

Implementation of Spatial-Level Augmentation on Pneumonia Classification with Convolutional Neural Network

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Abstrak—Pneumonia merupakan penyakit dengan gejala sulit bernafas, demam, batuk kering, dan nyeri dada. Sebagai indikasi seseorang terkena COVID-19, penyakit pneumonia perlu segera diidentifikasi oleh dokter apakah citra rontgen paru pada pasien tersebut tergolong pneumonia atau bukan pneumonia. Pentingnya diagnosis sedini mungkin dapat mengurangi resiko kematian pada pasien. Convolutional Neural Network merupakan salah satu bidang studi dalam ranah Ilmu Komputer yang dapat melakukan klasifikasi objek berbasis citra. CNN dapat dimanfaatkan pada identifikasi pneumonia berbasis citra thorax berdasarkan fitur atau ciri yang ditampilkan pada citra. Salah satu elemen penting dalam CNN adalah banyaknya data yang dapat digunakan sebagai bahan pelatihan, validasi, dan pengujian. Umumnya, semakin banyak data yang dimasukkan maka semakin banyak pula bahan belajar bagi sistem CNN sehingga sistem dapat melakukan klasifikasi dengan lebih akurat. Penelitian ini bertujuan untuk mengukur tingkat akurasi model CNN pada citra toraks-pneumonia dengan ubahan augmentasi jenis spatial level. Augmentasi citra diimplementasikan untuk meningkatkan varian citra dengan data awal adalah sebanyak 5856 citra. Augmentasi yang diterapkan adalah Affine, Flip, Pixel Dropout, Random Sized Crop, dan Shift Scale Rotate. Adapun tahapan dari penelitian ini adalah melakukan pengelompokan citra secara manual, implementasi augmentasi pada citra, penerapan pelatihan-validasi-pengujian pada CNN, dan analisis hasil output dari sistem yang dikembangkan. Dengan menggunakan 5 jenis augmentasi, dataset yang digunakan sebagai bahan pembelajaran dapat ditingkatkan hingga 5x lipat dari jumlah aslinya. Dari penelitian yang dijalankan, diperoleh hasil bahwa augmentasi jenis Random-sized Crop memberikan nilai akurasi tertinggi yakni sebesar 94,719% atau adanya peningkatan sebesar 3,808% dari data testing non-augmentasi. Dari penelitian ini, diharapkan studi terkait augmentasi dapat menjadi rujukan mengenai jenis proses augmentasi beserta hasilnya dalam mencari nilai akurasi CNN, khususnya pada kasus klasifikasi pneumonia.

Kata Kunci: Covid-19; Augmentasi; Apatial-level; Klasifikasi Pneumonia; CNN

Abstract—Pneumonia is a disease with symptoms of difficulty breathing, fever, dry cough, and chest pain. As an indication that a person has COVID-19, it is necessary to immediately identify pneumonia by a doctor whether the lung X-ray image of the patient is classified as pneumonia or not. The importance of early diagnosis can reduce the risk of death in patients. Convolutional Neural Network is one of the fields of study in the realm of Computer Science that can perform image-based object classification. CNN can be used to identify pneumonia based on thorax images based on the features or features displayed on the image. One of the important elements in CNN is the amount of data that can be used for training, validation, and testing. Generally, the more data entered, the more learning material for the CNN system so that the system can classify more accurately. This study aims to measure the accuracy of the CNN model on thoracic-pneumonia images with spatial level augmentation changes. Image augmentation is implemented to increase image variance with initial data of 5856 images. The applied augmentations are Affine, Flip, Pixel Dropout, Random Size Crop, and Shift Scale Rotate. The stages of this research are manually grouping images, implementing augmentation on images, applying training-validation-testing on CNN, and analyzing the output results of the developed system. By using 5 types of augmentation, the dataset used as learning material can be increased up to 5x the original amount. From the research carried out, it was found that the Random-sized Crop type augmentation gave the highest accuracy value of 94.719% or an increase of 3.808% from the non-augmentation testing data. From this research, it is hoped that studies related to augmentation can be a reference regarding the type of augmentation process and its results in finding the CNN accuracy value, especially in the case of pneumonia classification.

Keywords: Covid-19; Augmentation; Spatial-level; Pneumonia Classification; CNN

1. INTRODUCTION

COVID-19 emerged at the end of 2019 and began to enter Indonesia since the beginning of 2020. This disease has a wide impact on life and opens up the fact that medical facilities in Indonesia are still overwhelmed in preventing and dealing with pandemics. In addition, until now the government has not been able to monitor the rehabilitation process for patients so that they cannot know the long symptoms that occur in the community. This has resulted in a high death rate from COVID-19 in Indonesia [1]. One of the things that causes COVID-19 to become a global pandemic is that it is easy to transmit the virus between humans, either through air or liquids, either by direct or indirect contact. COVID-19 when it enters the host's body will give symptoms of illness that resemble acute pneumonia, such as shortness of breath, cough, fever, runny nose, and headache [2]. These symptoms can be more severe if the patient has a history of comorbidities (congenital diseases) such as hypertension, diabetes, heart disease, and respiratory disorders [3].

One of the symptoms caused by COVID-19 is pneumonia, which is a condition in which the lungs are infected by viruses, microbes, bacteria, or fungi in the alveoli. This results in inflammation of the alveoli and infection that closes the capillaries resulting in blockage of the airways [4]. The several types of viruses that cause pneumonia are influenza, swine flu, and coronavirus. Meanwhile, bacteria that can cause infection are pneumococci and mycoplasma pneumonia [5].

Pneumonia enters the body through the nose, mouth, and sometimes also enters through the eyes with intermediary media such as air, water, and touch. When microbes enter the respiratory tract, they cause infection. This infection is then indicated by an increase in the volume of fluid in the lung cavity because the immune system is trying to fight microbes [6]. Infections that occur in the human respiratory tract are characterized by coughing runny nose and shortness of breath that can lead to Middle East Respiratory Syndrome (MERS) and Severe Acute Respiratory Syndrome (SARS). This can be fatal and lead to death [7], [8].

Detection of pneumonia is important in diagnosing pneumonia in a person, one of which is through x-ray images. Experts and medical personnel can use x-ray images to analyze and study the characteristics of pneumonia in a patient; whether pneumonia is indicated or not. Figure 1 illustrates an x-ray image of a normal lung and a lung affected by pneumonia.



Figure 1. Image of Normal Thorax (left) and Pneumonia Thorax (right) [9]

The expertise of an expert has a subjective nature, which means that it is strongly influenced by the experience and personal observations of the expert. This subjective nature allows for misdiagnosis due to errors in observing the characteristics of the symptoms that occur, including the characteristics contained in the x-ray image in this case of pneumonia. Knowledge in the field of Computer Science which is increasingly applicable allows the knowledge possessed by an expert to be transferred to a computing machine [10]. In COVID-19 and pneumonia, images of the thorax (chest cavity) of patients can be used as learning material for computing machines in order to classify whether the thorax image is classified as pneumonia or normal. This can help doctors in diagnosing diseases more precisely, so that treatment efforts can be carried out as early as possible and the risk of death can be reduced.

Convolutional Neural Network (CNN) is one of the focuses of studies in the realm of Computer Science that can classify objects based on image data. CNN will conduct training to train computational machines in order to learn the features of the image, perform validation to confirm the level of truth in learning, and conduct tests to determine the value of accuracy in grouping objects [11], [12]. CNN is known as one of the breakthroughs in machine learning studies that have the opportunity of high accuracy and detection speed [13]. Although CNN is known to take a long time to carry out the classification process [11].

This study applies CNN to classify x-ray images of the chest cavity (thorax) which are classified as pneumonia and not pneumonia. In [14] a study was conducted on the detection of cancer nodules on lung images using 3D images of the thoracic cavity. The framework applied is Faster R-CNN with CmixNet architecture. From the results of the study obtained a sensitivity value of 98%. In addition, [9] developed a deep architecture model of ShuffleNet and ResNet to detect COVID-19. The result of this research is an accuracy of 86.93% using 1125 thoracic x-ray images. Studies on pneumonia in the lungs were also carried out by [15] in detecting COVID-19 with the VGG-16 architecture and the accuracy obtained is 92.86%. Based on a literature review of research related to pneumonia, it shows that CNN has been widely applied in health-related research, especially in diagnosing pneumonia through thoracic images. In order to highlight the difference, this research is taking focus on the implementation of augmentation process to increase the variation of data, instead comparing CNN architecture as stated on the earlier research in [9], [14], [15].

One of the parameters in increasing the classification accuracy on CNN is the variation of image data entered in the CNN system. CNN uses image as a learning material for computing machines to recognize the features in the image [16], [17]. Augmentation is one of the techniques in image processing that can increase image variance and reduce overfitting in the training process and data testing [18]

In this study, spatial-level augmentation was applied to determine CNN's performance from thoracic image classification with the intention to increase the variation of data. Augmentation at the spatial-level is a term or terms created by Alumentations; one of the augmentation libraries that are often used on Python-based systems. In Computer Vision studies, spatial-level augmentation is similar to geometric transformation. The 5 types of augmentation are Affine, Flip, Pixel dropout, Random-sized Crop, and Shift Scale Rotate. When each type of

augmentation is applied to the image, it is expected to increase the data variance which has the opportunity to be directly proportional to the increase in classification accuracy. This study may take advantage or contribution in study of CNN for pneumonia classification in Covid-19 domain commonly.

2. RESEARCH METHOD

The flow of this research conducted is illustrated in Figure 2.

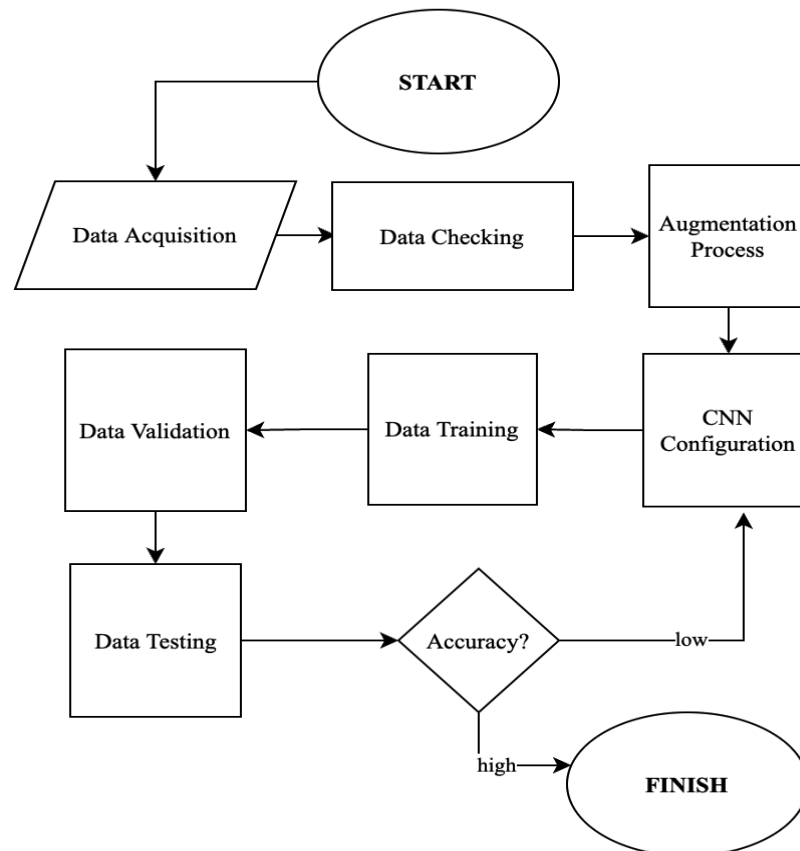


Figure 2. Research Flowchart

- a. Data collection was carried out using secondary data taken from the Kaggle Dataset at <https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia>. The data consisted of 5856 data consisting of normal thoracic images, viral pneumonia thoracic images, and bacterial pneumonia thoracic images. Pneumonia-virus and pneumonia-bacteria images were then grouped as pneumonia thoracic images. The data is in JPG format with a resolution of about 1500x1500 pixels.
- b. At the Data Checking stage, the data obtained is filtered first to ensure that the data to be used is the correct image, has a resolution that tends to be uniform, and has good image quality. Quality image conditions will have a high role in running CNN.
 1. Correct image: ensure that all data is an image related to the thoracic image of a person. This is characterized by an x-ray image of the chest cavity in the image and not another image other than the thorax
 2. Uniform resolution: the images in the dataset have different sizes. Even though there are differences in the resolution size of the images, it is expected that the differences in each image will not have a significant difference from the average resolution, which is 1500x1500 pixels.
 3. Good image quality: no specific calculations are carried out in determining image quality, but visual observations are made using the sense of sight to ensure that the image used has a clear appearance and there is no noise like blur that can interfere with the appearance of the image.
- c. Augmentation is done to increase the variance of the image. The quantity of the image affects the learning stage on CNN and affects the accuracy of the image. The augmentations carried out in this study are Elastic Transform, Pixel Dropout, Random Brightness, Random Scale, Safe Rotate. From each augmentation process, data will be generated as much as 1x the amount of the original data. For example, from the Elastic Transform augmentation process, with 5856 original images as input data, 5856 Elastic Transform augmented images will be generated. From the augmentation process, a total of 30,000 thorax images will be generated with 5 augmentation variants. Figure 3 demonstrates examples of various augmentation processes on an image.

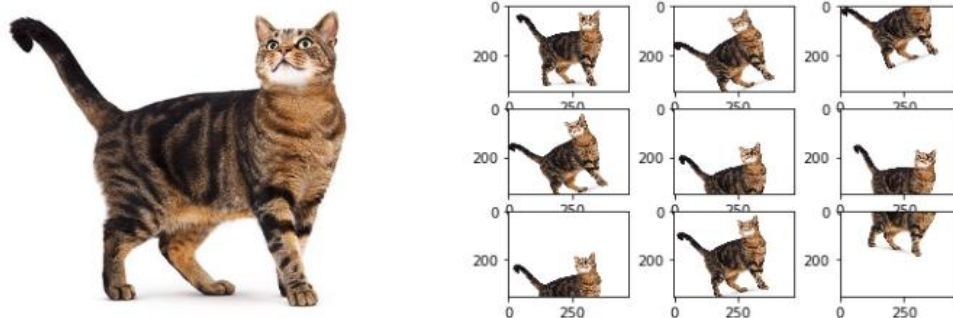


Figure 3. Example of the augmentation process on the image [19]

In Python Environment, this augmentation process is carried out using the Albumentations library which is popular among researchers [20].

- d. CNN procedure is carried out by determining the CNN configuration and continued by determining the distribution of training, validation, and testing data. This study applies the composition of the data that is popularly used, namely 8-1-1. Data sharing is applied to the training and validation process. The training process is used as learning material on CNN. The validation stage is used to test in a narrow scope the results of the training. After that, the testing phase was continued to test the actual data. The distribution of training, validation, and testing data is 80:10:10 which is divided randomly. Table 1 shows the amount of data sharing for training, validation, and testing.

Table 1. Dataset Composition

Type	Training (80%)	Validation (10%)	Testing (10%)	Amount
Toraks-Normal	1267	158	158	1583
Toraks-Pneumonia	3419	427	427	4273
Total				5856

1. In general, the CNN architectural configuration is adapted to the CNN research configuration that has been carried out by [21]. In this study, a classification model was developed for cases of pneumonia associated with COVID-19. The technique used is CNN with the main focus of research is data testing that is subjected to the Contrast Limited Adaptive Histogram Equalization (CLAHE) operation which is useful for sharpening the framework objects in the thoracic image. The CNN parameters in running CNN consist of Pooling Layer, Reshaping Layer, Convolution Layer, Metrics, Activation Layer, Core Layer, Losses, and Optimizer according to the configuration guide listed on the official Keras Tensorflow page [22] to be able to run CNN.
2. The image resolution used in this study is 128x128 which is a popular measure in CNN-based research. One of the studies that applies this resolution is [23] which uses CNN in classifying the cases being worked on. Changing the image resolution is done so that the image has a uniform size. In addition, by changing the image size to a smaller size, it is hoped that the CNN process can work more optimally as stated by [24]. The new image resolution is applied at each stage of training, validation, and testing which affects the output of the CNN model.
3. In the training and validation stages, the CNN design model is carried out using training and validation data. The epoch used is 200 epoch to obtain the output value. No experiments were carried out with different epoch values because these 200 epochs were generally high enough to run CNN to obtain results in the form of training accuracy, training loss, validation accuracy and validation loss.
4. The CNN model that has been carried out by training and validation processes is continued with testing to test the system and determine the accuracy value. This accuracy value generally describes the classification performance of the model. In the measurement of the CNN model, the Confusion Matrix is used which is a popular matrix.

3. RESULT AND ANALYSIS

3.1 Augmentation Process

The augmentation process was carried out on all data which amounted to 5856 thoracic images. There are 5 types of augmentation, namely Elastic Transform, Pixel Dropout, Random Brightness, Random Scale, Safe Rotate. Each type of augmentation becomes the main parameter compared in this study. Figure 4 illustrates the results of the augmentation process on a normal thoracic image and Figure 5 illustrates the results of the augmentation process on a pneumonia thoracic image. The explanation of each image result is described subsequently.

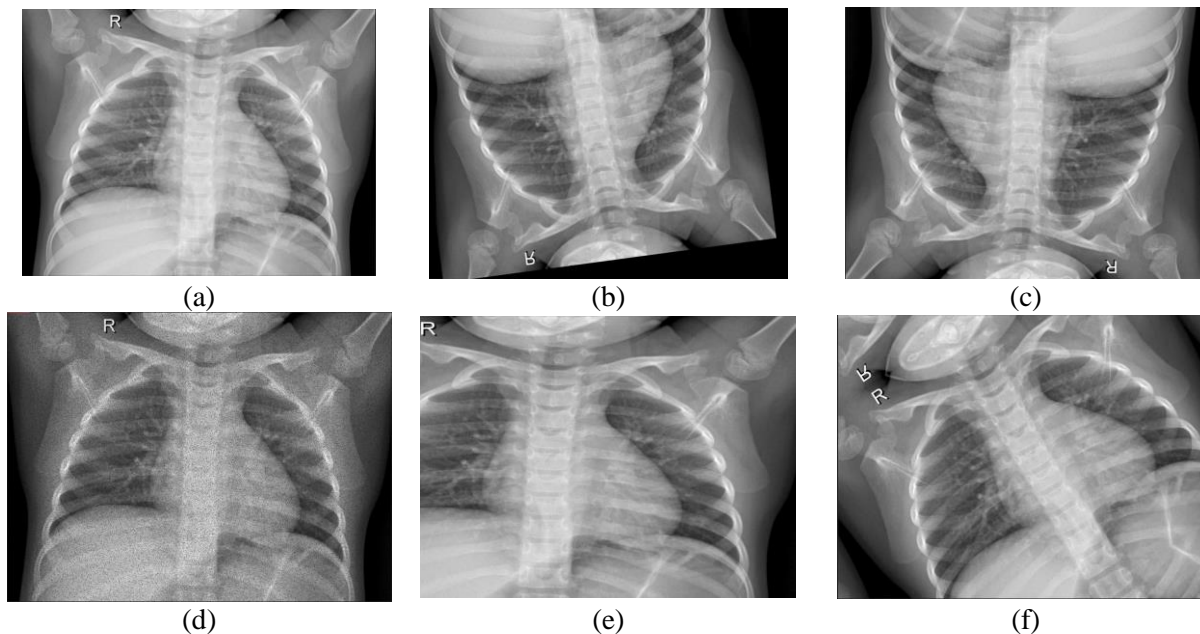


Figure 4. Augmentation results on normal thoracic images (a) Non-augmented images (b) Affine (c) Flip (d) Pixel dropout (e) Random-sized Crop (f) Shift Scale Rotate

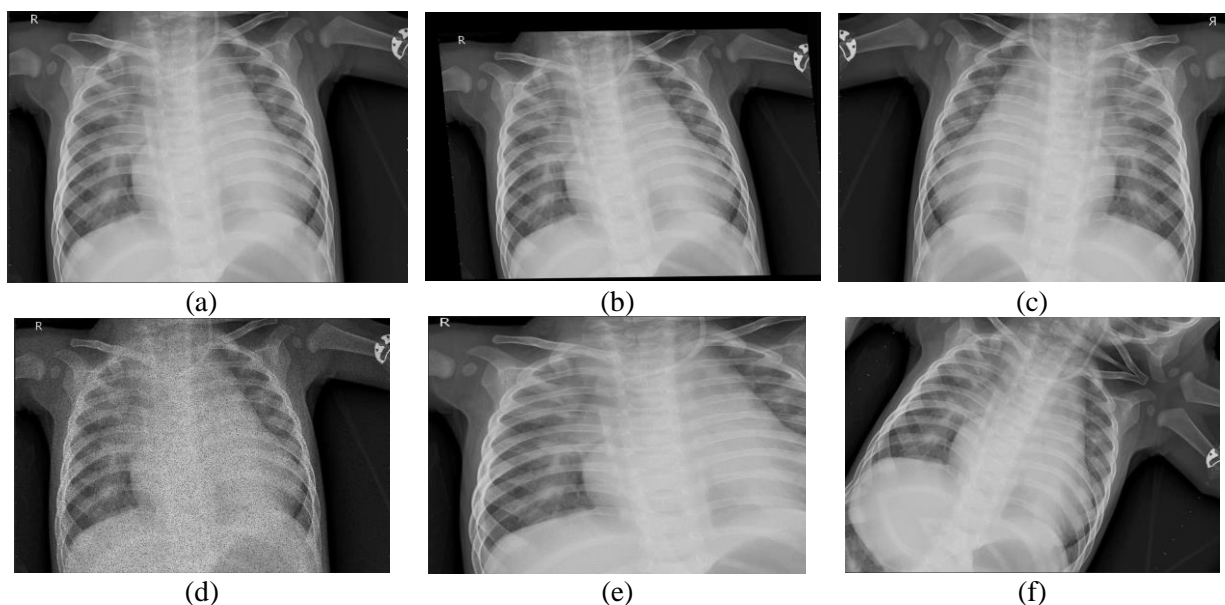


Figure 5. Augmentation results on pneumonia thoracic images (a) Non-augmented images (b) Affine (c) Flip (d) Pixel dropout (e) Random-sized Crop (f) Shift Scale Rotate

Explanation of the results of the augmentation performed on the thoracic image:

- a. Affine: indicates a change in the position of the image in the frame where the area left by pixels will be replaced with black
- b. Flip: shows the image area like a flipped paper on the front page
- c. Pixel Dropout: the white area of the image will be covered with a fine distribution of black dots that are evenly distributed like dust
- d. Random-sized Crop: crop part of the image area
- e. Shift Scale Rotate: like affine augmentation but no empty areas are replaced with black

3.2 CNN Implementation

3.2.1. CNN Architecture

The CNN architecture applied for classification is 4 Convolution Layer "Conv2D" with Activation Layer "ReLU" in each layer. Combined with 4 layers of "Max Pooling" type Pooling that go hand in hand with Conv2D. Then, a "Flatten" Reshaping Layer is applied to change or manipulate the feature map as a result of the convolution process. From here, the feature map continues on the "Dense/Fully-Connected Layer" as the Core Layer that is implemented.

In the final stage, an Activation Layer of type “Softmax” is used to determine the final result of a series of classification processes.

To obtain the classification of the training process carried out on the model, "Accuracy" is applied as a unit to obtain the accuracy value from the CNN configuration, while "Categorical Crossentropy" is applied as Losses to obtain the loss value. “Adam Optimizer” is used in the Optimizer parameter so that the training process can be carried out better. A summary of the CNN architecture applied in this study can be seen in Figure 6.

```

Model: "sequential"
-----
Layer (type)                Output Shape                Param #
-----
conv2d (Conv2D)             (None, 126, 126, 32)       896
max_pooling2d (MaxPooling2D) (None, 63, 63, 32)         0
conv2d_1 (Conv2D)           (None, 61, 61, 64)         18496
max_pooling2d_1 (MaxPooling2D) (None, 30, 30, 64)         0
conv2d_2 (Conv2D)           (None, 28, 28, 64)         36928
max_pooling2d_2 (MaxPooling2D) (None, 14, 14, 64)         0
conv2d_3 (Conv2D)           (None, 12, 12, 128)        73856
max_pooling2d_3 (MaxPooling2D) (None, 6, 6, 128)          0
flatten (Flatten)           (None, 4608)                0
dense (Dense)                (None, 2)                   9218
-----
Total params: 139,394
Trainable params: 139,394
Non-trainable params: 0
    
```

Figure 6. CNN Architecture

a. Accuracy of training and validation results for each type of augmentation

The augmentation process aims to increase the variance of the image by manipulating the image without removing information from the image as a whole. The results of the training and validation processes show that each type of augmentation has a different accuracy value according to the image changes in the augmentation process. In this process, the level of accuracy of the augmentation process is shown in accordance with the amount in the training and validation processes.

Table 2 and Table 3 show that there is an effect of augmentation on the accuracy of the results of training and validation. Each type of augmentation has its own characteristics that cause differences in accuracy results, where there is an increase and decrease in the accuracy value of each type of augmentation on non-augmented images, as illustrated in Figure 7 and Figure 8.

Table 2. Result of Training Phase

Augmentation Type	Epoch	Amount of Image	Training accuracy	Training Loss
Normal	200	4684	0.89625	0.218452
Affine	200	4684	0.90625	0.272080
Flip	200	4684	0.93750	0.165130
Pixel Dropout	200	4684	0.90625	0.261765
Random-sized Crop	200	4684	0.84375	0.325504
Shift Scale Rotate	200	4684	0.90625	0.2981152
Normal+ALL Augmentation	200	28106	0.81259	0.413023
Average	-	-	0,886977	0,279152743

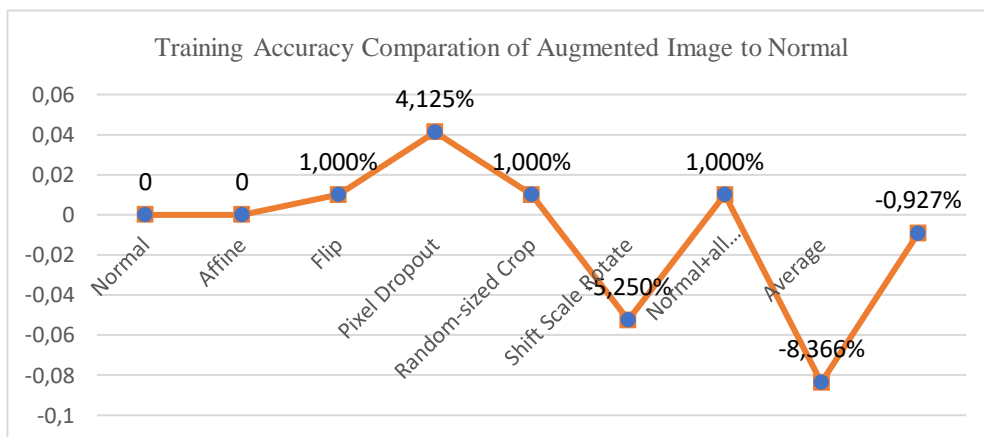


Figure 7. Comparison of Image Augmentation on Training Phase

From the results of the training process, the Flip type augmentation provides the highest accuracy value of 93.750% compared to other types of augmentation. This shows an increase in the accuracy value of 4.125% from the non-augmentation image or by 5.052% from the overall average value of the training which has an average value of 88.698%. The increase and decrease in the value of accuracy in the training process shows that augmentation has an influence on the CNN training process in studying image characteristics.

Meanwhile, training loss is likened to the error rate in studying image characteristics in the training process. From this study, the loss rate cannot be ascertained if there is a correlation that the higher the accuracy is inversely proportional to the lower loss in the training process.

Table 3. Result of Validation Phase

Augmentation Type	Epoch	Amount of Image	Validation accuracy	Validation Loss
Normal	200	585	0.90875	0.306629
Affine	200	585	0.93750	0.221345
Flip	200	585	0.93750	0.175327
Pixel Dropout	200	585	0.96875	0.109556
Random-sized Crop	200	585	0.87500	0.259219
Shift Scale Rotate	200	585	0.81250	0.374405
Normal+ALL Augmentation	200	3510	0.90625	0.257349
Average	-	-	0,906607	0,243404

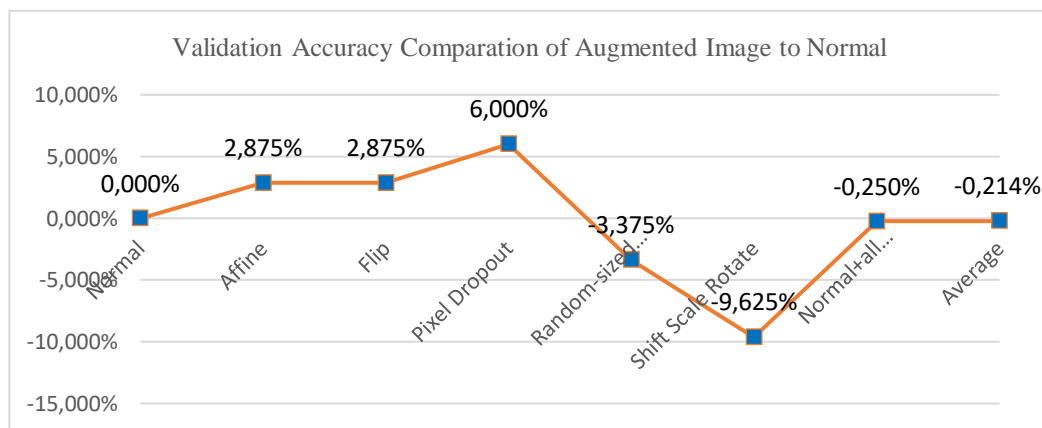


Figure 8. Comparison of Image Augmentation on Validation Phase

From the results of the validation process, the Pixel Dropout type augmentation provides the highest accuracy value of 96.875% compared to other types of augmentation in the validation phase. This shows an increase in the accuracy value of 6% from the non-augmentation image or 6.214% from the overall average validation value which has an average value of 90.660%. The increase and decrease in the value of accuracy in the validation process shows that augmentation has an influence on the model selection process in CNN in studying image characteristics.

Meanwhile, validation loss is likened to the error rate in determining the best model for the CNN architecture from the training process. From this study, the level of loss cannot be ascertained if there is a correlation that the higher the accuracy is inversely proportional to the lower loss in the validation process.

The training process is the stage where the machine learns the characteristics of the objects entered on the CNN and makes the best model in studying the data. Meanwhile, the validation stage is used to determine which model is the best in studying the characteristics of the data. The training and validation processes are carried out sequentially before the data is finally tested in the testing process. From Table 2, Table 3, Figure 7, and Figure 8 demonstrated that it cannot be ascertained that there is a direct correlation between the training and validation processes which indicates that a high training value will determine a high validation value as well. The opposite also applies to the low value of accuracy in the training and validation processes.

2. Accuracy of testing phase based on image augmentation

The training and testing process is used to train CNN with available data and determine the best model of the training process. This stage is then followed by a testing process to test how the model has been trained. Table 4 shows the results of the image testing process. Figure 9 illustrate the difference between its accuracy.

Table 4. Result of Testing Phase

Augmentation Type	Epoch	Amount of Image	Testing accuracy
Normal	200	567	0.909114
Affine	200	567	0.873935
Flip	200	567	0.930818

Pixel Dropout	200	567	0.936998
Random-sized Crop	200	567	0.947189
Shift Scale Rotate	200	567	0.892675
Normal+ALL Augmentation	200	3522	0.895230
Average			0,91227986

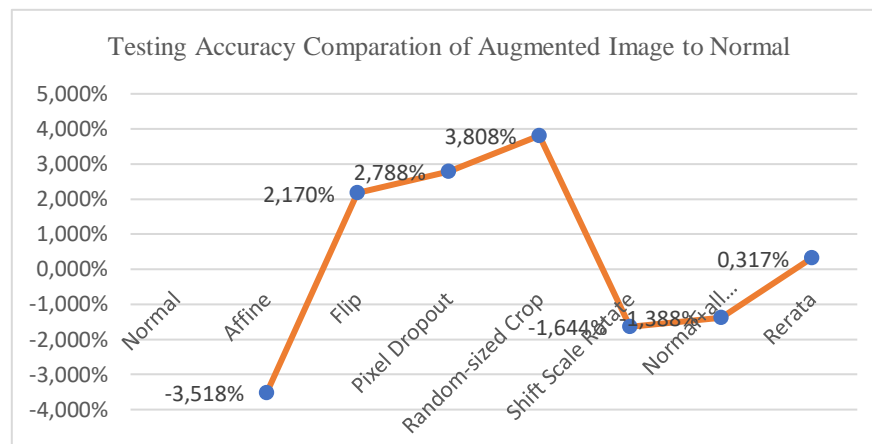


Figure 9. Comparison of Image Augmentation on Testing Phase

From the results of the testing process, the Random-sized Crop augmentation gave the highest accuracy value of 94,719% compared to other types of augmentation in the testing phase. This shows an increase in the accuracy value of 3.808% from the non-augmentation image or 3.419% from the overall average test value which has an average value of 91.227%. The increase and decrease in the value of accuracy in the testing process shows that augmentation has an influence on the data testing process that describes how the model is when applied to real data. Although the data used is still derived from the same thoracic image dataset, at least the final results of the testing process show how the overall system performance when implemented in real cases.

Regarding augmentation, from the test results, it can be seen that the random-sized crop augmentation provides the highest test value compared to the other five types of data. The assumption is that the random sized crop does not remove too much information contained in the image compared to other augmentations. Even in some random-sized results it appears that this operation removes areas that contain information that is not really needed, namely the black area outside the thoracic skeleton that actually contains the most information. One of the results of a random-sized crop that can provide can be seen from Figure 10.

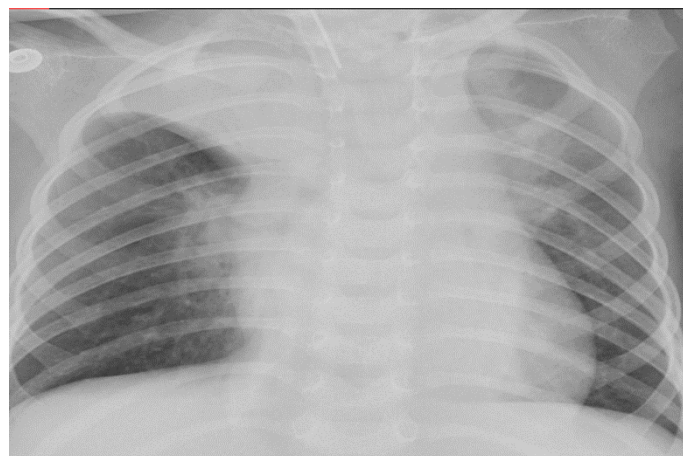


Figure 10. Result of Random-sized Crop

Based on the test results, from the CNN model developed in classifying pneumonia, it is known that random-sized pixel augmentation provides the highest increase in accuracy compared to non-augmented images.

4. Conclusion

From the research committed, the following conclusions can be obtained. Of the 5 types of spatial-level augmentation applied, the Flip type augmentation provides the highest accuracy value in the training process, which is 93.750%. At the validation stage, the Pixel Dropout type augmentation provides the highest accuracy value with 96.875%. Meanwhile, in the testing phase, Random-sized Crop has a value of 94.719% as the highest accuracy. Augmentation

has an influence on the accuracy value of the CNN model, although it cannot guarantee an escalation in CNN performance. Also, the accuracy value obtained in the training process is not always directly proportional to the accuracy value at the validation and testing stages when the augmentation process is applied.

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REFERENCES

- [1] Moch. D. Nugraha, “Analisis Faktor Risiko Kematian Akibat Infeksi Covid-19,” *Jurnal Ilmu Kesehatan Bhakti Husada: Health Sciences Journal*, vol. 12, no. 2, pp. 204–214, 2021, doi: 10.34305/jikbh.v12i2.343.
- [2] H. A. Diah Handayani, Dwi Rendra Hadi, Fathiyah Isbaniah, Erlina Burhan, “Penyakit Virus Corona 2019,” *Jurnal Respirologi*, vol. 40, no. 2, p. 119, 2020, [Online]. Available: <https://jurnalrespirologi.org/index.php/jri/article/download/101/110>
- [3] M. N. Afifah, “8 Penyakit Bawaan atau Komorbid Covid-19 yang Perlu Diwaspadai,” *Kompas.com*, 2021. <https://health.kompas.com/read/2021/07/31/120100668/8-penyakit-bawaan-atau-komorbid-covid-19-yang-perlu-diwaspadai?page=all> (accessed Jan. 21, 2022).
- [4] Andrew M. Freeman and J. Townes R. Leigh, “Viral Pneumonia,” National Library of Medicine. StatPearls Publishing, Jan. 2022.
- [5] J. M. Galván and O. Rajas, “Review of Non-bacterial Infections in Respiratory Medicine : Viral Pneumonia &,” vol. 51, no. 11, pp. 590–597, 2015.
- [6] L. Gattinoni et al., “COVID-19 pneumonia : pathophysiology and management,” *European Respiratory Review*, no. June, pp. 1–13, 2021, doi: 10.1183/16000617.0138-2021.
- [7] W. H. Organization, “Middle East respiratory syndrome coronavirus (MERS-CoV),” WHO WEB, 2019. [https://www.who.int/news-room/fact-sheets/detail/middle-east-respiratory-syndrome-coronavirus-\(mers-cov\)](https://www.who.int/news-room/fact-sheets/detail/middle-east-respiratory-syndrome-coronavirus-(mers-cov)) (accessed Feb. 28, 2022).
- [8] Y. T. Y. Steve, “Penjelasan tentang Pneumonia & Novel Coronavirus COVID-19,” *mountelizabeth*, 2020. <https://www.mountelizabeth.com.sg/id/healthplus/article/pneumonia-and-coronavirus> (accessed Mar. 01, 2022).
- [9] N. Yudistira, A. W. Widodo, and B. Rahayudi, “Deteksi Covid-19 pada Citra Sinar-X Dada Menggunakan Deep Learning yang Efisien,” *Jurnal Teknologi Informasi dan Ilmu Komputer*, vol. 7, no. 6, p. 1289, 2020, doi: 10.25126/jtiik.2020763651.
- [10] M. T. Cicerone and C. H. Camp, “Potential Roles for Spectroscopic Coherent Raman Imaging for Histopathology and Biomedicine,” in *Neurophotonics and Biomedical Spectroscopy*, Elsevier, 2019, pp. 547–570. doi: 10.1016/B978-0-323-48067-3.00021-4.
- [11] A. Peryanto, A. Yudhana, and R. Umar, “Klasifikasi Citra Menggunakan Convolutional Neural Network dan K Fold Cross Validation,” *Journal of Applied Informatics and Computing*, vol. 4, no. 1, pp. 45–51, 2020, doi: 10.30871/jaic.v4i1.2017.
- [12] Y. Chen, L. Song, Y. Liu, L. Yang, and D. Li, “A review of the artificial neural network models for water quality prediction,” *Applied Sciences (Switzerland)*, vol. 10, no. 17, 2020, doi: 10.3390/app10175776.
- [13] R. Yamashita, M. Nishio, R. K. G. Do, and K. Togashi, “Convolutional neural networks: an overview and application in radiology,” *Insights Imaging*, vol. 9, no. 4, pp. 611–629, Aug. 2018, doi: 10.1007/s13244-018-0639-9.
- [14] N. Nasrullah, J. Sang, M. S. Alam, M. Mateen, B. Cai, and H. Hu, “Automated Lung Nodule Detection and Classification Using Deep Learning Combined with Multiple Strategies.,” *Sensors (Basel)*, vol. 19, no. 17, Aug. 2019, doi: 10.3390/s19173722.
- [15] W. Swastika, “Studi Awal Deteksi Covid-19 Menggunakan Citra Ct Berbasis Deep Preliminary Study of Covid-19 Detection Using Ct Image Based on,” *Jurnal Teknologi Informasi dan Ilmu Komputer*, vol. 7, no. 3, pp. 629–634, 2020, doi: 10.25126/jtiik.202073399.
- [16] X. Chen, “Image enhancement effect on the performance of convolutional neural networks,” no. June, pp. 1–40, 2019, [Online]. Available: www.bth.se
- [17] C. Luo, X. Li, J. Yin, J. He, D. gao, and J. Zhou, “How Does the Data Set and the Number of Categories Affect CNN-based Image Classification Performance?,” *Journal of Software*, vol. 14, no. 4, pp. 168–181, 2019, doi: 10.17706/jsw.14.4.168-181.
- [18] M. Xu, S. Yoon, A. Fuentes, and D. S. Park, “A Comprehensive Survey of Image Augmentation Techniques for Deep Learning,” May 2022, [Online]. Available: <http://arxiv.org/abs/2205.01491>
- [19] Su. Lau, “Image Augmentation for Deep Learning | by Suki Lau | Towards Data Science,” *Towards Data Science*, Jul. 11, 2017. <https://towardsdatascience.com/image-augmentation-for-deep-learning-histogram-equalization-a71387f609b2> (accessed Aug. 31, 2022).
- [20] “Albumentations Documentation.” <https://albumentations.ai/docs/> (accessed Sep. 01, 2022).
- [21] S. Adi Widiarto, W. Andi Saputra, and A. Ratna Dewi, “Klasifikasi Citra X-Ray Toraks Dengan Menggunakan Contrast Limited Adaptive Histogram Equalization Dan Convolutional Neural Network (Studi Kasus: Pneumonia).”
- [22] “Keras API reference.” <https://keras.io/api/> (accessed Sep. 01, 2022).
- [23] H. X. Huynh, B. Q. Truong, K. T. Nguyen Thanh, and D. Q. Truong, “Plant Identification Using New Architecture Convolutional Neural Networks Combine with Replacing the Red of Color Channel Image by Vein Morphology Leaf,” *Vietnam Journal of Computer Science*, vol. 07, no. 02, pp. 197–208, May 2020, doi: 10.1142/S2196888820500116.
- [24] M. Dhouibi, A. K. ben Salem, and S. ben Saoud, “Optimization of CNN model for image classification,” in *2021 IEEE International Conference on Design & Test of Integrated Micro & Nano-Systems (DTS)*, Jun. 2021, pp. 1–6. doi: 10.1109/DTS52014.2021.9497988.