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Deep learning for COVID-19 by X-ray images Analysis and Designing Diagnostic Application

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ABSTRACT

Nearly every element of life is being significantly impacted by the COVID-19 pandemic. Since COVID-19 was just recently identified, there isn't much known about the illness, how to identify it, or how to treat it. This has increased interest in the creation of AI-based automated detection systems, and deep learning is a group of machine learning algorithms used in AI that aim to automatically extract key properties from a dataset. Based on their architecture and learning principles, these neural networks are classified into a number of groups. Artificial neural networks (ANN), recurrent neural networks (RNN), and convolutional neural networks (CNN) are a few of the popular deep learning categories. Deep learning is therefore a powerful tool that could be used to classify data in ways that humans might not be able to. This makes it possible for computers to learn from modest quantities of data and provide excellent outcomes. For the first task in this investigation, multiple Convolutional neural networks (CNN) models were used.To maximize accuracy during training with maintain constant conditions. After training on x-ray images, VGG16, VGG19, and ResNet50V2, were found to ResNet50V2 have the highest accuracy (96%) and can be used in future chest x-ray studies and applications. Second, we designed a COVID-19 Diagnostic application. This app uses a chest x-ray to determine if a person has the disease or is healthy, saving medical staff time and energy and helping with preventative isolation. Test huge numbers from images in record time.

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Introduction

SARS-CoV-2 emerged in December 2019 (Uzun, 2021). On March 12, 2020, World Health Organization (WHO) declared a pandemic (Organization, 2020). As death rates rise, many governments must implement social separation and lockouts. To stop COVID-19 transmission, patients must be divided, and close contacts must be tracked down and isolated. Patients with COVID-19 require precise illness tracking. Chest X-rays are used to detect and monitor COVID-19 pneumonia. Radiotherapy diagnosis is aided by artificial intelligence.Artificial Intelligence eliminates RT-PCR (stands for Reverse Transcription Polymerase Chain Reaction. It is a highly sensitive and widely used laboratory technique used to detect and quantify the presence of specific genetic material, usually RNA (Ribonucleic Acid), in a sample. RT-PCR is commonly employed to identify and measure RNA viruses, including coronaviruses like SARS-CoV-2 (the virus responsible for COVID-19)) test kit shortages, high costs, and long test results wait times. Radiology has recently found COVID-19. Medical image analysis benefits from deep learning. The main issue is that lengthy work hours can wear doctors out, causing them to diagnose patients incorrectly and putting them at risk for contracting the disease. Some patients with COVID-19 may have incorrect results from chest x-rays. Because of this, the healthcare sector needs diagnostic aids to ensure proper diagnosis, which can help people achieve better results without making mistakes or contracting diseases. Artificial intelligence is dominated by deep and machine learning. Machine learning based on experience doesn't need programming. Massive, complex data are produced through machine learning. These techniques find epidemics. The forecasting actions for the COVID-19 series are outlined in this literature review (Kassania et al., 2021). In the planned work, Shankar Shambhu, Deepika Koundal, et al. are suggested in 2022 when citing various literature reviews. To discriminate between infected and uninfected people, airway CT images are examined. With an accuracy of 86.9%, the deep learning binary algorithms for classification have been applied to 746 CT scan chest cavity pictures with COVID-19-related symptoms (Shambhu et al., 2021). The proposed solution in this study, Naresh Trivedi, uses a chest X-ray data set for the CNN-based prediction of Covid-19 patients in 2020. The experimental findings show a 92.4 accuracy (Trivedi et al., 2021). A study looking at the effectiveness of multi-CNN for the automated identification of COVID-19 in X-ray pictures was proposed by B. Abraham in 2020. Two datasets that are available to the public were used to assess the suggested approach. The approach achieved 91.16 percent accuracy in a dataset with 453 COVID-19 images and 497 non-COVID images (Abraham & Nair, 2020). The identification from chest X-ray images suggested EDL-COVID, a collaborative deep learning models utilizing deep learning and collaborative learning, which was proposed by Tang in 2022. The EDL-COVID model (Tang et al., 2021) is produced by combining multiple a picture models of COVID-Net, which is an open-source COVID-19 case detection method, with deep neural network processed chest X-ray images, Experimental results demonstrate that EDL-COVID provided results for COVID-19 case identification with a 95% accuracy (Tang et al., 2021) . This paper contributed in two important areas. First: knowing the best model used within the Convolutional neural networks (CNN) algorithms in terms of performance and the highest accuracy. The second: create an application that serves the medical field. The difference in the application is the link between the two libraries, which is concerned with graphical user interfaces and deep learning offices and thus gives results on the decision to read the images entered for the test.

Materials and methods

1. Deep learning

Deep learning (DL) is predicated on a model, which chooses the features with the highest value. A deep neural network (DNN) is a classic instance of deep learning; it is a model with multiple input and output layers (Abraham & Nair, 2020). Computationally less expensive but can worsen expansion limits. On the other hand, deep learning requires a large amount of data to draw a solid conclusion and is consequently harder to implement. However, the learned models could be stronger (Khan et al., 2018) (Castillo et al., 2020). The learning process split-can be either supervised or unsupervised (Cleophas & Zwinderman, 2020).

2. Convolutional neural network

Convolutional Neural Networks (CNN) are a type of deep neural network (Kamilaris & Prenafeta-Bold, 2018) . This is the kind of network used in this study. I chose to utilize a CNN because it is the most operational network for the binary classification of images. In addition, there are numerous CNN architectures available, providing a solid foundation for network development. A CNN was a neural network with convolution and pooling layers as its core layers. Nevertheless, they work together to identify similarities and differences in the areas of arrays of values within the same category. By analyzing portions of arrays rather than every cell, better results are able to be obtained from microarrays in which nearby cells are closely related than those that are farther apart. CNNs are excellent at recognizing patterns or features in a set of numbers, which makes them excellent classifiers. CNNs are capable of classifying a wide variety of data types, so

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long as the data is able to be switched to the array of numbers (AL-Malali & Ramo, 2021).

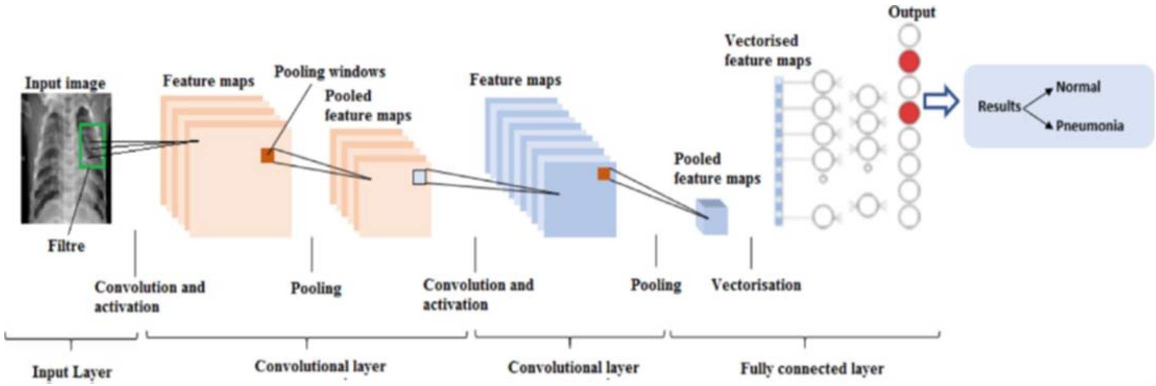


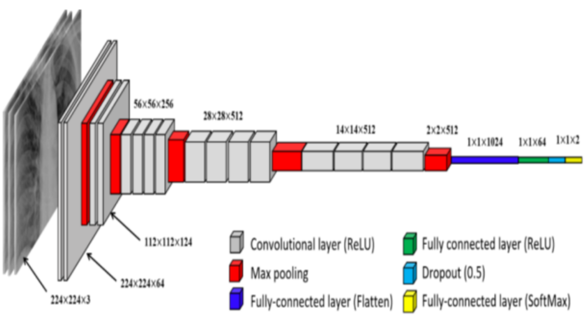
Figure 1 : CNN architecture layers to image classification (AL-Malali & Ramo, 2021)

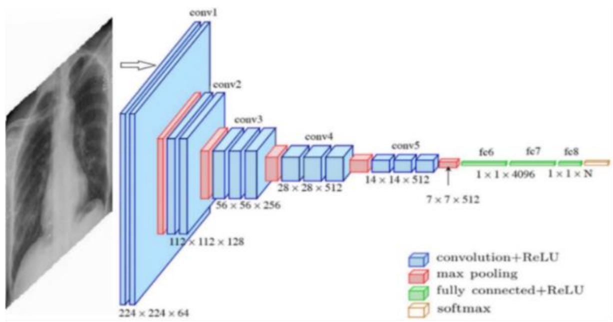
3. Pre-Train Convolutional Neural Networks

Pre-trained models use multi-class data. Few people train Convolutional Networks with random initialization because large datasets are rare. CNN algorithms are pre-trained on ImageNet (1.2 million images with 1000 categories) for initialization or fixed feature extraction (AL-Malali & Ramo, 2021).

3.1. VGG 16 Architecture:

Hence the name (Uzun, 2021), VGG16 has 16 layers of varying weights. This relatively extensive network is comprised of 138 million parameters. The simplicity of the VGG16 architecture, on the other together, piqued my interest. This architecture is extremely consistent. To reduce the height and width of the volume, an additional pooling layer is utilized. Looking at the total number of filters utilized, we can see that we begin with 64 filters, then 128 filters, 256 filters, and finally 512 filters. Every step or a stack of convolutional layers increases the number of filters used, which is another basic idea utilized in the design of this network's architecture. Consequently, there were a multitude of factors to take into account, which was a disadvantage (Uzun, 2021). The input for the cov1 layer consists of a 224 x 224 RGB image of fixed dimensions. The image is processed using a convolutional (Conv.) layer stack in a very narrow open field of 33 (the smallest size necessary to capture the concepts of left/right, up/down, and center). In addition, one of the settings employs eleven convolution filters, which can be viewed as a linear transformation of the channels that are input. ReLU applies to all buried layers. Except for one, not one of the networks use Local Responding Normalization (LRN), which requires more memory and longer computation times while improving performance with the ILSVRC dataset. VGG has sixteen model layers. According to Fig.2, the initial two layers are convolutional layers with 3x3 filters, and the first a pair layers use 64, achieving a volume of 224x224x64 because of the use of the same convolutions. The filters operate on a 3x3 grid with one stride. The height and width of the volume were decreased from 224x224x64 for 112x112x64 via a pooling layer with a maxpool size of 2x2 and stride 2. After that, there are two additional convolution layers, each with 128 filters. As a result, the new dimension was 112 by 112 by 128. After the pooling layer is applied, the volume is reduced to 56 x 56 x 128. Two additional 256-filter convolution layers, each followed by a lower sampling layer, are added, reducing the size to 28x28x256. A max-pool layer separates two additional stacks of three convolution layers each. The 7x7x512 volume has been flattened to create a Fully Connected (FC) layer in 4096 channels as well as a softmax output with 1000 classes following the final pooling layer.





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3.2. VGG 19 Architecture:

VGG19 is a convolutional neural network proposed by Simonyan as well as Zisserman (2014) that consists of 19 layers with 16 convolution layers and also 3 fully connected layers to classify images into 1000 object categories. VGG19 is trained using the ImageNet database, which contains one million images divided into one thousand categories. Due to the use of multiple 3x3 filters in every one convolutional layer, it is a very common method for image classification. Fig.3 illustrates the architecture of VGG19. This demonstrates that 16 convolutional layers are employed for feature extraction, while the following 3 layers are used for classification. The layers that are used for the extraction of features are divided into 5 groups, with a max-pooling layer following each group. This model receives an input image of size 224x224 and outputs the label of the protest in the image (Bansal et al., 2021). Fig. 3 illustrates the architecture of VGG19.

3.3. ResNet50 Architecture:

ResNet (Residual Network), named the winner of ILSVRC 2015, was created by He , (He et al., 2016) . Their goal was to create an ultra-deep network devoid of the problem of vanishing gradients, as opposed to previous networks. Based on the number of layers, various types for ResNet were developed, ranging from 34 layers to 1202 layers. ResNet50, which contained 49 convolutional layers and a single FC layer. The innovative concept of ResNet is its use of the bypass pathway concept, as depicted in Fig.4, which was employed in 2015 by Highway Nets to solve the problem of training a deeper network. Unlike the highway network, ResNet enabled cross-layer connectivity via parameter-free and data-independent shortcut connections within its layers. Note that the layers represent non-residual highway network functions when a secured shortcut is closed. In contrast, ResNet's individuality shortcuts remain closed, whereas residual information is continuously transmitted. Moreover, ResNet possesses the potential to prevent gradient diminishing problems, as connections with shortcuts accelerate the convergence of deep networks (Alzubaidi et al., 2021)

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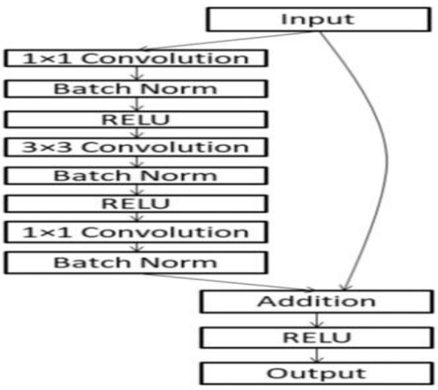

Fig. 4: Traditional Architecture of ResNet-50 (Tahir et al., 2021)

Implementation of models and Designing COVID-19 Application

We can discuss the training and testing processes for the models that were chosen as the subject of the research study, as well as the results that result from the training, the value of accuracy for each model, and the results accompanying all operations, and beginning with a flowchart illustrating the stages of work.

Preparation of dataset

The first stage from the beginning of the practical part is to prepare the images and store them in a specific place in the computer and divide it into folders to a specific technique. We were able to prepare a number of a dataset of 2000 chest X-ray, 1000 of which are of people with COVID-19 and 1000 of healthy people, downloaded the images from the Kaggle website.

A- The general flowchart of the proposed models and their stages:

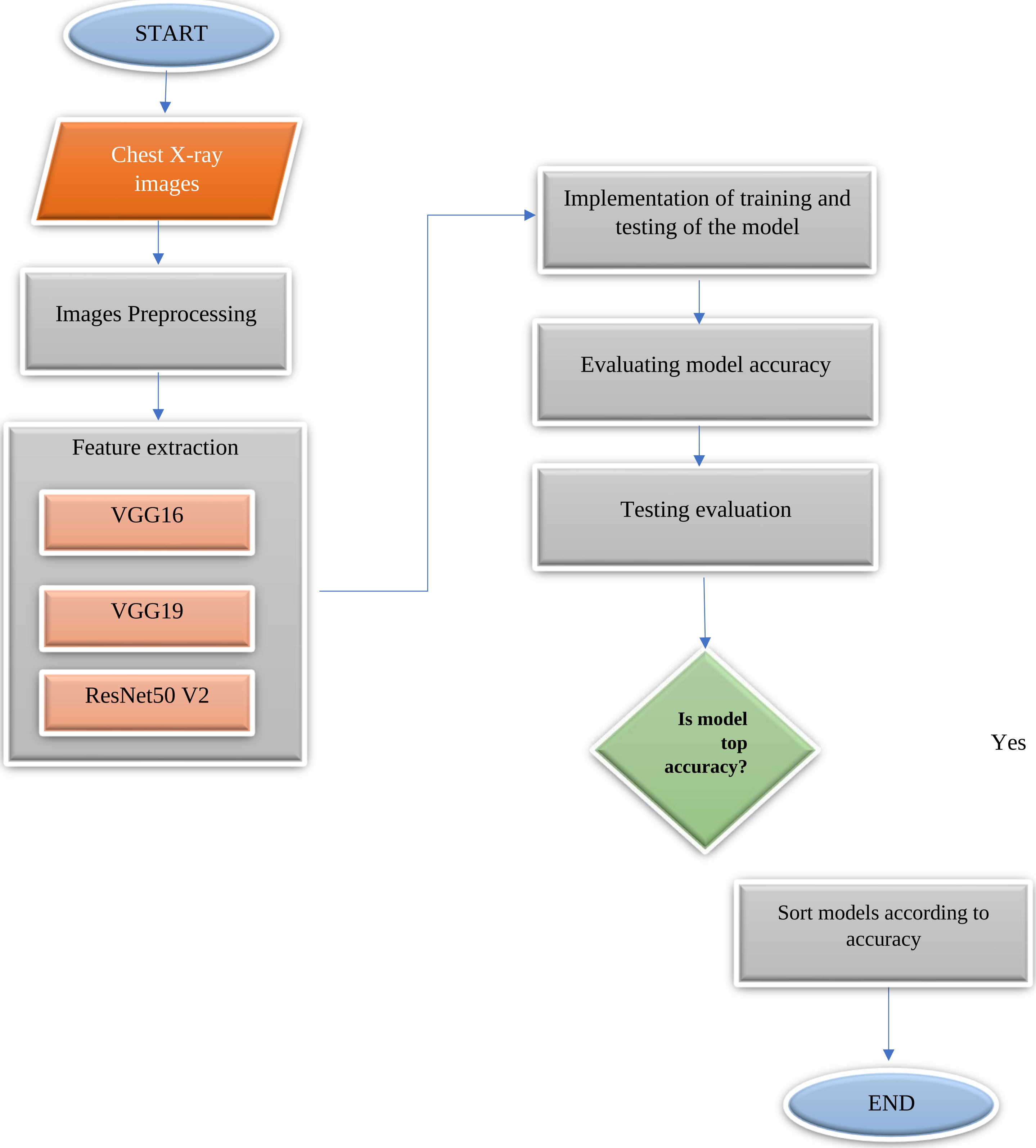

Fig. 5: The general flowchart of the proposed models

It was fixed the number of dataset and working conditions in terms of the number of EPOCHS and the image processing Technique in all stages with the personal computer, we implemented

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all models under the same conditions. The main characteristics that were identified in the research study to distinguish between the best model in terms of accuracy resulting from the training are shown in the following table:

Table 1: The main characteristics of the training process

Number of images used	optimizer types	Ratio of test from train	epochs	Batch size
2000	ADAM	20%	40	2

Result of The Training

1. VGG16 model

The early stopping function stopped training the 40-epoch VGG-16 model at Epoch 27 to avoid overfitting. 2739 seconds per epoch. Table 2 shows the computer's 20.5-hour training accuracy. 191 correct COVID images and 9 read errors out of 200 after training. 9 of 191 non-infected images were misread. Fig.6 shows confusion matrix results.

Table 2: result accuracy training and testing of VGG-16

No.	model	Accuracy training	Accuracy testing	Time per epochs(s)
1	VGG-16	96.12	95.5	2739

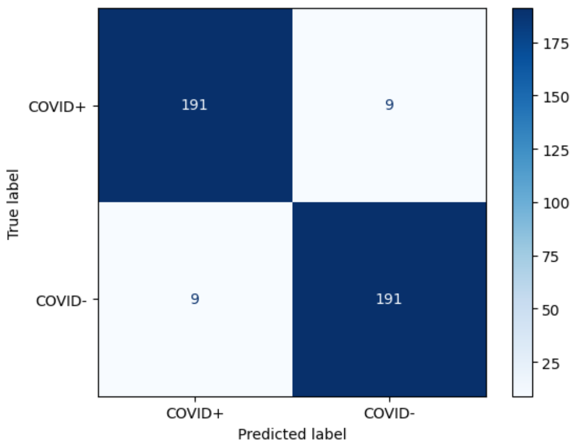

Fig.6: result confusion matrix of VGG-16

2. VGG-19 model

Each 40-epoch VGG-19 model training epoch took 3455 seconds. Table 3 shows the training and testing accuracy from 38.3 hours of computer training. A confusion matrix showed 177 correct COVID images and 23 incorrect ones out of 200. 198 non-infected images were correctly identified, 2 were misread. Fig.7 shows confusion matrix results.

Table 3: result accuracy training and testing of VGG-19

No.	model	Accuracy training	Accuracy testing	Time per epochs(s)
2	VGG-19	94.68	93.75	3455

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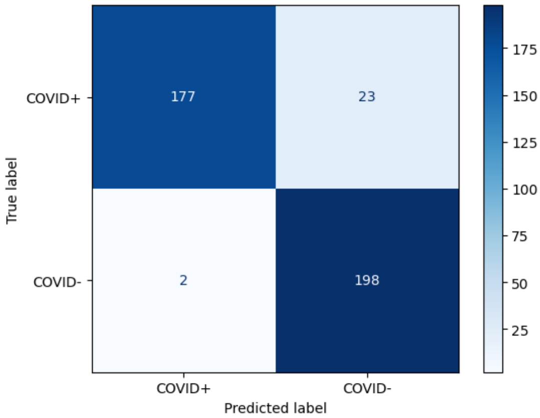

Fig. 7: result confusion matrix of VGG-19

3. ResNet50V2

The early stopping function stopped ResNet50V2 training after 36 epochs to avoid overfitting. 548 seconds per epoch. Table 4 shows the computer's training and testing accuracy after 5.4 hours. The confusion matrix showed 192 correct COVID images and 8 misread images out of 200. 8 non-infected images were misread, 192 were correct. Fig.8 shows confusion matrix results.

Table 4: result accuracy training and testing of ResNet50V2

No.	Model	Accuracy training	Accuracy testing	Time per epochs(s)
3	ResNet50V2	97.87	96	548

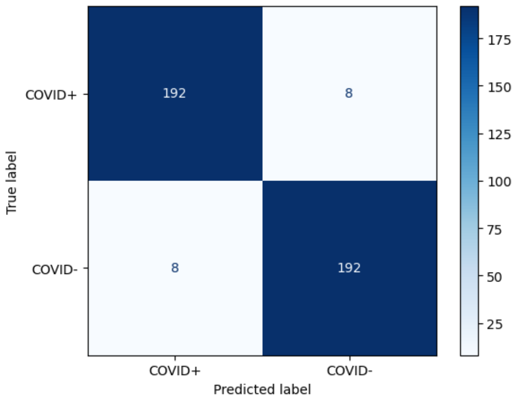

Fig. 8: result confusion matrix of ResNet50 V2

- **To compare models, accuracy results are in one table**

The accuracy results have been compiled in one table so that you may compare.

Table 5: Accuracy comparison between all models in our Research study

No.	model	Training accuracy	Testing accuracy
1	VGG16	96.12	95.5
2	VGG19	94.68	93.75
3	ResNet50V2	97.87	96

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The table 5 shows the accuracy resulting from each of the models of the CNN algorithm that has been trained and tested in advance, knowing the difference more clearly, and it was found that the highest accuracy obtained is ResNet50v2 model.

Comparison with previous studies

After training the models that were selected in this research, it was found that the pre-trained models showed better and more accurate results than the previous research, and ResNet50v2 issued the highest accuracy list between the current research and the previous research, especially in dealing with x-ray images in accuracy 96. Where the researcher S. Shambhu trained the CNN algorithm and obtained an accuracy of 86.9 and the researcher N. Trivedi also, after completing his training, obtained an accuracy of 92.4, B. Abraham achieved accuracy 91.1 and Tang in EDL-COVID model achieved a curaccy 95. when comparing it with the models used in the research, all the pre-trained models found that the models used in the research gave better results compared to the percentage of accuracy. The following table shows the results of previous studies with the model that obtained the best accuracy in our study.

Table 6: Accuracy comparison between previous studies and model top accuracy obtained in our research study

No.	searcher	Model	year	Testing accuracy
1	S. Shambhu	CNN	2022	86.9
2	N. Trivedi	CNN	2020	92.4
3	B. Abraham	CNN	2020	91.1
4	Tang	EDL-COVID	2022	95
5	proposed system	ResNet50V2	2023	96

As shown in the table, the research ResNet50V2 model obtained the highest accuracy compared to the rest of the models in the same study, and also compared to previous studies**.**

A.Designing COVID-19 Application

After all models are trained, the highest-accuracy model inferred by the exercises in this paper is used and trained in the application writing part in Python using the Jupyter code editor. After creating the GUI, it created a function that integrates the Keras training library with the Tkinter library to bind deep learning interfaces to the GUI. The application design steps can be summarized as follows:

1.Training ResNet50V2 model.

2.Writing GUI code (Tkinter library) with a design that matches the mission and needs of medical diagnostics.

3.Write fuction code that connects deep learning and graphical user interfaces.

4.Implementation of the application and testing images of chest x-rays.

5.The application consists of only one interface and there are no sub-windows to make it easy to use

Fig.9: The main interface of application.

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The steps is to design the interface with all the options that we will need for the main function of the application, are:

Option: 1 Enter the images to be tested by path the image.

Option: 2 Is the process of testing the image and returning the result, Does the image contain Covid-19 or not.

Option: 3 The process of displaying images in case the user needs them viewing.

Option: 4 Deleting all options to start a new test.

Option: 5 The program can be exited after pressing the exit button.

The following Fig.10 shows the use of the application during testing process:

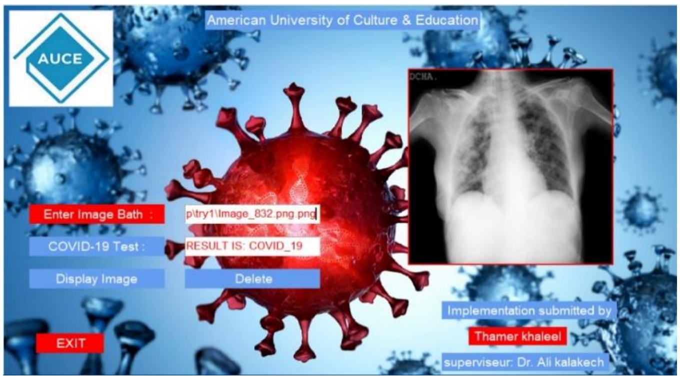

Fig.10: The main interface during implementation

Conclusions

COVID-19 is straining healthcare worldwide. RT-PCR tests cannot identify all respiratory patients. Radiologists and experienced professionals are needed for the insensitive, laborious tests. We studied several chest X-ray classification models to train the machine. VGG16, VGG19, and ResNet50V2 had the highest accuracy under constant conditions in all training tests, with 95.5, 93.75, 96, and 94.25. ResNet50V2 used for training and testing chest X-rays, was most accurate (96%). After extracting the most accurate results, choosing the best model to share in an image testing application was easy. We COVID-19 apps solve pandemic issues. Combining deep learning libraries to train and test images with a Graphical User Interface (GUI) library can produce an application that tests chest X-ray images quickly and accurately.

References

Abraham, B., & Nair, M. S. (2020). Computer-aided detection of COVID-19 from X-ray images using multi-CNN and Bayesnet classifier. *Biocybernetics and Biomedical Engineering*, *40*(4), 1436–1445.

AL-Malali, M. K., & Ramo, F. M. (2021). Behavioral Sense Classification using Machine Learning Algorithms. In *Doctoral dissertation, Mosul University*. Mosul University.

Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., Santamaría, J., Fadhel, M. A., Al-Amidie, M., & Farhan, L. (2021). Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. In *Journal of Big Data* (Vol. 8, Issue 1). Springer International Publishing. https://doi.org/10.1186/s40537-021-00444-8

Bansal, M., Kumar, M., Sachdeva, M., & Mittal, A. (2021). Transfer learning for image classification using VGG19: Caltech-101 image data set. *Journal of Ambient Intelligence and Humanized Computing*, 1–12.

Castillo, O., Melin, P., & Kacprzyk, J. (2020). *Intuitionistic and type-2 fuzzy logic enhancements in neural and optimization algorithms: Theory and applications* (Vol. 862). Springer Nature.

Cleophas, T. J., & Zwinderman, A. H. (2020). Machine learning in medicine - a complete overview. *Machine Learning in Medicine - A Complete Overview*, *1706*, 1–667. https://doi.org/10.1007/978-3-030-33970-8

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 770–778.

Kamil, M. Y. (2021). A deep learning framework to detect Covid-19 disease via chest X-ray and CT scan images. *International Journal of Electrical & Computer Engineering (2088-8708)*, *11*(1).

https://doi.org/10.25130/tjps.v28i4.1398

Kamilaris, A., & Prenafeta-Bold, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, *147*, 70–90.

Kassania, S. H., Kassanib, P. H., Wesolowskic, M. J., Schneidera, K. A., & Detersa, R. (2021). Automatic detection of coronavirus disease (COVID-19) in X-ray and CT images: a machine learning based approach. *Biocybernetics and Biomedical Engineering*, *41*(3), 867–879.

Khan, S., Rahmani, H., Shah, S. A. A., Bennamoun, M., Medioni, G., & Dickinson, S. (2018). *A guide to convolutional neural networks for computer vision* (Vol. 8, Issue 1). Springer.

Organization, W. H. (2020). *WHO announces COVID-19 outbreak a pandemic*.

Shambhu, S., Koundal, D., Das, P., & Sharma, C. (2021). Binary classification of covid-19 ct images using cnn: Covid diagnosis using ct. *International Journal of E-Health and Medical Communications (IJEHMC)*, *13*(2), 1–13.

Tahir, H., Iftikhar, A., & Mumraiz, M. (2021). Forecasting COVID-19 via registration slips of patients using resnet-101 and performance analysis and comparison of prediction for COVID-19 using faster r-cnn, mask r-cnn, and resnet-50. *2021 International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT)*, 1–6.

Tang, S., Wang, C., Nie, J., Kumar, N., Zhang, Y., Xiong, Z., & Barnawi, A. (2021). EDL-COVID: Ensemble deep learning for COVID-19 case detection from chest X-ray images. *IEEE Transactions on Industrial Informatics*, *17*(9), 6539–6549.

Trivedi, N. K., Simaiya, S., Lilhore, U. K., & Sharma, S. K. (2021). COVID-19 Pandemic: Role of Machine Learn-ing & Deep Learning Methods in Diagnosis. *Int J Cur Res Rev*, *13*(06), 150–156.

Uzun, O. (2021). *Artificial intelligence application in covid-19 diagnosis and orediction using CT scan*. A THESIS TO THE INSTITUTE OF GRADUATE STUDIES OF NEAR EAST UNIVERSITY.

Yang, D., Martinez, C., Visuña, L., Khandhar, H., Bhatt, C., & Carretero, J. (2021). Detection and analysis of COVID-19 in medical images using deep learning techniques. In *Scientific Reports* (Vol. 11, Issue 1). https://doi.org/10.1038/s41598-021-99015-3