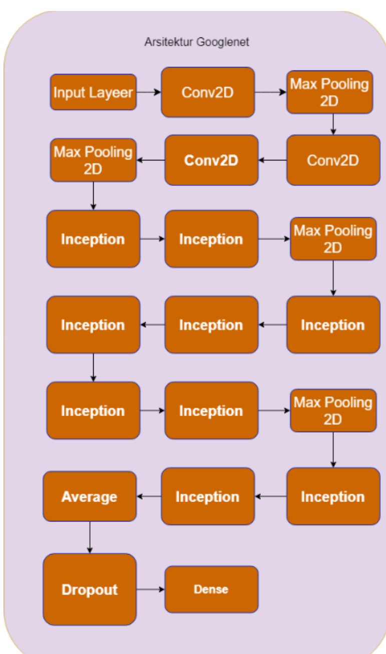


Figure 12. GoogleNet architecture

Figure 12 is the GoogleNet architecture, the training stage is the process of data that has been prepared will be entered into the GoogleNet architecture, where the input layer is the initial stage in the GoogleNet architecture, this layer receives input (150x150x3) pixels. Three Conv2D layers with filter 64 kernel_size 7 x 7, and strides 2. After the convolution process, the resulting feature maps are more compact. Two layers of MaxPooling2D with pool_size 3 x 3 and strides 2. This aims to produce more compact feature maps and remove unimportant details. Each layer of the Inception block combines multiple layers of Conv2D with different filters and the same kernel_size. Inception block aims to reduce computational load and increase data depth. Average combines the results of the previous layers into a scale of 1 x 1 x 2. Dropout is used to reduce overfitting by randomly removing some neurons. Dense This layer produces class predictions using the softmax activation function.

Figure 10 shows the GoogleNet testing procedure. This procedure is executed after the training phase. where a test of the model is conducted on 10% of the data. The testing's outcomes are presented as a confusion matrix, which determines the testing procedure's accuracy value.

J. EVALUATION MODEL

The testing of the model design that has been made is by obtaining the accuracy value. The results of the testing model displayed by the confusion matrix are tested to determine the performance of CNN in the classification of pneumonia diseases. The confusion matrix helps to understand the extent to which the model is successful or unsuccessful in performing classification[22].

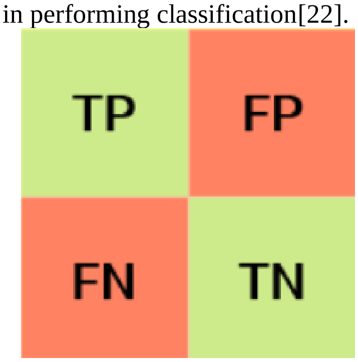


Figure 13 Confusion matrix

Figure 13 shows the data obtained based on the confusion matrix system testing there are True Positive (TP), True Negative (TN), False positive (FP), and False Negative (FN) values. From the confusion matrix, we can calculate precession, recall, F1-score, and accuracy.

Precision is used to calculate how many cases are predicted as positive by the model that should be predicted as positive, following the precision equation.

4. RESULT AND DISCUSSION

This study was conducted using a dataset containing x-ray images of patients with and without pneumonia, in jpeg format, with a total of 5,856 data. The Guangzhou Women and Children's Medical Center's retrospective cohort of pediatric patients, ages one to five, provided the data set. Every chest X-ray was completed as a standard clinical procedure for the patients. This study used the same data but differed in feature extraction as it used two different architectures, AlexNet and GoogleNet. The images included in both architectures have been preprocessed so that the input data has no difference from other datasets. This research will have two results, namely training model and model testing results.

The results of this study use Python tools using pneumonia image data. The image data is divided into 90% training data and 10% testing data. The results of the study discuss the analysis of the comparison of pneumonia image classification with GoogleNet and AlexNet architectures.

A. TRAINING MODEL

This training uses Adam optimization which helps the model in training. Adam optimization is one of the methods used to calculate the learning rate for each different parameter. The dataset used in this study is 5856 roentgen thorax data with such a large amount of data, it takes a long time to train the data simultaneously because the memory in the computer has limitations, this requires parameters such as batch size and epoch. Batch size is a parameter that divides the dataset into several groups. The model training process is carried out with Epoch 20 where each model will iterate 20 times There are other parameters carried out in this study such as the ReduceLROnPlateau parameter which will reduce the learning rate if the learning rate at the epoch causes the model to not show progress towards what is learned. After the mode training is completed, the results of each model experiment are stored in .h5 format so that they can be retrieved later in training. The results of the training dataset can be seen in Table 1.

Epoch	*GoogleNet*			*AlexNet*		
	Time(s)	*Accuracy*	*Loss*	*Time(s)*	*Accuracy*	*Loss*
1	245	0.2736	0.8366	255	0.8151	2.0417
2	186	0.7297	0.5834	210	0.8912	0.4067
3	189	0.7529	0.4878	206	0.9353	0.1684
4	188	0.8360	0.3570	210	0.9427	0.1525
5	183	0.8828	0.2845	213	0.9481	0.1442
6	848	0.8906	0.2731	206	0.9498	0.1350
7	176	0.9199	0.2081	208	0.9597	0.1108
8	174	0.9355	0.1728	211	0.9694	0.0790
9	175	0.9403	0.1490	207	0.9766	0.0660
10	900	0.9608	0.0996	208	0.9793	0.0554
11	178	0.9703	0.0774	21	0.9764	0.0658
12	172	0.9684	0.0737	209	0.9882	0.0337
13	1348	0.9755	0.0627	211	0.9905	0.0269
14	171	0.9806	0.0535	208	0.9935	0.0201
15	172	0.9899	0.0277	208	0.9937	0.0189
16	171	0.9935	0.0182	207	0.9962	0.0105
17	425	0.9966	0.0116	208	0.9977	0.0086
18	187	0.9977	0.0102	210	0.9981	0.0079
19	190	0.9975	0.0084	225	0.9975	0.0073
20	140	0.9977	0.0083	218	0.9985	0.0062

Table 1 Training Result is the result of training data with 20 iterations, there are columns of accuracy and loss time. the first model used by GoogleNet iteration length is 245/s with an accuracy value of 0.2736 with a loss of 0.8366 this result is relatively low because the GoogleNet model learns new data so to increase the iteration value must learn the next data given. In the second iteration, the accuracy rose to 0.7297 and loss to 0.5834, this can be interpreted that Google Net experienced a significant increase in accuracy of 0.4561 and can be interpreted that Google Net can increase accuracy and reduce the loss required in iterations. For the AlexNet model, the initial old iteration 255/s gets an accuracy value of 0.8151 this result is quite low compared to the next iteration in AlexNet. The second iteration gets an accuracy of 0.8912 with a loss value of 0.4067 this shows that AlexNet can learn to increase accuracy and reduce loss. After running 20 iterations in the GoogleNet column there are 2 highest accuracy values of 0.9977 with a time of 187 / s loss value of 0.0102 and with a time of 140 / s loss of 0.0083. this shows that GoogleNet can learn the data given well. the AlexNet column has the highest accuracy value of 0.9985 with a time of 218 / s loss of 0.0062. this can be interpreted that AlexNet has a higher accuracy even though the accuracy value is only 0.0008 different.

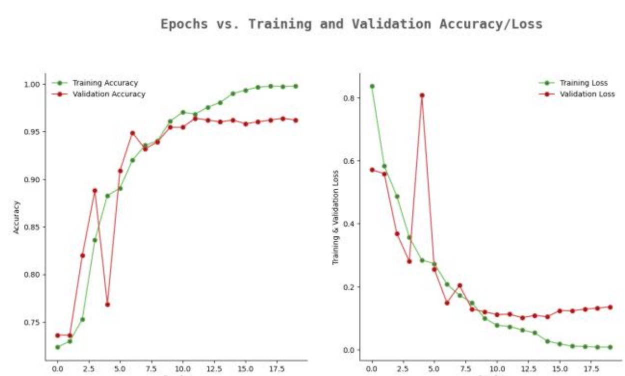


Figure 14 Accuracy graph of GoogleNet training and loss

Figure 14 is a graph of GoogleNet training accuracy and loss, it can be seen from the graph that the accuracy of GoogleNet in the first iteration is very low and has increased in subsequent accuracy. The loss value for each iteration decreased, proving that the model can reduce errors in learning the pneumonia dataset. This proves that GoogleNet can learn the dataset well.

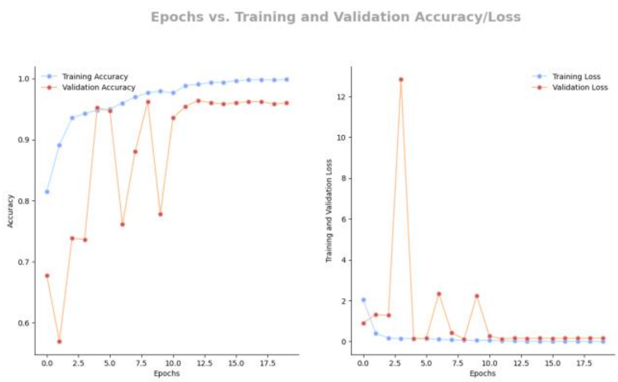


Figure 15 Accuracy graph of AlexNet training and loss

Figure 15 is a graph of AlexNet training accuracy and loss, it can be seen based on the graph that the accuracy of AlexNet in the first iteration is very low and has increased in subsequent accuracy. The loss value for each iteration decreased, proving that the model can reduce errors in learning the pneumonia dataset. This proves that AlexNet can learn the dataset well.

B. TESTING MODEL

The dataset used is 90% for training the model and 10% for testing the model, testing this model aims to determine the accuracy level of the model used. Images were used for testing 162 normal images and 424 pneumonia images. The results of the classification are visualized in the form of confusion matrix models AlexNet and GoogleNet.

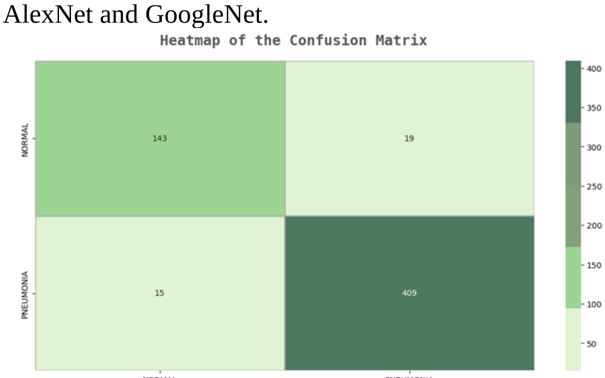


Figure 16 GoogleNet confusion matrix results

Figure 1.12 is the result of the confusion matrix GoogleNet, it can be seen that the results of the confusion matrix of GoogleNet test results with a total of 5856 data divided into 90% training data and 10% testing data. 10% of 5856 is 586 images used for testing the model. The test results on the confusion matrix are visualized in Table 2.

Table 2 classification results of GoogleNet model

Index	Class	Classification True	Total Data	Accuracy(%)
0	NORMAL	143	162	89
1	PNEUMONIA	409	424	96

Table 2 shows that the highest classification result is in the pneumonia class with an accuracy of 96% of images successfully classified by class. While normal accuracy has an accuracy of 89%. The data obtained from the confusion matrix is entered into the accuracy formula to get the accuracy value.

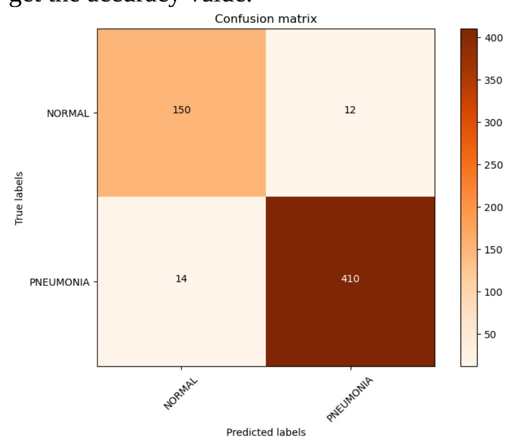


Figure 17 AlexNet confusion matrix result

Figure 17 displays the results of the confusion matrix of the test results from AlexNet with a total of 5856 data divided into 90% training data and 10% testing data. 10% of 5856 is 586 images used for testing the model. The test results on the confusion matrix on the AlexNet model are visualized in Table 3.

Table 3 AlexNet model classification results

Index	Class	Classification True	Total Data	Accuracy(%)
0	NORMAL	150	162	92
1	PNEUMONIA	410	424	97

Table 3 shows that the highest classification result is in the pneumonia class with an accuracy of 97% of images successfully classified by class. While normal accuracy has an accuracy of 92%. The data obtained from the confusion matrix is entered into the accuracy formula to get the accuracy value.

5. CONCLUSION

In this study, pneumonia classification was conducted using GoogleNet and AlexNet architectures. From the research that has been done, it can be concluded that the AlexNet architecture has a higher accuracy than the GoogleNet accuracy. The accuracy of AlexNet is 96%

and the accuracy of GoogleNet is 94%. However, both of these architectures are highly recommended for the classification of rotgen thorax pneumonia images.

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Rio Subandi received his bachelor's degree from the Department of Informatics Engineering, Faculty of Industrial Technology, Ahmad Dahlan University, Yogyakarta, Indonesia in 2021, and his master's degree in informatics in 2024. His research interests include artificial intelligence, deep learning and machine learning.

Herman is a lecturer at the Master of Informatics at Ahmad Dahlan University, Yogyakarta. He studied Bachelor's degree at the Perbanas Institute of Information Engineering, Jakarta, then continued his Master's and Doctoral studies at Computer Science Universiti Teknologi Malaysia. His area of expertise is Mobile and Multimedia Technologies

Anton Yudhana holds the academic rank of Professor in Electrical Engineering. He obtained his Bachelor of Electrical Engineering from Institut Teknologi Sepuluh Nopember in 2001, his Master of Electrical Engineering from Universitas Gadjah Mada in 2005, and his Doctorate from Universiti Teknologi Malaysia in 2011. Currently, he has been a permanent lecturer at the University of Ahmad Dahlan (UAD) since then, and he serves as the leader at the Centre for Electrical and Electronic Research and Development (CEERD). His research interests include precision agriculture, biomedical engineering, and IoT-based food engineering