ORIGINAL ARTICLE

COVID-19 Severity based on Deep Convolutional Neural Networks Chest X-Ray Image in Aceh, Indonesia

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ABSTRACT

Introduction: Every area of our lives has been devastated by the worldwide Coronavirus disease 2019 (COVID-19) epidemic. However, the development of artificial intelligence has made it possible to build advanced applications that can fulfill this level of clinical accuracy. This study aimed to create a deep learning model that can detect COVID-19 from a chest image dataset of confirmed patients treated at the provincial hospital in Aceh.
Methods: Eight hundred confirmed COVID-19 patients' chest X-ray photos were gathered locally from Dr. Zainoel Abidin General Hospital, Banda Aceh. Performance was evaluated in several ways. First, the dataset was used for training and testing. Second, the data was used to train and test the model. VGG16 is a robust network adapted to an enhanced dataset constructed from a confirmed COVID-19 chest X-ray pool. To artificially produce a huge number of chest X-ray pictures, this study used data augmentation techniques such as random rotation at an angle between 10 and 10°, random noise, and horizontal flips.
Results: The experimental results were encouraging: the proposed models classified chest X-ray pictures as normal or COVID-19 with an accuracy of 97.20% for Resnet50, 98.10% for InceptionV3, and 98.30% for VGG16. The results showed the outstanding performance of straightforward COVID-19 diagnosis with the classification of COVID-19 severity, such as mild, severe, and very severe.
Conclusion: These made it possible to automate the X-ray image interpretation process accurately and could also be applied when materials and reverse transcription polymerase chain reaction (RT-PCR) tests are scarce.

INTRODUCTION

Chest X-ray is one of the most common clinical diagnostic tests performed on Coronavirus disease 2019 (COVID-19) patients. However, achieving maximum detection required special knowledge and experience interpreting chest X-rays. The number of radiologists in Indonesia is inadequate for increasingly tired health workers. The transmission rate is very high when conducting an examination, causing the need for new solutions, such as sophisticated technological innovations to detect COVID-19 in the lungs quickly.[1] Advances in artificial intelligence (AI) have enabled the adoption of sophisticated applications that can meet clinical accuracy requirements and deal with significant problems associated with large amounts of data. Furthermore, incorporating computer-assisted diagnostic data into the medical hierarchy can reduce errors, improve workload conditions, increase reliability, improve performance, and reduce diagnostic errors by providing radiologists with a reference base.[2]

The struggle against COVID-19 has been conducted in various forms and efforts. Innovative computerized solutions offer alternatives, such as patient-free examinations, to prevent this disease. Some examples include robotic solutions for the collection of examination materials, monitoring of vital signs, and assistance with the use of disinfectants.[3] In addition, image recognition and AI can actively be used to identify confirmed cases that do not follow quarantine

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protocols.[4] A study in Jordan proposed an alternative diagnostic using an AI system that can identify COVID-19 pneumonia from chest X-ray images with a high degree of accuracy, using convolutional neural network (CNN) and pre-trained models (i.e., MobileNet and VGG16). Meanwhile, pulmonary specialists collected chest images of confirmed patients from large local hospitals and examined over six months. These images were used to enrich the public dataset which was also collected in limited numbers and formed a larger group of training/test images compared to the related literature. The reported results were obtained from testing and evaluating the model using several chest X-ray data.[5]

Even though imaging-based diagnostic tests, such as chest X-ray and computed tomography (CT) scans, can screen for disease quickly, the interpretation of the results is still required in detail to confirm the possibility of COVID-19.[6] With the availability of this deep learning model, early diagnosis and detection will be more comprehensive and can detect the damage caused to the patients' lungs.[7] Therefore, several deep learning techniques can automate detection to overcome these challenges. This study aimed to create a deep learning model that can detect COVID-19 from a chest image dataset of confirmed patients treated at the provincial hospital in Aceh.

METHODS

The selected images were obtained based on polymerase chain reaction (PCR) swabs at Dr. Zainoel Abidin General Hospital, Banda Aceh. This was approved by the Health Research Ethics Committee, Faculty of Medicine, Universitas Syiah Kuala, Dr. Zainoel Abidin General Hospital, Banda Aceh (No: 043/EA/FK-RSUDZA/2022). Successful chest X-ray was obtained from subjects with a positive reverse transcription PCR (RT-PCR) test result and required hospitalization as determined by the clinician. Hospital stays ranged from five days to one month, with several subjects dying. The chest X-ray included as data was taken at admission.

Deep Learning Models

Deep learning is the most common and up-to-date AI method for categorization issues. It has been successfully employed in various applications, particularly in the medical industry.[8] The models utilized are described as follows:

Sequential 2D CN in the deep learning literature, CNN model represents one class. It belongs to a particular family of feed-forward neural networks, and studies showed that it is particularly effective in analyzing multidimensional data. In contrast to multilayer perceptrons, CNN saves memory since it shares parameters and makes sparse connections. The input images are converted into a matrix for the various components of the process.[9] The model comprises numerous convolution and pooling layers that alternate as follows:

Convolutional Layer

Convolutional layer (Conv2D) is responsible for defining pattern features. In this layer, the input image is passed through a filter, and the value generated from filtering consists of a feature map. This layer applies multiple kernels through the pattern to extract low- and high-level features (extract low- and high-level) in the pattern. The kernel is a 3×3 or 5×5 shaped matrix to be transformed with an input pattern. Furthermore, the step parameter is the set number of steps to shift the input matrix.[10]

Pooling Layer

The pooling layer reduces the number of feature maps and network parameters by applying appropriate mathematical calculations. This study used max-pooling and global average pooling. The max-pooling process only selects the maximum value using the specified matrix size in each feature map, resulting in reduced output "neurons". A global average pooling is used before a fully connected layer, reducing the data to one dimension. This connects to the fully connected layer after the global average pooling layer. Another intermediate layer used was the dropout to prevent overfitting and divergence.[11]

Dropout

Overfitting affects neural networks frequently, and dropout is employed as a tactic to introduce regularization into the network, which subsequently enhances generalization. It operates by arbitrarily ignoring some visible and hidden units, training the network to manage numerous separate internal representations.[12]

Fully Connected Layer

Fully connected layer is CNN's last and most crucial layer, which functions as a multilayer perceptron. The rectified linear unit (ReLU) activation function is used in the fully connected layer. In contrast, the softmax activation function predicts the output image in the fully connected layer. The mathematical calculations of the two activation functions are as follows:[13]

$$\mathrm{ReLU}(x) = \begin{cases} 0, & \text{if } x < 0 \\ x, & \text{if } x \geq 0 \end{cases}$$

$$\mathrm{Softmax}(x_i) = \frac{e^{x_i}}{\sum_{y=1}^{m} e^{x_y}}$$

Where x_i and m represent the input data and the number of classes, respectively (this study used 4 groups of chest X-ray). Neurons in the fully connected layer have full connection to all activation functions in the previous layer.

Pre-Trained Models

The VGG16 represents numerous models in the literature. It has been subjected to several modifications to enhance the accuracy, performance, and resource usage (e.g., VGG-19).[14] The VGG16 architecture proposed is as follows:

- The input layer is an X-ray image with a size of 224×224×3
- Two convolutional layers with 64 filters followed by a max pooling layer
- Two convolutional layers with 128 filters followed by a max pooling layer
- Three convolutional layers with 256 filters followed by a max pooling layer
- Two stacks, each with 3 convolutional layers with 512 filters and separated by a max pooling layer
- One final layer of max pooling
- Two layers are interconnected with 4608 channels
- Softmax output layer with the final classification

During training, the input to konvnet is a fixed-size RGB (224×224) image. The average calculated for each pixel is pre-processed by VGG16. The image is passed through a convolution layer stack, where the filter has a very small receptive field: 3×3 (which is the smallest size for capturing left/right, up/down, and center ideas and has an effective receptive field equal to one 7×7). This process is deeper (deep), has more non-linearity, and fewer parameters. The configuration used is a 3×3 convolution filter, seen as a linear transformation of the input line (followed by non-linearity). The input layer is set to 1 pixel for the 5×5 convolution layer, ensuring the spatial resolution is maintained. Furthermore, five max-pooling and multiple convolutional layers assist in spatial pooling. Max-pooling is conducted through a 2×2 pixel window (frame), with step 2.[15]

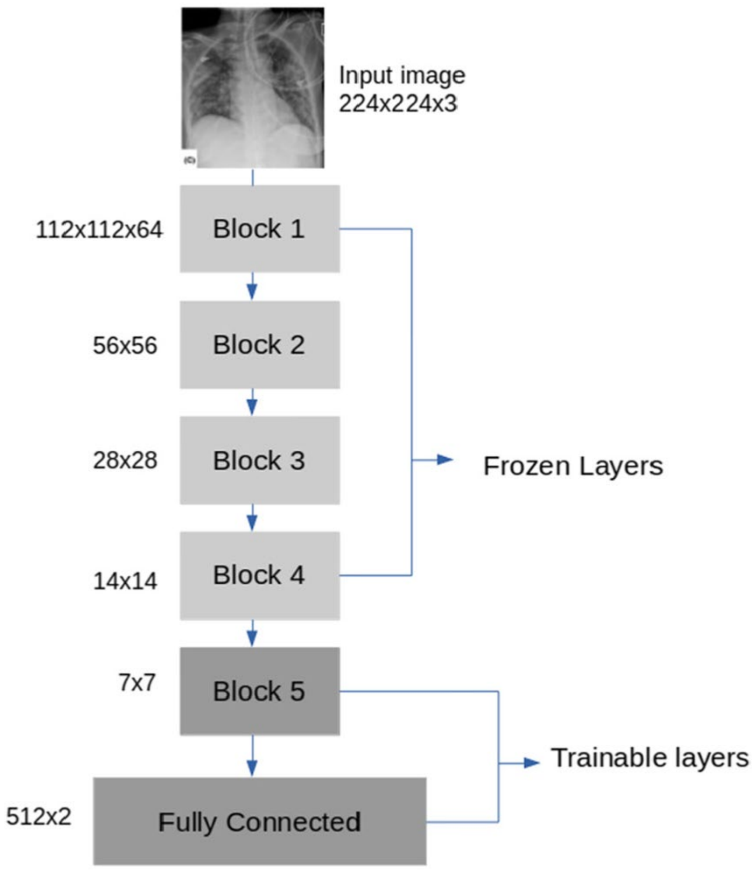

Figure 1. Utilized VCC16 architecture[17]

RESULTS

This study minimized false positives and negatives by using a transfer learning process with CNN on an enlarged data set by applying a strategy without augmentation on chest X-ray images collected at the PINERE Radiology installation at Dr. Zainoel Abidin General Hospital, Banda Aceh. In addition, it has collected 800 chest radiographs of confirmed COVID-19 patients treated at PINERE Dr. Zainoel Abidin General Hospital, Banda Aceh, in 2021. The patients' chest images are shown in Figure 2.

During data pre-processing, it is possible to resize the chest X-ray image. This indicates that different algorithms require different inputs, and the image should be normalized according to the given model standard. The images are processed and rendered by resizing to 224×224 pixels, regardless of the original dimensions. From the CNN 800 process, chest photographs of confirmed COVID-19 patients resulted in 4 classes, namely = ["Normal," "Mild," "Medium," and "Severe"] with 800 data.

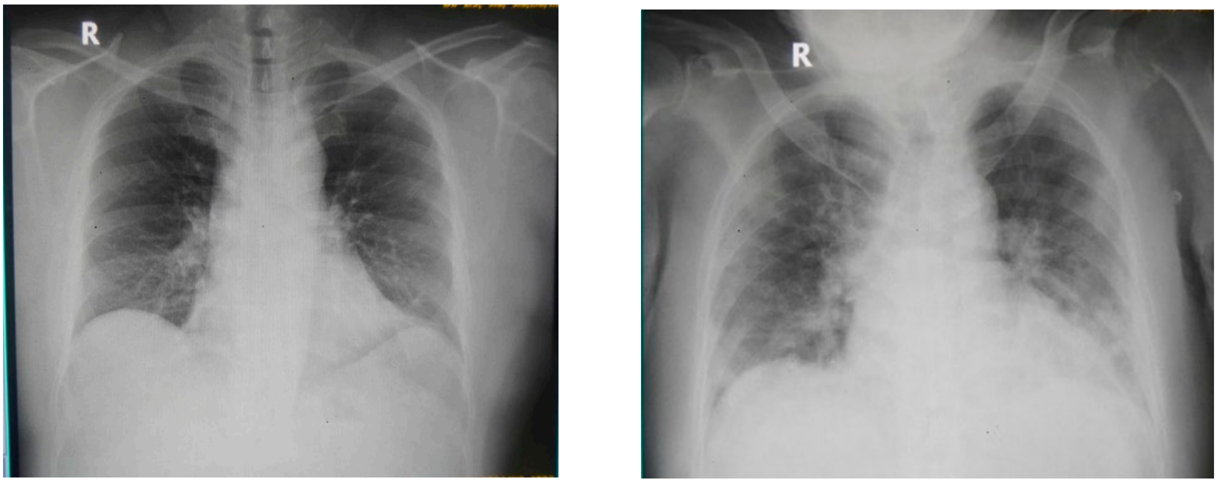

Figure 2. Chest images of confirmed COVID-19 patients

Explanation of the characteristics of each category is as follows:

- Normal = It is a condition of the lungs without any damage. Part of the lung can be seen intact, and there is no density, indicating tissue damage.
- Mild = It is a condition of the lungs that are seen intact, but some parts with small portions indicated as dark colored due to organ tissue damage
- Medium = It is a condition of the lungs that can be seen in a reasonably large portion or at several points as an indication of organ tissue damage
- Severe = It is a lung condition that shows significant damage to organ tissue in a fairly large quantity/area and at several points of the organs

The testing data will be divided by 50% to validate the result. This study used training and testing data of 80% and 20%, respectively. The values for the performance evaluation metrics and the corresponding confusion for the 2D sequential CNN model are shown in Table 1. The architecture achieved the best accuracy of 93.48% overall training and testing methods.

Each image is equalized to 300 x 300 px (pixels).

```
sample = random.choice(df['filename'])
image = load_img(sample)
plt.imshow(image)
plt.show()
```

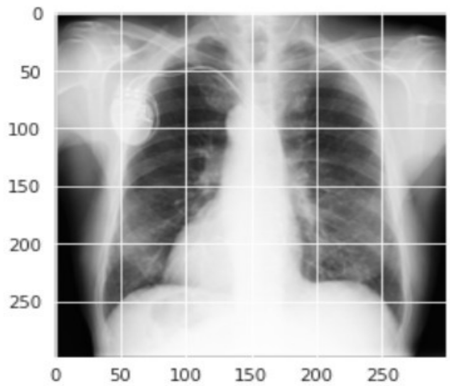

Figure 3. Chest x-ray image equalization

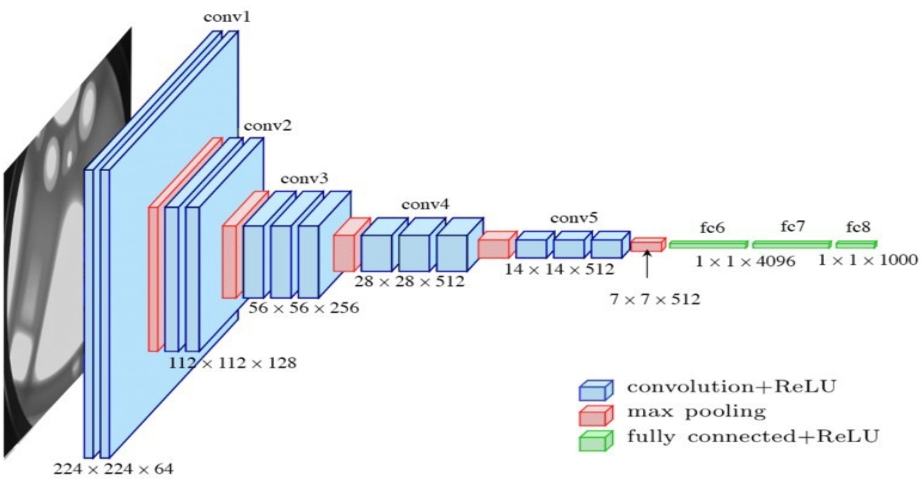

Figure 4. Architectural style VGG16[18]

Table 1. Performance evaluation matrix for the adjusted CNN model (accuracy and precision)

	Accuracy	Precision	Recall	F1-Score
VGG16	93.48%	95.2%	94.3%	96%

Figure 5 and 6 show the comparison of training with validation and the loss value. The comparison of training and validation was analyzed using 50 epochs and CUDA to complete the training process for 50 minutes.

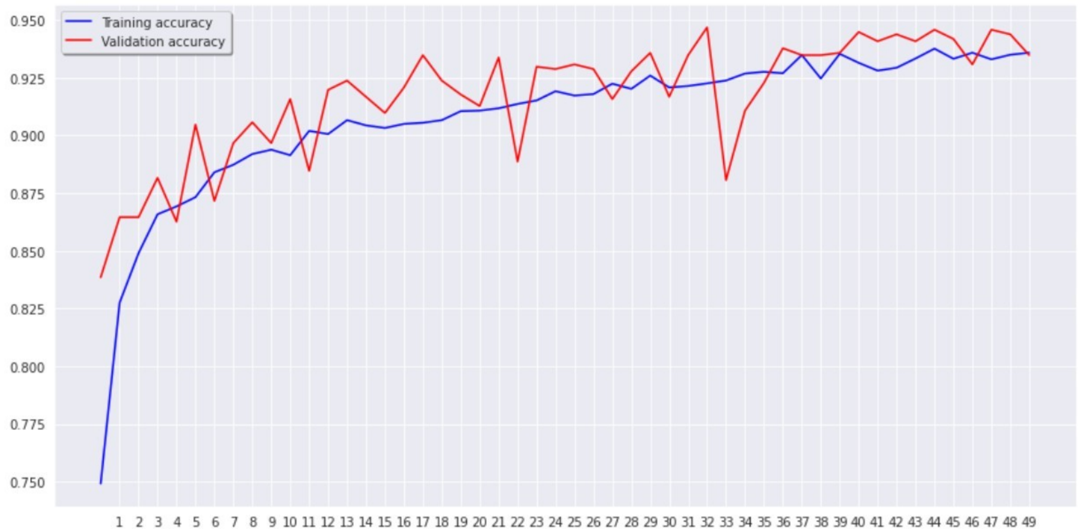

Figure 5. Using the dataset, CNN was trained

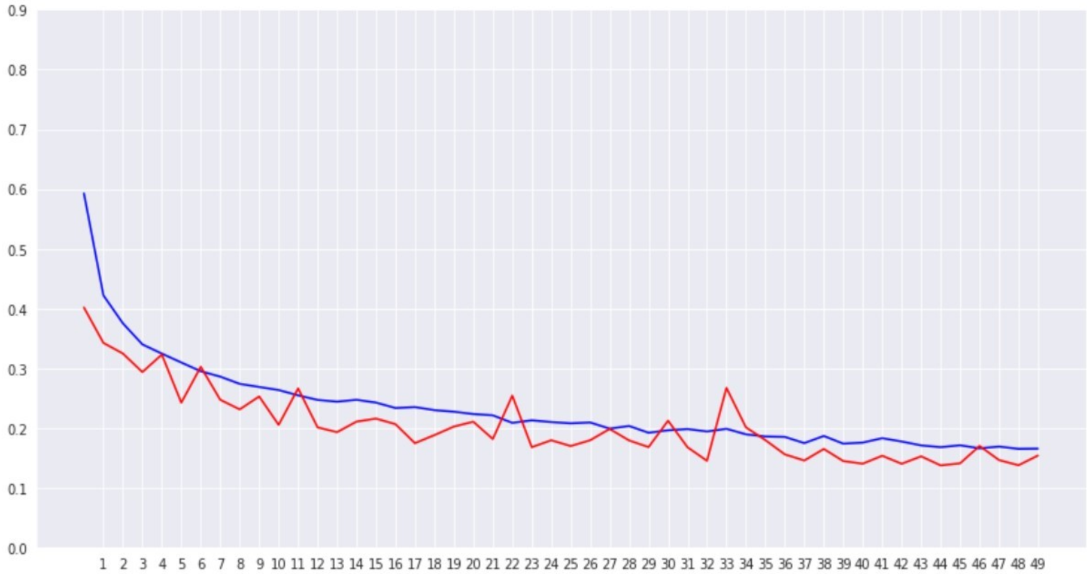

Figure 6. Using the validated COVID-19 chest X-ray dataset for VGG16 training

DISCUSSION

This study developed a learning model based on the CNN architecture to detect COVID-19 cases from chest X-ray images. The proposed model was tested on a single data set and achieved an accuracy of 93.48%. Other positive observations from these results were precision (PPV) and recall (sensitivity) for COVID-19 cases. A higher recall value means lower false negative (FN) cases, and a lower number of FN is an encouraging result. The primary objective was to minimize missing COVID-19 instances as much as feasible.

Wang and Wong (2020) presented architecture in residuals called COVID-Net for detecting COVID-19 from chest X-ray images.[17] COVID-Net is one of the early works that uses deep neural networks to classify chest X-ray images into four categories, namely COVID, normal, bacterial pneumonia, and viral pneumonia. Furthermore, it achieved 83.5% accuracy for the four classes. From the CNN process, 800 chest

X-rays of confirmed COVID-19 patients resulted in four classes, namely “Normal”, “Mild”, “Medium”, and “Severe”, with 93.48% accuracy, 95.2% precision, and 94.3% recall. Apostolopoulos and Mpesiana (2020) evaluated various sophisticated deep architectures on chest X-ray images with the best transfer learning model using VGG19 and achieved an accuracy of 93.48% and 98.75%, respectively.[18]

CNN performs automatic feature extraction from the input data according to the classification using a classifier such as Softmax. The classifier is the default but not a mandatory option for CNN and can be replaced with a support vector machine (SVM). The model acts as a feature extractor, and SVM serves as the target classifier, estimated to achieve 95.38% accuracy on two class problems.[5] Öztürk, *et al*. (2018) proposed a CNN model based on the DarkNet architecture to detect and classify COVID-19 cases from X-ray images. The model achieved binary and 3-class classification accuracy of 98.08% and 87.02% in a data set consisting of 125 COVID-19, 500 pneumonia, and 500 normal chest X-ray images using VGG16.[19]

This study used the visual geometry group (VGG) model as the CNN structure developed at the University of Oxford. The number ‘16’ implies that this architecture has 16 layers. VGG16 is CNN architecture, which was used to win the ImageNet large scale visual recognition challenge (ILSVRC) in 2014.[20]

The promising and promoting result of the deep learning model is that it can detect COVID-19 from radiographic images. Therefore, it has a more significant role in combating the current pandemic. Some restrictions may be solved by a more in-depth examination that will be feasible after additional data are collected.

CONCLUSION

During this health emergency, the COVID-19 pandemic cost all nations money to detect instances of infection. Therefore, this study proposes a deep learning approach to detect cases from chest radiography images. The proposed method is the CNN designed to identify COVID-19. The model has been trained and tested on a collection of 800 chest radiographs of confirmed patients. It is also computationally processed at a lower cost and achieves promising results. The availability of training data can enhance performance. Since the model has high accuracy and sensitivity for COVID-19 cases, it can be useful for radiologists and health professionals to detect critical aspects quickly.

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Conflict of Interest

The authors declared there is no conflict of interest.

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Authors’ Contributions

Handling manuscript and gathering data: BY, YN. Reviewing and improvising: BY, YN, and TG. All authors reviewed and approved the final version of the manuscript.

REFERENCES

1. Yanti B, Hayatun U. Peran Pemeriksaan Radiologis pada Diagnosis Coronavirus Disease 2019. *J Kedokt Syiah Kuala* 2019; 20: 53–57. [Journal]
2. Puaschunder JM. The Potential for Artificial Intelligence in Healthcare. *SSRN Electron J* 2020; 6: 94–98. [Journal]
3. Albalawi U, Mustafa M. Current Artificial Intelligence (AI) Techniques, Challenges, and Approaches in Controlling and Fighting COVID-19: A Review. *Int J Environ Res Public Health* 2022; 19. [PubMed]
4. Abd-Alrazaq A, Alajlani M, Alhuwail D, *et al*. Artificial Intelligence in the Fight against COVID-19: Scoping Review. *J Med Internet Res* 2020; 22. [PubMed]
5. Khasawneh N, Fraiwan M, Fraiwan L, *et al*. Detection of COVID-19 from Chest X-Ray Images Using Deep Convolutional Neural Networks. *Sensors* 2021; 21: 1–15. [PubMed]
6. Kwee TC, Kwee RM. Chest CT in COVID-19: What the Radiologist Needs to Know. *Radiographics* 2020; 40: 1848–1865. [PubMed]
7. Hasan JM, Alom SM, Ali SM. Deep Learning based Detection and Segmentation of COVID-19 Pneumonia on Chest X-ray Image. *Int Conf Inf Commun Technol Sustain Dev* 2021; 210–214. [WebPage]
8. Jiang F, Jiang Y, Zhi H, *et al*. Artificial Intelligence in Healthcare: Past, Present and Future. *Stroke Vasc Neurol* 2017; 2: 230–243. [Journal]
9. Alzubaidi L, Zhang J, Humaidi AJ, *et al*. Review of Deep Learning: Concepts, CNN Architectures, Challenges, Applications, Future Directions. *J Big Data* 2021; 8. [Springer]
10. Zhang Q, Zhang M, Chen T, *et al*. Recent Advances in Convolutional Neural Network Acceleration.

Neurocomputing 2019; 323: 37–51. [Journal]
11. Gholamalinezhad H, Khosravi H. Pooling Methods in Deep Neural Networks, A Review. arXiv [Internet]. 2020; Available from: http://arxiv.org/abs/2009.07485
12. Liu M, Xie T, Cheng X, *et al*. FocusedDropout for Convolutional Neural Network. *Appl Sci* 2022; 12: 7682.
13. Nwankpa C, Ijomah W, Gachagan A, *et al*. Activation Functions: Comparison of Trends in Practice and Research for Deep Learning. arXiv [Internet]. 2018; 1–20. Available from: http://arxiv.org/abs/1811.03378
14. Mogan JN, Lee CP, Lim KM, *et al*. Applied Sciences VGG16-MLP : Gait Recognition with Fine-Tuned VGG-16 and Multilayer Perceptron. *Appl Sci* 2022; 12: 1–12. [ResearchGate]
15. Guefrechi S, Jabra MB, Ammar A, *et al*. Deep Learning based Detection of COVID-19 from Chest X-Ray Images. *Multimed Tools Appl* 2021; 80: 31803–31820. [PubMed]
16. Bezdan T, Bačanin DN. Convolutional Neural Network Layers and Architectures. *Int Sci Conf Inf Technol DATA Relat Res* 2019; 445–451. [ResearchGate]
17. Wang L, Lin ZQ, Wong A. COVID-Net: A Tailored Deep Convolutional Neural Network Design for Detection of COVID-19 Cases from Chest X-Ray Images. *Sci Rep* 2020; 10: 1–12. [PubMed]
18. Apostolopoulos ID, Mpesiana TA. COVID-19: Automatic Detection from X-Ray Images Utilizing Transfer Learning with Convolutional Neural Networks. *Phys Eng Sci Med* 2020; 43: 635–640. [PubMed]
19. Öztürk S. Convolutional Neural Network based Dictionary Learning to Create Hash Codes for Content-Based Image Retrieval. *Procedia Comput Sci* 2021; 183: 624–9 [ScienceDirect]
20. Deffo LLS, Tagne FE, Tonye E. CNNSFR: A Convolutional Neural Network System for Face Detection and Recognition. *Int J Adv Comput Sci Appl* 2018; 9: 240–4. [ResearchGate]