

COVID 19 Diagnosis Analysis using Transfer Learning

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Abstract

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Original Manuscript

COVID 19 D IAGNOSI S ANALYSIS USING DEEP LEARNIN P G TRANSFER LEARNIN G

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ABSTRACT

Coronaviruses, including SARS-CoV-2, are responsible for COVID-19, a highly transmissible disease that emerged in December 2019 in Wuhan, China. During the past five years, significant advancements have been made in understanding and mitigating the virus. Although the initial outbreak led to global crises, improved vaccination strategies, antiviral treatments, and AI-driven diagnostic tools have contributed to better disease management. However, COVID-19 continues to pose risks, particularly for immunocompromised individuals and those with pre-existing conditions. This study explores the use of deep learning for a rapid and accurate diagnosis of COVID-19, addressing ongoing challenges in infrastructure and testing accessibility. We propose an enhanced automated system leveraging state-of-the-art convolutional neural networks (CNNs), including updated versions of VGG16, VGG19, and ResNet50, to classify COVID-19 infections from chest radiographs and computerized tomography (CT) scans. Our results, based on an expanded dataset of over 6000 medical images, demonstrate that the optimized ResNet50 model achieves the highest classification performance, with 97.77% accuracy, 100% sensitivity, 93.33% specificity, and a 98.0% F1-score. These findings reinforce the potential of AI-assisted diagnostic tools in improving early detection and pandemic preparedness.

Keywords Computer Vision · COVID-19 Diagnosis · Transfer Learning · Medical Imaging Analysis

1 Introduction

1.1 Introduction of COVID-19

On 31 December 2019, WHO was informed of cases of pneumonia of unknown cause in Wuhan City, China [1]. In addition to causing illnesses as mild as a cold, Coronaviruses cause diseases of varying severity. On 30 January 2020, Tedros Adhanom Ghebreyesus, WHO Director-General, declared the novel coronavirus outbreak a Public Health Emergency of International Concern (PHEIC), WHO's very best level of alert. At that point, there have been confirmed cases and no reported deaths in 18 countries outside China. On 11 March 2020, the rapid increase in the number of cases outside China led the WHO Director-General to announce that the outbreak might be characterized as an epidemic. As of 28 April 2020, 63% of worldwide mortality from the virus was from the Region. [1] the of people at large, their health, and the economy of a rustic is affected by this deadly viral disease. On 26 March 2020, WHO detected a new variant of Coronaviruses named Omicron. [2] By 2025, the global response to COVID-19 has improved with revised vaccines, antiviral treatments, and AI-driven diagnostic technologies. Although the virus continues to pose a public health challenge, enhanced immunity, and mitigation strategies have significantly decreased cases and mortality rates. Ongoing surveillance and adaptation to emerging variants continue to be crucial in managing the disease's long-term impact.

1.2 Symptoms of COVID-19

As of March 2025, COVID-19 continues to be a prevalent global health concern, presenting a wide range of symptoms such as cough, headache, fatigue, difficulty breathing, and loss of taste or smell [3]. Notably, a significant [unpublished, non-peer-reviewed preprint]

In summary, while COVID-19's acute phase may result in mild to severe symptoms, the potential for long-term health

As of March 2025, while global COVID-19 mortality rates have significantly declined, accurate and timely diagnosis is crucial to interrupt transmission chains, especially since no universally effective treatment has been established. Early detection is vital to control the spread of the virus. Traditional diagnostic methods, such as serologic tests, have limitations, including low sensitivity and longer processing times. Consequently, there has been a concerted effort to develop faster and more accurate diagnostic assays [9]

[12]. The paper is an overview of the existing COVID-19 patient supportive related challenges, and possible technologies. A study of COVID-19 by detecting when people are not wearing masks [13]. Scientists are using CT-scan and facial images as a complementary screening method for COVID-diagnosis [14, 15, 16, 17, 18, 19]. Recently, researchers studied the transfer learning approach using pre-trained learning architecture [20, 21]. The study [22, 23] represents the COVID-19 diagnosis with X-ray images dataset resulted in accuracy of 95.7%, with sensitivity of 99% and specificity of 95.80% with a small number of parameters.

3 THE PROPOSED SYSTEM

3.1 COVID-19 Diagnosis Using Deep Learning

The report describes the implementation of a supervised classification neural network system based on deep learning using different medical imaging modalities such as Computer Tomography (CT) and X-ray. This report explains the systems developed for COVID-19 diagnosis using deep learning. We propose an intelligent system for distinguishing COVID-19 patients from normal patients based on chest X-ray and CT-scan images. COVID-19 patients can be expeditiously identified using our system, which reads the image structure and predicts hidden patterns to recognize patients, and does not require external instructional pre-processing. Findings obtained from 6259 total images of patients collected using CT-scan and X-rays show that 4651 images belong to COVID-19 and 1608 images belong to normal patients. Our proposed system can detect and predict COVID-19 patients with an accuracy of 97.73%. Using generated datasets from real-world cases, we have trained and tested the proposed system, achieving predictions with a mean accuracy ranging from 90% to 97.73%. Healthcare providers can implement AI in several ways, such as disease diagnosis. One of the most significant advantages of AI is that it can be implemented within a highly trained model to classify complex images. In 2012, a breakthrough ML system called AlexNet [unpublished, non-peer-reviewed preprint]

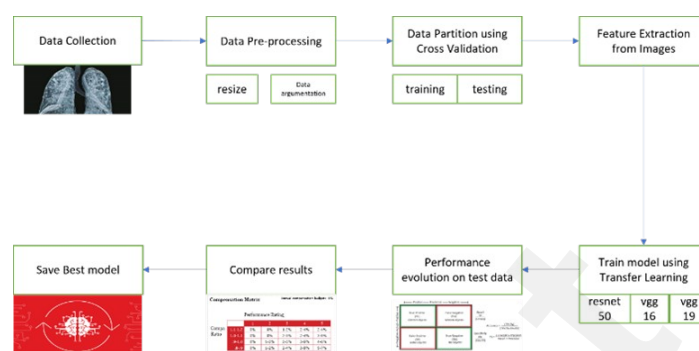


Figure 1: MODEL ARCHITECTURE DEEP LEARNING-BASED COVID-19 DETECTION

deep learning was introduced, which relies on convolutional neural networks (CNN). The CNN won the classification competition for computer vision. Deep learning algorithms enable computational models composed of multiple processing layers to search for data representation through several hidden layers. The deep learning model is trained to perform tasks from audio, video, image, or text. In this study, we focus on the image binary classification model using deep learning. Deep learning models feature high accuracies and can handle complex tasks. X-ray machines use high-energy X-rays or radio waves as radiation to examine the affected parts of the body due to cancers, lung diseases, bone dislocations, and injuries [24]. Furthermore, CT scans, which are more sophisticated X-ray machines, are used to examine the soft tissues and organs of active body parts. The advantages of using X-rays over CT scans are that X-rays are quicker, safer, simpler, and less harmful than CT scans. A CNN-based model was used to detect COVID-19 patients using 6259 chest X-ray images, of which 4651 belong to COVID-19 patients and 1608 belong to healthy people. The images were resized to 150×150. The study evaluated three CNN models—ResNet-50, VGG16, and VGG19—using a 70%-30% cross-validation and reported that ResNet-50 achieved the highest detection accuracy. They collected two datasets: the first dataset contained chest X-ray images in 3 folders, with the first training set having 1341 non-infected patients and 3875 infected patients, the second set having 234 non-infected patients and 390 infected patients, and the third validation set having 8 non-infected patients and 8 infected patients. The second dataset contained chest CT-scan images in a folder, with a total of 309 non-infected and infected patients [25].

3.2 Data Collection

Dataset Two kinds of datasets were employed within the evaluation, the initial dataset (without augmentation) and the augmented dataset, which are summarized in Table. The dataset contained the following:

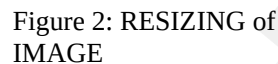
- **COVID-19 X-ray images** Chest X-ray all images performed as an element of patients' routine clinical care. Chest radiographs were initially screened for control for quality or unreadable chest radiographs. COVID-19 X-ray images dataset could also be a database of COVID-19 cases with chest X-ray or CT images which contains COVID-19 cases. [26]
- **Chest X-Rays in Patients with Pneumonia** The dataset contains subfolders for each image category (Pneumonia/Normal). There are 6259 chest X-ray images, 4651 of which belong to COVID-19 patients and thus 1608 belong to healthy people. [27]

3.3 Exploratory Data Analysis (EDA)

Exploratory data analysis (EDA) used to explore the formal modelling of dataset and hypothesis analysis using statistical techniques. EDA provides the better understanding of dataset variables and relationship between them. With the help of EDA, data scientists can ask right questions to stakeholders and find answers using standard deviations, variances, and confidence intervals. We can create graphs and visualize high-dimensional dataset, summary of data.

3.4 Data Exploration

Data Exploration defines to the primary stage to analysis the dataset using visualization and statistical methodologies. It describes characteristics of data like, size, quantity, accuracy of data. In data exploration, we collect increasing amount of data, investigate the current world requirement around that data and build application to handle the problem.



we used multichannel information processing technique for image pre-processing, the quality of an scanned images contain a lot of irrelevant of . The raw scanned images do not give valuable information. The pre-processing involves the image conversion, image resizing of image, image

Data Augmentation technique used to handle overfitting in deep learning model. With Data Augmentation, we increase the size and quality of datasets. The geometric transformation, color spacing, and feature space, and kernel files are some of the techniques involved in data augmentation. This technique increases performance generalization on new data. VGG-16, VGG-19, and ResNet-50 deep learning model architecture.

- **geometric transformation** In this method, we applied rotations and flips on image data
- **colour space** colour space method, to change the intensity values and light alterations in images
- **Feature space** Feature spaces involve handling the features like, noise injection, crop images, rotation in images, translation and shifting image to left, right, up or down
- **Kernel filters** Sharpen and blur the images are popular techniques to apply the kernel filtering methods.

Regularization methods are responsible to handle overfitting in the model. Dropout Regularization, batch normalization, and other regularization techniques, which we describe following:

- **Dropout Regularization** In this method we reduce neurons values to zeros during the training process of model. In this our model force to learn more robust features to train the model.
- **Batch normalization** It is a regularization method, which normalizes the set of activations. In this method we subtract the batch mean of activation and divide the resulted value by batch standard deviation.

Labeling
In the process of label encoding, labels are converted into numeric data so they can be converted into machine-readable data. Machine-learning algorithms then determine what to do with those labels. COVID-19 was encoded as 1, Normal as 0, and Pneumonia as 2.

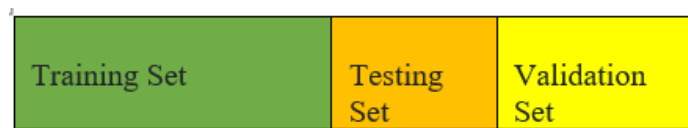


Figure 3: DATA PARTITION

3.9 Image

Normalisation

It's a process in image processing where pixels' intensity values are altered so that their range can be more familiar normal to the senses. "Normalization" is the term used to describe this process.

3.10 Data Partition using Cross

Validation

In this experiment, the dataset is divided into a proportion of 80%, 10%, and 10% for training, testing, and respectively using scikit-learn train test split method. DL models can be evaluated using cross-validation by separating DL models on parts of the input file and evaluating them on the other. Cross-validation can be used to detect overfitting, i.e., failure to generalize a pattern.

3.11 Image

Visualisation

A process of converting (rendering) image pixel into 2D graphical representation using Matplotlib. As the developer and perceives information, the visualization is important for conveying the information effectively. We use the automatic visualization methods to write visualization queries, like data lake. This includes data discovery, integration and data planning. We can use visualization for data debugging and explore wrong data sources, wrong visualization queries.

3.12 Feature Extraction from

Images

Feature Extraction is useful method in image classification model. In this method, we transform the image data to the feature set. We can apply feature extraction after pre-processing of images. this process has two parts:

- **Feature Selection** Feature selection can be applied on images which contains different features in each class. It permits limited number of class and dataset.
- **Classification** We use feature vectors to classify the images by exploring the existing Template and Defrangible of Transform the Unitary of graph projection of profiles, zoning, histograms, geometric moment invariants, Fourier descriptions, Zernike moments, spline approximation, Gradient feature, and Gabor features.

3.13 Load the Pre-trained Model

Architecture

- **VGG16 and VGG19** VGG16 and VGG19 are convolutional neural network (CNN) architectures. These architectures have small 3x3 convolution filters, and A stride to achieve high accuracy on image applications. There is different implementation in the depth of convolutional, max-pooling and fully connected layers. Whereas, VGG16 having 16 layers in the base model and VGG19 having 19 layers [29].
- **ResNet50** ResNet50 was designed to handle vanishing gradient problem in deep neural networks by skip connections between the layers called residual learning. This architecture is more efficient to train and deeper networks to design impactful and accurate model with 50 layers of residual learning [29].

3.14 Model

Selection

In this process, we optimized the hyperparameters of deep learning models:

- Learning Rate = 0.01 to 0.0001
- Batch Size = 8 to 16
- Dropout = 0.2 to 0.5

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We applied different combinations of hyperparameters on three model VGG-16, VGG-19 and ResNet-50. And the resulted precision, recall, accuracy and F1-score along with accuracy and loss curves and confusion matrices for further analysis. We repeated model training for learning rate between 0.01 and 0.0001, batch size varied between 8 and 16 and Dropout between 0.2 to 0.5 range. We tried different number of epoch to handle overfitting. We realized the more complex model exhibiting a higher training metrics deviation.

3.15 Compile the Model

- Regularization is a technique to combat overfitting, a phenomenon where we fit our training data more closely to our underlying distribution. During this experiment, you might have noticed that if you changed the distribution or the hyperparameters, the model eventually closes the gap between the training and test data with enough neurons, layers, and training epochs.
- we reviewing to the difference between training error which calculates on training dataset and generalization expected error from model. we can never calculate the generalization error exactly. The reason is the stream of infinite data is a hypothetical object. For example, consider the black and white images.

4 EVALUATION

The objective of this experiment to analyse CT-scan and X-rays chest images to identify the abnormal (COVID-19) from normal (healthy) person chest using Deep learning CNN-based pre-trained networks VGG-16, VGG-19 and ResNet-50. CNN-based networks VGG-16, VGG-19 and ResNet50 were trained and validated for each repeated cross-validation experiment using different partitions of the dataset, producing total of 15 learning curves (Loss/Accuracy vs Epoch) confusion matrices for each model. To analyze further statistically significant difference in the performance of Deep Learning models, we applied the cross validation using the Scikit – learn python library and evaluated performance on basis of Accuracy, Precision, Recall and F1-score. Table 1 and Table 2 includes the results with the CNN-based models VGG-16, VGG-19 and ResNet50 with different hyperparameters. We can observe that the three VGG-16, VGG-19 and ResNet-50 model achieved the similar accuracy 97.73%, sensitivity 100%, specificity 93.33% and F1-score 98.00% with the different combinations of hyperparameters for instance, ResNet-50 got 97.73% accuracy with 0.001 learning rate, 100 epoch, 0.5 dropout and batch size 16. Whereas VGG-16 got accuracy with different hyperparameters values. VGG-19 shows accuracy on 93.18%, Sensitivity 93.10%, Specificity 93.33% and F1-score on 95% with learning rate 0.001, 50 epochs, 20% dropout rate and batch size 8. This increasing accuracy on 95.45%, Sensitivity 96.55%, Specificity 93.33% and F1-score on 97% with learning rate 0.0001, 50 epochs, 20% dropout rate and batch size 8. VGG-19 increasing accuracy 97.73% with the small (0.0001) and (0.001) learning rate values, dropout rate 50% and batch size 8 and 16. In the ResNet-50 with the learning rate 0.0001, 50 epochs, 20% dropout rate and batch size 8 the accuracy 90.91%, Sensitivity 86.21%, Specificity 100.00% and F1-score on 91%. Then Sensitivity increases to 93.10% with the learning rate 0.001, 100 epochs, 50% dropout rate and batch size 8 the accuracy 93.18%, Specificity 93.33% and F1-score on 93.33%. In the 4th iteration for ResNet-50 got increased accuracy 95.45%, Sensitivity 96.55%, Specificity 93.33% and F1-score on 93.33% with the learning rate 0.001 and 0.001, 50 and 100 epochs, 20% and 50% dropout rate and batch size 8. As per the observation, VGG-16 is underfit the result and showing the same accuracy, sensitivity, specificity, and f1-score with the various combinations. If we increase the dataset size VGG-16 might improve the performance. Whereas VGG-19 hyperparameter accuracy from 93.18% to 95.45% and finally reached on 97.73% accuracy rate. Similarly, ResNet-50 shows progressive result with hyperparameter tuning it increases accuracy rate from 90.91% in 1st iteration, 93.18% in 2nd iteration, 95.45% in 3rd and 4th iteration and achieved 97.73% accuracy in 5th iteration.

5 CONCLUSION AND FUTURE

WORK

5.1 Conclusion

Using Deep Learning CNNs, pre-trained networks like VGG-16, VGG-19 and ResNet50 and CT-Scan and X-Ray chest images, this experiment aimed to determine abnormal (COVID-19) from normal (healthy) chest using CT-scan and X-ray chest images. The CNN-based networks VGG-16, VGG-19 and ResNet50 were trained and validated using a different partition of the dataset was used, carrying out 15 repeated cross-validation experiments and producing confusion matrices (Loss/Accuracy vs Epoch Number) for each model. To investigate further the statistically significant difference between Deep Learning models, we used cross validation and evaluated their accuracy, precision, recall, and F1-score. With various hyperparameter combinations, VGG-16, VGG-19, and ResNet-50 all achieve 97.73% accuracy, 100% sensitivity, 93.33% specificity and 98.00% F1-score. Thus, ResNet50 achieves 97.73% accuracy with 0.001 [unpublished, non-peer-reviewed preprint]

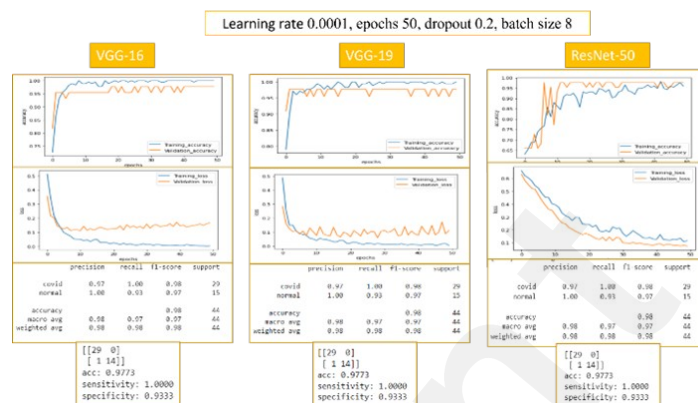


Figure 4: the accuracy graph vs number of epochs, the loss graph vs number of epochs and the performance and confusion matrix for each model with the 80%-20% cross -validation, with learning rate 0.0001, epoch 50, 0.2 dropout and batch size 8

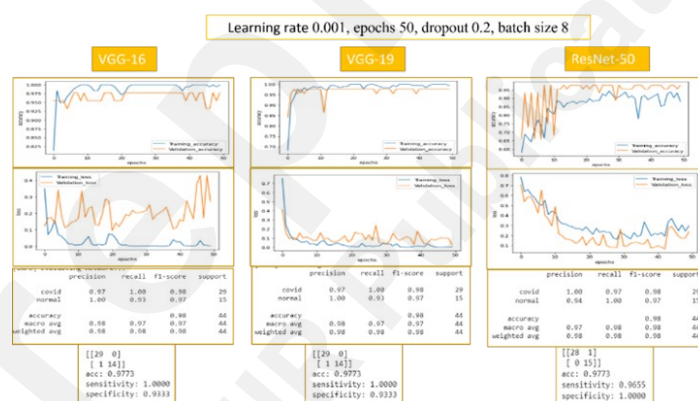


Figure 5: the accuracy graph vs number of epochs, the loss graph vs number of epochs and the performance and confusion matrix for each model with the 80%-20% cross -validation with learning rate 0.001, epoch 50, 0.2 dropout and batch size 8

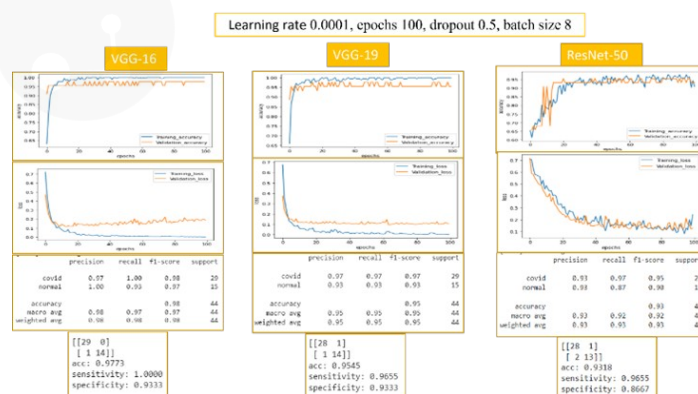


Figure 6: the accuracy graph vs number of epochs, the loss graph vs number of epochs and the performance and confusion matrix for each model with the 80%-20% cross -validation with learning rate 0.0001, epoch 100, 0.5 dropout and batch size 8

	0.0001	100 50	0.2	
VGG16	0.9773	1.00	0.933	0.98
	0.9773	1.00	0.933	0.98
	0.9773	1.00	0.933	0.98
	0.9773	1.00	0.933	0.98
	0.9773	1.00	0.933	0.98
VGG19	0.9545	0.9655	0.9333	0.97
	0.9318	0.9310	0.9333	0.95
	0.9773	1.00	0.933	0.98
	0.9773	1.00	0.933	0.98
	0.9773	1.00	0.933	0.98
ResNet50	0.9091	0.8621	1.000	0.91
	0.9545	0.9655	0.9333	0.95
	0.9545	0.9655	0.9333	0.95
	0.9318	0.9310	0.9333	0.9333
	0.9773	1.00	0.933	0.98

Table 2: Model performance metrics

learning rate, 100 epoch, 0.5 dropout and batch size 16. VGG-19 achieved accuracy 97.73% with the small (0.0001) learning rate values, dropout rate 50% and batch size 8 and The VGG-16 showed the accuracy, sensitivity, specificity, and f1-score for the various combinations of hyperparameters, whereas the VGG-16 showed the same accuracy, sensitivity, specificity, and f1-score. Accordingly, VGG-16 is underfitting and showing the same accuracy, sensitivity, specificity, and f1-score. In contrast, VGG-19 increases accuracy from 93.18% to 95.45% and finally reaches an accuracy rate of 97.73% when increase the dataset size. In the same way, ResNet-50 demonstrates incremental gains as a result of hyperparameter tuning. The accuracy rate increased from 90.91% in the 1st iteration to 93.18% in the 2nd iteration, 95.45% in the 3rd and 4th iterations and 97.73% in the 5th iteration. Using the enhanced deep learning models as a starting point, we were able to build an effective model that incorporates the features derived from those models. In the future, as part of our research, we will investigate multi-class classification to separate images from datasets that contain patients with problems caused by various illnesses such as tuberculosis, AIDS, COVID-19, etc. Our plan is to work on this issue in cooperation with doctors in hospitals.

5.2 Future Work

The experiments were carried out on an open access dataset of CT-scan and X-rays of COVID-19, healthy people and other lung diseases. With a larger dataset we can develop a fine-tuned version of the evaluation techniques. In the future, a classification model trained on a huge dataset of hundreds or even thousands of patients will be needed to validate the generalization of an automated diagnostic assistant tool. In the future, we will collect the dataset with different lung diseases CT-scan and X-rays images and applied multi class classification model to identify COVID-19 and other lung diseases classes. Currently, we are currently working on decreasing the false positives and enhancing our calibration techniques.

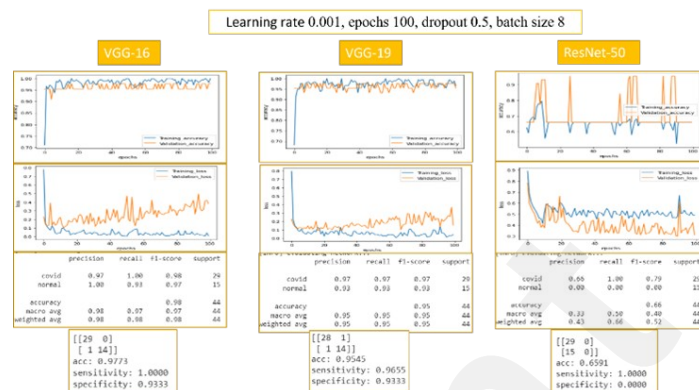


Figure 7: the accuracy graph vs number of epochs, the loss graph vs number of epochs and the performance and confusion matrix for each model with the 80%-20% cross-validation with learning rate 0.001, epoch 100, 0.5 dropout and batch size 8

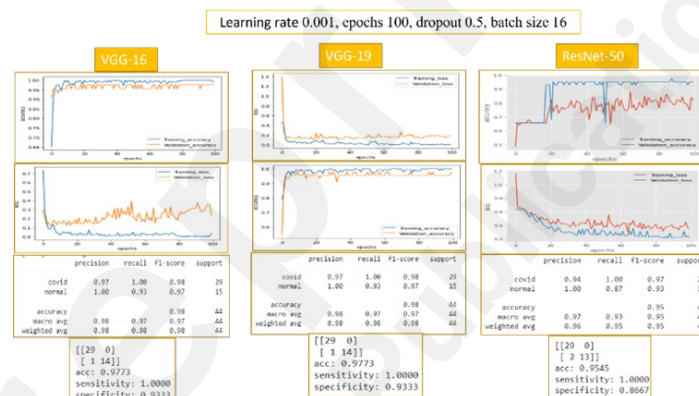


Figure 8: the accuracy graph vs number of epochs, the loss graph vs number of epochs and the performance and confusion matrix for each model with the 80%-20% cross-validation with learning rate 0.001, epoch 100, 0.5 dropout and batch size 16

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Reference

- [1] World Health Organization. Pneumonia of unknown cause – china, December 31 2019. [Online; accessed March 2025].
- [2] World Health Organization. Update on omicron, November 28 2021. [Online; accessed March 2025].
- [3] Ecker et al. Long covid symptoms persist for up to two years in over half of affected individuals, March 2023. [Online; accessed March 2025].
- [4] American Psychological Association. Defining long covid: Understanding its impact, March 2025. [Online; accessed March 2025].
- [5] The Times. One in ten people in uk may suffer from long covid, March 2025. [Online; accessed March 2025].
- [6] The Times. Long covid is the pandemic's dark shadow. why does no one in power in britain want to talk about it? March 2025. [Online; accessed March 2025].
- [7] The Scottish Government. Scotland's decades-long covid legacy revealed - from nhs chaos to classroom crisis, March 2025. [Online; accessed March 2025].

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- [8] USC The top trends in diagnostic imaging for 2025, March [Online; accessed March 2025].
- [9] Journal of Ultrasound. Computed tomography for covid-19 pneumonia diagnosis, March 2025. [Online; accessed March 2025].
- [10] S. M. A. Ullah et al. Scalable telehealth services to combat novel coronavirus (covid-19) pandemic. *Sci.*, 2:18, 2021. *SN Comput. Sci.*, 1:32019, 2020.
- [11] M. M. Islam et al. Wearable technology to assist the patients infected with novel coronavirus (covid-19). *Comput. Sci.*, 1:274, 2020.
- [12] M. M. Islam et al. Breathing aid devices to support novel coronavirus (covid-19) infected patients. *SN Comput. Sci.*, 1:274, 2020.
- [13] M. M. Rahman et al. An automated system to limit covid-19 using facial mask detection in smart city network. *2020 IEEE International Conference on Electronics and Mechatronics Conference (IEMTRONICS)*, pages 1–5, 2020.
- [14] A. Asraf et al. Deep learning applications to combat novel coronavirus (covid-19) pandemic. *SN Comput. Sci.*, 1:363, 2020.
- [15] M. Z. Islam et al. A combined deep cnn-lstm network for the detection of novel coronavirus (covid-19) x-ray images. *Inf. Med. Unlocked*, 20, 2020.
- [16] P. Saha et al. Ensemble of machine learning classifiers for covid-19 diagnosis from x-ray images using convolutional neural network. *Inf. Med. Unlocked*, 22, 2021.
- [17] M. M. Islam et al. Diagnosis of covid-19 from x-rays using combined cnn-rnn architecture with transfer learning. *medRxiv*, 2020.
- [18] E. J. Muhammad et al. Predictive data mining models for novel coronavirus (covid-19) infected patients' recovery. *SN Comput. Sci.*, 1:206, 2020.
- [19] M. M. Islam et al. A review on deep learning techniques for the diagnosis of novel coronavirus (covid-19). *Access*, 9:30551–30572, 2020.
- [20] Z. Wu et al. Unsupervised feature learning via non-parametric instance discrimination. *IEEE Conference on Computer Vision and Pattern Recognition*, pages 3733–3742, 2018. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*.
- [21] S. J. Pan and Q. Yang. A survey on transfer learning. *IEEE Trans. Knowl. Data Eng.*, 22:1345–1359, 2010.
- [22] P. Ashar et al. Covid-caps: A capsule network-based framework for identification of covid-19 cases from x-ray images. *arXiv preprint arXiv:2004.02696*, 2020.
- [23] M. E. Chowdhury et al. Can ai help in screening and covid-19 pneumonia?, 2020. *arXiv preprint arXiv:2003.13145*.
- [24] Md. Islam, F. Karray, R. Alhajj, and J. Zeng. A review on deep learning techniques for the diagnosis of coronavirus (covid-19). *IEEE Access*, vol. 9, pp. 30551–30572, doi: 10.1109/ACCESS.2021.3058537, 2021.
- [25] M. Alhabano. Automated malware detection in mobile app stores based on robust feature generation. *3rd Generation*. doi: 10.3390/electronics9030435, 2020.
- [26] Michael Goldbaum Daniel Kernan, Kang Zhang. Labeled optical coherence tomography (oct) and chest x-ray images for classification. Available: <https://data.mendeley.com/datasets/rschjbr9si/2>.
- [27] Covid19-chest-xray-image-dataset, Available: <https://www.kaggle.com/alifrahman/covid19-chest-xray-image-dataset>.
- [28] Chest x-ray pneumonia dataset, Available: <https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia-dataset>.
- [29] Mohammed K. Hassan, Ali I. El Desouky, Sally M. Elghamrawy, and Amany M. Samir. A hybrid real-time monitoring framework with nb-woa algorithm for patients with chronic diseases. *Future Generation Computer Systems*, Volume 10, Pages 77–95, 2019. <https://doi.org/10.1016/j.future.2018.10.021> ISSN 739X.