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Implementation of generative adversarial network (GAN) method for pneumonia dataset augmentation

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Abstract
As a communicable disease, most pneumonia cases are brought on by bacteria or viruses, which cause the lungs' alveoli to swell with fluid or mucus. Pneumonia may arise from this and further making breathing challenging since the lungs' air sacs are unable to contain enough oxygen for the body. Pneumonia may generally be diagnosed clinically (by a physician based on physical symptoms) as well as through a photo chest radiograph, CT scan, and MRI. In this case, the lower cost of a chest radiograph examination making it as one of the most popular medical imaging tests. However, chest radiograph photo readings have a disadvantage, where it takes a long time for medical staff or physicians to identify the patient's illness since it is difficult to detect the condition. Therefore, an identification of chest radiograph imagery into various forms using machine learning becomes one way to address this issue. This research focuses on building a deep neural network model using techniques from the Generative Adversarial Network algorithm. GAN is a category of machine learning techniques using two models to be trained simultaneously, one is a generator model to generated fake data and the other is a discriminator model used to separate the raw data from the real data set images. The dataset used is Chest X-Ray images obtained from repo GitHub and repo Kaggle totaling 5,863 with normal data 1583 images and pneumonia data 4273 imagesThe results showed that the use of the Generative Adversarial Network method as augmentation data proved to be more effective in improving the generalization of neural networks, this can be seen from the results the result of the accuracy value obtained is 97%.

1. Introduction
Bacteria or viruses often carry on a contagious illness called pneumonia, which causes the lungs' alveoli to fill with fluid or mucus. This further cause the lungs' inflamed state and inability of the lungs' air sacs to adequately accommodate the body's requirement for oxygen, thus breathing becomes challenging [1]. Children under the age of five and those over the age of 65 are the primary targets of this infectious disease since they often have weak immune systems and have poorer recovery rates [2]. Pneumonia can cause up to 15% of child fatalities worldwide, more than any other naturally preventable illness, especially in developing nations [2]. Globally, pneumonia can kill more than any other naturally preventable disease, accounting for up to 15% of child deaths per year, especially in developing countries [3]. There are several causes of pneumonia, but there is currently no treatment for any of them [4]. Pneumonia can be caused by other microorganisms from the bacterial group such as staphylococcus aureus, from the viral group such as influenza, para influenza, adenovirus, respiratory syncytial virus, and others while from the fungal group such as candidiasis, histoplasmosis and aspergyphosis. Pneumonia can also be caused by food, liquids, poisons, chemicals, cigarettes, dust, or gas [5], [6]. Pneumonia may generally be diagnosed clinically (by a physician based on physical symptoms) as well as through a photo chest radiograph, CT scan, and MRI [7]. In this case, chest radiograph photo readings have a disadvantage, where it takes a long time for medical staff or physicians to identify the patient's illness since it is difficult to detect the condition. Therefore, an identification of chest radiograph imagery into various forms using machine learning becomes one way to address this issue [8].

Modernization in the field of artificial intelligence (AI), has produced annotated datasets marking the most recent period of successful analysis of medical images where CT images are processed in several stages to be used in disease diagnosis [9]. In this case, even radiology professionals frequently misdiagnose viral and bacterial pneumonia, thus it can complicate therapy [10]. Lack of resources, particularly in rural regions, for a computer-assisted method to aid radiology specialists in the detection of pneumonia served as another factor for the completion of this study.

Several studies have been conducted related to pneumonia classification using the CNN method where the study used the same dataset as this study and obtained a fairly high accuracy value of around 95% [11]. Saman Motamed, Patrik Rogalla, Farzard Khalvadi. Saman Motamed, Patrik Rogalla, and Farzad Khalvati. This study compares the Deep Convolutional-GAN (DCGAN) method and the Inception-Augmentation GAN (IAGAN) model [12]. Sagar kora Venu, Sridhar Revula in this study the model used is CNN (Convolution Neural Network) to classify while in the additional data set uses the DCGAN (Deep Convolution Generative Adversarial Network) model to perform Data Augmentation [13]. Noor Eldeen M. Khalifa, Mohamed Hamed N. Taha, Aboul Ella Hassanien, Sally Elghammary. Current research aims to reveal the GAN method efficiency by using the Alexnet, Squeezenet, Googlenet and Resnet18 models [14]. Shobhita Sundaram, Neha. also conducted a research project where they examined, evaluating the use of GAN-based data augmentation artificially extends the CheXpert data set of chest radiographs [15].

The difference in the research that has been done with this research focuses on the GAN method as data augmentation and also reproduces the data and combines it with the CNN method as a method for classification. So that we can find out data augmentation techniques to increase the generalization of neural networks by using data generated from the GAN method more effectively and to know that the GAN model can detect pneumonia through X-ray data as well as detect X-ray data anomalies.

Based on these issues, this study proposes an image identification or enhancement technique using publicly available datasets of X-ray and CT images of patients diagnosed or suspected of having viral or bacterial pneumonia (MERS, SARS, and ARDS) to assist radiologists in the early detection of pneumonia.

2. Research Method

This study uses a Generative Adversarial network algorithm that combines the convolution technique of CNN (Convolution Neural Network) which is commonly called DCGAN (Deep Convolution Generative Adversarial Network). DCGAN can generate new images based on images that have been seen in the training process so that it can overcome problems in terms of lack of datasets. But DCGAN itself has a drawback, namely that the model is always changing in conducting training so that it can cause the results of the training to be less clear.

GAN is a technical part of machine learning that uses two neural network models that can train data simultaneously. First, the generator model as input data processing which produces output data in the form of fake data (generated images), whether the data is in the form of images, audio, etc. so that it can fool the discriminator model. Second, the discriminator model in this model tries to distinguish data that has been degenerated by the model generator as fake data and samples of original data [16], [17].

The model generator in this design accepts an input of a random noise vector of size 100 x 1. Then, to scale to the relevant 128 x 128 x 3 picture size, four convolutional-transpose layers and batch norm layers were used with interwoven ReLU activation functions. The discriminator model receives as input an image with dimensions of 128 x 128 x 3, which was then processed by five strung-together convolutional layers, a batch norm layer, and ReLU as the activation function. In this case, whether the picture is actual data or created data is determined by the activation function's sigmoid shape [7], [18]. As illustration of GAN Model Architecture can be seen on Figure 1.

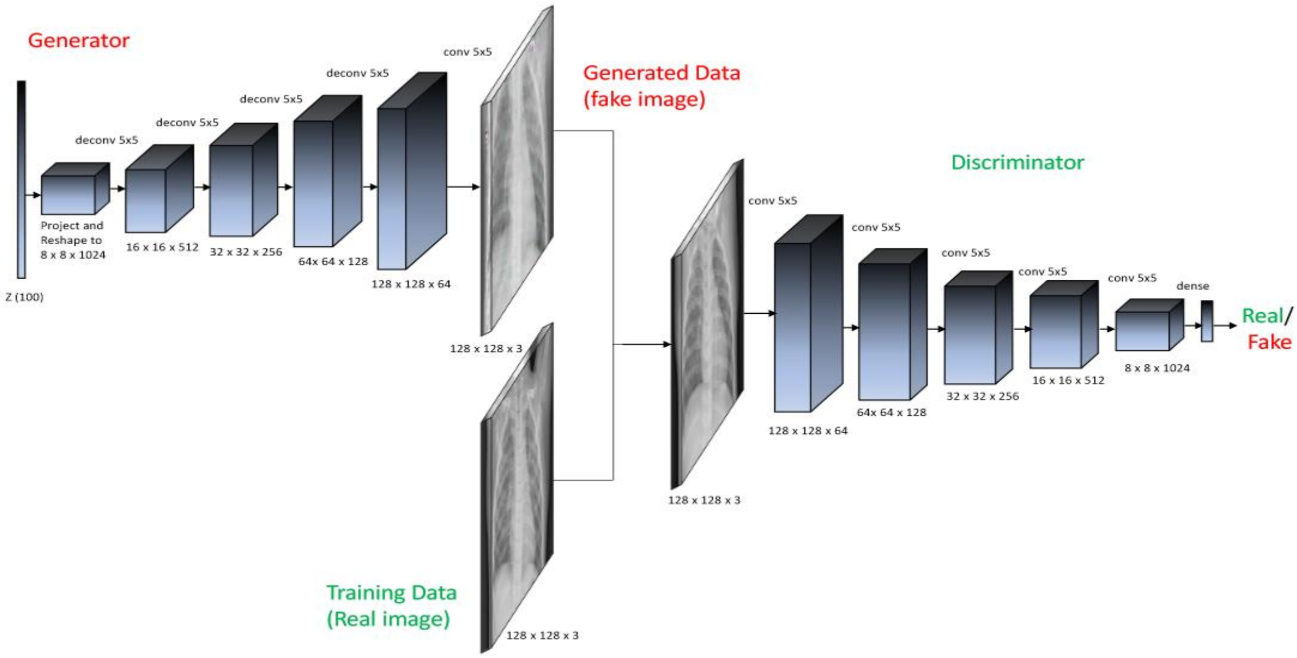
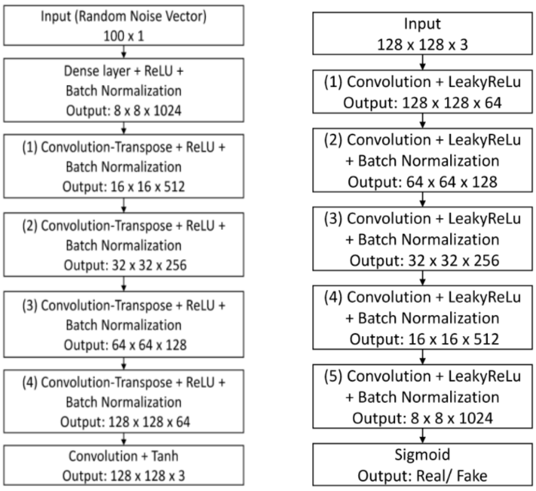


Figure 1. GAN Model Architecture



(a) (b)

Figure 2. Model Network Architecture: (a) Generator, (b) Diskriminator

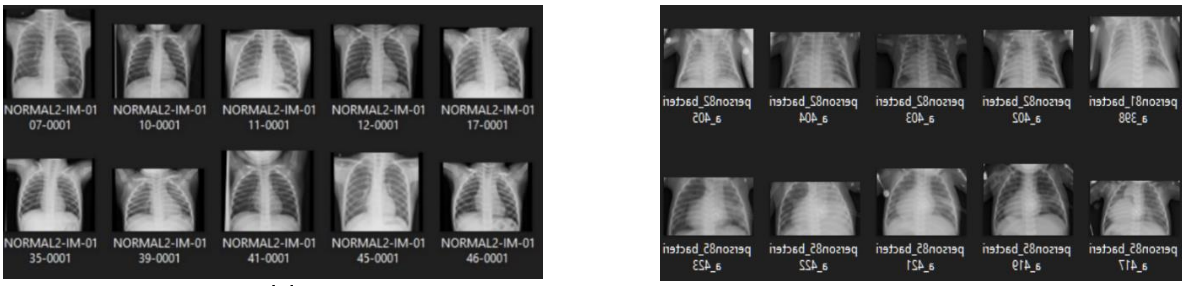
The dense layer receives a random noise vector with a size of 100 x 1 as input from the model generator and transforms it into a representation with a size of 8 x 8 x 1024 [13]. In order to expand the representation's sample size, it creates an image with a size of 128 x 128 x 3, then the output of the dense layer is followed by a succession of convolution-transpose layers. Furthermore, all levels in the network employ ReLU activation, with the exception of the output layer, which uses Tanh activation. This enables the model to shorten the training distribution period [19]. After that, batch normalization is used to reduce the gradient for all layers except the output layer in order to prevent overfitting during the learning phase [20]. In this design, we depict sizes ranging from 8 x 8 x 1024 pictures to 128 × 128 x 3 images using four layers of transpose convolution on the upsample. A combination of real pictures from the original dataset and images produced by the generator network are sent into the discriminator network together with 128 x 128 x 3 pixels of input data. This network uses many convolution layers on the input picture, followed by a sigmoid activation function to determine if the image is real or false [20]. The illustration of Model Network Architecture in GAN can be seen on Figure 2.

3. Summary Results and Discussion

This chapter describes results from the implementation of proposed approaches for detecting pneumonia diseases. This study uses the dataset as the research subject to evaluate the performance with the previously proposed approach, while the pneumonia disease as the research object.

3.1 Dataset

The dataset used amounted to 5,863 Chest X-Ray images.[21]. The dataset was split into 2 categories, namely a normal dataset of 1583 images and a pneumonia dataset of 4273 images [22]. Examples of data used in this study can be seen in the following Figure 3.



(a) (b)

Figure 3. Examples of Chest X-Ray Image: (a) Normal, (b) Pneumonia

3.2 Model Generator and Discriminator Architecture

At this stage, two model architectures were created: the generator and the discriminator, as shown in the following table, i.e Table 1 andn Table 2.

Table 1. Model Architecture (Generator)

Layer (type)	*Output Shape*	*Param #*
dense_1 (Dense)	(None, 8192)	827392
leaky_re_lu_5 (LeakyReLU)	(None, 8192)	0
Reshape (Reshape)	(None, 8, 8, 128)	0
conv2d_transpose (Convd2DTranspose)	(None, 16, 16, 128)	0
leaky_re_lu_6 (LeakyReLU)	(None, 16, 16, 128)	12832
conv2d_transpose_1 (Convd2DTranspose)	(None, 32, 32, 128)	128
leaky_re_lu_7 (LeakyReLU)	(None, 32, 32, 128)	25632
conv2d_transpose_2 (Convd2DTranspose)	(None, 64, 64, 128)	128
leaky_re_lu_8 (LeakyReLU)	(None, 64, 64, 128)	0
conv2d_transpose_3 (Convd2DTranspose)	(None, 128, 128, 128)	18496
leaky_re_lu_9 (LeakyReLU)	(None, 128, 128, 128)	256
conv2d_5 (Convd2D)	(None, 128, 128, 3)	9603
Total Params:	**1,886,083**	
Trainable params:	**1,886,083**	
Non-trainable params:	**0**	

Table 2. Model Architecture (Discriminator)

Layer (type)	*Output Shape*	*Param #*
conv2d (Conv2D)	(None, 128,128,128)	9728
leaky_re_lu (LeakyReLU)	(None, 128,128,128)	0
conv2d_1 (Conv2D)	(None, 64, 64, 128)	409728
leaky_re_lu_1 (LeakyReLU)	(None, 64, 64, 128)	0
conv2d_2 (Conv2D)	(None, 32, 32, 128)	409728
leaky_re_lu_2 (LeakyReLU)	(None, 32, 32, 128)	0
conv2d_3 (Conv2D)	(None, 16, 16, 128)	409728
leaky_re_lu_3 (LeakyReLU)	(None, 16, 16, 128)	0
conv2d_4 (Conv2D)	(None, 8, 8, 128)	409728
leaky_re_lu_4 (LeakyReLU)	(None, 8, 8, 128)	0
flatten (Flatten)	(None, 8192)	0
dropout (Dropout)	(None, 8192)	0
dense (dense)	(None, 1)	8193
Total Params:	**1,656,883**	
Trainable params:	**0**	
Non-trainable params:	**1,656,883**	

The Table 1 shows the Generator Model processing the original image input into a fake image with a convolution size of 8*8 to 128*128 using Tanh activation and Relu activation. While in the Discriminator model (Table 2) there are two models. The first input comes from the generator as the result of a fake images and the inputs from the original data set. Then the discriminator performs image processing so that it can classify the original data of the dataset and the generator's fake image. This model uses a 128*128 convolution layer to become an 8*8 convolution layer.

3.3 GAN Model Architecture

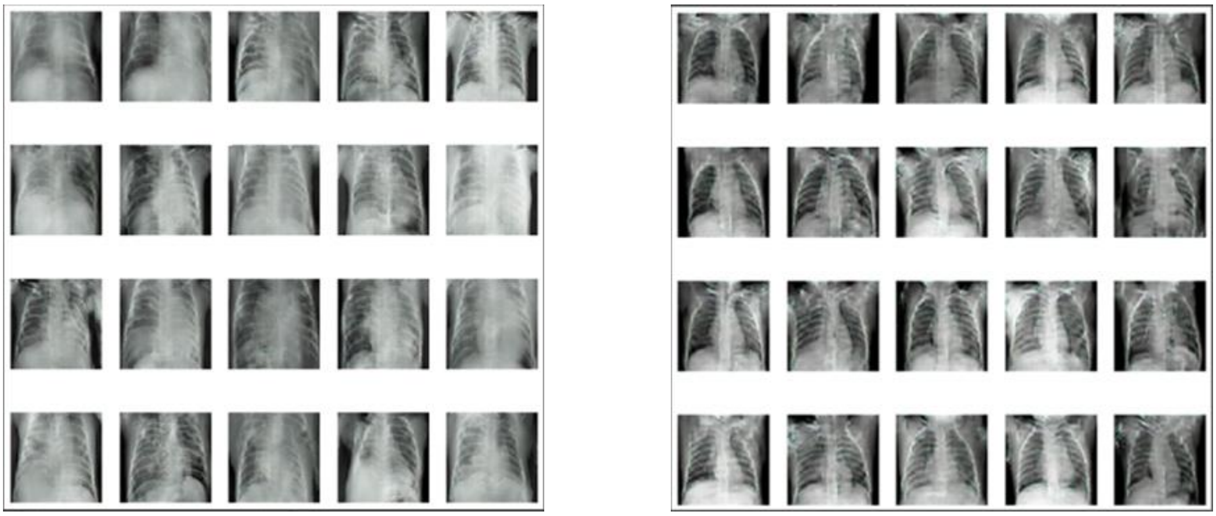
At this stage, the Discriminator and Generator models are combined. This is shown in the following Table 3. The Table 3 shows the number of GAN model parameters used by combining the Discriminator model and the Generator model.

Table 3. GAN Model Architecture

Layer (type)	Output Shape	Param #
sequential_1 (Sequential)	(None, 128, 128, 3)	1886083
sequential (Sequential)	(None, 1)	1656833
Total Params:	**3,543,916**	
Trainable params:	**1,886,083**	
Non-trainable params:	**1,656,833**	

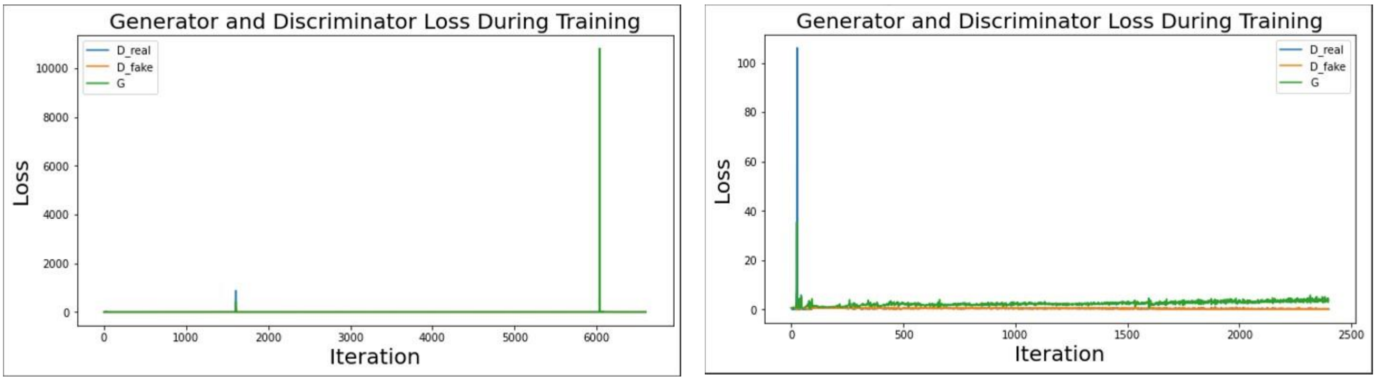
3.4 Training Model GAN

This stage requires two processes where the process will generate a normal image and generate a Pneumonia image, thus getting different loss values in each iteration process and the results of the Generate Image will be used for the classification process and can be seen on the Figure 4. During the GAN model training process, each image has a periteration accuracy value and it can be seen on the Figure 5.



(a) (b)

Figure 4. GAN Model Training Results: (a) Pneumonia Dataset, (b) Normal Dataset



(a) (b)

Figure 5. Accuracy Results of the GAN Model: (a) Pneumonia Dataset, (b) Normal Dataset

3.5 CNN (Convolutional Neural Network) Classification

At this stage using image datasets generated from GAN-generated image models totaling 4000 Normal image data and 4000 Pneumonia image data. Then the total amount of data will be divided with a data ratio of 80% used for training data, 20% used for test data. This can be seen in the Figure 6.

```
Data Train Normal : 3184
Data Test Normal : 800
Data Train Pneumonia : 3184
Data Test Pneumonia : 800
Data val Normal : 16
Data val Pneumonia : 16
```

Figure 6. Dataset Division

3.6 CNN Model Architecture

This stage is a CNN model design that is built using 3 layers with the number of filters (16, 32, 64) and using Averagepool pooling, softmax activation on the output layer and Relu activation as a fully connected layer [23]. This can be found in Table 4.

Table 4. CNN (Convolutional Neural Network) Model Architecture

Layer (type)	*Output Shape*	*Param #*
conv2d (Conv2D)	(None, 64, 64, 16)	800
batch_normalization (BatchNormalization)	(None, 64, 64, 16)	64
conv2d_1 (Conv2D)	(None, 64, 64, 16)	12560
max_pooling2d (MaxPooling2D)	(None, 12, 12, 16)	0
conv2d_2 (Conv2D)	(None, 12, 12, 32)	12832
batch_normalization_1 (BatchNormalization)	(None, 12, 12, 32)	128
conv2d_3 (Conv2D)	(None, 12, 12, 32)	25632
batch_normalization_2 (BatchNormalization)	(None, 12, 12, 32)	128
average_pooling2d (AveragePooling2D)	(None, 2, 2, 32)	0
conv2d_4 (Conv2D)	(None, 2, 2, 64)	18496
batch_normalization_3 (BatchNormalization)	(None, 2, 2, 64)	256
conv2d_5 (Conv2D)	(None, 2, 2, 64)	36928
batch_normalization_4 (BatchNormalization)	(None, 2, 2, 64)	256
average_pooling2d_1 (AveragePooling2D)	(None, 1, 1, 64)	0
flatten (Flatten)	(None, 64)	0
dense (Dense)	(None, 64)	4160
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 2)	130
Total Params:	**112,370**	
Trainable params:	**111,954**	
Non-trainable params:	**416**	

3.7 Training Model CNN

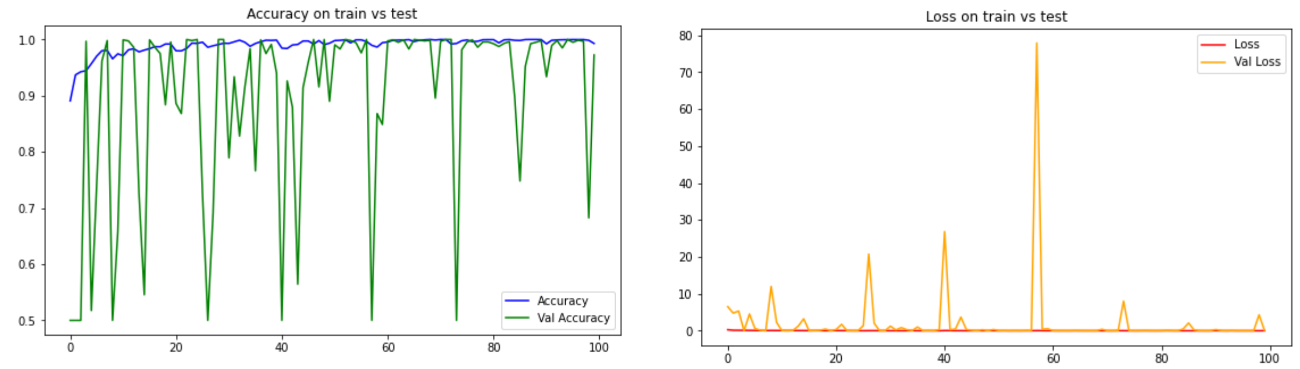
In the CNN training process, there are several batch size parameters. Batch_size is how many image models are trained in each iteration. Epoch is an iteration or a hyperparameter that will determine how much the model repeats on the entire dataset. This can be seen in the Figure 7.

```
Epoch 96/100
199/199 [==============================] - 5s 27ms/step - loss: 5.6104e-04 - accuracy: 0.9998 - val_loss: 0.0156 - val_accuracy: 0.9950
Epoch 97/100
199/199 [==============================] - 5s 27ms/step - loss: 3.9790e-04 - accuracy: 0.9998 - val_loss: 0.0015 - val_accuracy: 0.9987
Epoch 98/100
199/199 [==============================] - 5s 27ms/step - loss: 3.7303e-04 - accuracy: 0.9998 - val_loss: 0.0116 - val_accuracy: 0.9969
Epoch 99/100
199/199 [==============================] - 5s 26ms/step - loss: 0.0051 - accuracy: 0.9986 - val_loss: 4.3127 - val_accuracy: 0.6825
Epoch 100/100
199/199 [==============================] - 5s 26ms/step - loss: 0.0181 - accuracy: 0.9929 - val_loss: 0.0935 - val_accuracy: 0.9725
```

Figure 7. CNN (Convolutional Neural Network) Model Architecture

3.8 CNN Model Performance

At this point, the model performance graph will be displayed which is a form of visualization of the training model that has been built. The results can be found on Figure 8.



(a) (b)

Figure 8. CNN Model Performance: (a) Model Accuracy (b) Model Loss Value

3.9 Confusion Matrix Result

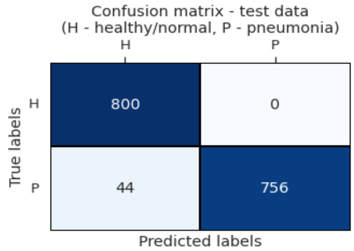
After knowing the results of the model graph that has been trained, the last step in the research is to evaluate the model was built using Confusion Matrix. Then, after knowing the results of the model graph that has been trained, then the last stage is to evaluate the model that has been built using confusion matrix. Confusion matrix is a predictive analytic tool that compares the actual value with the predicted value of the model that can be used to generate evaluation metrics such as Accuracy, Precision, Recall, and F1-Score or F-Measure [24] [25]. The results show the classification of images on test data with an accuracy of 97%. This can be seen in the Figure 9 (a). Based on Figure 9 (b), the Confusion Matrix results explain that the model can correctly predict normal data on the correct target of 800 and predict normal data on the wrong target of 0. Meanwhile, to correctly predict pneumonia data on the correct target of 756, and correctly predict pneumonia data on the wrong target of 44.

```
Classification report on test data
              precision    recall  f1-score   support

           0       0.95      1.00      0.97       800
           1       1.00      0.94      0.97       800

    accuracy                           0.97      1600
   macro avg       0.97      0.97      0.97      1600
weighted avg       0.97      0.97      0.97      1600
```

(a)



(b)

Figure 9. Evaluation Results: (a) Model Evaluation (b) Confusion Matrix Results

3.10 Analysis

The results obtained from the analysis presented in Table 5 provide compelling evidence that supports the superiority of the GAN (Generative Adversarial Network) method in enhancing image classification accuracy. In the specific case of the Pneumonia disease dataset, employing the GAN method as image augmentation data resulted in remarkable accuracy, achieving an impressive accuracy value of 97%. This notable improvement in accuracy, when compared to the CNN (Convolutional Neural Network) method that did not utilize Generated Data or Augmentation Data using the GAN method, further highlights the effectiveness of the GAN approach.

The GAN method's ability to generate synthetic data and augment the existing dataset plays a pivotal role in its superior performance. By introducing additional variations and diversity into the data, the GAN method enhances the neural network's capacity to generalize and make accurate predictions on unseen instances. This augmentation technique proves particularly valuable in the domain of medical image classification, such as Pneumonia diagnosis, where precise and dependable predictions are crucial.

Moreover, the substantial difference in accuracy values between the GAN and CNN methods underscores the limitations of relying solely on conventional CNN-based approaches without data augmentation. When the CNN method is not augmented with Generated Data or Augmentation Data using the GAN method, it falls short in capturing the intricate details and complexities of the Pneumonia dataset, resulting in a lower accuracy rate. This discrepancy can be attributed to the absence of diversity and variation in the training data, impeding the model's ability to generalize and adapt to different patterns and features.

In conclusion, the findings derived from this analysis convincingly demonstrate the significant impact of incorporating the GAN method as image augmentation data in enhancing the accuracy of neural networks, particularly in Pneumonia disease classification. The GAN method's capacity to generate diverse and realistic synthetic data enhances the neural network's generalization capabilities, leading to an impressive accuracy rate of 97%. These results highlight the importance of leveraging GAN-based data augmentation techniques in medical image classification tasks, enabling more accurate diagnoses and potentially improving patient outcomes.

Table 5. Comparison of Results

Model	Train Accuracy	Train Loss	Val Accuracy	Val Loss	Precision	Recall	F1 Score
CNN	94.45%	12.8%	87.18%	36.96%	94%	92%	93%
CNN with GAN	97%	1.81%	97.25%	9.35%	97%	97%	97%

4. Conclusion

In conclusion, the research findings provide compelling evidence supporting the substantial advantages of integrating the GAN (Generative Adversarial Network) method as a data augmentation technique to enhance the generalization capabilities of neural networks. The obtained results clearly establish the superiority of this approach, as exemplified by the remarkable accuracy rate of 97% achieved. In contrast, the CNN (Convolutional Neural Network) method, which did not employ Generated Data or Augmentation Data using the GAN method, yielded a comparatively lower accuracy rate of 94.45%.

These findings underscore the significance of adopting GAN-based data augmentation to enhance the overall performance and resilience of neural networks across diverse applications. By harnessing the power of the GAN method, neural networks are empowered with improved generalization capabilities, enabling them to make more precise predictions and classifications on previously unseen data. This heightened generalization ability holds crucial importance in real-world scenarios where adaptability to various input variations and novel instances is paramount.

The achieved accuracy rate of 97% serves as a testament to the effectiveness of GAN-based data augmentation in mitigating the challenges associated with limited or non-representative training data. Through the generation of synthetic data and the introduction of additional variations, the GAN method enables neural networks to learn from a broader and more diverse dataset. This expanded exposure to diverse patterns and features enhances the model's capacity to generalize effectively and make accurate predictions on unseen examples.

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