CXRcovNet: COVID-19 detection from CXR images using transfer learning approaches.

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INRODUCTION

The new COVID-19 (coronavirus disease 2019) pandemic has caused over 516 million illnesses and 6.2 million deaths worldwide as of May 12th, 2022, with a total of 11.5 + million vaccination doses provided. As a result of the virus's ongoing dissemination over the world, the SARS-CoV-2 mutations produced a new COVID-19 wave. Among the variants identified were the Beta, XE, and omicron types. There were fears that a new variant based on the original SARS-CoV-2 strain might be more extremely contagious. In many places, COVID-19 detection takes place through reverse transcription polymerase chain reaction (RT-PCR) tests, which may take longer than 48 h. This is one major reason for its severity and rapid spread.

In this work, we propose an automatic detection method called CXRcovNet, an 11-layer custom-designed CNN model, and three state-of-the-art models wereevaluated with CXR images to detect COVID-19. Transfer learning techniques were used on the three pre-trained CNN models (VGG-16, ResNet-50, and EfficientNetB3),while the CXRcovNet models were designed and trained from scratch. As part of the experiment, all pre-trained and CXRcovNet models were trained with the same hyperparameters and their performance was checked for matrix-like sensitivity, specificity, f1-score, precision, accuracy, and ROC curve.

MOTIVATION

The gold standard COVID-19 detection technique is real-time polymerase chain reaction (RT-PCR). However, RT-PCR kits are costly and take 6–9 hours to verify infection in a patient. Due to the lower sensitivity of RT-PCR, it provides high false-negative results.

To resolve this problem, radiological imaging techniques like chest X-rays and CT scans are used as alternatives to detect and diagnose COVID-19. In this paper, we found out the chest x-ray tests are economically affordable, and the results are relatively easy to use. Chest X-ray tests are easily available, have portable versions and low risk of radiation. On the other hand, CT scans have high risk of radiation, are expensive, need clinical expertise to handle and are non-portable. This makes the useof X-ray scans more convenient than CT scans.

Moreover, COVID-19 reveals some radiological signatures that will be easily detected through CXRs. For this, radiologists are required to research these signatures. However, it's a time-consuming and error-prone task. Hence, there's a necessity to automate. Therefore, our objective is to develop an automatic DL system for the detection of COVID-19 samples from healthy and pneumonia cases using CXR images.

SCOPE OF THE PROJECT

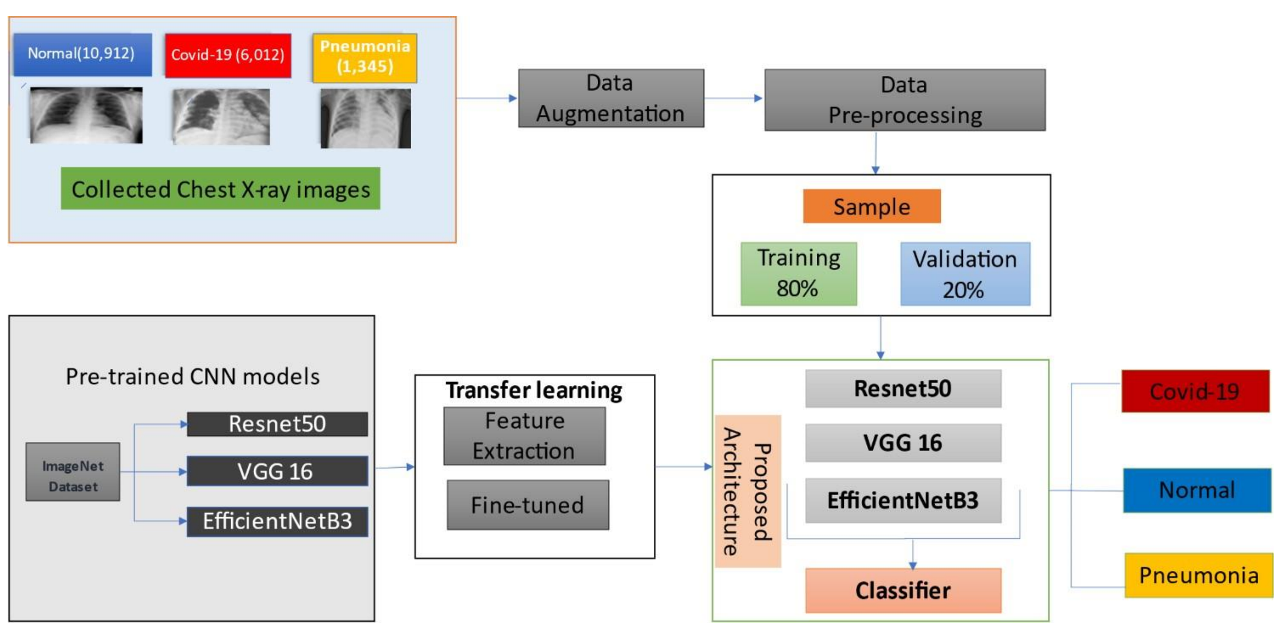
Our suggested CXRCOVNet and 3 pre-trained model is especially essential for countries where laboratory testing kits are unavailable. The use of a chest X-ray to prioritize patients for further RT-PCR testing, which might be useful in an inpatient setting where existing systems are confused whether to retain the patient on the ward with other patients or segregate them in COVID-19 zones.

Our research advances the prospect of an accurate, automated, quick, and low-cost technique for aiding in the diagnosis of COVID-19 using chest X-ray images. This would allow hospitals and medical clinics all around the world to diagnose illnesses in chest X-rays.

METHODOLOGY

Approach 1 is to examine covid-19 infection using three pretrained models (VGG-16, Resnet-50, and efficient Net Net-B3). The concept of transfer learning is used to fine-tune three pretrained models for covid identification in this method. The purpose of this technique is to investigate if a neural network can detect the difference between a covid-19 infection and other lung abnormalities

Approach 2, CXRcovNet, an 11-layer custom-designed CNN architecture that is trained from scratch, is used to classify covid-19 and its performance is compared to the three pretrained models (VGG-16, Resnet-50, and efficient Net Net-B3) toassess the significance of transfer learning when we have a small number of data sets.



RESULTS

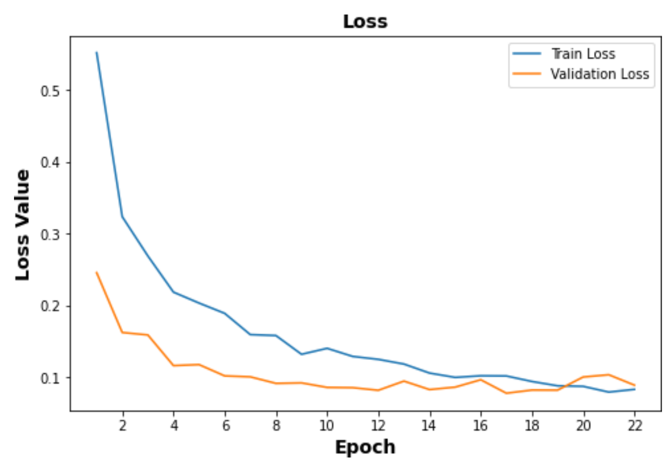
For both the fine-tuned (EficentNetB3, VGG16, and ResNet50) and CXRcovNet (11-layer custom design CNN) models, its train accuracy and loss values for their best epochs during the training and testing phase summarize in table 1 and the model performance matric in terms of Accuracy, precision, Sensitivity, F-Score, Specificity and ROC value summarize in table 2.

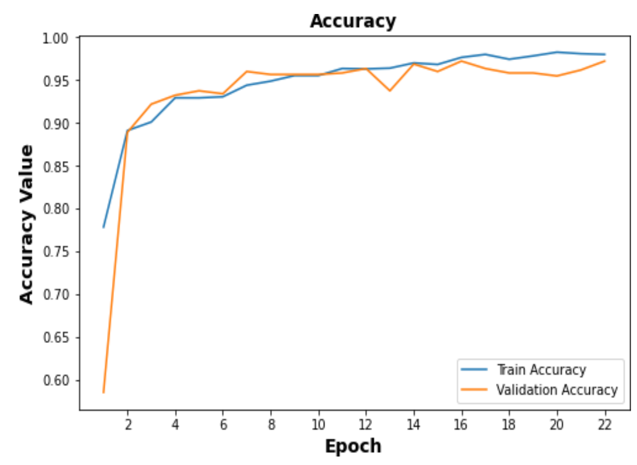
Table 1. Compression of the models for the best epoch in terms of TrainAcc and ValLoss

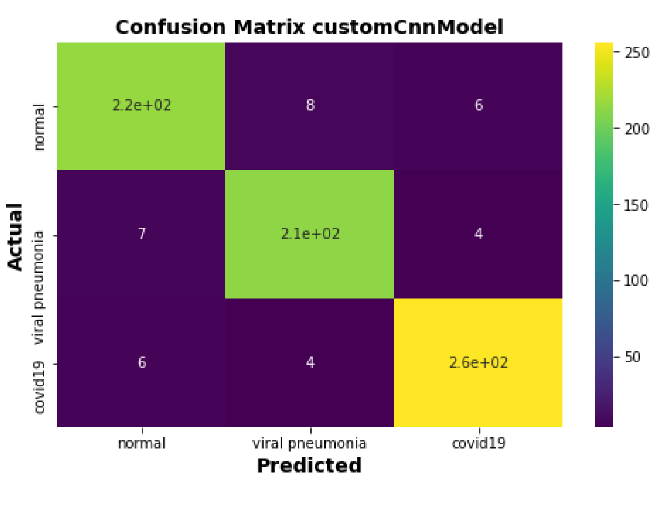
Model	Best Epoch	BS	TrainLoss	TrainAcc	ValLoss	ValAcc
VGG-16	22	32	0.083	0.964	0.089	0.973
ResNet-50	22	32	0.005	0.99	0.157	0.969
EfficientNet-B3	22	32	1.413	0.997	1.440	0.966
CXRcovNet	22	32	0.045	0.984	0.106	0.972

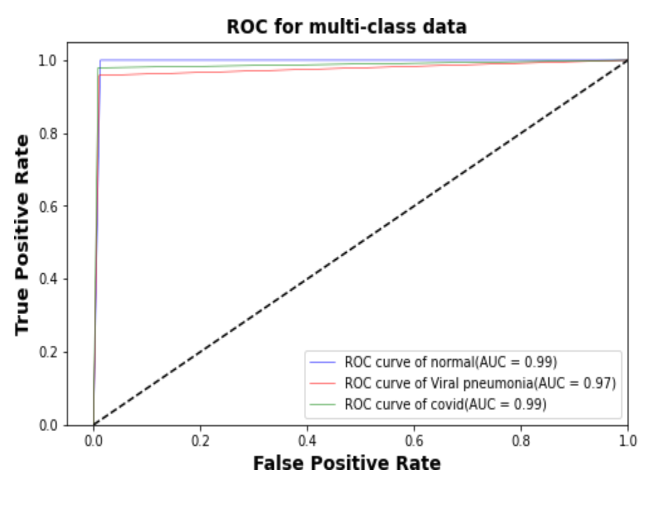
Table 2. The performance of each proposed model to classify covid-19, non-covid-19, and viral-pneumonia occurrences.

Classification model	Class	Precision %	Recall %	F1-score %	AUC %	Accuracy %
EfficientNet-B3	Covid-19	97	100	98	98	97
	Normal	99	93	96	99	
	Pneumonia	96	98	97	97	
VGG-16	Covid-19	97.5	100	98.7	99	97.9
	Normal	97.8	95.8	96.8	99	
	Pneumonia	98.3	97.9	98.1	97	
ResNet-50	Covid-19	98.7	96	97	99	97.6
	Normal	96	98	97	98	
	Pneumonia	98.7	98	98	98	
CXRcovNet	Covid-19	96.2	96.2	94.8	97	95
	Normal	94.3	93.9	94.1	96	
	Pneumonia	94.6	95.0	94.8	96	









SUMMARY

The technique of transfer learning was used on three pre-trained neural networks (eficentNetB3, VGG16, and ResNet50) in the first approach, while CXRcovNet, an 11-layer custom-designed CNN model, was trained from scratch and evaluated with the same hyperparameters in the second approach.

VGG-16 was the most accurate out of the pre-trained models, obtaining 98.48% accuracy, followed by ResNet-50 and efficient Net-B3, achieving 97.9% and 97%, respectively. CXRcovNet achieved 95% accuracy. In our study, transfer learning-based models learned the properties and classified the images with minimal error after just 22 training epochs.

REFERENCES

[1] WHO, "WHO Coronavirus (COVID-19) Dashboard | WHO Coronavirus (COVID-19) Dashboard With Vaccination Data," 2022. https://covid19.who.int/ (accessed May 12, 2022).

[2] M. E. H. Chowdhury *et al.*, "Can AI Help in Screening Viral and COVID-19 Pneumonia?," *IEEE Access*, vol. 8, pp. 132665–132676, 2020, doi: 10.1109/ACCESS.2020.3010287.