COVID PREDICTION USING ENSEMBLED LEARNING

A PROJECT REPORT

for

SOFT COMPUTING (ITE1015)

in

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by

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Vellore Institute of Technology

(Deemed to be University under section 3 of UGC Act, 1956)

School of Information Technology and Engineering

MAY, 2021

DECLARATION BY THE CANDIDATE

We here by declare that the project report entitled **"COVID PREDICTION USING ENSEMBLED LEARNING"** submitted by us to Vellore Institute of Technology University, Vellore in partial fulfillment of the requirement for the award of the course **Soft Computing (ITE1015)** is a record of bonafide project work carried out by us under the guidance of **Prof. Agilandeeswari L.** We further declare that the work reported in this project has not been submitted and will not be submitted, either in part or in full, for the award of any other course.

Place : Vellore Signature

Date : May 21, 2021

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CERTIFICATE

This is to certify that the project report entitled **"COVID PREDICTION USING ENSEMBLED LEARNING"** submitted by **Abhimanyu Singh (18BIT0105), Nitin Sharma (18BIT0145)** to Vellore Institute of Technology University, Vellore in partial fulfillment of the requirement for the award of the course **Soft Computing (ITE1015)** is a record of bonafide work carried out by them under my guidance.

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COVID Prediction using Neural Networks

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Abstract

The new coronavirus (COVID-19), declared by the World Health Organization as a pandemic, has infected more than 115 million people and killed more than 2 million deaths. An infection caused by COVID-19 can develop into pneumonia, which can be detected by a chest X-ray exam and should be treated appropriately. In this work, we propose an automatic detection method for COVID-19 infection based on chest X-Ray images. We propose an architecture using CNN which will take Chest X-Rays as a dataset. The dataset will contain images of COVID positive, negative and pneumonia infected X-Rays. The model uses an ensemble of ResNet, MobileNet and Inception for the extraction of features from the images and the classification/prediction o f the test case. An F1-Score of above 95% is to be achieved from the system.

Keywords – CNN, Image classification, ResNet, MobileNet, Inception, Ensemble

I. INTRODUCTION

The ongoing COVID-19 pandemic has brought about a scarcity of medical equipment related to testing of the virus. To combat this challenge, the aim of the project is to create a neural-network based model to efficiently detect and classify COVID-19 infected patients using Chest X-Ray images.

The model uses 3 pre-trained CNN models that are ResNet50, MobileNetV2 and InceptionV3. The ensembled average of these models are taken to reduce the error. The proposed model can take an CXR image as input and provide the output whether the patient is COVID-19 positive or negative.

The report begins with a thorough literature survey proceeding with a proposed architecture and comparative study with experimental results.

II. BACKGROUND

The COVID-19 pandemic continues to have a devastating effect on the health and well-being of the global population. Even though the vaccines are being rolled out in many parts of the world it will take some time before a majority of the mass gets vaccinated. Right now, there is a threat of a second wave in some nations. So, keeping that in mind we need to have an effective, easy to diagnose approach for the test of COVID-19.

Thus, a critical step in the fight against COVID-19 is effective screening of infected patients, with one of the key screening approaches being radiology examination using chest radiography. It was found in early studies that patients present abnormalities in chest radiography images that are characteristic of those infected with COVID-19.

Chest X-Rays are an efficient method of screening patients since it is rapid, accessible and portable. However, one of the biggest challenges the world faces is the need for expert radiologists to interpret the radiography images, since the visual indicators can be subtle. As such, computer-aided diagnostic systems that can aid radiologists to more rapidly and accurately interpret radiography images to detect COVID-19 cases is highly desired.

Therefore, with the advancement of deep learning technologies like neural networks, difference between infected X-Rays and normal X-Rays, which is almost indistinguishable to the average eye, can be differentiated with a high accuracy.

III. Literature Survey

Author & Year	Methodologies & Technologies Used	Advantages	Issues	Metrics Used
[1]Das et al. (2020)	3 Deep Convolutional Neural Networks (DenseNet, Resnet and Xception), Adam Optimization	Very accurate system with an accuracy of 95% and a sensitivity of 98%. If one model is performing better than the other two models i.e. having lower validation error, it is assigned a higher weight so that its contribution in deciding the class value is higher.	The images are resized into 224x224 shaped images leading to lower resolution which may result in loss of crucial discriminative texture information	Classification Accuracy, Sensitivity and F1 Score
[2]Boran et al. (2020)	38 experiments using CNN, 10 experiments using ML models, 14 experiments using pre-trained models for transfer learning.	Variety of algorithms used to find out the most accurate algorithm. Comparative study between ML models and NNs. Resultant model with high accuracy of 96%.	Limited dataset. Requires a higher configuration of PC to run the program.	Sensitivity, Specificity, Accuracy, Mean ROC AUC
[3]Ohata et al. (2020)	Convolutional Neural Networks, Transfer Learning	Transfer Learning helps keep the computational costs of training a CNN from scratch low. Also, the use of a large dataset for initial training enables higher performance in smaller datasets.	The system has problems distinguishing between pneumonia and COVID 19 and the dataset used was very small	Accuracy, Sensitivity, Precision, False positive rate, F1-score
[4]Jain et al. (2020)	3 different CNN architectures are used(Xception net, Inception net V3 and ResNeXt) have been used and compared,	Compared 3 different CNN architectures and it was found that Xception model produced the best	Dataset is very small. The high accuracy obtained may be a result of overfitting	Precision, Recall, F1-Score and confusion matrix

	Adam optimization along with LeakyReLu activation function and Categorical Cross-entropy loss function	results and was highly accurate		
[5]Minaee et al. (2020)	4 popular CNN's are trained(ResNet18,ResNet50,SqueezeNet and DenseNet-161), data augmentation is used to increase number of samples by 5,transfer learning is used by fine-tuning the last layer of the pre-trained version of these models on ImageNet.	High number of samples due to data augmentation leads to high accuracy. A heatmap of the infected regions is provided as well for further understanding of the disease.	Small dataset	Sensitivity, Specificity,ROC curve, precision recall curve, confusion matrix
[6]Wang et al. (2020)	CNN is used to detect COVID 19 from cxr images using their own database called COVIDx using their own architecture called COVID-Net	Created their own database containing a large number of samples	Sensitivity and PPV can be improved as well as prediction of patient risk status can be implemented.	Confusion matrix, Positive predictive value, Sensitivity, Accuracy
[7]Terry Gao (2020)	A deep CNN based on VGG-19 architecture is implemented to distinguish bacterial from viral pneumonia, ReLu activation function is used	The CNN is able to distinguish between bacterial pneumonia and COVID 19	Only 1 model of CNN was implemented and therefore it produces limited results.	Precision, recall, accuracy, F1-score
[8]Ozturk et al.(2020)	A CNN is used based on the darknet-19 classifier model known as DarkCOVIDNet model.	The model performed outstandingly well in detecting COVID 19 cases, The model is sensitive in detecting pneumonia disease. Although the model can predict pneumonia positively	The model made the incorrect predictions in poor quality X-ray imagery and in patients with acute respiratory distress syndrome (ARDS), in which the lung image is diffuse and much lung ventilation is lost	Average accuracy, average sensitivity, specificity, F1-score
[9]Chandra et al. (2020)	COVID screening (ACoS)	The system can be easily modelled	Dataset is limited. Problems in	Accuracy, specificity,

	system that employs hierarchical classification using conventional ML algorithms (SVM) and radiomic texture descriptors to segregate normal, pneumonia, and nCOVID-19 infected patients.	using the limited number of annotated images and can be deployed even in a resource-constrained environment.	differentiating between COVID-19 and pneumonia.	precision, recall, F1-score, Area Under Curve (AUC), Matthews Correlation Coefficient(MCC)
[10]Mangal et al. (2020)	The model contains a pre trained CheXNet which is an architecture for pneumonia detection from chest X rays and the final output is obtained through a sigmoid activation function. Adam Optimizer is used.	It is based on a previously trained model; therefore, it is more reliable	It is not as accurate as the models previously described as it has an accuracy of only about 90%. Dataset size is small	AUROC, Sensitivity, Accuracy, Positive Predictive Value, Confusion Matrix
[11]Azemin et al.(2020)	ResNet-101, a convolutional neural network with 101 layers, was adopted in this research with cross entropy loss function	The strength of this study lies in the use of labels that have a strong clinical association with COVID-19 cases and the use of mutually exclusive publicly available data for training, validation, and testing.	The dataset used was very small and the evaluation metrics were very low. Also, no comparison was made between different architectures.	AUC, Confusion matrix, specificity, sensitivity, accuracy
[12]Narin et al. (2020)	The study implemented 5 different CNN models (ResNet50, ResNet101, ResNet152, InceptionV3 and Inception-ResNetV2) with ResNet50 and ResNet101 having the highest overall performance	The study was able to distinguish between COVID-19 and pneumonia accurately	The images were resized to 224x224 pixel size leading to lower resolution which may result in loss of crucial discriminative texture information	Accuracy, recall, precision, specificity, F1-score
[13]Purohit et al. (2020)	The study compares 3 CNN models (LeNet, ResNet-50 and VGG-16). Multi image	The study also gives a comparison between X ray	The system faces issues as it is not able to distinguish between COVID-19 and	Accuracy, F1-score, sensitivity, specificity,

	augmentation is used to increase the sample size of the dataset. ReLu and sigmoid activation functions are used with stochastic gradient optimizer and cross entropy loss function.	and CT scan images. One of the main advantages is the larger dataset used through image augmentation	pneumonia	precision, AUC
[14]Hirano et al. (2020)	The study utilised the model used in an earlier study and focussed on its vulnerability to UAP's (Universal Adversarial Perturbation) which can induce DNN failure in most classification tasks	The study took into account the common vulnerabilities present in deep neural networks and increased the robustness of COVID-Net models to UAP's using adversarial retraining	The study did not try to implement any other architectures other than the COVID-Net model from Wang et al.	Accuracy, confusion matrix, fooling rate
[15]Chatterjee et al. (2020)	The paper used 5 different CNN models (ResNet18, ResNet34, InceptionV3, InceptionResNetV2, and DenseNet161) and their Ensembles. Interpretability techniques (occlusion, saliency, input x gradient) were used to interpret the classification decisions of the neural network	The model was able to differentiate between COVID19 and pneumonia. The study also conducted an interpretability analysis of this model which showed where the lesion was located which can be utilized for severity estimations	The study worked only on x ray images and didn't take into account CT images. Also, there were some false negatives for patients having COVID 19 in their best performing model. The study also utilises the whole image instead of segmenting the lung image	Confusion matrix, accuracy, precision, recall, F1-score
[16] Chuansheng Zheng et al. (2020)	3-D deep convolutional neural network (ResBlock and Progressive classifier) using PyTorch framework 2D UNet for lung segmentation	Rapid screening of patients using chest CT scans. Does not require annotating lesions of COVID-19 which reduces strain on radiologists.	The research is not fully done. Limited dataset used. The algorithm ran in a black-box manner. UNet model trained using imperfect ground-truth mask.	Receiver Operating Characteristic (ROC) Curve Precision Recall (PR) curves ROC AUC PR AUC
[17] Xueyan Mei et al. (2020)	For input Full CT Scan and non-image information is used. CNN model is used	Pretrained model used to slice 3-D CT scans which reduces	3-D deep-learning model not implemented.	ROC AUC Specificity

	to process the image data. Machine-learning based model is used to process the non-image data. Output is taken as the probability calculated from both the models.	computation to train 3-D CNN.	Low interpretable CNN model used. Small sample size.	Sensitivity
[18] Aram Ter-Sarkisov (2020)	Lightweight Mask R-CNN (Ground glass opacity and consolidation). Truncated ResNet18 and ResNet34	Various models are tested to conclude ResNet34 gives best accuracy of 93%. Various statistical tools used to demonstrate the experimental results.	Architecture used is very complicated to implement. Most of the algorithms give very low accuracy of around 80—85% which cannot be tolerated in medical systems.	Average Precision Sensitivity Accuracy
[19]Farah E. et al. (2020)	We first introduce our image pre-processing pipeline then formulate the adverse event prediction task and present our multi-modal approach which utilizes both chest X-ray images and clinical variables. Next, we formally define deterioration risk curve (DRC) and introduce our X-ray image-based approach to estimate DRC.	The consistent advantage of the ensemble model in our results is especially encouraging. Investigating more complex strategies for fusion of information from these two modalities could further improve the results and this will be a subject of our future research.	The decrease in accuracy is expected and may indicate changes in the patient population and treatment guidelines as the pandemic progressed. When practically deployed, our system would still need periodical retraining with the latest data.	Area under the receiver operating characteristic curve, area under the precision-recall curve
[20] Mohammed Rahimzadeh (2020)	At the first stage, they proposed an image processing algorithm to filter the proper images of the patients' CT scans, which show inside the lung correctly.	The advantage of using medical imaging is the ability to visualize viral infections by machine vision. To report more real and accurate results, they separated the	Limited Dataset.	Accuracy (for all the classes), specificity, sensitivity, Precision, Accuracy (for each class)

	At the next stage, they trained three different deep convolution networks for classifying the CT scan images into COVID-19 or normal. At the final and main evaluation phased of the proposed automated system, the ResNet50V2 with FPN obtained the best results and correctly identified approximately 237 patients from 245 patients averagely between five folds. .	dataset into five folds for training and validation.		
[21] Aram Ter-Sarkisov (2020)	First, they train an instance segmentation model to predict masks of GGO and C areas. After validation, this model is augmented with a classification module S that uses ranked bounding box predictions to classify the whole input image	1.The model with the classifier head + batch normalization layers produces precision > 90% across all classes. 2.of COVID-CT-Mask-Net's methodology is the ability to train on very small amounts of data without any balancing and augmentation tweaks.	a challenge to find a sufficiently large dataset to train models for accurate predictions of COVID.	To evaluate each model, they computed the sensitivity/recall and precision/positive predictive value (PPV) for each class C and the overall accuracy of the model:
[22] Afshar Shamsi Jokandan et al. (2020)	Input is Chest X-Rays and CT images. Transfer Learning based model Layers used are VGG16, ResNet50,	Transfer Learning requires lower input sample size. The model is computationally less demanding	Performance of the model not comparable to CNN/ANN. High number of uncertainty parameters.	Accuracy Sensitivity Specificity AUC

	DenseNet121 and InceptionResNetV2.	than other models.		
[23] Pengyi Zhang et al. (2020)	Synthesized diverse radiological images with COVID-19 infection. CoSinGAN with three key components, including multi-scale architecture with a pyramid of two-stage GANs, a mixed reconstruction loss, and a hierarchical data augmentation module.	Low segmentation performance gap even with small sample dataset. Highest accuracy of 92% is obtained from OC-TS training set with ResNet50 model.	A very big sample dataset needed to train the model. Computationally very demanding to train and run the model.	Accuracy Sensitivity Specificity
[24] Murat Canayaz (2021)	After the data set is created, a new data set was obtained with the image enhancement method ICEA In the second step of the approach, deep neural networks are trained with both the original and enhancement datasets. The models obtained as a result of training of deep neural networks with the data set in 3 classes were used to extract the features in the third step. In the last stage of o approach, they tried to select the most effective features by using BPSO and BGWO meta-heuristic algorithms among the 1000 fea- tures obtained from	The advantages of the study include showing the effect of image pre-processing on classification success, reducing the computation time by selecting the most effective features with the help of meta-heuristic algorithms, and showing the performance of different deep learning models for COVID-19 disease diagnosis. Another advantage is that the MH-COVIDNet approach developed a different solution in this area since there is no	The disadvantages are that not every deep learning model is able to achieve sufficient success with the pro- posed approach, and it is necessary to investigate new deep learning models that will ensure success.	Sensitivity (Se), Specificity (Sp), F-score (F-Scr), Precision (Pre), and Accuracy (Acc). True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) values are used to calculate the metrics.

	deep neural networks with the enhancement data set.	previous study about contrast enhancement in diagnosing COVID-19 disease in X-ray images.		
[25] Gianluca Maguolo et al. (2020)	The images were pre-processed by resizing them so that their smallest dimension was equal to 360, then a square of fixed size was turned to black in the centre of the image. patient. We only considered the samples whose labels were Pneumonia, No Finding and COVID-19, except for the test set of Chexpert, since it was too small. Since we wanted to detect the dataset and we removed the lungs from the images, we considered this a safe protocol.	deduced that several testing protocols for the recognition are not fair and that the neural networks are learning patterns in the dataset that are not correlated to the presence of COVID-19.	Less data sets	ROC-AUC
[26] Aram Ter-Sarkisov (2021)	they presented a model that fuses instance segmentation, Long Short-Term Memory Network and Attention mechanism to predict COVID-19 and segment chest CT scans. The model works by extracting a sequence of Regions of Interest that contain class-relevant	The model is trained and evaluated in one shot, which includes both segmentation and classification branches, only on 3% of the total data, and evaluated on the remaining part thereof, 2.achieved a	limited the number of publicly available benchmarks to which to compare results.	Per-class sensitivity and F1 score Accuracy of the model is computed using sensitivity/recall

	information, and applies two Long Short-Term Memory networks with attention to this sequence to extract class-relevant features. The model is trained in one shot: both segmentation and classification branches, using two different sets of data.	95.35% COVID-19 sensitivity and 98.10% F1 score, which are among the best results for such a large Dataset.		
[27] Saman Motamed et al. (2020)	Transfer learning to segment the lungs in the COVID dataset. Next, we show why segmentation of the region of interest (lungs) is vital to correctly learn the task of classification, specifically in datasets that contain images from different resources as it is the case for the COVIDx dataset. Finally, we show improved results in detection of COVID-19 cases using our generative model (RANDGAN) compared to conventional generative adversarial networks (GANs) for anomaly detection in medical images, improving the area under the ROC curve from 0.71 to 0.77.	results. One of the advantages of our semi-supervised model compared to supervised models is the ability to test our model on not only a subset, but all of COVID-19 positive images as we do not use any of the images to train our model.	it is important to validate the model on external data Sources, which isn't done for this model.	AUC, ROC curve
[28] Young-Gon Kim et al. (2020)	A segmentation model to separate left and right lung is firstly applied, and then a carina and	algorithm can have potential to be widely adopted as the first step for analysis	model performance highly depends on the quality of labelling data though same number of	Dice value, mean intensity, density

	left hilum detection network is used, which are the clinical landmarks to separate the upper and lower lungs. To improve the segmentation performance of COVID-19 images, ensemble strategy incorporating five models is exploited. Using each region, we evaluated the clinical relevance of the proposed method with the Radiographic Assessment of the Quality of Lung Edema (RALE).	of lung regions in chest radiography for COVID-19 patients.	training set with labeling data were used.	
[29] Pedro R. A. S. Bassi et al. (2021)	We fine-tuned neural networks pretrained on ImageNet and applied a twice transfer learning approach, using NIH ChestX-ray14 dataset as an intermediate step. We also suggested a novelty called output neuron keeping, which changes the twice transfer learning technique. In order to clarify the modus operandi of the models, we used Layer-wise Relevance Propagation (LRP) to generate heatmaps.	The generated heatmaps allowed us to analyses how each part of the input X-rays influenced the DNN classification 2. to help radiologists and provide a better interaction between experts and artificial intelligence. 3.also allowed us to discover that words and letters can influence the DNN classifications.	LRP revealed that words on the X-rays can influence the networks Predictions. 2.data set only had 150 images thus these DNNs can make mistakes in a bigger database.	Test Accuracy graphy with number of training epochs in COVID 19

[30] Talha Anwar et al. (2020)	In this work, they used EfficientNet architecture and performed 5-fold cross-validation strategy to predict the test data in each fold. The test predictions of each fold are averaged and evaluated against the ground truth.	1.Not very time consuming, 2. With CT scans there is no shortage of any sort of medical kits.	In this approach, domain generic transfer learning is used, because to date no other COVID CT-scan dataset is available publicly. Thus, they didn't work on actual data.	accuracy, precision, recall, F1 score and AUC score as the evaluation criteria.

Issues with existing system:

- The major issue present with existing systems is that they were trained on a very small sample size as most of the studies were conducted when a large number of samples were not available.
- Many of the studies failed to distinguish between COVID-19 and pneumonia.
- In many of the studies images were resized to lower pixel size which led to loss of crucial discriminative texture information.
- Some of the studies reported incorrect predictions due to poor X-Ray imagery and in patients with Acute Respiratory Distress Syndrome (ARDS)

Review of each step:

a. **Screening Technique:**

Various screening techniques exist for collecting image data with respect to human lungs. The best techniques that are used for modern applications are **X-Rays** and **CT Scans** [31]. The following table provides some comparative study on these two techniques:

Author	Review of X-Ray and CT scans
[3] Ohata et al.	Since X-rays are very fast and cheap, they can help to triage patients in places where the healthcare system has collapsed or in places that are far from major centres with access to more complex technologies. Furthermore, there are portable X-ray devices that can be easily transported to where it is needed. CT scans make use of the principles of X-ray in an advanced manner to examine the soft structures of the body. It is also used to obtain clearer images of organs and soft tissues. On the other hand, X-rays use less radiation, thus using an X-ray is faster, less harmful, and presents lower cost than a CT scan.
[10] Mangal et al.	1. X-Ray imaging is much more widespread and cost effective than the conventional diagnostic tests. 2. Transfer of digital X-Ray images does not require any transportation from point of

	acquisition to the point of analysis, thus making the diagnostic pro- cess extremely quick. 3. Unlike CT Scans, portable X-Ray machines also enable testing within an isolation ward itself, hence reducing the requirement of additional Personal Protective Equipment (PPE), an extremely scarce and valuable resource in this scenario. It also reduces the risk of hospital acquired infection for the patients.
[31] C. Huang et al.	Concluded that CXR images are better than any other means in the detection of Covid-19 because of their promising results along with the availability of CXR machines and their low maintenance cost.

From the above table we can infer that X-Ray images are much better than CT scans and have more benefits in detecting COVID-19.

Fig 2: Chest X-Ray Sample from dataset

b. <u>Pre-processing and Enhancement:</u>

Data pre-processing is required tasks for cleaning the data and making it suitable for a CNN model which also increases the accuracy and efficiency of the model. Based on the research review, the following techniques were encountered along with the advantages and disadvantages:

Author	Technique Used	Advantages	Disadvantages
[1]Das et al.	Image Resizing (240 x 240)	Image resizing is computationally feasible.	The images are resized to a lower resolution which may result in loss of crucial discriminative texture information
[2] Boran et al.	Used the Average Pixel Per Node (APPN) approach	APPN is based on dividing the image into	The APPN approach led to the images being very blurry. Using the Laplacian filter for sharpening

		segments with predetermined sizes, and taking the mean of the pixels within the corresponding segment. Thus, statistically reduced dimensions of images are obtained.	the images led to increase in computational time.
[4] Jain et al.	Image augmentation which includes rotation, zoom and flipping of images	Leads to a large number of images and incorporates the possible variability in the images, which might occur due to diverse imaging conditions.	The dataset is being expanded artificially.
[9] Chandra et al.	Image resizing(512x512), pixels), format conversion (Portable Network Graphics), colour space conversion (Gray Scale) and texture preserving guided filter are applied.	The guided filter is applied to reduce the inherent quantum noise.	PNG images require more memory space for storage.

Fig 3: a) Unprocessed Image [2]

b) Laplacian Filter applied after APPN image [2]

c) APPN applied image [2]

The images that gave the best results with the ConvNet experiments and statistical measurement experiments were the **Unprocessed Images**.[2] Therefore, the best pre-processing technique is image resizing and augmentation as it leads to obtaining a larger set of images and is also highly feasible and computationally less demanding.

c. Feature Extraction:

Feature Extraction aims to reduce the number of features in a dataset by creating new features from the existing ones (and then discarding the original features). These new reduced set of features should then be able to summarize most of the information contained in the original set of features. From the literature survey, the following techniques were found to be used:

Author	Technique Used	Advantages	Disadvantages
[3] Ohata et al.	Feature Extraction via Transfer Learning	The transfer learning approach is mostly used to work around computational costs of training a network from scratch or to keep the feature extractor trained during the first task.	Currently, one of the biggest limitations to transfer learning is the problem of negative transfer. Transfer learning only works if the initial and target problems are similar enough for the first round of training to be relevant.
[9] Chandra et al.	8 First order statistical features (FOSF), 88 Grey level co-occurrence matrix features and 8100 histogram of oriented gradients (HOG) are used. Binary grey wolf optimization is also used.	The global texture patterns can be quantified easily. The binary grey wolf optimization method does not get trapped in local minima unlike other evolutionary algorithms.	The FOSF does not contemplate the local neighbourhood information. Also, not all the extracted features are relevant for accurate characterisation of visual indicators associated with nCOVID-19, hence BGWO is used.
[24] M. Canayaz	Used 4 different CNN's - 'FC8' from AlexNet, 'FC8' from VGG19, 'loss3-classifier' from GoogleNet and 'fc1000' from ResNet for feature extraction. Feature selection was done with the help of 2 meta-heuristic algorithms which were Binary particle swarm optimization (BPSO) and Binary grey wolf optimization.	The effective features obtained from each algorithm are combined among themselves, and the success of multiple classifications is increased.	Around 1000 features were extracted from each model, which is comparatively less than the number of features in other studies.

From the above table, we can say that transfer learning is the best method as one of the key issues with existing systems for COVID detection is the lack of sample size and **Transfer Learning** helps us with extracting a large number of features.[3] In medical applications, the most accepted practice of transfer learning is to utilize the CNNs that achieved the best results in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) which assesses algorithms for object detection and classification in large scales.

TABLE I

CNNs ARCHITECTURES, CONFIGURATIONS, AND THEIR INPUT IMAGE SIZE AND NUMBER OF FEATURES EXTRACTED

Architectures	Configurations	Input image size (in pixels)	Number of features extracted
VGG [38]	VGG16	224 x 224	512
	VGG19	224 x 224	512
Inception [36]	InceptionV3	299 x 299	2048
ResNet [37]	InceptionResNetV2 [35]	299 x 299	1536
	ResNet50	224 x 224	2048
NASNet [39]	NASNetLarge	331 x 331	4032
	NASNetMobile	224 x 224	1056
Xception [40]	Xception	299 x 299	2048
MobileNet [41]	MobileNet	224 x 224	1024
DenseNet [42]	DenseNet121	224 x 224	1024
	DenseNet169	224 x 224	1664
	DenseNet201	224 x 224	1920

Fig 4: Features extracted by various CNN architectures via transfer learning. [3]

d. <u>Classification using Neural Networks:</u>

Classification is the process of categorising an image in classes based on the various factors/features. In our case, Neural Networks and specifically Convolutional Neural Networks will be used. The various ConvNet architectures studied are as following:

Author	Technique Used	Advantages	Disadvantages
[2]Boran et al. (2020)	ResNet50	1)Higher speed of training deep NNs. 2)Increased depth of network with less parameters / features. 3)High accuracy	1)Lower ROC AUC compared to other architectures.
[22] Afshar Shamsi Jokandan et al. (2020)	MobileNetV2	1)Best classification accuracy 2)One of the better architectures wrt specificity 3)Low feature extraction time	1) Computationally intensive to train
[12]Narin et al. (2020)	InceptionV3	1)Faster training time 2)Computationally less demanding	1)Low accuracy (~80%)
[9]Chandra et al. (2020)	ML Techniques	1)Lower training time 2)Requires comparatively lower dataset size.	1)Worse performing than CNNs
[1]Das et al. (2020)	Ensemble Learning	1)Ensemble of various models works better than single model	1)Computationally demanding

Based on the above table, the first thing we can conclude that is traditional Machine Learning models are far inferior than CNNs in classifying images.[2] Also, no individual CNNS architecture (ResNet, MobileNet, Inception) provide all the advantages and disadvantages, hence, **Ensemble** of all these architectures can provide a better result.

Models	**Parameters**	**Validation Accuracy**	**Sensitivity**	**F1-Score**
Individual networks				
DenseNet201	18,325,826	93.6%	92%	94.4%
ResNet50_v2	23,568,898	95.3%	**98%**	95.8%
Inception_v3	21,806,882	94%	93%	94.8%
Ensembled networks				
Unweighted average		94.5%	95%	95.1%
Weighted average (accuracy)[37]		94.5%	95%	95.1%
Weighted average (rank)[37]		95.3%	97%	95.8%
Proposed Approach		**95.7%**	**98%**	**96.2%**

Fig 5: Metrics of measure for individual networks vs Ensembled networks [1]

IV. PROPOSED ALGORITHM

We obtain the input from online public repositories which are pre-processed and segmented to obtain a clearer picture of the chest. Pre-processing is done on the images which includes resizing the image to get a clear view of the affected areas which leads to more efficient training. These images are separated into COVID positive and COVID negative. We split the dataset into training (comprises around 80% of the complete database) and testing (comprises around 80% of the complete database) sets. The training set is given as input to the ensemble CNN. From our literature survey, we found out that the best CNN architectures for COVID-19 image classification were ResNet50, MobileNetv2 and Inception. Therefore, we will be using an ensemble of these three architectures to improve the accuracy of our model.

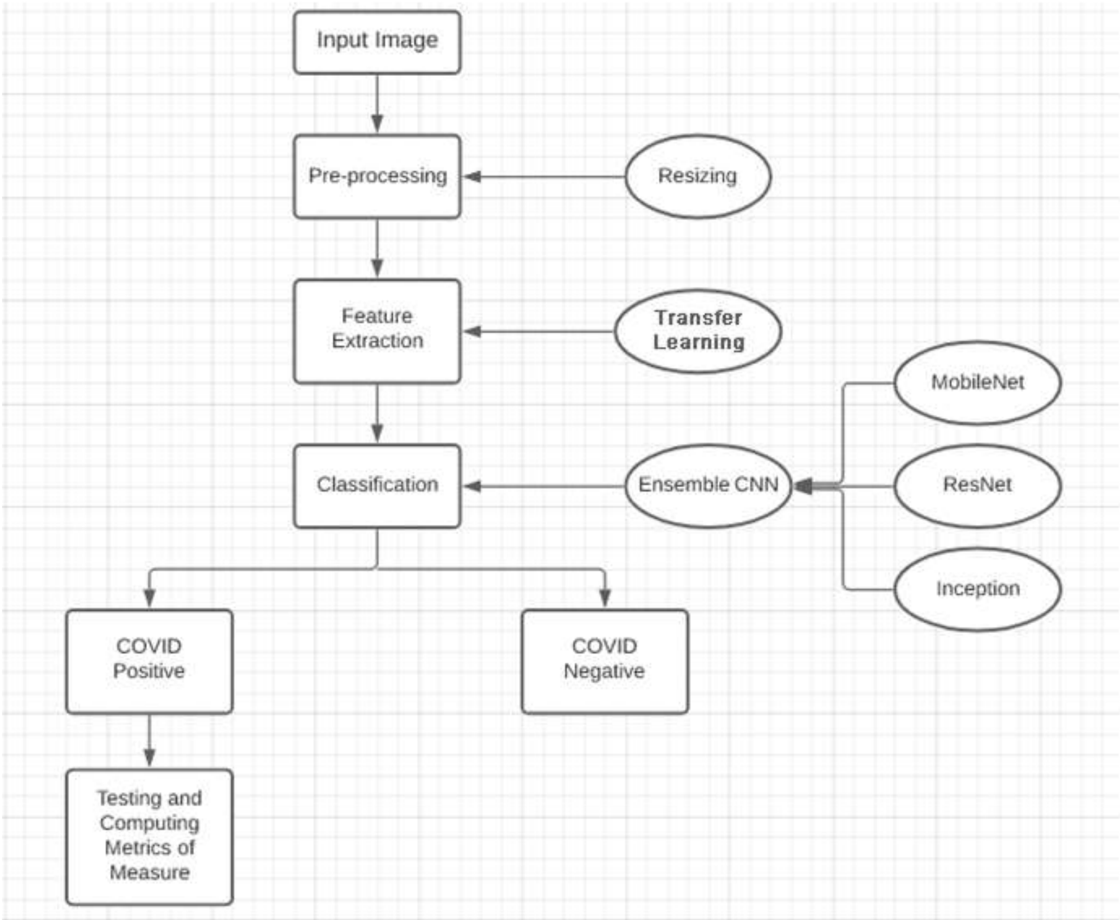

Fig 6: Proposed algorithm

Transfer Learning - Transfer learning is the reuse of a pre-trained model on a new problem. Here, a model which is trained using a big dataset is used to train with smaller dataset, hence inheriting the learnings from the bigger dataset.

ResNet50 - ResNet, short for Residual Networks is a classical neural network used as the backbone for many computer visions tasks. The ResNet-50 model consists of 5 stages each with a convolution and Identity block. Each convolution block has 3 convolution layers and each identity block also has 3 convolution layers. The ResNet-50 has over 23 million trainable parameters.

MobileNetV2 - MobileNet is a convolutional neural network architecture It is based on an inverted residual structure where the residual connections are between the bottleneck layers. The intermediate expansion layer uses lightweight depth wise convolutions to filter features as a source of non-linearity. As a whole, the architecture of MobileNetV2 contains the initial fully convolution layer with 32 filters, followed by 19 residual bottleneck layers.

Inception V3 - Inception-v3 is a convolutional neural network architecture from the Inception family that makes several improvements including using Label Smoothing, Factorized 7 x 7 convolutions, and the use of an auxiliary classifier to propagate label information lower down the network (along with the use of batch normalization for layers in the sidehead).

Ensemble is a method to combine predictions from multiple Neural Network models to increase accuracy.
A successful approach to reducing the variance of neural network models is to train multiple models instead of a single model and to combine the predictions from these models. This is called ensemble learning and not only reduces the variance of predictions but also can result in predictions that are better than any single model.

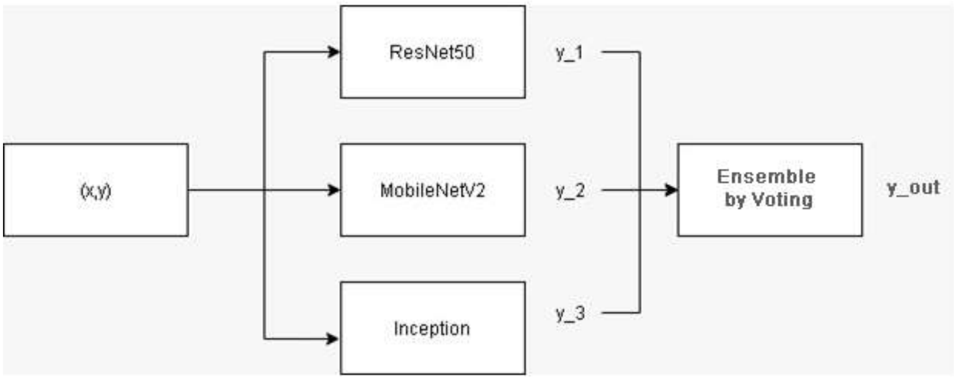

Fig 7: Ensemble Learning model

V. SAMPLE CODING

```
from google.colab import drive
drive.mount('/content/gdrive', force_remount=True)

import tensorflow as tf
from tensorflow import keras
import os
import shutil
import numpy as np
import matplotlib.pyplot as plt
import scipy
from scipy import stats
from tensorflow.keras.applications.inception_v3 import InceptionV3
from tensorflow.keras import layers
from tensorflow.keras import Model
from tensorflow.keras.optimizers import Adam
from keras.callbacks import ModelCheckpoint
from tensorflow.keras.layers import Input, Dense, GlobalAveragePooling2D
from tensorflow.keras.applications.resnet50 import ResNet50
from tensorflow.keras.applications.resnet50 import preprocess_input, decode_predictions
from tensorflow.keras.applications import MobileNetV2
from keras.preprocessing import image

tf.compat.v1.logging.set_verbosity(tf.compat.v1.logging.ERROR)
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '2'

#Create Train Dataset
train_ds = tf.keras.preprocessing.image_dataset_from_directory(
    directory='/content/gdrive/MyDrive/data',
    labels='inferred',
    label_mode='categorical',
    color_mode='rgb',
    batch_size=100,
    image_size=(224,224),
    validation_split=0.2,
    seed=123,
    subset='training')

#Create Test Dataset
test_ds = tf.keras.preprocessing.image_dataset_from_directory(
    directory='/content/gdrive/MyDrive/data',
```

```
    labels='inferred',
    label_mode='categorical',
    color_mode='rgb',
    batch_size=100,
    image_size=(224,224),
    validation_split=0.2,
    seed=123,
    subset='validation')

import matplotlib.image as mpimg
import cv2

directory = os.listdir('/content/gdrive/MyDrive/data')
for each in directory:
  plt.figure()
  currentFolder = '/content/gdrive/MyDrive/data/' + each
  for i, file in enumerate(os.listdir(currentFolder)[:10]):
    fullpath = currentFolder + '/' + file
    img = mpimg.imread(fullpath)
    plt.subplot(2,5,i+1)
    plt.title(fullpath.split('/')[5])
    plt.axis('off')
    plt.imshow(cv2.cvtColor(img, cv2.COLOR_BGR2RGB))

#Inception V3
inceptionv3 = InceptionV3(input_shape = (224,224,3), #shape of resized image
                          include_top = False,
                          weights = None)

x = inceptionv3.output
x = GlobalAveragePooling2D()(x)
x = Dense(1024, activation='relu')(x)
predictions = Dense(2, activation='softmax')(x)

#Create Model 1
model1 = Model(inceptionv3.input, outputs=predictions)
model1.compile(optimizer='Adam', loss='categorical_crossentropy',
              metrics=['acc',
                      tf.keras.metrics.Precision(),
                      tf.keras.metrics.Recall(),
                      tf.keras.metrics.AUC()]
              )

#Show Layers for Model 1
for i, layer in enumerate(inceptionv3.layers):
   print(i, layer.name)

#Fit Model 1
history = model1.fit(
          train_ds,
          validation_data = test_ds,
          steps_per_epoch = 5,
          epochs = 5,
          validation_steps = 5,
          verbose = 1)
```

```
# summarize history for accuracy
plt.plot(history.history['acc'])
plt.plot(history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
# summarize history for loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
#summarize history for auc
plt.plot(history.history['auc_2'])
plt.plot(history.history['val_auc_2'])
plt.title('model auc')
plt.ylabel('auc')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()

#Show metrics for Model 1
precision = history.history['precision'][4]
recall = history.history['recall'][4]
f1_score = (2*precision*recall)/(precision + recall)
print('precision:',precision)
print('recall:',recall)
print('F1 score:',f1_score)

#ResNet50
resnet50 = ResNet50(input_shape = (224,224,3), #shape of resized image
                    include_top = False,
                    weights = None)

x = resnet50.output
x = GlobalAveragePooling2D()(x)
x = Dense(1024, activation='relu')(x)
predictions = Dense(2, activation='softmax')(x)

#Model 2
model2 = Model(inputs=resnet50.input, outputs=predictions)
model2.compile(optimizer='Adam', loss='binary_crossentropy',
        metrics=['acc',
            tf.keras.metrics.Precision(),
            tf.keras.metrics.Recall(),
            tf.keras.metrics.AUC()])

#Show Layers for model 2
for i, layer in enumerate(resnet50.layers):
  print(i, layer.name)

#Fit Model 2
```

```
history2 = model2.fit(
        train_ds,
        validation_data = test_ds,
        steps_per_epoch = 5,
        epochs = 5,
        validation_steps = 5,
        verbose = 1)

# summarize history for accuracy
plt.plot(history2.history['acc'])
plt.plot(history2.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
# summarize history for loss
plt.plot(history2.history['loss'])
plt.plot(history2.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()

#Show metrics for Model 2
precision = history2.history['precision_1'][4]
recall = history2.history['recall_1'][4]
f1_score = (2*precision*recall)/(precision + recall)
print('precision:',precision)
print('recall:',recall)
print('F1 score:',f1_score)

# model3 = MobileNetV2
mobilenetv2 = MobileNetV2(input_shape = (224,224,3), #shape of resized image
                          include_top = False,
                          weights = None)

x=mobilenetv2.output
x=GlobalAveragePooling2D()(x)
x=Dense(1024,activation='relu')(x)
x=Dense(1024,activation='relu')(x)
x=Dense(512,activation='relu')(x)
preds=Dense(2,activation='softmax')(x)

model3=Model(inputs=mobilenetv2.input,outputs=preds)

#Model 3
model3.compile(optimizer='Adam',loss='categorical_crossentropy',
          metrics=['acc',
              tf.keras.metrics.Precision(),
              tf.keras.metrics.Recall(),
              tf.keras.metrics.AUC()])

#Show Layers for Model 3
for i, layer in enumerate(mobilenetv2.layers):
```

```
  print(i, layer.name)

#Fit Model 3
history3 = model3.fit(
        train_ds,
        validation_data = test_ds,
        steps_per_epoch = 5,
        epochs = 5,
        validation_steps = 5,
        verbose = 1)

# summarize history for accuracy
plt.plot(history3.history['acc'])
plt.plot(history3.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
# summarize history for loss
plt.plot(history3.history['loss'])
plt.plot(history3.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()

#Show metrics for Model 3
precision = history3.history['precision_2'][4]
recall = history3.history['recall_2'][4]
f1_score = (2*precision*recall)/(precision + recall)
print('precision:',precision)
print('recall:',recall)
print('F1 score:',f1_score)


#Predicting Set of Images
paths = []

for filename in os.listdir('/content/gdrive/MyDrive/data/test'):
   if filename.endswith("jpg") or filename.endswith("png"):
      paths.append(filename)
i = 0
for path in paths:
  img = image.load_img(path, target_size=(224, 224)) #path and size
  x = image.img_to_array(img)
  x = np.expand_dims(x, axis=0)
  images = np.vstack([x])
  labels = []
  for m in models:
     predicts = np.argmax(m.predict(images), axis=1)
     labels.append(predicts)

  # Ensemble with voting
  labels = np.array(labels)
```

```
labels = np.transpose(labels, (1, 0))
labels = scipy.stats.mode(labels, axis=1)[0]
labels = np.squeeze(labels)
if labels == 0:
  print('Covid Negative')
else:
  print('Covid Positive')
plt.subplot(2,5,i+1)
plt.title(path.split('/')[5])
plt.axis('off')
plt.imshow(cv2.cvtColor(img, cv2.COLOR_BGR2RGB))
i = (i+1)%6
```

VI. EXPERIMENTS RESULTS

The input to the proposed system is an image of size 224x224. This dataset was obtained from the following sources:

- https://github.com/ieee8023/covid-chestxray-dataset
- https://github.com/agchung/Figure1-COVID-chestxray-dataset
- https://github.com/agchung/Actualmed-COVID-chestxray-dataset
- https://www.kaggle.com/tawsifurrahman/covid19-radiography-database
- https://www.kaggle.com/c/rsna-pneumonia-detection-challenge

The images from these datasets were combined and divided into COVID positive and COVID negative. Preprocessing was applied to resize all the images to the size 224x244.

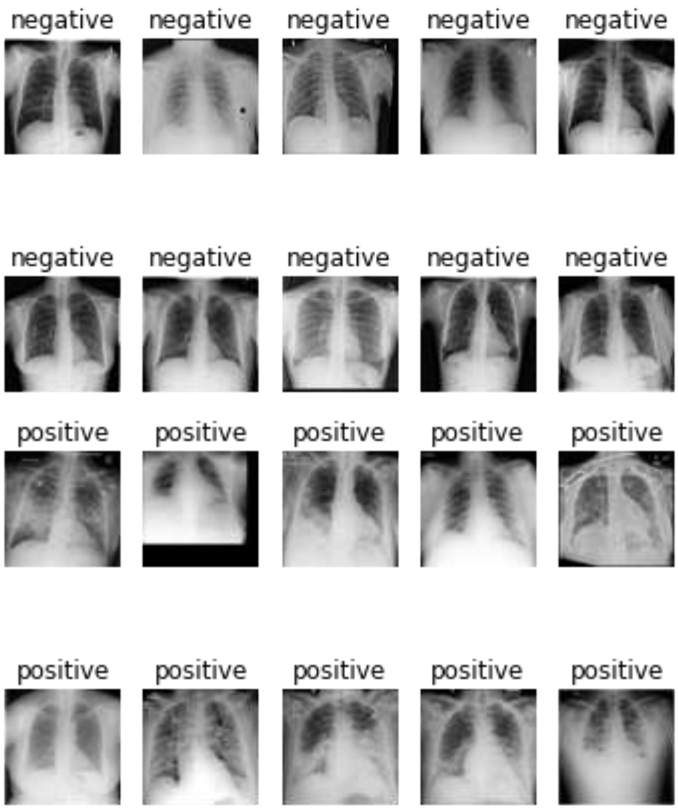

Fig 8: Sample dataset

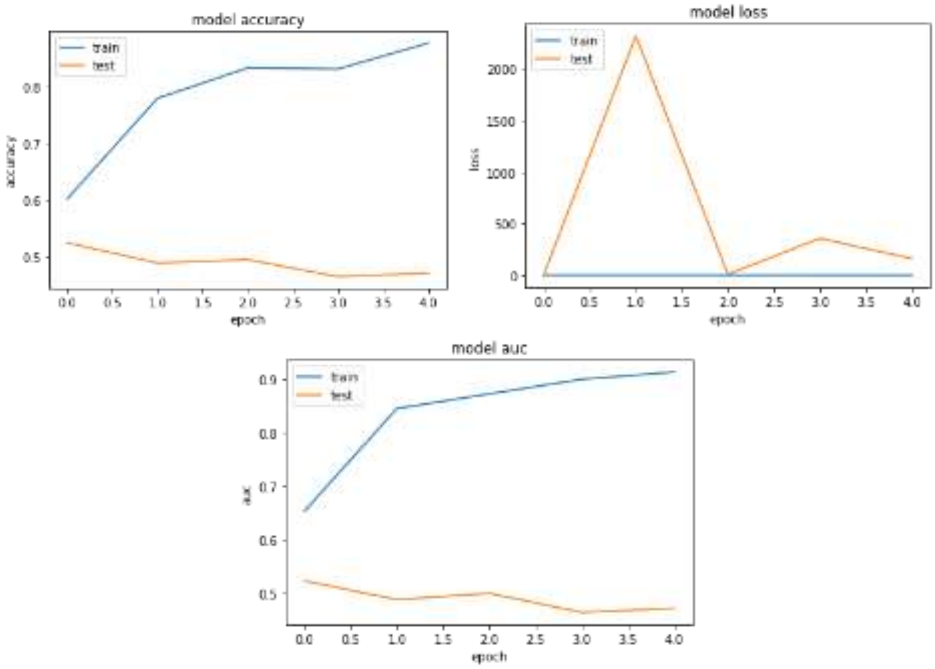

Fig 9: Accuracy, Loss and AUC plot for InceptionV3

```
Epoch 1/5
5/5 [==============================] - 123s 23s/step - loss: 1.4536 - acc: 0.5022 - precision_2: 0.5022 - recall_2: 0.5022 - auc_2: 0.5028
Epoch 2/5
5/5 [==============================] - 110s 23s/step - loss: 0.5920 - acc: 0.6921 - precision_2: 0.6921 - recall_2: 0.6921 - auc_2: 0.7641
Epoch 3/5
5/5 [==============================] - 110s 23s/step - loss: 0.5342 - acc: 0.7656 - precision_2: 0.7656 - recall_2: 0.7656 - auc_2: 0.8177
Epoch 4/5
5/5 [==============================] - 109s 23s/step - loss: 0.4800 - acc: 0.7783 - precision_2: 0.7783 - recall_2: 0.7783 - auc_2: 0.8545
Epoch 5/5
5/5 [==============================] - 110s 23s/step - loss: 0.4300 - acc: 0.8139 - precision_2: 0.8139 - recall_2: 0.8139 - auc_2: 0.8846
```

Fig 10: Fitting model for MobileNetV2

```
Accuracy =  85.32 %
```

Fig 11: Accuracy for ensembled model

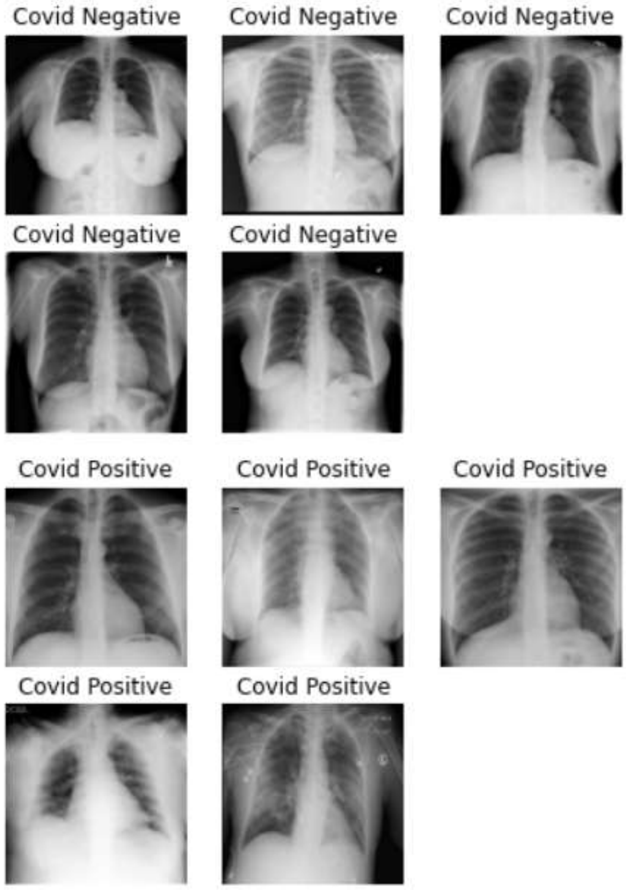

Fig 12: Sample Prediction

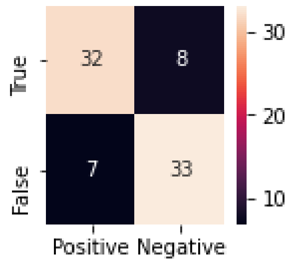

Fig 13: Confusion Matrix for Ensemble Model

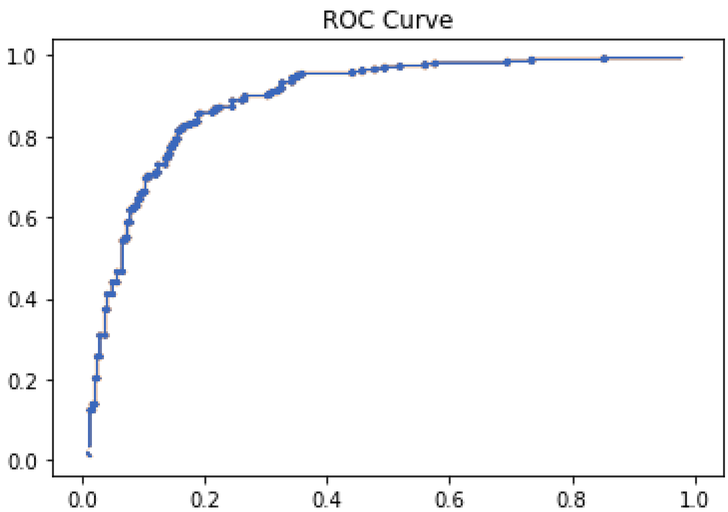

Fig 14: ROC Curve for Ensemble Model

The metrics calculated from the experiment are as follows:

Approach	Accuracy	AUC	F1-Score	Precision	Recall
MobileNetV2	80.86%	87.97%	80.86%	80.86%	80.86%
ResNet50	78.14%	84.29%	78.14%	78.14%	78.14%
InceptionV3	84.93%	90.43%	84.93%	84.93%	84.93%
Ensemble	85.32%	89.02%	85.32%	85.32%	85.32%

As it is visible, the proposed ensembled network provides better metrics compared to any single model. Ensemble increases the accuracy by reducing the mean error. As discovered during the literature survey phase, MobileNetV2 provides low accuracy, ResNet50 provides a lower AUC and InceptionV3 is highly demanding to train. But, the ensembled model provides a better system with a higher accuracy and AUC than any individual model hence providing a better system.

VII. COMPARATIVE STUDY

Comparing our proposed approach with Sekeroglu et al. [2] and Ohata et al. [3], we obtain the following table of metrics:

Author	Number of images in dataset	Approach	Method	Results
Our approach	COVID positive: 2180 COVID negative: 2211 (Mix of healthy+Pneumonia)	Transfer Learning + Ensemble	ResNet50 + MobileNetV2 + InceptionV3 + Ensemble	Accuracy: 85.32% AUC: 89.02% F1-Score: 85.32%
Sekeroglu et al. [2]	COVID positive: 225 Healthy: 1583	CNN	DenseNet121	Sensitivity: 93.92 Specificity: 99.04 Accuracy: 98.39
Ohata et al. [3]	Dataset A: 194 healthy + 194 COVID positive Dataset B: 194 healthy + 194 COVID positive	Transfer Learning + ML	MobileNet + SVM (Linear)	Accuracy: 98.62% F1-Score: 98.461%

The dataset used in our approach consists of 2180 COVID positive images along with 2211 COVID negative and Pneumonia images. The approached used by Sekeroglu et al. [2] consists of 225 COVID positive and 1583 Healthy images. Whereas, Ohata et al. [3] used two dataset groups each consisting of 194 COVID positive and 194 COVID negative images.

Compared to the various state of art models, the proposed approach provides lower metrics but provides increased computational efficiency as the models used require lower computational power.

VIII. CONCLUSION AND FUTURE WORK

Detection of COVID-19 virus is a vital part in the process of ending the ongoing pandemic. Using AI and deep learning it not only reduces the diagnostic time but the cost attached to it too. Deep learning is capable of recognizing patterns in images and classifying them. This feature is used in the proposed approach. In this study, various approaches were executed to come up with a system with great accuracy. For each step in the algorithm like pre-processing, all the options like resizing, CNN etc. were researched to come up with the optimum solution.

Finally, a system is built with prediction accuracy of 85.32%, AUC of 89.02%, F1-score of 85.32%. Further work is required to improve on these metrics but also in increasing the dataset size. Increasing the number of hidden layers may also lead to better weight adjustment. Furthermore, experimental study is required to find out the efficacy and scope of such models in comparison to the medical equipment-based testing.

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