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Research/Review

Ground glass opacity detection convolutional neural network method efficient net-b0 architecture in corona virus disease 2019 cases

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Abstract

COVID-19 is an infectious disease caused by a new type of coronavirus. The gold standard diagnosis of COVID-19 is a PCR test. Thorax radiographic examination is an alternative to the diagnosis of COVID-19 against initial screening. Thorax radiography sensitivity is lacking in GGO detection of COVID-19. CNN's deep learning architecture EficientNet-B0 has the ability to represent the same diagnostic prediction features as radiologists. The purpose of this study resulted in CNN's EfficientNet-B0 architecture that is able to classify radiographic images of the thorax automatically in detecting GGO COVID-19 and has similar results with the results of the doctor's experiment. This type of research is a quasi-experimental design Post-test Only Control Group Design. Build the CNN EfficientNet-B0 architecture through the MATLAB R2021a program. The sample totaled 78 radiographic images of the thorax. The data analysis is a statistical test of Chi-Square. Research proves CNN's performance of the EfficientNet-B0 architecture is excellent in detecting GGO COVID-19 with an AUC value of 0.994range (0.90-1.00). The deep learning model can be considered as an alternative tool for establishing a diagnosis of COVID-19with the condition that the verification of the diagnosis decision remains based on the confirmation and justification of the radiologist.

Keywords: GGO COVID-19, thorax, CNN, EfficientNet-B0

INTRODUCTION

Corona Virus Disease 2019 (COVID-19) is an infectious disease caused by a new type of *coronavirus*[1]. Wednesday, March 11, 2020, COVID-19 was designated by the *World Health Organization* (WHO) as pandemic[2][3]. Most people infected with the COVID-19 virus will experience mild, moderate to specific symptoms. The elderly and those with health problems such as cardiovascular disease, chronic respiratory disease, diabetes and cancer will have a greater risk of getting the COVID-19 virus[1][4]

COVID-19 began to spread from Wuhan to most of China within a span of 30 days[5] although the spread was not as significant as what happened within Hubei province itself, in Indonesia there were more than 4.25

million confirmed cases of COVID-19 and more than 144 thousand confirmed deaths due to the COVID-19 pandemic[6].

The gold standard for diagnosing COVID-19 disease is the PCR (*Polymerase Chain Reaction*)[7] test. The advantages of the PCR test are simple techniques that are easy to understand, use, provide results quickly [6]and can detect virus variants[8]. However, to get a large number of PCR test results for a diagnosis of COVID- 19 takes a relatively long time[9]. Radiological examination can be an alternative to the initial diagnosis of COVID-19.

Thoracic radiological examinations such as *computed tomography scan* (CT *Scan*) of the thorax and radiography of the thorax can help diagnose COVID-19 early 10[10]. Detection of COVID-19 using radiographic imagery can provide information on the severity of the disease from asymptomatic to critically ill patients, which the 6:11 PCR test cannot do [6] [11]. Patients usually have normal CT *Scan* images within the first 0-2 days since symptoms of COVID-19 12 appear[12]. Based on research conducted by F. Pan et al 13 stated that on the image of the results of CT *Scan* thorax examination, patients who were declared free of COVID-19 disease, again showed significant signs of COVID-19, which appeared ten days after the onset of symptoms [13].

Thorax radiographic examination is one of the alternatives to handling COVID-19 in the initial diagnosis process. Thorax radiographic examination is a *non-invasive* procedure and is able to describe the condition of the lungs of COVID-19 patients. In addition, thoracic radiography does not require expensive costs and device settings and does not require large resources when applied for *screening* in large populations when compared to CT *Scan* examination.

One of the problems that arises is that diagnostic tests carried out after 5–13 days on patients who have actually recovered, are again found positive for COVID-19[14]. These important findings suggest that recovered patients may continue to spread the virus. Therefore, a more accurate method of diagnosis is needed. One of the most important weaknesses of thoracic radiographic image analysis is the inability to detect the early stages of COVID-19 because it does not have a high enough sensitivity in the detection of [10] *Ground Glass Opacity* (GGO) which is commonly found in COVID-19 patients[15].

The relatively rapid increase in the COVID-19 disease epidemic has also increased the workload of radiologists. This causes radiologists to experience burnout, and triggers inaccurate diagnoses, missed or delayed diagnoses[16]. The utilization of artificial intelligence can detect points invisible to the human eye[17]. This increases interest in developing automated detection systems based on *deep learning methods.* Therefore, accurate and fast *deep learning* methods are expected to help overcome this problem. Although radiologists are important because of their extensive experience in this field, in this case *deep learning* technology can help to get a quick and accurate diagnosis [15] [18].

Deep learning is a method formed from the basis of computational science, where in carrying out the digital image processing process this method uses pattern recognition techniques. One model of *deep learning* is*the Convolutional Neural Network* (CNN). CNN can support doctors to more easily interpret the findings of medical images. In addition, CNN is several used for segmentation of brain tumors on *Magnetic Resonance Imaging* (MRI) modalities, detecting polyps with virtual colonoscopy or CT *Scan* in colon cancer as well as in detecting breast cancer[19].

CNN is a popular *deep learning* method of pattern recognition in images. CNN is excellent at automatically and efficiently extracting complex features for image classification at a large scale of [20]. *Deep* learning methods can clearly distinguish images with similar characteristics that are difficult to recognize by traditional *machine learning* methods. Even *deep* learning can extract features objectively automatically and candirectly process image data in two dimensions, whereas traditional *machine* learning methods require extractingspecial features in the *feature learning* process[21]. CNN is the type of *neural network* most often used for detection and recognition of objects in an image that is superior in performing *computer vision* and *pattern recognition* tasks and has a development model that is *transfer learning* [22].One method of *transfer learning* is EfficientNet-B0. EfficientNet-B0 is a new architectural model that usesnetwork depth, width and resolution to deliver good performance, especially in terms of compute and parameter size. When compared to the latest EfficientNet architecture, EfficientNet-B7 with 66 million parameters, the EfficientNet-B0 architecture has the least number of parameters at 5.3 million parameters. The EfficientNet-B0 architecture has fast computation times and accuracy that can compete with other CNN architectures[23].

Based on the background above, researchers will examine the results of the performance of *deep learning* algorithm models in diagnosing COVID-19. The formulation of the problem in this study is whether there are similarities between CNN's *deep learning* model EfficientNet-B0 architecture in detecting GGO COVID-19 on thoracic radiographic images.

The purpose of this study was to analyze the similarity in the performance of CNN *deep learning* models in automatically detecting COVID-19 on thoracic radiographic images. The benefits of research can improve radiology services by utilizing *deep learning* and certainty in handling COVID-19 patients.

METHOD

This research will be conducted using a quasi-experimental method with *a posttest only control group design*[24]. This study aims to determine the difference between the CNN *deep learning* model of the EfficientNet-B0 architecture with the results of the expertise of radiology specialists through thoracic radiographic image analysis. The data source used is secondary data, obtained from PACS in the form of data in DICOM format.

The study began by creating a *deep learning* program with the CNN algorithm method, the Efficient Net-B0 architecture, then trained to recognize patterns or features from normal thoracic radiographic images and thoracic radiographic images with COVID-19 GGO. The method used to extract features automatically is the CNN method.

Deep learning performance assessment data analysis is assessed based on the classification results, which are performed with diagnostic tests to measure accuracy, sensitivity, specificity, positive presumptive value(NDP) and negative presumptive value (NDN) from model[25]. In addition, it is assessed based on the *ReceiverOperating Characteristic* (ROC).

RESULT AND DISCUSSION

The study used 226 thoracic radiographic image data which were divided into 148 training data sets consisting of 78 thoracic radiographic images with COVID-19 GGO and 70 normal thoracic radiographic images, while for the test data set consisting of 46 GGO COVID-19 thoracic radiographic images and 32 normal thoracic radiographic images, So the total sample used is 78. Normal samples and GGO COVID-19 based on the results of radiology specialists' experiments.

The purpose of classification in the COVID-19 GGO detection study can be classified based on several pathological characteristics in general such as bronchopneumonia and pneumonia both extra-sinistra and bilateral. The classification output that appears in the deep learning model is the greatest value. So the higher the similarity value of test data to training data, the greater the accuracy of the EfficientNet-B0 architecture deep learning model in detecting COVID-19 GGO thoracic images and normal thoracic images.

The last step is to analyze the performance of the deep learning model through the results of the CNN deep learning model classification of the EfficientNet-B0 architecture. In the GGO COVID-19 data classification test process with the CNN deep learning model of the EfficientNet-B0 architecture, 99.94% classification results were obtained according to the test data label. 46 COVID-19 GGO classification test data were detected read as COVID-19 GGO and 0 COVID-19 GGO classification test data read as normal. Therefore, the total prediction error in the classification of GGO COVID-19 test data is 0%. In the normal data classification test process with the CNN deep learning model of the EfficientNet-B0 architecture, 97.87% classification results were obtained according to the test data label. 31 normal test data were detected read as normal and 1 normal classification test data read as GGO COVID-19. So the total prediction error in the normal test data classification is 2.13%.On the performance classification of the CNN deep learning model of the EfficientNet-B0 architecture with:

Table 1: CNN deep learning performance of EfficientNet-B0 architecture

Kinerja	***Value***	**CNN (%)**
Akurasi	0,9871	98,71%
Sensitivitas	1	100%
Spesifisitas	0,9687	96,87%
Nilai duga positif	0,9787	97,87%
Nilai duga negatif	1	100%

The results of the performance classification of the EfficientNet-B0 architecture CNN deep learning model in table 1 above show that the level of accuracy, sensitivity, specificity and positive presumptive values are above the range of 0.90-1.00 which means that the CNN deep learning model of the EfficientNet-B0 architecture is "very good" used. The negative presumptive value (NDN) which shows results in the range of 0.90-1.00 which means that the ability of the CNN deep learning model of the EfficientNet-B0 architecture to detect normal thoracic images and classify them as normal is "excellent".

ROC curves are an effective performance measurement tool for deep learning. The table of ROC calculation results is shown in table 2 below with the AUC value as follows:

Table 2: Area Under the Curve (AUC) model deep learning CNN arsitektur EfficientNet-B0

AUC	Std.Error
0,994	0,006

Based on table 2 above, it shows that diagnostic tests with ROC value measurement methods show that AUC values obtained above the range of 0.90-1.00 which means that the CNN deep learning model of EfficientNet-B0 architecture shows performance in the "very good" category. Therefore, based on ROC measurement standards, the CNN deep learning model of the EfficientNet-B0 architecture is feasible and very good to be used to detect both COVID-19 and normal GGO thoracic radiographic images.CONCLUSION

The deep learning model can be considered as an alternative diagnostic tool for COVID-19 disease with the condition that verification of diagnosis decisions still refers to it based on the confirmation and justification of radiology specialists.

Suggestion

1. CNN's deep learning model of the EfficientNet-B0 architecture developed its ability to classify COVID-19 GGO levels in categories, typical or atypical of COVID-19 GGO
2. The EfficientNet-B0 architecture CNN deep learning model can be developed using larger data sets to increase accuracy and generalizability.
3. It is necessary to develop classification capabilities (add classification classes) from the CNN deep learning model of the EfficientNet-B0 architecture based on other supporting clinical types in COVID-19 cases, such as pneumonia, bronchopneumonia and others.

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