Automatic Detection of Covid-19 Infection using Chest X-Ray Images through Transfer Learning

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Article Info
Page Number: 5338 - 5355
Publication Issue:
Vol 71 No. 4 (2022)

Abstract

The World Health Organization has called the new corona virus (COVID-19) a pandemic. It has infected more than 1 million people and killed more than 50,000. A COVID-19 infection can lead to pneumonia, which can be found with a chest X-ray and should be treated properly. In this paper, we show how chest X-rays can be used to automatically find COVID-19 infections. For this study, 194 X-ray images of people with coronavirus and 194 X-ray images of healthy people were put together to make two sets of data. We use the idea of transfer learning for this task because there aren't many images of COVID-19 patients that are available to the public. We use different architectures of convolutional neural networks (CNNs) trained on ImageNet and change them to work as feature extractors for the X-ray images. The CNNs are then combined with consolidated machine learning methods like k-Nearest Neighbor, Bayes, Random Forest, multilayer perceptron (MLP), and support vector machine (SVM). The results show that for one of the datasets, the best extractor-classifier pair is the Mobile Net architecture with the SVM classifier using a linear kernel, which gets an accuracy and F1-score of 98.5%. For the other set of data, the best combination is DenseNet201 and MLP, with a 95.6% accuracy and F1-score. So, the proposed method works well for spotting COVID-19 in X-ray images.

Article History
Article Received*: 25 March 2022*
Revised*: 30 April 2022*
Accepted*: 15 June 2022*
Publication*: 19 August 2022*

I. INTRODUCTION:

Since December 2019, when it was first reported, the COVID-19 pandemic has become a very serious health problem. About 74% of the time, the COVID-19 causes symptoms that are either mild (18%) or moderate (56%). But the rest of the cases range from being very serious (20%) to being serious (6%). As of today (2020-04-03), there have been about 1015,667 cases reported, 53,200 deaths around the world, and 2,12,991 cases where the person got better. Also, there are 749,476 cases that are still open.

When an infection is suspected, the main signs are trouble breathing, a fever, and a cough. When the virus attacks really hard, it can also lead to pneumonia. In addition to pneumonia, the infection can cause severe acute respiratory syndrome, septic shock, failure of multiple organs, and death. Studies showed that men (about 60%) were more affected than women (about 40%), and that there were no significant death rates in children younger than nine years old. Even though they are developed, the healthcare systems in many first world countries are collapsing because of the growing need for intensive care units at the same time.

As new technologies are made all over the world, virus tests take less and less time. COVID-19 infections are diagnosed with a chest scan to check the health of the lungs. If the scans show that the patient has pneumonia, they are thought to have a COVID-19 infection. With this method, authorities can quickly and effectively separate and treat patients who are sick.

1.1 Computed Tomography Scan (CT scan): A computed tomography scan of the chest is one way to find out if someone has pneumonia (CT scan). Using artificial intelligence, automated image analysis is being made to find, measure, and track COVID-19 infections and to tell the difference between healthy and sick lungs. It uses the image's basic features and looks at how the neural network and heuristic algorithms work together. Using CT scan images and deep learning techniques, they made an early diagramming model that could tell the difference between COVID-19 pneumonia, Influenza-A pneumonia, and healthy lungs. CT scans that can take pictures and give a clinical diagnosis much faster than waiting for the pathogen test. HRCT scan is an effective method for detecting COVID disease at low to severe levels.

HRCT stands for high-resolution computed tomography.
It is a way to check for and track diseases of the lung tissue and airways that is more accurate than the chest 2-rat method. With modern CT equipment, a volume HRCT scan can be done that looks at all of the lung tissue. Contrast-enhanced CT scans of the whole body's chest can also be used to make HRCT slices. HRCT of the lungs can be used to diagnose both short-term and long-term diseases of the lung tissue and airways that are spread out. Idiopathic interstitial pneumonias, like idiopathic pulmonary fibrosis, are one of the most well-known reasons to use HRCT. High-resolution computed tomography is also used to diagnose pneumoconiosis, which can be caused by things like asbestosis. Some of the most urgent reasons to get an HRCT are inflammations, drug reactions, and injuries to the alveoli that are spread out. The medical history is the most important part of figuring out what a lung HRCT shows, because imaging results are often not very clear. So, it's important to have a good test requisition.
1.2 X-ray:
It is a type of imaging that is used to look into broken bones, moved bones, pneumonia, and tumours. X-rays have been used for many decades. They are an incredibly fast way to see inside the lungs and can help find COVID-19 infections because of this. They can make pictures that show damage to the lungs, like the pneumonia caused by the SARS-CoV-2 virus. Since X-rays are quick and cheap, they can help triage patients in places where the health care system has broken down or where people live far away from big cities where more complex technologies are available. There are also portable X-ray machines that can be moved easily to where they are needed. CT scans use X-ray technology in a more advanced way to look at the soft parts of the body. It is also used to see organs and soft tissues more clearly. On the other hand, X-rays use less radiation than CT scans. This means that getting an X-ray is faster, less dangerous, and cheaper than getting a CT scan. Three classes are being looked at: COVID-19, common pneumonia, and

normal conditions.

1.3 Motivation: The reason for this study is to find out how the deep learning algorithm will help better detect COVID and how the combination of these models will work better than the existing one, since there is no single paper that talks about the detections done in this. Lastly, to know and understand how these models can be used to find the Corona virus disease and how they can be different from each other.

1.4 Problem Statement: The problem is binary classification, low data availability, and feature extraction with transfer learning. This lets a large number of features be extracted by making the problem more general and avoiding too many adjustments.

1.5 The goal of this project is to make an image classification model that can predict with a fair amount of accuracy whether a chest X-ray scan belongs to one of three groups.

1.6 The work to be done:
The goal of this work is to: • Use CT scan and X-Ray images to find COVID-19 disease.
• In this case, chest X-rays could be used to find infected patients using deep learning techniques.

1.7 How CT scans and X-rays are used: • This lets doctors see almost every part of the body and is used to diagnose illness or injury and plan medical, surgical, or radiation therapy.
• Check for symptoms in the body: X-ray technology is used for many things in medicine.
• Diagnosing injuries: A small amount of ionising radiation is used in a bone x-ray.
• Broken Bones: People who hurt their bones are usually asked to get x-rays.

2. Research Contribution: With the help of deep learning algorithms, research has been done to find COVID. CNN hasn't been used much to figure out what's wrong with detection. This investigation helps to make COVID-19 Detection better. The deep learning model calculates a comparison graph for our problem statement, which is driven by nature. This research is a big part of how CT scan and X-ray images can be used to automatically find COVID. III. Plan for the System:

In this project, we are using a deep learning algorithm called Convolution Neural Networks (CNN) to see if a chest x-ray shows COVID-19 disease. We taught CNN how to do this project by giving it more than 500 COVID and NORMAL chest X-ray images to look at. Also suggested was that the disease could be found automatically by looking at three groups: COVID-19, common pneumonia, and normal conditions.

In this paper, we propose an automatic system that uses transfer learning and convolution neural networks to tell if a chest X-ray is from a COVID-19 patient or a healthy patient (CNNs). We did 144 experiments with 12 CNNs and six classifiers in two different datasets.

3.1 Algorithm:

3.1.1 TRANSFER LEARNING WITH CONVOLUTIONAL NEURAL NETWORKS:

Transfer learning is a way for a CNN to use what it learned from one problem to solve a different but similar problem. This new dataset, which is usually smaller than what would be needed to

train a CNN from scratch, uses this transferred knowledge.
In deep learning, this method needs a large dataset to train a CNN for a certain task at the beginning. The main thing that makes sure the method works is having a large dataset, since the CNN can learn to pull out the most important parts of a sample. If the CNN is able to pick out the most important parts of an image, it can be used for transfer learning.
Then, during transfer learning, the CNN is used to look at a different dataset and pull out its features based on what it learned during the first training. Feature extraction via transfer learning [23] is a common way to use the capabilities of a CNN that has already been trained. With this method, the CNN will keep its structure and weights between its layers. Because of this, the CNN is only used to pull out features. The features are then used in a second network/classifier that will process its classification.

Most of the time, the transfer learning method is used to avoid the high cost of training a network from scratch or to keep the feature extractor trained while the first task is being done. Most people agree that the best way to use transfer learning in medical applications is to use the CNNs that did the best in the ImageNet large scale visual recognition challenge (ILSVRC), which tests algorithms for finding and classifying objects on a large scale. Using large datasets to train the network in the beginning lets it do well with smaller datasets. Transfer learning also makes it possible to classify medical images using the Internet of Things (IoT). For example, an IoT system can tell if a CT image shows a stroke and classify EEG signals. In the step of feature extraction for COVID-19 detection, the transfer learning method is used.

Neural networks are the idea behind the CNN (Convolutional Neural Network) algorithm. There are three types of layers in a typical Neural Network.

Input Layers: This is where we tell our model what we want it to do. The total number of features in our data is equal to the number of neurons in this layer (number of pixels in the case of an image).
Hidden Layer: The information from the Input layer goes into the hidden layer. Depending on our model and the size of our data, there could be a lot of hidden layers. The number of neurons in each hidden layer can be different, but it's usually more than the number of features. The output of each layer is calculated by multiplying the output of the layer before it by the weights of that layer, which can be learned, and then adding biases that can also be learned, followed by an activation function that makes the network nonlinear.

Output Layer: The output of the hidden layer is then fed into a logistic function like sigmoid or soft max, which turns the output of each class into the probability score of each class.

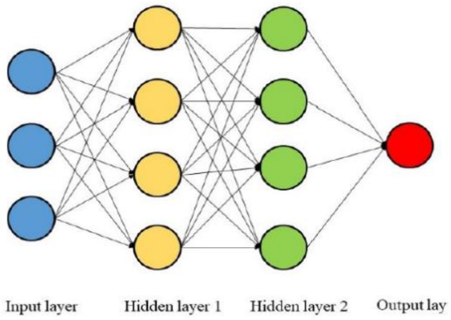

Fig.1. CNN

3.3 Architecture/Framework:

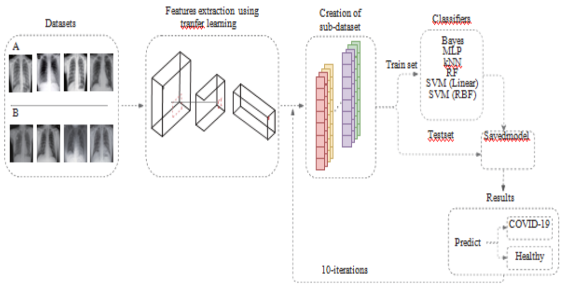

Fig.2. Framework

3.4 Algorithm and Process Design:

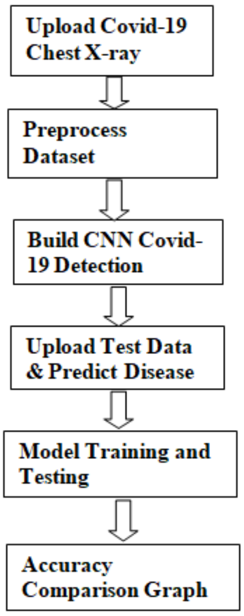

Fig.3. Process Design

MODULES:

Upload Covid-19 Chest X-ray Dataset: This module will be used to upload images from the chest X-ray dataset to the application. Preprocess Dataset: This module will read all of the images, resize

them to a size that works with CNN, and then normalise them by dividing all of the 0s and 1s in the images by 256. As we know, all images have colour values between 0 and 255 for each pixel, so dividing a pixel by 256 gives a value between 0 and 1. This normalises the values, which helps us build a CNN model that works better. Once the data has been cleaned up, CNN can be used to train it.
Make CNN Covid-19 Detection Model: This module will take processed dataset images and then start training with CNN. To train CNN, we used 10 EPOCH.
Upload Test Data and Predict Disease: With this module, we will upload a test chest X-ray image, and CNN will tell us if the X-ray is NORMAL or has COVID-19 disease.
Model Training: In this step, we train the model by using 80% of the sub-dataset. We look at how the hyperparameters in Table III are set up to figure out how the classifiers on the training set should be set up. The 20-iterations search is done by the classifiers that were set up for a random search. Except for the Bayes classifier, all of the hyperparameters are found through 10-fold cross-validation. Then, each classifier has a set of optimal hyper parameters that are saved on the computer.

Model Testing: In this step, we use the saved classifiers to test the model on the last 20% of the sub-dataset. For each sample of the sub-dataset, the system picks one class. In this step, the metrics are also worked out.

Processes 1) and 2) are done again and again. The sub-datasets are split randomly into more train and test sets. The seed used makes sure that these sets are different from the rest. Then we do ten times over.

Comparison of Accuracy This module will be used to make a graph of CNN's accuracy and loss values.

IV. How it was done and what happened: In this section, First, we will talk about the image sets that were used in this study. Then, we talk about the transfer learning theory-based process of feature extraction. Then, we talk about the classification methods used and the steps of how they are trained. Lastly, we define the metrics we'll use to evaluate the results and compare them to other approaches. Data augmentation was used to get more information so that a more general model could be made.

4.1 About the set of numbers:
In our study, we look at chest X-rays from the front.
The only X-ray views that were taken were from the back to the front and from the front to the back. We put the samples into two groups: X-rays of people who were diagnosed with COVID-19 and X-rays of people who were healthy. We made two sets of data, called Dataset A and Dataset B, so that we could better test the proposed method. The images for the COVID-19 class are the same in both datasets, but the images for the healthy class are different. In both datasets, there are 194 images in each class, for a total of 388 images in each dataset. In the Figs that follow, we show

some images from the datasets. Figure (a) shows a PA view of a chest X-ray of a patient with Corona virus disease, and Figure (b) shows an AP view of a chest X-ray of a healthy patient.

All of the images in the datasets are either in the joint photographic experts group (JPG/JPEG) format or in the portable network graphics (PNG) format. Within the dataset, the image resolution ranges from as low as 249 by 255 pixels to as high as 3520 by 4280 pixels. But the resizing technique was used on all of the images before they were used.

4.2 Metrics for Evaluating:
We use the metrics accuracy (Acc), F1-score, and false positive rate to look at the results of this paper (FPR).
Accuracy
It tells how often the model is correctly classifying things.
Accuracy (%) = TP+TN/TP+FN+FP+TN 100
Precision is the number of correct positive predictions out of the total number of positive predictions.
Accuracy = TP/TP + FP

Remember that it is the number of positive observations that can be predicted correctly out of all the observations in the original data.
Recall = TP/TP plus FN

F1-score is the harmonic mean of Sensitivity and Precision. This metric can give a number that shows how good the approach is as a whole.
F1-score (%) = 2 SensitivityAccuracy/Sensitivity+Accuracy100

False Positive Rate (FPR): It shows how often healthy people are wrongly labelled as sick.
FPR(%) = FP/TP+T N 100
True positives (TP) is the number of times the model correctly guessed that an image was COVID-19.
False negative (FN) is the number of times that COVID-19 images were mistakenly labelled as coming from healthy patients.
False positives (FP) show how many times the model wrongly put a healthy patient into a certain group. The number of true negatives (TN) shows how many images of healthy patients were correctly labelled.
We also look at the training, extraction, and test times in addition to the metrics we've already talked about. The training time is the amount of time it takes from when the classifier training starts until it is ready to do the classification. From the time it gets the X-ray to the time it sends out the attribute vector, this is called the "extract time." Also, the test time is the amount of time it takes for the classifier to guess the image's class after getting its attribute vector. So, training time is very important when building a model. After this step, the times for extraction and testing mean more. The time between getting the X-ray and getting the classification back is called the classification

time.

TABLE I

CNNsArchitectures,Configurations,andTheirInputImageSizeandNumberofFeaturesExtractedVGG [33]

Architectures	Configurations	Input image size (pixels)	Number of features extracted
VGG16		224 × 224	512
VGG19		224 × 224	512
Inception [34]	InceptionV3	299 × 299	2048
	InceptionResNetV2 [36]	299 × 299	1536
ResNet [35]	ResNet50	224 × 224	2048
	NASNetLarge	331 × 331	4032
NASNet [37]	NASNetMobile	224 × 224	1056
Xception [38]	Xception	299 × 299	2048
MobileNet [39]	MobileNet	224 × 224	1024
	DenseNet121	224 × 224	1024
DenseNet [40]	DenseNet169	224 × 224	1664
	DenseNet201	224 × 224	1920

TABLE II

Data Split According to Dataset and Class

	Train	Test	Train	Test	
A	155	39	155	39	388
B	155	39	155	39	388
Awithdata	658	39	658	39	1394

TABLE III

SetuptoSearchforHyperparametersoftheClassifiers

Classifier	Search type	Parameter	Setup
Bayes	-	-	Gaussian probability density function
RF	Random	Number of estimators criterion	50 to 3000 in steps of 50 Gini or entropy
MLP	Random	Neurons in hidden layer algorithm	2 to 1000 Levenberg-Marquardt method
kNN	Grid	Number of neighbors	3, 5, 7, 9, 11, 13, 15
SVM (Linear kernel)	Random	C	2^{-5} to 2^{15}

SVM (RBF kernel)	Random	C γ	2^{-5} to 2^{15} 2^{-15} to 2^{3}

TABLEIV
MetricsObtainedbyClassifyingFeaturesExtractedFromDatasetAbyDifferentCNNArchitecturesofthe TopFiveResults

CNN	Extraction time (ms)	Classifier	Training time (s)	Test time (ms)	*Acc* (%)	*F*1-*score* (%)	*FPR* (%)
MobileNet	21.021 ± 0.513	SVM (Linear)	0.057 ± 0.002	0.443 ± 0.011	98.462 ± 0.959	98.461 ± 0.960	1.026 ± 1.256
MobileNet	21.021 ± 0.513	SVM (RBF)	0.079 ± 0.001	0.474 ± 0.008	98.205 ± 0.628	98.205 ± 0.628	1.538 ± 1.256
DenseNet121	68.649 ± 1.300	SVM (Linear)	0.144 ± 0.008	0.502 ± 0.190	98.205 ± 0.628	98.205 ± 0.628	1.538 ± 1.256
InceptionResnetV2	162.651 ± 1.262	SVM (Linear)	0.163 ± 0.011	0.779 ± 0.121	98.205 ± 0.628	98.205 ± 0.628	1.538 ± 1.256
InceptionResnetV2	162.651 ± 1.262	SVM (RBF)	0.428 ± 0.014	0.806 ± 0.114	98.205 ± 0.628	98.205 ± 0.628	1.538 ± 1.256

TABLE V
FinalConfusionMatrixoftheTestSetfortheClassifica-tionofChestX-rayImagesAsHealthyorCOVID-19 formobilenetWithSVM(Linear)forDatasetA
Predicted class

	COVID-19	Healthy
COVID-19 True class	382	8
Healthy	4	386

TABLE VI
MetricsObtainedbyClassifyingFeaturesExtractedFromDatasetBbyDifferentCNNArchitecturesoftheT opFiveResults

CNN	Extraction time (ms)	Classifier	Training time (s)	Test time (ms)	*Acc* (%)	*F1-score*	*FPR* (%)

						(%)	
DenseNet201	100.955 ± 1.630	MLP	25.677 ± 1.125	0.282 ± 0.154	95.641 ± 2.640	95.633 ± 2.645	4.103 ± 3.838
DenseNet201	100.955 ± 1.630	SVM (Linear)	0.404 ± 0.001	1.529 ± 0.295	94.103 ± 2.235	94.093 ± 2.242	3.590 ± 1.256
VGG19	131.250 ± 11.621	MLP	15.601 ± 0.097	0.127 ± 0.082	94.103 ± 4.336	94.064 ± 4.408	4.103 ± 2.615
VGG16	100.458 ± 2.024	SVM (RBF)	0.065 ± 0.001	0.559 ± 0.093	93.590 ± 2.433	93.586 ± 2.435	4.103 ± 2.615
DenseNet201	100.955 ± 1.630	SVM (RBF)	0.578 ± 0.037	1.786 ± 0.165	93.590 ± 1.147	93.574 ± 1.159	5.128 ± 3.626

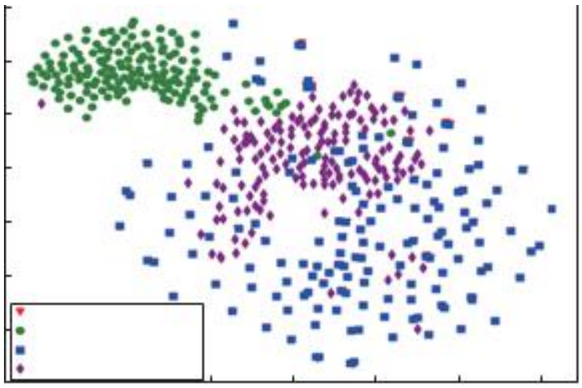

Fig.4

Visualization of the features extracted by DenseNet201 from bothdatasets using t-SNE.

In above Fig. the features are extracted by DenseNet201 from both datasets using the t-distributed stochastic neighbor embedding (t-SNE) technique [58]. We can observe that, although DenseNet201 is not in the top five of Dataset A, a hyperplane can separate the classes, which justifies the three combinations with SVM (Linear) in the top five of this dataset. As mentioned in Section III-A, the healthy X-ray images from Dataset A are of pediatric patients, which explains the easily distinguishable cluster formation of the features from this class. In contrast, when analyzing Dataset B, the healthy class features are scattered, which indicates a wider variety of sources in the original dataset. Also, this dataset needs a classifier that can classify non-linear data, which justifies MLP as the best classifier for this dataset.

4.3 Outcome:

In this paper author is using Chest X-Ray dataset and Convolution Neural Network to predict Covid-19 disease. CNN gaining popularity in almost all fields for its better prediction accuracy compare to traditional machine learning algorithms such as SVM, Random Forest etc.

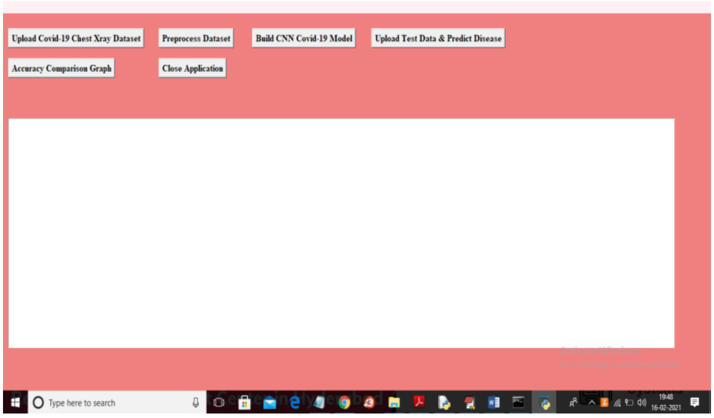

Fig.5‘Upload Covid-19 Chest X-ray Dataset’

In above diagram click on ‘Upload Covid-19 Chest X-ray Dataset’ button and upload dataset

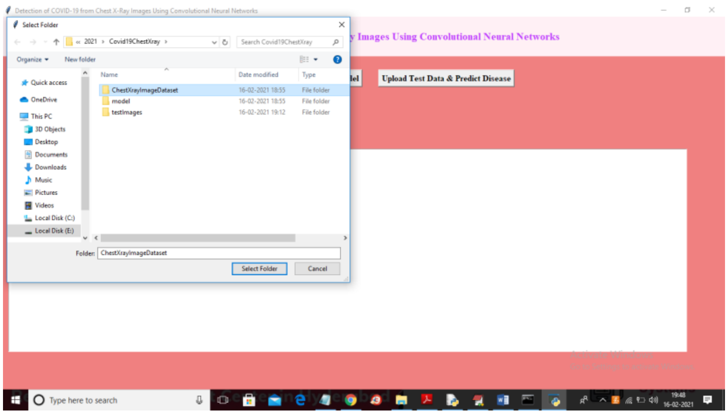

Fig.6‘Select Covid-19 Chest X-ray Dataset’

In above diagram selecting and uploading ‘ChestXrayImageDataset’ folder which contains dataset images and then click on ‘Select Folder’ button to get below diagram

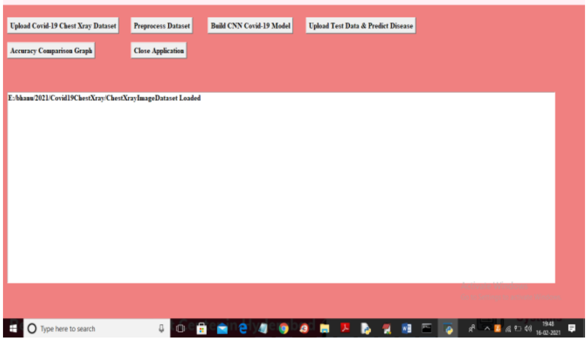

Fig.7. Dataset loaded

In above diagram dataset loaded and now click on ‘Preprocess Dataset’ button to read all images and then convert all images into equal size and then normalize all pixels of images to have better prediction result

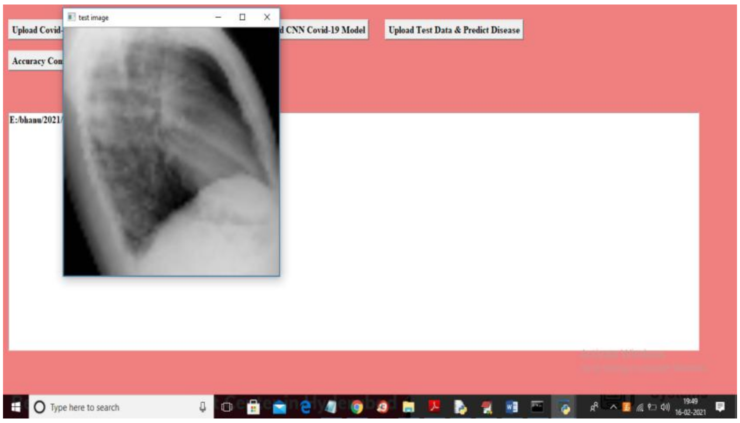

Fig.8. Dataset processed

In above diagram dataset processed and to test whether application reading all images properly so I am displaying one loaded sample image and now close above image to get below diagram

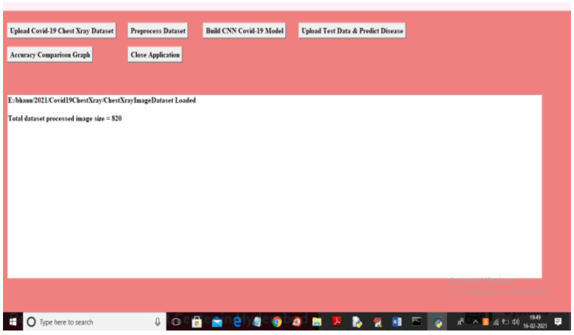

Fig.9. 'Build CNN Covid-19 Model'

In above diagram application found total 820 images and now images are ready and now click on 'Build CNN Covid-19 Model' button to generate CNN model on loaded dataset and to get below diagram

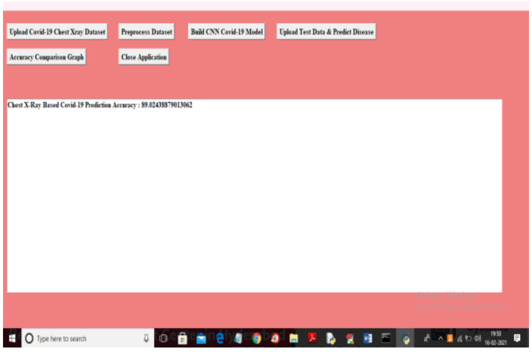

Fig.10. accuracy is 89%

In above diagram CNN model generated and its prediction accuracy is 89% and we can see below black console to see CNN layer details or its summary

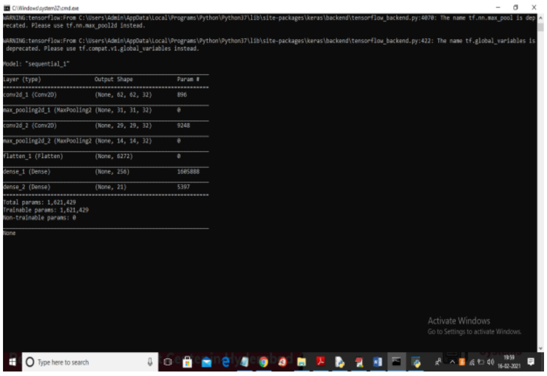

Fig.11. images are filtered

In above console we can see images are filtered at different layer with different image sizes where at first layer 62 X 62 image size was used and in second layer 31 X 31 and goes on. Now CNN model is ready and now click on 'Upload Test Data & Predict Disease' button to upload new test image and then application will predict disease from that image

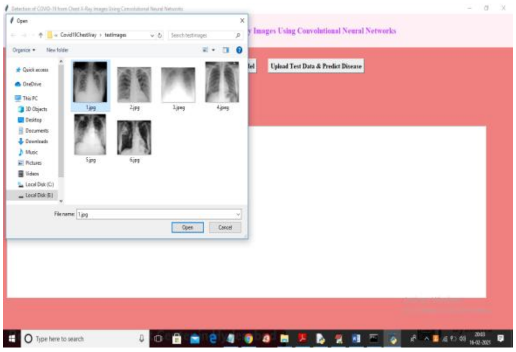

Fig.12. uploading '1.jpg'

In above diagram selecting and uploading '1.jpg' and then click on 'Open' button to load image and to get below prediction result

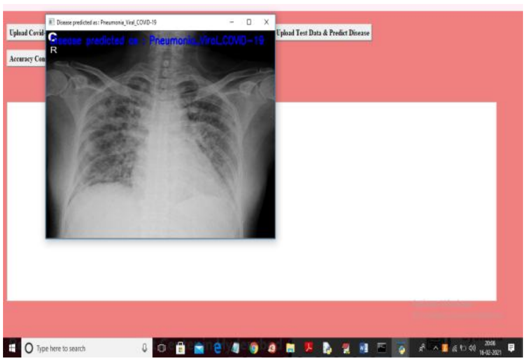

Fig.13. blue colour text printing detected disease

In above diagram in blue colour text printing detected disease in uploaded image and now upload another image and test

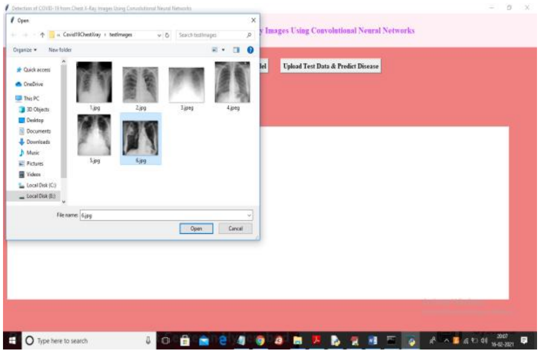

Fig.14. uploading ‘6.jpg’

In above diagram selecting and uploading ‘6.jpg’ and then click on ‘Open’ button to get below prediction result

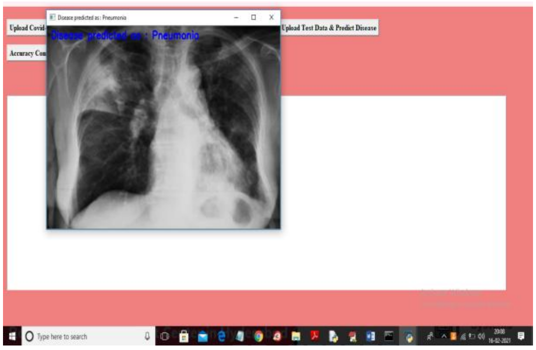

Fig.15. disease predicted as ‘Pneumonia’

In above diagram disease predicted as ‘Pneumonia’ and similarly you can upload other images and get prediction result. Now click on ‘Accuracy Comparison Graph’ button to get below graph

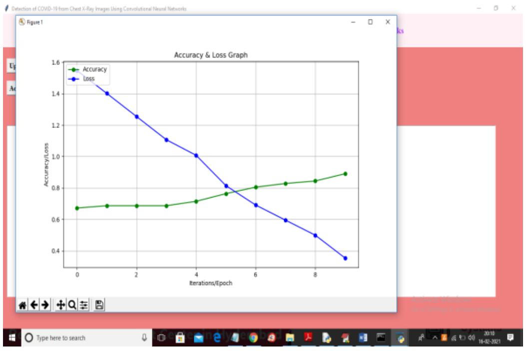

Fig.16. green line represents accuracy and blue line represents LOSS

In above graph green line represents accuracy and blue line represents LOSS.In above graph x-axis represents epoch/iteration and y-axis represents accuracy and loss values and to build CNN i took 10 iterations and we can see at each increasing iteration Accuracy get increase

Extension Outcomes:

In propose work we have trained CNN algorithm directly on Chest X-Ray images but not applied any optimization techniques on image features so as extension work we are apply Grey Wolf

Optimization algorithm to optimize image features and then retraining with CNN algorithm and the accuracy obtained after GWO is better than propose CNN.

GWO is a nature inspired algorithm which depict behaviour of grey wolf which hunt in group of 5-12 and all wolf will calculate fitness of their position by seeing prey location and the wolf which is nearer to prey will have high fitness and other wolf will follow him.

In machine learning also we will calculate fitness of each attributes in image or dataset and the attribute which gives high accuracy or fitness will be accepted and the lower accuracy features will be removed out and then we will left out with high accuracy features and when we train this with other algorithm then it will give better performance.

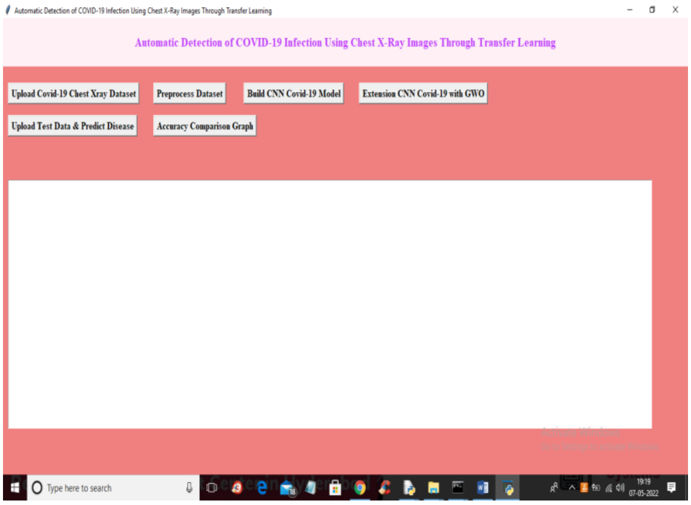

Fig.17. accuracy

In above diagramrun all the buttons and when we click on ‘Build CNN Covid-19 Model’ button then we will get below accuracy

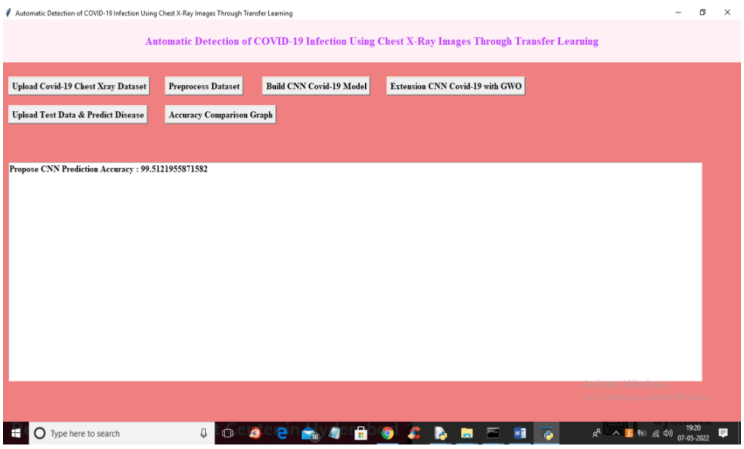

Fig.18. with Normal CNN we got 99.51% accuracy

In above diagram with Normal CNN we got 99.51% accuracy and now click on ‘Extension CNN Covid-19 with GWO’ button to train GWO CNN and get below output

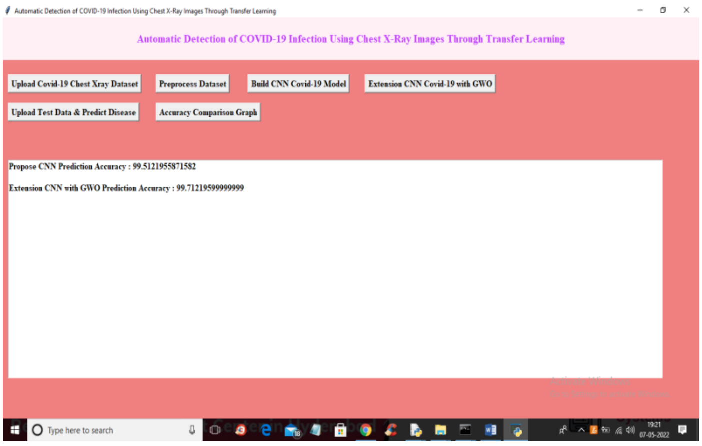

Fig.19. GWO Extension CNN we got 99.71% accuracy

In above diagram with GWO Extension CNN we got 99.71% accuracy which is higher than propose algorithm and now click on 'Accuracy Comparison Graph' button to get below output

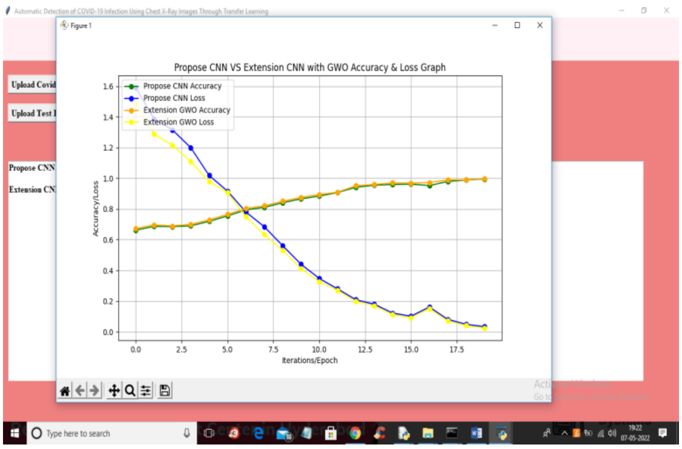

Fig.20. epoch vs accuracy

In the above graph, the x-axis shows the training EPOCHS and the y-axis shows the Accuracy and Loss values. The green line shows CNN accuracy and the orange line shows Extension accuracy. You can see that the orange line is slightly higher than the green line. The blue line shows propose CNN loss and the yellow line shows extension loss. You can see that extension has less loss than propose CNN.

CONCLUSION:

Early detection of patients with the new coronavirus is crucial for choosing the right treatment and for preventing the quick spread of the disease. Our results show that using CNNs to extract features, applying the concept of transfer learning, and then classifying these features with consolidated machine learning methods is a good way to tell if an X-ray image is normal or positive for COVID-19. For Dataset A, the MobileNet with SVM (Linear) combina- tion had the best performance, achieving a mean Acc of 98.462% and a mean F1-score of 98.461%. In addition, it was able to classify a new image in only 0.443 ± 0.011 ms, proving to not only be accurate but fast as well. For

Dataset B, the best pair was DenseNet201 and MLP, which got an average accuracy of 95.641% and an average F1-score of 95.633%. Even though its Acc-score and F1-score were slightly lower, it could classify an image in only 0.282 0.154 ms, which is faster than the best combination in DatasetA.

No clinical study has been done on the proposed method. Thus, it does not replace a medical diagnosis since a more thorough investigation could be done with a larger dataset. Under those circumstances, our work contributes to the possibility of an accurate, automatic, fast, and inexpensive method for assisting in the diagnosis of COVID-19 through chest X-ray images.

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