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A New Approach to Detect COVID-19 in X-Ray Images of Indonesians

Anggraini Dwi Sensusiati[1], Aji Sapta Pramulen[2], Dewinda Julianensi Rumala[2], I Ketut Eddy Purnama[2], Alfian Nur Rosyid[3], Muhammad Amin[3], Rofida Lathifah[4]

[1] Department of Radiology, Faculty of Medicine, Universitas Airlangga, Surabaya, Indonesia

[2] Department of Electrical Engineering, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia

[3] Department of Pulmonology and Respiratory Medicine, Faculty of Medicine, Universitas Airlangga, Surabaya, Indonesia

[4] School of Health Sciences, University of London, London, United Kingdom

Abstract: The coronavirus disease 2019 or COVID-19 is a current global pandemic. This disease has a high prevalence in Indonesia, with 307,120 positive cases and 11,253 deaths on October 6, 2020. COVID-19 can be detected in various manners, one of which is through chest X-Ray. This present research applies an approach to COVID-19 detection through X-Ray that features preprocessing, augmentation, ELU activation function application, and optimizer use. The results show that the best performance is generated by applying the ReLU activation function at epoch 76 with a testing accuracy of 96.44%, the sensitivity of 97.4%, specificity of 95.95%, and DICE of 95.77%.

Keywords: COVID-19, X-ray, augmentation.

在印度尼西亚人的 X 射线图像中检测新冠肺炎 的新方法

摘要：2019 年冠状病毒病或新冠肺炎是当前的全球大流行病。这种疾病在印度尼西亚的流行率很高，2020 年 10 月 6 日有 307,120 例阳性病例和 11,253 例死亡。新冠肺炎可以通过多种方式检测到，其中之一是通过胸部 X 光检查。本研究采用了一种通过 X 射线检测新冠肺炎的方法，该方法具有预处理、增强、指数线性单元激活函数应用和优化器使用的特点。结果表明，在时代 76 应用整流线性单元激活函数产生最佳性能，测试准确率为 96.44%，灵敏度为 97.4%，特异性为 95.95%，持续时间完整性承诺努力框架为 95.77%。

关键词：新冠肺炎，X 射線，增強。

1. Introduction

A recent cluster of pneumonia cases in Wuhan, China, has been reported to the WHO on December 31, 2019. These pneumonia cases were identified as novel betacoronavirus, novel coronavirus 2019 (2019-nCoV or SARS-CoV-2, the cause of the coronavirus disease 2019) [1]. Over 1,045,955 had died from COVID-19. The virus poses a serious threat to numerous countries worldwide as it can disturb or even destroy various life sectors. Currently, COVID-19 has become a common enemy; everyone must combat it to avert the worst conditions. In Indonesia, per se, 307,120 have been infected with the disease, and 11,253 have died [2]. Due to the lack of a special antivirus agent to cure the infection and the absence of a vaccine, some control measures have been introduced both in China and worldwide to prevent transmissions [1].

Several strategies have been applied to suppress the relatively rapid increase in the number of patients. Efforts to deny this disease are extremely hard or even impossible, but we can still curb this high growth rate to

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About the authors: Anggraini Dwi Sensusiati, Department of Radiology, Faculty of Medicine, Universitas Airlangga, Surabaya, Indonesia; Aji Sapta Pramulen, Dewinda Julianensi Rumala, I. Ketut Eddy Purnama, Department of Electrical Engineering, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia; Alfian Nur Rosyid, Muhammad Amin, Department of Pulmonology and Respiratory Medicine, Faculty of Medicine, Universitas Airlangga, Surabaya, Indonesia; Rofida Lathifah, School of Health Sciences, University of London, London, United Kingdom

maintain equilibrium with the medical treatment capacity. This way, the mortality rate can be reduced. These strategies include tracing patients' origins, city/country isolation, and mass testing. At present, main diagnoses are enforced through polymerase chain reaction (PCR) and throat swab tests, in tandem with a confirmation approach to provide accurate diagnoses [3]. Yet, these methods are time-consuming and costly. It is impossible for the diagnosis process or initial screening to employ these methods. According to the symptoms exhibited, an alternative way to be considered is a non-invasive measure through lung imaging. COVID-19 diagnoses usually are linked to pneumonia symptoms and chest X-Ray. The latter is the first imaging technique that plays an essential role in diagnosing COVID-19 [4].

Abbas et al. [4] conducted a study focusing on an offered novel model. After X-Ray feature extraction by deep learning, decomposition is performed to increase the classification's accuracy and sensitivity. However, this model comes with a new inefficiency problem since the model features an added computation process that is more time-consuming and difficult to perform. Another work uses X-Ray data for detection. Abolfazl et al. [5] has classified the chest X-ray image using machine learning. The classification is to distinguish between COVID-19, normal, and pneumonia. However, in this study, there are shortcomings of feature extraction used, but they cannot say it is the best because it is still not compared to other feature extraction. In addition, the use of datasets is still small, so the robustness of the model from all data conditions has not been properly verified. Mohamed et al. [6] used Fractional Multichannel Exponent Moments (FrMEMs) as feature extraction for chest X-Ray images with modified Manta-Ray Foraging Optimization (MRFO).

In contrast, the classification used the KNN classifier. However, this research is still limited to the use of the extraction feature. The total feature extraction resulting from the proposed method is 961 features. It causes a lot of time-consuming for computations to produce these features. Mohd Zulfaezal et al. [7] conducted a study on Covid-19 chest X-ray classification using ResNet-101. However, in this study, the sensitivity, specificity, and accuracy were 0.82, 77.3%, 71.8%, and 71.9%, respectively. This result is below 80%, whereas the average sensitivity, specificity, and accuracy are above 80%.

Regarding problems that have arisen in the existing research, this paper proposes a new approach for COVID-19 classification based on chest X-Ray imaging using Convolutional Neural Network (CNN). The approach consists of preprocessing X-Ray image to exclude unwanted object, data augmentation to increase the number of data, applying ReLU activation function application, and utilizing ADAM optimizer.

2. Methods

2.1. Data Collection

In this research, chest X-Ray data for COVID-19 were obtained from Airlangga University Teaching Hospital. In contrast, chest X-Ray data for other diseases and health conditions were obtained from the National Institute of Health Chest X-Ray Dataset. The number of data used was 513 for COVID-19 and 750 for non-COVID-19. The composition of disease and normal data in the non-COVID-19 dataset was as shown in Table 1. The dataset acquired for this research was in the form of grayscale images.

2.2. Approach

In the past few years, deep learning has been popular, especially in convolutional neural networks (CNN), which can display better performance than traditional machine learning in image classification, medical images being no exception [8]. A variety of network architectures have been built from CNN, including Inception [9], MobileNet [10], Densenet [11], to name a few. CNN is composed of multiple layers, namely convolution layer, pooling layer, and fully connected layer, unlike traditional artificial neural network since CNN regulates neurons, giving it three dimensions (width, height, and depth). Every layer in CNN transforms 3D inputs into 3D outputs from neuron activation. This research is to use a new approach to detecting COVID-19 in the X-Ray images of Indonesians.

Table 1 Non-COVID-19 data composition

Pleural Thickening	50
Cardiomegaly	50
Effusion	50
Atelectasis	50
Nodule	50
Edema	50
Normal	50
Hernia	50
Pneumonia	50
Infiltration	50
Pneumothorax	50
Mass	50
Emphysema	50
Consolidation	50
Fibrosis	50
Total: 750	

This new approach starts with a method described as presented in Figure 1. Preprocessing is performed on X-Ray images to meet the need, as seen in Figure 2.

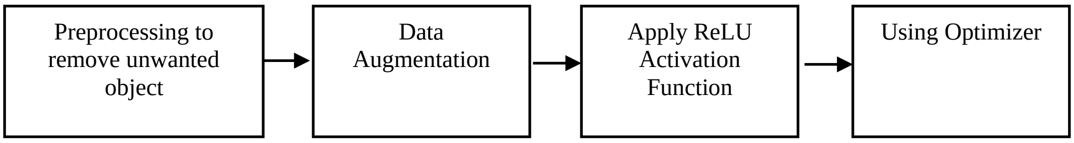

Fig. 1 Block diagram of the COVID-19 detection system

2.2.1. Preprocessing

The first stage in this study is preprocessing. This stage is prominent as it allows for uniformity in the dataset, influencing the learning outcomes. Without this stage of preprocessing, there will arise a high contrast between one datum and another. The COVID-19 dataset used in this research initially appears, as shown in Figure 2.a. However, the Non-COVID-19 dataset used had a different color composition. More specifically speaking, the colors in non-COVID-19 images are the negative of COVID-19, as shown in Figure 2.b.

The first step in this preprocessing stage is to convert negative images. This treatment is only applicable to COVID-19 data to have the same color composition as non-COVID-19 data. Then, border cropping is performed on X-Ray data of the COVID-19 class. This technique is necessary to make the images more focused on the chest. Therefore, the frame in the image pointed out in Figure 2.a. can be removed. Besides, the text that interferes with the object is also eliminated.

(a) Sample COVID-19 data

(b) Sample Non-COVID Atelectasis data

Fig. 2 Sample COVID-19 dataset

The following steps should be followed to perform border cropping:

1. Do binary thresholding on the COVID-19 X-Ray images, where the threshold pixel value provided is 185. Hence, the pixel value in images that are below 185 will be converted into 0.

$$dst(x,y) = \begin{cases} maxValue \ \ if \ src(x,y) > T(x,y) \\ 0 \ otherwhise \end{cases} \tag{1}$$

2. Then, perform morphological closing to eliminate the noise in the foreground area in the X-Ray images, which have been adjusted to the threshold. In this step, the kernel ellipse used is sized 11 × 11.

3. Find a maximum contour for the area used to find the outline or silhouette of an object. The contour search can be carried out after separating the foreground and the background, in which case, after thresholding, the image background is black in color or pixel-valued 0. In contrast, the foreground is white in color or pixel-valued 255.

4. After the contour is found, image cropping can be performed according to the area contour.

Upon the background cropping of the COVID-19 X-Ray images, the images are resized. Hence, all images, both COVID-19-labeled and non-COVID-19-labeled, will be sized 150×150. Image resizing is needed to keep the computation load from becoming too big, shortening the training execution time. From this preprocessing stage, X-Ray images, as shown in Figure 3, are produced.

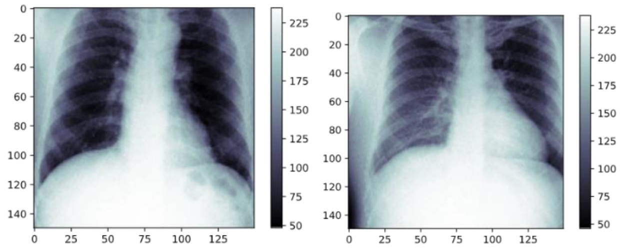

Fig. 3 X-Ray images preprocessing results

2.2.2. Data Augmentation

Data augmentation is conducted to multiply the number and variants of data through operations such as rotation, vertical flip, shear, and zoom, with values that are also varied. In this research, an operation is done to multiply data threefold. Therefore, a total of 3,789 data are obtained from this data augmentation stage. The results of data augmentation are as shown in Figure 4.

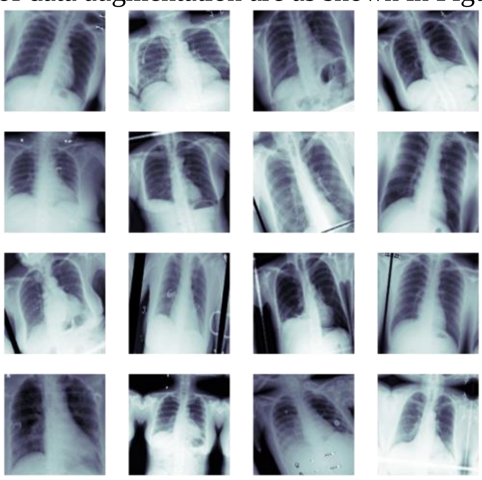

Fig. 4 Data augmentation results

After augmentation to a common number, data are separated into 90% training (1,361) and 10% testing (152). In data training, data are divided into training and validation in the following proportions: 80% training

(1,088) and 20% validation (273). From this data separation, the composition for COVID-19 and non-COVID-19 data is as shown in Table 2.

Table 2 Data composition after augmentation

	COVID	non-COVID
Training	340	468
Validation	68	134
Testing	105	148

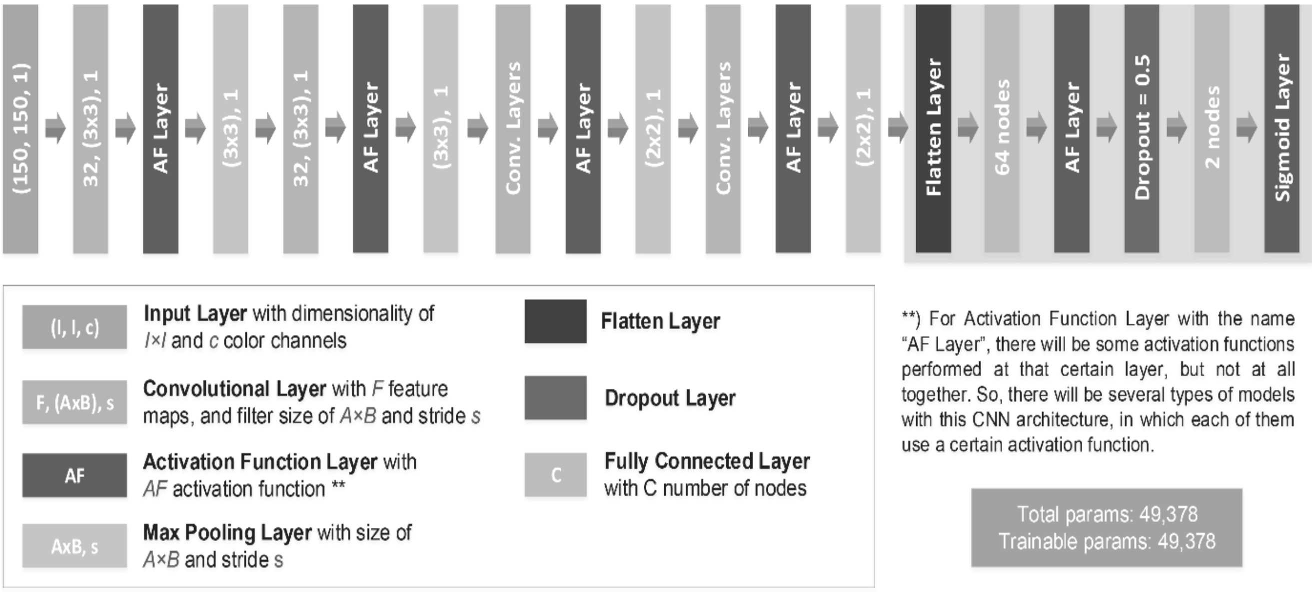

Fig. 5 CNN architecture extracted from [12]

2.2.3. CNN Architecture

The Deep Learning method used in this research is the Convolutional Neural Network. The architecture used follows the paper written by Rumala et al. [12], as shown in Figure 5. The CNN architecture building has a total of 19 layers, including the input and output layers. The CNN architecture in this research consists of the following:

- Input layer: this layer takes X-Ray image inputs.
- The convolutional layer will perform feature extraction in images by a convolutional process between the matrix filter and the image input. With many layer levels and different matrix filters, high levels will be obtained, such as edge, curve, and color features.
- Pooling layer: this layer is used to reduce the spatial size in order not only to lower the number of parameters and computation but also to prevent overfitting conditions in which the model is highly accurate in predicting the training data but fails to recognize non-training data. The pooling approaches frequently used are max pooling and average pooling. Max pooling takes a maximum value in a given area, while average pooling takes an average value.
- Activation function layer: the activation functions used in this research are the ReLU and ELU functions. In the study by Rumala et al. [12], a significant classifier model performance is obtained using ELU. However, the ReLU activation function can serve as an alternative when the ELU activation function is unusable. In this study, experiments with the two activation functions are to be conducted, from which the results are to be compared to find the best between the two functions.
- Fully connected layer: this layer is a feedforward artificial neural network that consists of an input layer, hidden layer, and output layer, in which case every neuron on a layer is fully connected to neurons on the previous and succeeding layers.

Other than applying the CNN architecture mentioned above, the dataset in this research is also to be trained using a more complex CNN architecture model, that is, Inception V3: This architecture has a depth of 42 layers, causing the computation to cost 2.5 times higher than GoogleNet and render a greater efficiency than VGGNet. This CNN architecture Inception V3 has the idea to conduct convolutional factorization, reducing the number of parameters obtained. However, this will not reduce the efficiency of the model.

2.2.4. Regularization Technique

In this research, a fully connected layer has been added with a drop-out layer with a rate of 0.5. Drop out layer is useful for overfitting. Besides, the Early Stopping technique was also performed. Too many epochs can cause overfitting in the training dataset, but too few can also cause underfitting. Therefore, epochs in the optimal number are needed to generate an optimal output. To overcome this issue, the Early Stopping Technique can be used. This way, we will terminate training upon achieving optimal accuracy or loss value of both the training and validation data.

3. Results

This experiment classifies COVID-19 and non-COVID-19 with a dataset of chest X-Ray images. Preprocessing is applied to the dataset of chest X-Ray images to remove undesirable objects from the images. This technique is shown in Figure 2.

After removing the undesirable object, augmentation is conducted to develop a greater variety of the dataset. The augmented data are shown in Figure 4.

The dataset is classified with CNN, in which case CNN architecture is implemented by changing the activation function. From the results of classification using this activation function, the best available is searched. The total dataset used is shown in Table 2.

The model's performance tried with a change in the activation function developed is shown in Table 3. The best performance is obtained using the ReLU activation function at epoch 76 with a testing accuracy of 96.44%, sensitivity of 97.4%, specificity of 95.95%, and DICE 95.

Table 3 Accuracy matrix of the activation function best performance

Activation Function/Model	Epoch	Validation		Testing							
		Accuracy	Loss	TP	FP	TN	FN	Accuracy	Sensitivity	Specificity	Dice
Simple CNN ReLU	44	97.03	0.10	98	7	141	7	94.47	93.33	95.27	93.33
	50	95.05	0.14	100	10	138	5	94.07	95.24	93.24	93.02
	56	97.03	0.11	101	9	139	4	94.86	96.19	93.92	93.95
	76	97.03	0.14	102	6	142	3	96.44	97.14	95.95	95.77
	100	97.03	0.96	99	7	141	6	94.86	94.29	95.27	93.84
	200	96.04	0.15	102	11	137	3	94.47	97.14	92.57	93.58
Simple CNN ELU	20	92.57	0.22	91	8	140	14	91.30	86.67	94.59	89.22
	100	95.05	0.67	97	11	137	8	92.49	92.38	92.57	91.08
	200	92.08	0.41	98	10	138	7	93.28	93.33	93.24	92.02
Inception V3	34	93.07	0.33	98	11	137	7	92.89	93.33	92.57	91.59
	100	97.03	0.15	97	6	142	8	94.47	92.38	95.95	93.27

Figure 4 shows the model performance graph during training made with the ReLU activation function with an initial initiation at epoch 200. At epoch 55, the best model is obtained after early stopping at epoch 76. After the best model is found, the model is then applied to the testing data, and the results are shown in Figure 5.

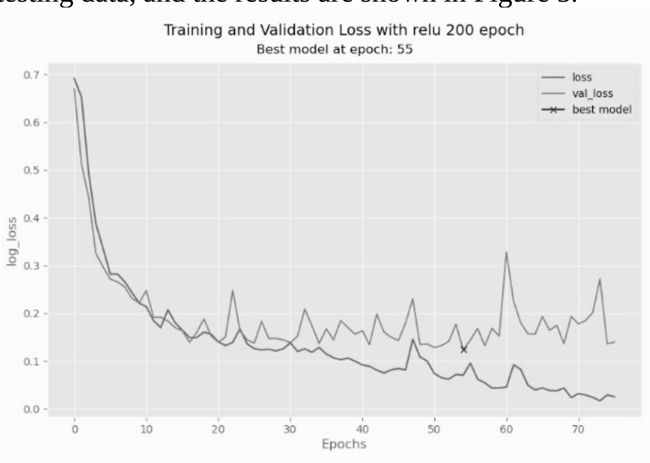

Fig. 4 Training and validation loss graph

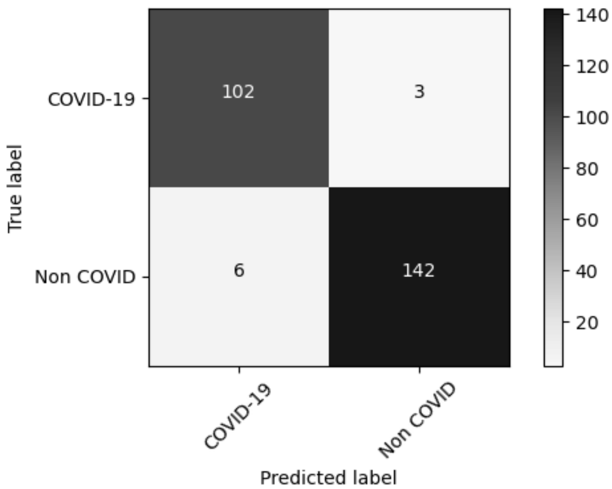

Fig. 5 Confusion matrix of the classifier

The results show the Confusion Matrix of the model obtained with high sensitivity, specificity, and accuracy. High sensitivity indicates that the model can detect that the image indeed shows a COVID-19 condition. In contrast, high specificity indicates that the model can detect that the image is not of a COVID-19 patient origin.

There are several benefits of having the automated system using the CNN method to classify COVID-19. A medical specialist can use the system to support the medical diagnosis he or she made. The system can learn to find detail and specific features in the X-ray image that human vision cannot detect. Then, the system can deliver real-time results. Hence, suitable to be applied in the case where a fast response time of medical diagnosis to be made. Although the automated system introduces several benefits, the limitation is in the non-technical issues such as how a medical specialist can accept the automated system and how the system can be used to support the diagnosis of the patients.

4. Conclusion

This paper proposes a new approach for COVID-19 classification based on chest X-Ray imaging using Convolutional Neural Network (CNN). The approach consists of preprocessing X-Ray image to exclude unwanted object, data augmentation to increase the number of data, applying ReLU activation function application, and utilizing ADAM optimizer. A comparison was done using the ELU activation function and also to the inception V3 model. The best performance is obtained using the ReLU activation function at epoch 76 with a testing accuracy of 96.44%, sensitivity of 97.4%, specificity of 95.95%, and DICE of 95.77%. The results show that our experiment has achieved classifying people infected and not infected with COVID-19 using CNN.

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