An Effective Deep Learning Model for COVID-19 Detection from Chest X-Ray

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***Abstract*: A new viral disease that easily spreads was in December 2019 discovered in Wuhan city in China and was named by the World Health Organization (WHO) as COVID-19. The symptoms can be either mild or severe and mostly in older people who have hypertension, diabetes, and heart or lung disease. Early screening has proved to be effective in reducing the spread and the RT-PCR test is been employed for testing which is expensive and time-consuming. Deep learning using CNN on Chest X-rays can be used to detect the infection.**

In this paper, three deep learning models (VGG16, Xception, and InceptionV3) were proposed for detecting COVID-19. These models were pretrained using images from ImageNet with the proposed Inception model achieving the highest accuracy of 98.28%. The f1-score for Xception, VGG, and Inception approaches are 98%, 95%, and 95% respectively. The proposed approaches achieved a precision score of 100%, 100%, and 96% in classifying COVID-19 cases for Inception, Xception, and VGG16 respectively.

***Keywords:* Deep learning, COVID-19, Chest X-Ray, RT-PCR test, CNN**

I. INTRODUCTION

A new viral disease that easily spreads was in December 2019 discovered in Wuhan city in China and was named by the World Health Organization (WHO) as COVID-19 [1]. Infection is transmitted mostly by droplets either saliva or mucous landing on the mouth, nose or eyes [2]. The symptoms can be either mild or severe and mostly in older people who have hypertension, diabetes, and heart or lung diseases [3]. The most common symptoms of this viral syndrome are fever, dry cough, fatigue, aches and pains, loss of taste/smell, and breathing problems[4]

According to the World Health Organization as of the 13th of October, 2021, there are about 238,229,951 confirmed cases of COVID-19, including 4,859,277 deaths [5]. Of the figures presented above, Nigeria accounts for about 208,153 confirmed cases with about 2,756 deaths [6]. As the COVID-19 epidemic has become a global pandemic, real-time analysis of epidemiological data is required to prepare society for better disease response plans [7].About 15% of COVID-19 cases are severe(Sharma & Sharma, 2020). This implies that Oxygen may be required for them to be treated in the hospital.

The main screening method used for detecting COVID-19 infections is reverse transcriptase-polymerase chain reaction (RT-PCR) testing, which can detect SARS-CoV-2 RNA from respiratory specimens which can be collected through a variety of means such as nasopharyngeal or oropharyngeal swabs [8]. However, despite being highly specific, the sensitivity of RT-PCR can be relatively low [9].An alternative screening method that has also been utilized for COVID-19 screening has been radiography examination [10] where chest radiography imaging e.g., chest X-ray (CXR) or computed tomography (CT) imaging is conducted and analyzed.

Machine learning algorithms have been used to analyze medical datasets[11]. Deep learning, a subset of machine learning will not only help to select and extract features but also construct new ones. Furthermore, it does not only diagnose the disease but can also measure predictive targets and provide prediction models to help the physician efficiently. Motivated by the urgent need to develop solutions to aid in the fight against the COVID-19, the success recorded in using deep learning algorithms in detecting Covid-19, and the gradual availability of chest X-ray images, this research aims to use one of the available datasets [12] to predict COVID-19 in patients.

The rest of this paper is structured as follows: In the next section, a brief literature review of related works is presented, then in section III a description of the dataset used is given. In section IV, the methodology for the research is explained. In sections V and VI, the training and results obtained are presented while section VII gives a comparison of the results gotten with some state-of-the art results. Section VIII gives conclusions of the research.

II. LITERATURE REVIEW

The sudden rise in the COVID-19 pandemic has necessitated the development of innovative ways to cope with the rising healthcare demands of this outbreak[13]. To this end, many recent models have been proposed for COVID- 19 detection.

[14]did a study on deep neural networks and Convolutional Neural Networks in image segmentation. [15], and proposed a model that uses CNN to predict COVID-19 from chest X-rays of patients showing symptoms of SARS-I. The paper uses end to end deep learning framework that directly predicts COVID-19 from the images provided. A deep neural network for the recognition of COVID-19 is proposed by [16], utilizing X-ray images of COVID-19 and X-Ray images of non- COVID-19. The study found 96% for COVID-19 detection and 70.65% for non- COVID-19 detection. As can be seen, the accuracy of this research is low for non-COVID-19 infections.

To detect COVID-19, normal, bacterial, and viral pneumonia with the help of Deep learning, [17] proposed a framework. The aim of their work was to be able to classify these four diseases using chest X-Ray. [18], in their paper provided a method that helps to improve model performance through the application of image augmentation technique on original data. Augmentation generates additional images by setting parameters like horizontal flip, vertical flip, shear range, and zoom range to certain values and also helps to avoid an imbalanced dataset. [19], in their paper, titled "Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images" created a COVID-Net CT which was able to achieve state-of-the-art COVID-19 detection performance. A dataset containing 1,489 Chinese patients was used for research. One potential limiting factor is the restricted quantity and diversity of CT imaging data used to learn the deep neural network, given the entirely Chinese patient cohort used in the study.[10] in their paper used RESNET-50 to classify chest X-Ray images as either normal or having COVID-19. The dataset used however contained only 147 images: 73 normal and 74 infected with CIOVID-19. They got a high accuracy on the training dataset [20] However, evidence was not shown for results gotten on test data.

III. DATASET USED

To create the dataset used for this research, data from two repositories were collected. For COVID-19 cases, data from (Github, 2020), which is a public open dataset of chest X-ray images of patients who are positive or suspected of COVID-19 or other viral and bacterial pneumonia (MERS, SARS, and ARDS) was used. The data is collected from public sources as well as through indirect collection from hospitals and physicians to make the dataset. The version used was the one available as of 15th July 2021. The details of the dataset are shown in figure 1.

Since the research is concerned with COVID-19, only the images of patients diagnosed with the COVID -19 are of importance. So in creating the dataset for the COVID-19 patients, extraction is done from this dataset to create a new folder containing only images of COVID -19.

Type	Genus or Species	Image Count
Viral	COVID-19 (SARSr-CoV-2)	468
	SARS (SARSr-CoV-1)	16
	MERS-CoV	10
	Varicella	5
	Influenza	4
	Herpes	3
Bacterial	*Streptococcus* spp.	13
	Klebsiella spp.	9
	Escherichia coli	4
	Nocardia spp.	4
	Mycoplasma spp.	5
	Legionella spp.	7
	Unknown	2
	Chlamydophila spp.	1
	Staphylococcus spp.	1
Fungal	*Pneumocystis* spp.	24
	Aspergillosis spp.	2
Lipoid	Not applicable	8
Aspiration	Not applicable	1
Unknown	Unknown	59

Figure 1: Description of the dataset from (Github, 2020)

An Image of a COVID-19 X-ray from the dataset is shown in figure 2 after extraction.

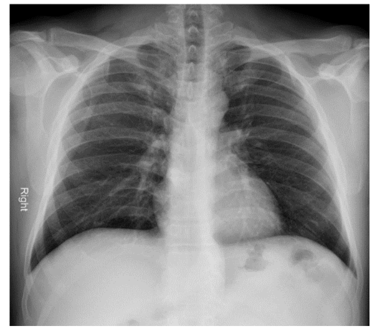

Figure 2: Covid-19 chest X-ray

To create a normal class for training the model, normal chest X-ray images were obtained from the Kaggle repository [21]. Only the normal images are needed for use for this project and hence downloaded. The sample image of a normal chest X-ray is shown in figure 3.

Figure 3: Normal chest X-ray

IV. METHODOLOGY

Many steps have been followed for creating the Deep Learning-based Models. The model's code was written using the Keras API of TensorFlow in Python Programming Language taking advantage of Google Colab for tainting of the models. The dataset used was first uploaded to Google Drive for easy access by Google Colab. To load the data, all paths to images in the dataset directory were grabbed from Google Drive. The image path was then defined for both classes that were extracted. The image was loaded and converted to an RGB channel ordering, and resizing to 224×224 pixels so it is ready for the Convolutional Neural Network. Figures 3.4 and 3.4 show the images when Pre-processing is done.

The data and label lists were updated, respectively. Pixel intensities of the images were set to the range [0, 1], and the labels were converted to NumPy array format. The labels were encoded and the dataset was split into both training and testing sets. Both images were then merged to form the final dataset to be used.

The various base networks to be used which are InceptionV3, Xception, and VGG16, were instantiated using pre-trained weights on ImageNet. The data augmentation generator object was initialized and then the model was trained, setting it up for fine-tuning. The methodology is illustrated in figure 4 below

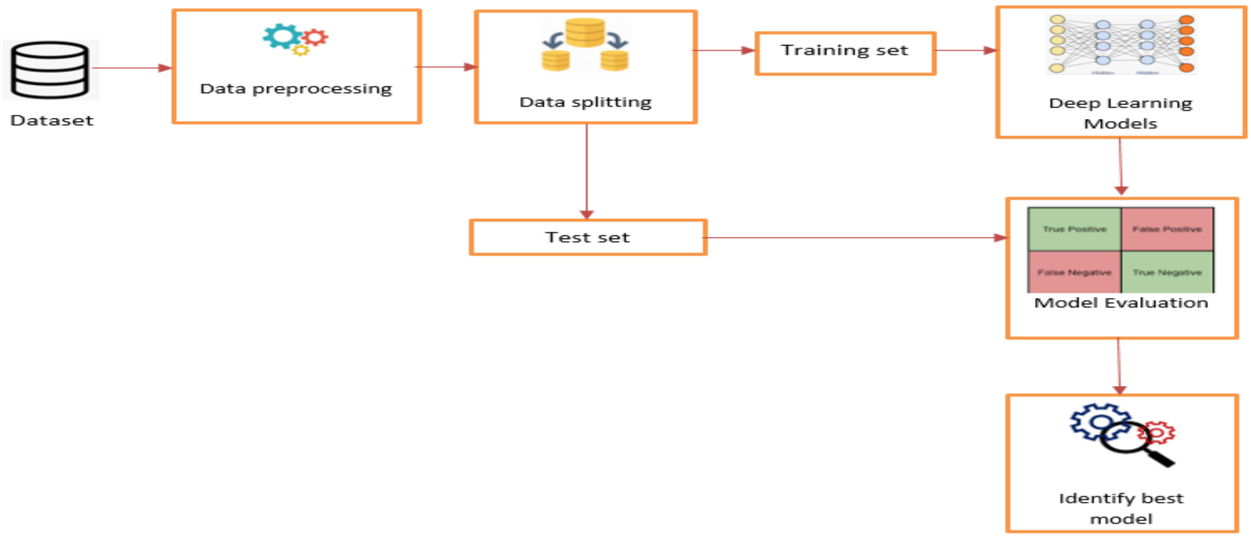

Figure 4: Proposed methodology

V. TRAINING THE MODELS

To train the proposed models, a good way would be to take advantage of a pretrained Convolutional Neural Network on a much bigger dataset due to the limited dataset available and train it. This project uses the architecture of the VGG16, InceptionV3, and Xception networks pretrained on the ImageNet dataset which includes more than 14 million images from over 20 thousand classes. Although the network was not trained on chest X-ray images, it is still useful for most computer vision tasks and can help this project achieve better results despite the lack of data.

VI. RESULTS AND DISCUSSION

The performance of the three developed deep convolutional neural network models for the two-class problem (normal, COVID-19) using the proposed approaches was evaluated by conducting experiments. The proposed approaches were evaluated, keeping the pretrained weights of the base networks frozen and only training the additional layers using the pretrained. To investigate the performance of the proposed models in a quantitative manner, the metrics classification report was used as shown in Tables I and II.

Table I: Inception Classification Report

	Precision	Recall	F1-score	support
0	0.96	0.93	0.95	29
1		0.97	0.95	29
Accuracy			0.95	58
Macro avg	0.95	0.95	0.95	58
Weighted avg	0.95	0.95	0.95	58

The proposed model based on Xception achieved an overall 98.28% accuracy on this task. This was the best-performing model based on accuracy. The VGG16 and InceptionV3 based models both achieved an accuracy of 94.83%. Since there is no class imbalance, this accuracy score of the Xception model shows the robustness of the classifier. The summary of the metrics sensitivity, accuracy, precision, and f-1 score is given in Table I. The sensitivity metric of 97% for the Xception approach means that out of 100 patients who do have COVID-19, the model accurately identifies 97 patients.

Table II: Vgg and Xception Classification Report

VGG classification report				
	Precision	Recall	F1-score	Support
0	1.00	0.90	0.95	29
1	0.91	1.00		29
Accuracy			0.95	58
Macro avg	0.95	0.95	0.95	58
Weighted avg	0.95	0.95	0.95	58
Xception Classification report				
	Precision	Recall	F1-score	Support
0	1.00			29
1	0.97			29
Accuracy			0.98	58
Macro avg	0.98	0.98	0.98	58
Weighted avg	0.98	0.98	0.98	58

From table III, the specificity metric of 100% means that out of 100 patients who do not have COVID-19, the model accurately identifies all 100 patients and misclassifies none of the patients. With a precision of 100% it means that all theimages labeled asCOVID**-**19areCOVID **-**19**,** whilefor the non-covid class, 97% are non**-**COVID-19**.** The sensitivity metric of 90% for VGG16 means that out of 100 patients who do have COVID-19, the model accurately identifies 90 patients correctly. The specificity metric of 100% means that out of 100 patients who do not have COVID-19, the model accurately identifies all 100 patients and misclassifies none patients.

Table III: Precision, Accuracy, and Recall For The Proposed Models

Model	Covid-19	Non Covid-19	Weighted Average
Precision			
Xception	100%	97%	98%
VGG	100%	91%	95%
Inception	96%	93%	95%
Sensitivity (Recall)			
Xception	97%	100%	98%
VGG	90%	100%	95%
Inception	93%	97%	95%
F-1 score			
Xception	98%		
VGG	95%		
Inception	95%		
Accuracy			
Xception	98.28%		
VGG	94.83%		
Inception	94.83%		

With a precision of 100% it means that all **the** images labeled as Covid-19 are Covid-19, while for the non-COVID-19 class, only 91% are non-COVID-19**.**

The sensitivity metric of 93% for Inception means that out of 100 patients who do have COVID-19, the model accurately identifies 93 patients. The specificity metric of 97% means that out of 100 patients who do not have COVID-19, the model accurately identifies all 97 patients and misclassifies 3 patients. With a precision of 96% it means that all the images labeled as Covid-19 are Covid-19, while for the non-COVID-19 class, only 93% are non-COVID-19.

From the analysis above, it can be observed that the proposed Xception based approach has achieved good sensitivity for COVID-19 cases (97% sensitivity), which is important since it is necessary to limit the number of missed COVID-19 cases as much as possible. The next performing model in terms of sensitivity is the inception model which has a sensitivity of 93%.

Secondly, it can be observed that the Xception based model achieves high precision for COVID-19 cases (100%) which indicates no false positive COVID-19 detections. This high precision is important given that too many false positives would increase the burden for the healthcare system due to the need for additional PCR testing and additional care.

VII. COMPARISON WITH THE EXISTING WORKS

All the experiments reported in this research, have been conducted on Google Colab's GPU. Here, the best-proposed models have been compared with works that are considered to be state-of-the-art approaches. However, it should be noted that there is a difference in the dataset used. The comparison between the best-performing model and the state-of-the-art approaches is shown in Table IV. The best-performing model is in bold.

From table 4, the proposed Xception based approach used in this experiment had the best accuracy score when compared to other works. The next performing model is the one developed by [22] which has an accuracy score of 95.38%. Their approach used Resnet and SVM for classification.

Table IV: Comparison with the Recent Studies

Method	Accuracy	Number of images for training	Methods used
[23]	93.84%	224 COVID-19(+) 700 Pneumonia 504 Healthy	VGG19
[22]	95.38%	53 COVID-19(+) 5526 COVID-19 (-) 8066 Healthy	ResNet50+ SVM
[24]	90%	25 COVID 25 Normal-19(+)	COVIDX-Net
[25]	94.7%	50 COVID-119	CNN
[26]	87.02%	125 COVID-19(+) 500 Pneumonia 500 No-Findings	DarkCovidNet
Proposed Xception	98.28%	142 Covid-19(+) 142 Covid-19(-)	Xception
Proposed VGG	94.83%	142 Covid-19(+) 142 Covid-19(-)	VGG
Proposed Resnet	50%	142 Covid-19(+) 142 Covid-19(-)	Resnet
Proposed Inception	94.83%	142 Covid-19(+) 142 Covid-19(-)	Inception

VIII. CONCLUSIONS

The main limitation of this project is the lack of data available for model testing and training. More specifically there is limited COVID-19 chest X-ray of infected patients due to privacy. Also, with the COVID-19 disease being novel, available data is still scarce as research is currently being done in this area. With the insufficient data available, the result of this research is simply not reliable enough for deploying the system for medical use. Another limitation is the use of only chest X-ray images for the task of detecting COID-19 positive cases.

As a result, of the above, future work will include a replication of the experiments on a much larger chest database of

COVID-19 images to determine the suitability of the proposed models by training and testing on diverse datasets from different sources and using different X-ray equipment.

REFERENCES

[1] Xu, Y. H. (2020). Clinical and computed tomographic imaging features of novel coronavirus pneumonia caused by SARS-CoV-2. Journal of Infection, 80(4), 394-400.

[2] Jaiswal, A., &Bist, A. S. (2020). Analysis of Deep Learning algorithms on COVID-19 Radiography Database. International Journal of Advanced Science and Technology, 29(11), 1268-1275.

[3] Prakash, K. B., Imambi, S. S., Ismail, M., Kumar, T. P., &Pawan, Y. N. (2020). Analysis, Prediction and Evaluation of COVID-19 Datasets using Machine Learning Algorithms. International Journal of Emerging Trends in Engineering Research, 8(5).

[4] Huang, C., Wang, Y., Li, X., Ren, L., Zhao, J., Hu, Y., Gu, X. (2020). Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. Lancet , 395, 497–506.

[5] WHO. (2021). WHO Coronavirus (COVID-19) Dashboard. Retrieved 07 25, 2021, from https://covid19.who.int/.

[6] NCDC. (2021). COVID-19 NIGERIA. Retrieved 07 25, 2021, from http://covid19.ncdc.gov.ng/

[7] Herath, H., Karunasena, G., Ariyathunge, S., Priyankara, H., Madhusanka, B., Herath, H., &Nimanthi, U. (2020). Deep Learning Approach to Recognition of Novel. In: SLAAI - International Conference on Artificial Intelligence.

[8] Wang, W., Xu, Y., R. Gao, R. L., Han, K., Wu, G., & Tan, W. (2020). Detection of sars-cov-2 in different types of clinical specimens. JAMA, 323(18), 1843–1844.

[9] Fang, Y., Zhang, H., Xie, J., Lin, M., Ying, L., Pang, P., & Ji, W. (2020). Sensitivity of chest ct for covid-19: Comparison to rt-pcr. Radiology, 296(2), 115–117.

[10] Aboughazala, L. M., & Mohammed, K. K. (2020). Automated Detection of Covid-19 Coronavirus Cases Using Deep. Al-AzharUn. Journal for Research and Studies, 2(1).

[11] Hashim, H., Mathew, N. G., Sabira, K., Nizamudeen, A., & Jacob, J. (2019). Advanced Medical Diagnosis and Prediction Using Deep Learning. Journal of Applied Information Science, 7(1), 11-15.

[12] Github. (2020). covid-chestxray-dataset. Retrieved July 22, 2021, from https://github.com/ieee8023/covid-chestxray-dataset

[13] Khasawneh, N., Fraiwan, M., Fraiwan, L., Khassawneh, B., &Ibnian, A. (2021). Detection of COVID-19 from Chest X-ray Images Using Deep Convolutional Neural Networks. Sensors , 21(5940).

[14] Razzak, M., Naz, S., &Zaib, A. (2018). Deep learning for medical image processing: Overview, challenges and the future. Classification in BioApps, 323-350.

[15] Patil, A. R. (2020). COVID-19 Detection using Chest X-Ray Images through a Convolutional Neural Network and transfer learning. International Journal for Research in Applied Science & Engineering Technology (IJRASET), 8(11), 518-523

[16] Zhang, J., &Xie, Y. (2020). COVID-19 Screening on Chest X-ray Images Using Deep Learning based Anomaly Detection. arXiv preprint arXiv:2003.12338.

[17] Mangal, A., Kalia, S., Rajgopal, H., Rangarajan, K., &Namboodiri, V. (2020). CovidAID:COVID-19 Detection Using Chest X-Ray. arXiv preprint arXiv:2004.09803.

[18] Loey, M., Smarandache, F., &Khalifa, N. E. (2020). Within the Lack of Chest COVID-19 X-ray Dataset: A Novel Detection Model Based on GAN and Deep Transfer Learning. Symetry, 12. 651. 10.3390/sym12040651.

[19] Wang, L., Lin, Z. Q., & Wong, A. (2020). Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images. Scientific Reports.

[20] Gozes, O. (2020). Rapid AI Development Cycle for the Coronavirus (COVID-19) Pandemic: Initial Results for Automated Detection & Patient Monitoring using Deep Learning CT Image Analysis. arXiv preprint arXiv:2003.05037.

[21] Kaggle. (2018). Chest X-Ray Images (Pneumonia). Retrieved July 22, 2021, from https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia

[22] Sethy, P. K., &Behera, S. K. (2020). Detection of coronavirus Disease (COVID-19) based on Deep Features.

[23] Ioannis, D. A., &Bessiana, T. (2020). COVID-19: Automatic detection from X-ray images utilizing Transfer Learning with Convolutional Neural Networks. arXiv:2003.11617.

[24] Hemdan, E. E., Shouman, M. A., &Karar, M. E. (2020). COVIDX-Net: A framework of deep learning classifiers to diagnose COVID-19 in x-ray images. arXiv preprint arXiv:2003.11055.

[25] Singh, D., Kumar, V., Yadav, V., & Kaur, M. (2020). Deep Neural Network-Based Screening Model for COVID-19-Infected Patients Using Chest X-Ray Images. Int. J. Pattern Recognit. Artif. Intell., 35.

[26] Narin, A. K., &Pamuk, Z. (2020). Automatic Detection of Coronavirus Disease (COVID-19) Using X-ray Images and Deep Convolutional Neural Networks. arXiv preprint arXiv:2003.10849.

[27] Sharma, S., & Sharma, J. (2020). Diagnosing COVID-19 Pneumonia using Deep Learning. International Research Journal of Engineering and Technology (IRJET), 7(7), 1840-1843.