Deep Learning Based Intelligent Classification Of Covid-19 & Pneumonia By Using Cough Ascultations Collected by Ascultation Sensor

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***Abstract*— The World Health Organization (WHO) has designated COVID-19 a pandemic because it has impacted more than 50 million individuals and killed 14 million worldwide as it has propagated. In this work, we present a method to autonomously diagnose the COVID-19 by evaluating cough auscultation to swiftly screen the patients. In this appear, we used the deep learning-based model MobileNet v2 to analyze a self-collected dataset (6757 coughs) acquired by a self-designed Auscultation Sensor at a 44.1kHz sampling rate and 8-bit rate. The experiment demonstrates the efficacy of the proposed technique in distinguishing between COVID-19 and Pneumonia, with a cumulative accuracy of 99.98% at a learning rate of 0.0005 and a validation loss of 0.0028.**

Keywords—COVID-19, Cough auscultation, Deep learning, MobileNet v2, Pneumonia.

I. Introduction

COVID-19, which began on December 31, 2019, with a report of unexplained reasons for pneumonia in Wuhan, Hubei Province, China, has quickly spread around the globe and was declared as a pandemic and contains the SARS-CoV-2 virus. Pneumonia caused by the influenza virus and other types may occur throughout the season. Differentiating COVID-19 from general pneumonia might be difficult in some cases, especially when clinical characteristics are considered. Fever, tiredness, dry cough, and expiratory dyspnea were the major symptoms of COVID-19 in the early stages, but individuals with general pneumonia had comparable symptoms. Because of its increased mortality and morbidity, COVID-19 placed a significant strain on the healthcare system. As a result, early detection and isolation of patients can help prevent the pandemic from spreading and will optimize the medical resource allocation. Early diagnosis and treatment of this condition rely heavily on chest radiological imaging such as computed tomography (CT) and X-ray [2]. CT- scan presentations of Pneumonia and COVID-19 had overlapping symptoms which initially produced insecurity and confusion. A real-time reverse transcription-polymerase chain reaction (RT-PCR) is the most prevalent test technique currently utilized for COVID-19 diagnosis. The healthcare sector is keen to find new techniques and processes to monitor and manage the development of the coronavirus outbreak in this global health catastrophe. At the moment, artificial intelligence (AI) is one of the most salaried techniques, because it can monitor and identify the rate of expansion and gravity of COVID-19. AI can also help us estimate the rate of future instances by extensively evaluating prior patient information, can help us combat the virus through conducting clinical trials, and advice on disease control. Machine Learning (ML) and Deep Learning (DL) are AI subfields that combine numerous methods to create intelligent models for identifying and clustering specific jobs. Deep Learning, is a subset of machine learning that focuses on creating deep structural Neural network (NN) models that learn from data using backpropagation and feedforward techniques. Transfer learning and generative models are two examples of DL that do not require significant amounts of data to train. Deep Belief Networks (DBN), Deep Neural Networks (DNN), and Deep Convolutional Neural Networks have commonly used algorithms in Deep Learning.

Research initiatives in the commercial, pharmaceutical, technical, and defense spheres have effectively integrated sophisticated AI-based ML and DL methods and achieved substantial advances. In medical image analysis, ML and DL help COVID-19 assessment and give non-invasive screening techniques to protect medical workers from obtaining infections, and the patient's severity level is also supplied for therapeutic applications. As COVID-19 pandemic has unleashed devastation all around the world on the global economy, public health, and daily lives from multiple points of view. It is crucial to detect this disease at an early stage as soon as possible to reduce its spread and mitigate its hazardous effects. With a similar motive in this study, we used the deep learning model MobileNet v2, applied the transfer learning approach, and successfully classified COVID-19 and Pneumonia cough using a self-collected dataset acquired through an Auscultation sensor.

II. Literature Review

Ozturk et al. implemented the techniques of Artificial intelligence with radiological imaging of the chest to design an accurate & automatic Covid diagnostic model. Their proposed model was based on two types of classifications including binary (Covid & Normal) and multi-class cases

(Covid, Normal & Pneumonia) [1]. Hariri et al. used the deep learning algorithms with chest tomography/x-ray images for efficient detection of respiratory viral diseases just like Severe acute respiratory syndrome Coronavirus (SARS-CoV). The noise was removed from X-ray images using certain pre-processing techniques, and then multiple deep models like generic neural networks and pre-trained models were to extract the deep features and perform further classification [2]. Narin et al. used X-ray images for pre-testing or diagnosis of Covid-19 [3]. Pahar et al. performed automatic detection of Covid-19 from cough sounds with acoustic cough signals and further classified them with a machine learning-based classifier into covid positive or negative cough signals [4]. Schullet et al. focused on the evaluation and comparison of seven ML classifiers. COVID-19 cough was easily detected by all classifiers but the highest AUC (Area under Curve) of 0.98 was achieved using the Resnet50 classifier. Breathing and coughing audio sounds were analyzed with spectrogram variations and classified as infected or non-infected using convolutional neural networks [5]. Brown et al. used features obtained through transfer learning with multiple classifiers. Support Vector Machines (SVMs), Gradient Boosting Trees (GBT), and Logistic Regression (LR) were tested and the highest AUC of 80% was achieved with a dataset of 141 Covid infected breath and cough sounds, 330 non-covid cough samples, and 20 asthma cough samples [6]. Walvekar et al. used Machine learning techniques with image analysis. Resnet50 architecture with Computed tomography (CT) achieved a classification accuracy of 96.23% with a dataset used of 359 X-ray images [7]. Similarly, Yildirim et al [8] & Soutodeh et al. [9] used the same Resnet50 architecture to detect COVID-19 from X-ray images with a classification accuracy of 96.30% and pneumonia with an accuracy of 96.7% respectively. In [10], Researchers developed noncontact experimental testing in which they used the bottleneck features in their deep transfer learning-based COVID-19 detection using speech, cough, and breath signals. These extracted features from the pre-trained model were provided as an input to SVM, multiple layer perceptron (MLP), LR, and k-nearest neighbor (KNN) classifiers. Imran et al. [11] achieved an overall classification accuracy of 88.76% with their proposed approach AI4COVID for the classification of coughs. The limitation of their study is that their dataset was quite limited as it contained only 70 Covid cough sound samples. Researchers in [12], used the empirical mode decomposition (EMD) for cough sound detection and classification. Audio sonography and a deep artificial neural network classifier clinically validated covid, as well as non-covid samples, with an overall AUC of 81.08%. In [13], Resnet 50 and pre-trained Deep Convolutional Network were used for the classification of X-ray images as covid and non-infected samples. 102 COVID-19 and pneumonia samples were used to tune Resenet50 with an accuracy of 89.2% and an AUC value of 0.95. Goel et al. used Gray Level Co-occurrence Matrix and autoencoder to extract discriminative features and then classified them with a random forest classifier to detect COVID-19 with a classification accuracy of 98.77%. Gifani et al. achieved 85% accuracy by the implementation of a pre-trained convolutional neural network (CNN) on computed tomography images with a deep transfer learning system [15]. In [16], two limited datasets of 224 COVID-19 X-ray, normal and abnormal X-ray images for detection of Coronavirus with a classification accuracy of 96.78%. In [17], a multi-channeled deep convolutional neural network (DCNN) was used with Gammatone Frequency Cepstral Coefficients (GFCC) & Inverse Mel Frequency Cepstral Coefficients (IMFCC) features with a De-noising autoencoder for the development of an accurate automatic COVID-19 diagnostic system. [18] used 338 X-ray images of 10 different classes and 510 images of Covid and non-covid persons. This proposed methodology based on Artificial Neural Networks achieved an accuracy of 83% with an AUC value of 0.907 and SVM achieved 98.05% accuracy with an AUC value of 0.989.

TABLE I. COPMARSION OF PREVIOUS STUDIES

Reference	Dataset	Data form	Techniques	Results
[1]	Covid positive: 127 Pneumonia: 127	X-ray Images	Deep Neural Networks	Binary: 98.08% Multiclass: 87.02%
[4]	1st Dataset Covid Positive: 92, Healthy: 1079 2nd Dataset Covid Positive: 18, Covid Negative: 26	Cough Sounds	Machine Learning	Highest AUC: 0.98 (Resnet50)
[5]	Healthy: 710 Covid: 282 Asthma: 42	Breathing & Cough Sounds	Deep Neural Network	ACC: 80.7% UAR: 74.9%
[6]	Covid Infected: 141 Non-Covid: 330 Asthma: 20	Respiratory Sound Data	Machine Learning	AUC: 80%
[7]	Dataset includes 359 X-ray Images of multiple categories.	CT images/X-rays	Machine Learning	ACC: 96.23%
[8]	Covid19: 136 Pneumonia: 162 Normal: 245	Chest X-ray Images	Deep Learning	ACC: 96.30%
[9]	12744 CT images of Pneumonia Patients induced by Covid or Influenza Virus	CT Images	Artificial Intelligence, Convolutional Neural Network	ACC: 96.7% (Covid 19) ACC: 92% (Influenza Virus)
[10]	Cough Dataset: 1732 samples Breath Dataset: 1150 samples Speech Dataset: 2934 samples	Audio Recordings	Deep Transfer Learning	AUC: 0.94 (SVM)

[12]	Covid 19 Positive:2339 Covid 19 Negative: 6041	Cough Sound	Generic Deep Learning, Convolutional Neural Network, EMD	Overall ACC: 81.08%
[13]	Covid 19:102 Pneumonia:102	X-ray Images	Deep Convolutional Neural Network	ACC: 89.2%
[13]	Covid Positive: 349 Covid Negative: 397	CT Scans	Deep Convolutional Neural Network, Deep Transfer Learning	ACC: 85%
[18]	1st Dataset: 338 (Multiclass) 2nd Dataset: 510 (Covid infected, Healthy)	X-ray Images	Convolutional Neural Network, Feed Forward Neural Network	KNN ACC: 83% AUC: 0.907 SVM ACC: 98.05% AUC: 0.989

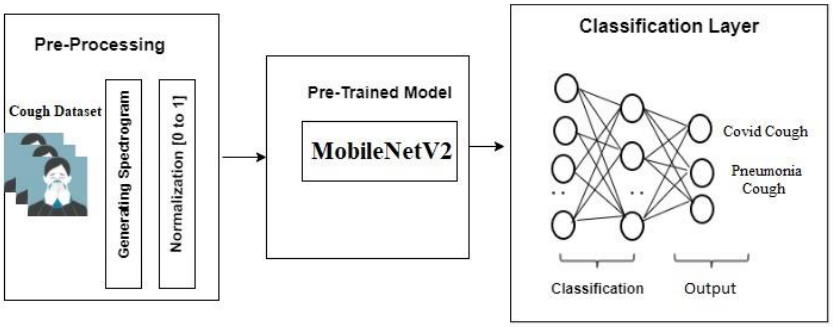

Fig. 1. Proposed Block Diagram of Our System.

TABLE II. SELF COLLECTED DATASET STATICTICS

Cough Auscultations	Female Subjects			Male Subjects			Total
	Female	Samples	Age	Male	Samples	Age	
COVID-19	60	600	15-54	70	753	11-60	1353
Pneumonia	340	3404	18-52	200	2000	21-64	5404

Fig. 2. Self-Designed Sensor [19-26].

III. RESEARCH METHDOLOGY

COVID-19 has severe side effects on the health of human beings and causes death. It has the same symptoms as pneumonia cough so we need a system that can differentiate between COVID-19 and pneumonia coughs. Recent advancements in the deep learning approaches bought resolution in the detection and classification that provide more accuracy without hand-crafted features. Fig. 1 shows the proposed methodology of our system. We used a CNN-based deep learning model named MobileNetV2 for the detection and classification of covid and pneumonia-cough.

A. Dataset Acquisition and Distribution

We acquired a self-collected dataset using a self-designed sensor named Auscultation Sensor (AS) [19-26] Fig. 3. The AS includes a stethoscope, sensitive microphone, sound card, and laptop. AS was placed on the backside of the thorax region where lungs are located. The diaphragm of steth sensed cough auscultations (CA), which were transmitted to a sound card by a sensitive microphone. Sound card converted oncoming analog signals to a digital one and in computer, a python program was running which saved these digital signals as .wave file in computer repository. The time duration of the collection of this dataset spans from March 2020 to July 2021. All CA's were collected at daytime with a sampling rate of 44.1k Hz, 8-bit rate, and mono channel. We gathered CA's from pneumonia and covid patients. Pneumonia patients were screened from local hospitals while the COVID-19 patient's dataset was acquired from nearby local residents. Related dataset details are given in Table II. Fig .3 (a) shows the CA's obtained from covid and pneumonia patients. Visually it can be seen that their amplitude range is the same. Covid cough has collected sharp peaks after regular time intervals, while pneumonia cough has continuous transmission. Fig. 3 (b) shows the CA in frequency domain. COVID-19 cough spectrum range is from 0-1.5 kHz while Pneumonia Cough is from 0 to 500 Hz. Thus, both signals are visually differentiable in both time and spectrum domain.

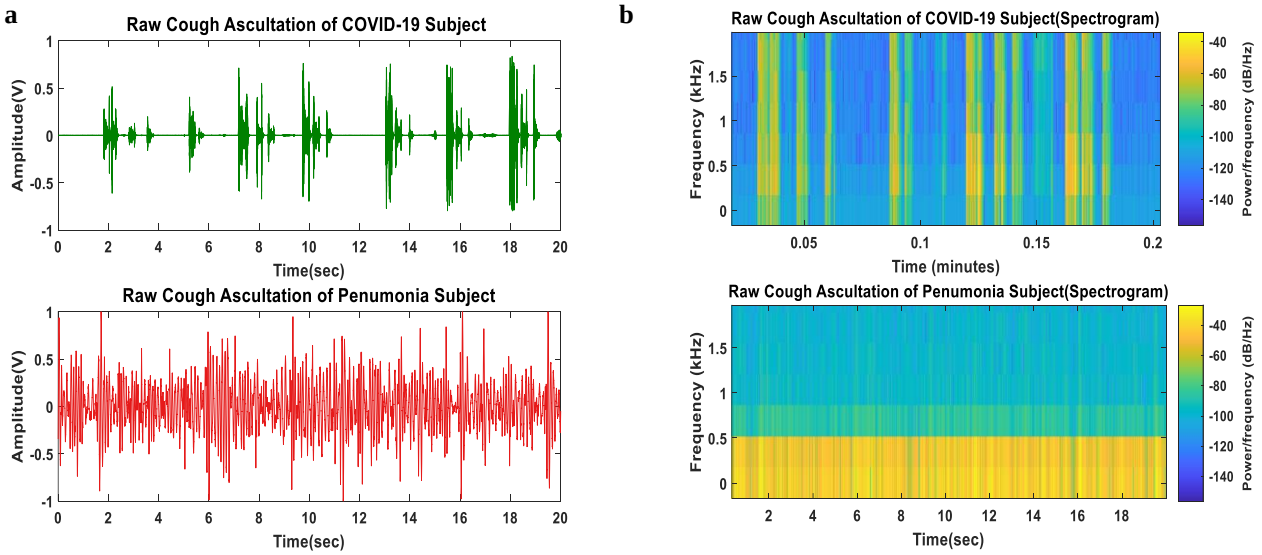

Fig. 3. Raw Signal Obtained from Cough Ascultation sesnor (a) Time Domain (b) Frequency Domain.

B. Pre-Processing

Following pre-processing steps are taken before giving input to the chosen deep learning model.

1) Spectrograms Generation

Raw cough dataset is converted into respective spectrograms because deep learning performs best when the input given to them is in an image form. That's why we converted each cough sample into a spectrogram wherein the x-axis contains the time of the sample and the y-axis amplitude of the frequencies against each time-space. Each cough sample is captured with a window size of 0.25ms, then converted into a spectrogram image and saved in the .png format as shown in Fig. 4.

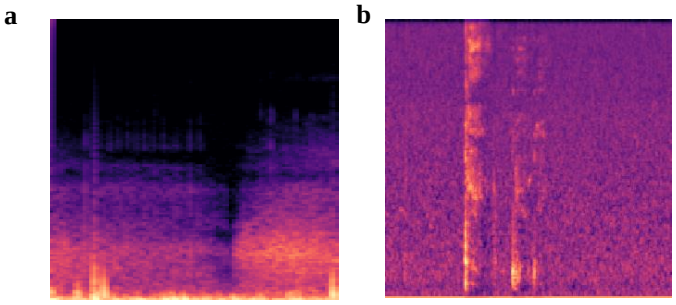

Fig. 4. Generated Spectrograms (a) Pneumonia (b) Cough.

2) Resize

Each spectrogram has a size of 400x400 during conversion. It was resized to 224x244 which is the required dimension of MobileNetV2, as shown in Fig. 5

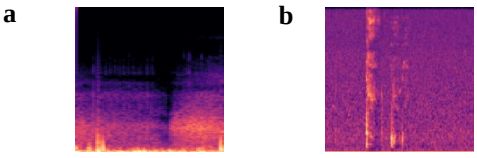

Fig. 5. Resized Spectrograms (a) Pneumonia (b) Covid.

3) Normalization

After resizing the spectrograms, all pixels are normalized. Pixel values have a range of 0 to 256 depending upon the intensity value of the pixel which has normalized into respective values. Mathematically,

$$Spectrogram_{Norm} \frac{Pixel-Value}{256} \quad (1)$$

C. Transfer Learning

Transfer learning is a machine learning approach in which a model that has been built for a task is utilized again as the reference basis for a second task model as shown in Fig. 6. In this article, we utilized trained base networks on a dataset (ImageNet [28]) and a task (classification of 1000 classes), and then reassigned or transferred the learning characteristics to a second target network to be trained in a desired dataset (self-collected) and task (cough detection and disease classification). Utilization of this approach succeeded for the classification of cough because the models were trained on generic attributes of 1000 classes, which means that they are suited for both the base and the target tasks classification [29].

D. MobileNet-V2 Deep Learning Model

Convolutional Neural Networks (CNNs) require a relatively wide range of training parameters [8]. They comprise alternating convolutional layer-CL (performs feature extraction) and pooling layers-PL (reduces extracted features) with fully linked layers. CL is supported by n filters where k is less than the incoming dimensions and q is typically different for every kernel. We selected CNN based MobileNet-V2 deep learning model for emotion detection and classification. We have finalized to apply it for the detection and classification of the emotions and their type with pertained weights of MobileNet-V2. The block diagram of MobileNet-V2 is shown in Fig. 7.

1) Architecture: MobileNetV2 uses fully separable convolution as efficient components. It includes two new architectural elements,

a) linear bottlenecks across the layers.

b) shortcut connections between the bottlenecks.

With approximately 350 GFLOP, the MobileNetV2 contains 53 convolution layers and 1 AvgPool. It is made up of two major parts:

i. Residual Block inverted
ii. Residual Bottleneck Block

And uses two types of Convolution layers:

i. Convolution 1x1
ii. Depth-wise Convolution 3x3

Bottlenecks indicate the model's inputs and outputs, whereas the input layer represents the model's ability to transition from lower-level notions (for example, pixels) to higher-level variables (for example categories of images). Finally, shortcuts, like classical residual connectivity, allow for faster training and higher accuracy.

E. Transferring MobileNet v2 weights

As seen in Fig. 6, our network training process consists of three major phases.

i. To begin, we use a MobileNet v2 model that has been pre-trained on the ImageNet dataset. This training is performed to categorize primary targets using full pictures as input rather than pre-selection attributes. Each picture has one main target that takes up a substantial amount of the image.
ii. Following that, we load all of the information from the previous six ImageNet-trained layers.
iii. Finally, after adjusting the settings of the different number of layers, we fine-tune on the self-collected dataset (KED).

F. Optimization

Optimization is the issue of finding a collection of variables that lead to the assessment of optimum or minimal features for an objective function. This article needs continuous function optimization, as there are true numerical values for the input parameters for the function, e.g., Floating-point values. The result of the function is also a realistic assessment of the input data. So, we used Adam optimizer (AO) which uses gradient descent optimization (GDO). AO is working phenomenally and considerably quicker than other methods since its preset hyperparameters generally function perfectly. The gradient is a multivariate continuous objective function's derivative (MCOF). MCOF is a vector, and every component in the vector is referred to as a partial derivative, or the degree of variation for a particular variable at a particular location provided all other variables stay unchanged. It is built on a convex function and continuously modifies its characteristics to reduce a specific task to its regional base level.

G. Softmax Layer

The softmax function is used to activate a multidimensional probability distribution in the output layer of neural network models. In reference to Eq 2, the incoming variables can be negative, positive, zero or higher, but softmax converts them to numbers from 0 to 1 to be understood as probabilities. Mathematically,

$$\text{Softmax}_{input} = \frac{exponential\ function^{input}}{\sum_{1}^{no.of\ classes} exponential\ function^{ouput}} \quad (2)$$

H. Model Training

The batch size was kept at the size of 128 images and epochs number to 20. Each epoch is further divided into 100 epochs combining all to have a total of 2000 epochs for each learning rate. Here, adam optimizer is used for the convergences of best weights.

I. Prediction and Classification

After successfully training MobileNetV2 using transfer learning and changing the softmax layer to 2 instead of 1000. We tested the model for the prediction and classification of two different types of coughs i.e., covid and pneumonia.

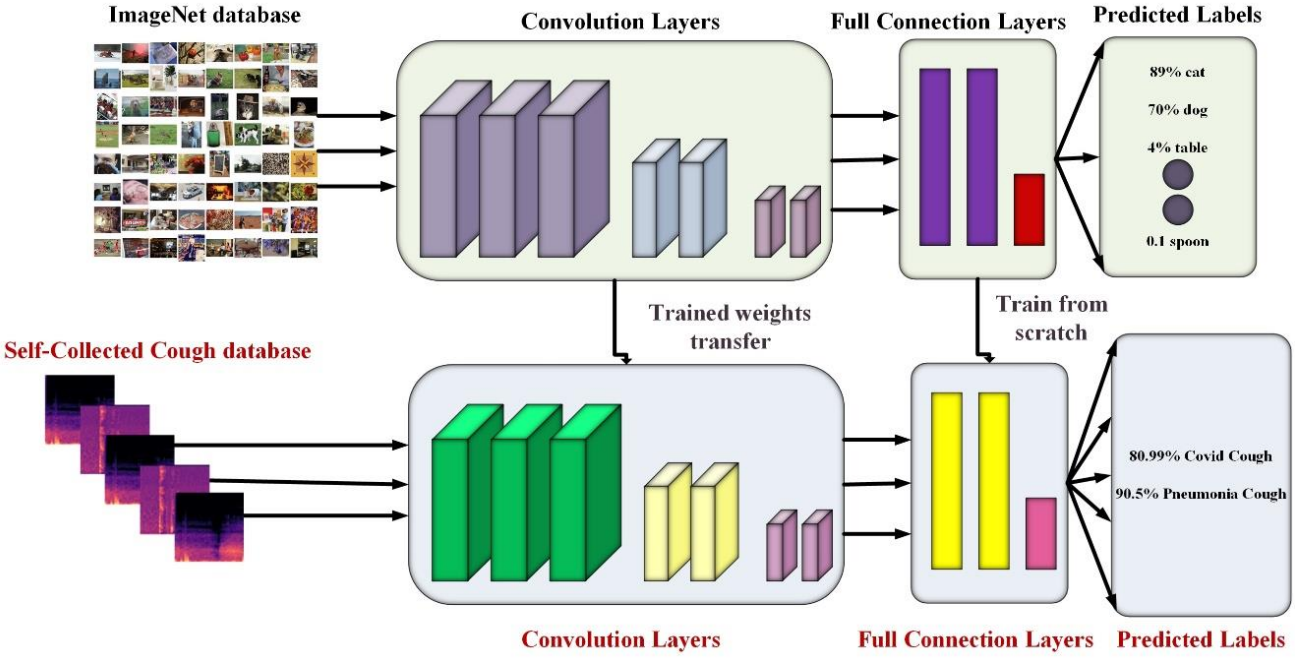

Fig. 6. Block Diagram of Transfer learning Approach.

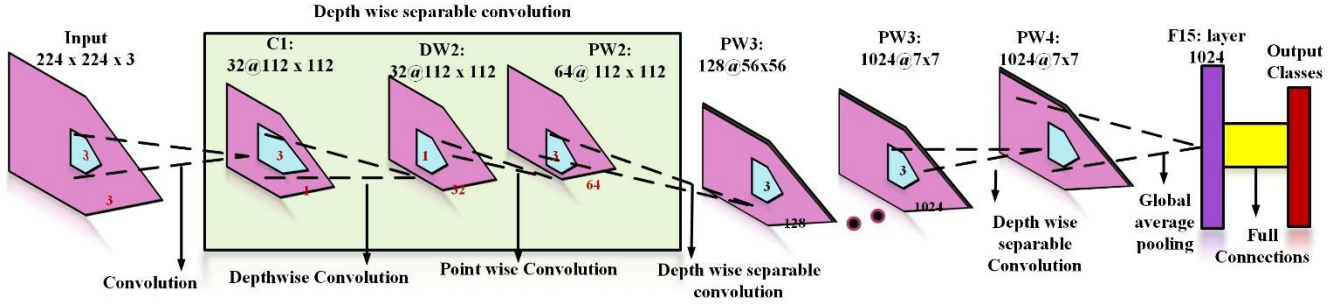

Fig. 7. Architecture Diagram of MobileNetV2 Deep Learning Model.

IV. Results and Discussions

The self-collected dataset which is in the form of 1-D signal is first converted into 2D-form by generating spectrograms of size 400x400 and stored as .png files. According to MobileNet v2 requirement they are resized to 224x224 and normalized. Then these images split into 80% training and 20% validation. The experimentation for 80-20 split is performed at three different learning rates (LR) of 0.05, 0.005, and 0.0005 Initially, the dataset was trained and validated using pre-trained weights with an accuracy of 95.83% at 0.05 LR. But when the dataset is trained and validated at learning rates of 0.005 and 0.0005, we achieved an accuracy of 99.45% and 99.98% respectively. It is observed that maximum accuracy is achieved by keeping the lowest learning rate. A comparison of LR and their achieved accuracies are shown in Table III.

TABLE III. Accuracy Achieved With Different Learning Rates

MobileNetV2			
Learning Rate	***0.05***	***0.005***	***0.0005***
Accuracy	95.83%	99.45%	**99.98%**

Table IV and Fig. 7 show the training and validation accuracy along with the respective loss against each epoch. It is observed that the training accuracy was initially low but got improved from the fifth epoch while the validation accuracy was improved from the second epoch which indicates that the validation accuracy was dominant throughout the epochs. Training loss was initially very much high which got improved up till the fifteenth epochs while the validation loss was initially about 0.355 which improved earlier from the fifth epoch and then remain almost constant. The validation loss was dominant throughout the epochs as compared to training loss.

TABLE IV. Accuracy Achieved With Different Learning Rates

Epoch No	***Training Loss***	***Training Accuracy***	***Validation loss***	***Validation Accuracy***
1	0.2661	0.9086	0.0701	0.0721
2	0.0578	0.9899	0.0201	0.0877
3	0.0341	0.9918	0.0110	0.0494
4	0.0244	0.9948	0.0117	0.0396
5	0.0199	0.9953	0.0190	0.0912
6	0.0160	0.9953	0.0156	0.0369
7	0.0117	0.9976	0.0118	0.0430
8	0.0097	0.9983	0.0095	0.0283
9	0.0093	0.9981	0.0092	0.0284
10	0.0068	0.9983	0.0062	0.0255
11	0.0076	0.9985	0.0071	0.0243
12	0.0076	0.9980	0.0068	0.0346
13	0.0065	0.9987	0.0054	0.0243
14	0.0067	0.9981	0.0047	0.0044
15	0.0040	0.9998	0.0030	0.0237
16	0.0048	0.9987	0.0040	0.0356
17	0.0046	0.9993	0.0030	0.0256
18	0.0030	0.9993	0.0023	0.0356
19	0.0059	0.9978	0.0046	0.0333
20	0.0028	0.9998	0.0028	0.0256

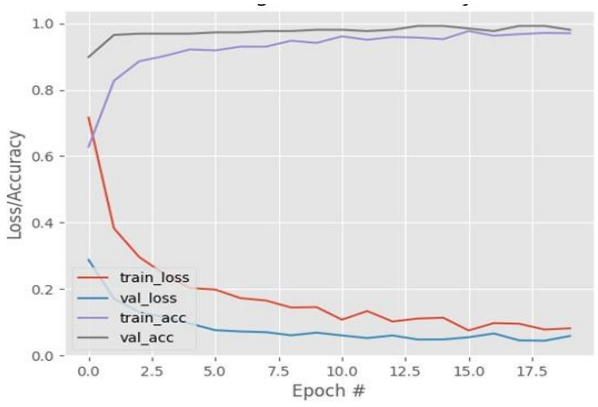

Fig. 8. Training and Validation Accuracy along with Loss Graph Using Learning Rate of 0.0005

Table V shows the classwise percion, recall and F1-sore achieved by Mobilenet V2. Mathematically,

$$\text{Accuracy} = \frac{\sum TP + TN}{\sum TP + FP + FN + TN} \quad (2)$$

$$\text{Precison} = \frac{\sum TP}{\sum TP + FP} \quad (3)$$

$$\text{Recall} = \frac{\sum TP}{\sum TP + FN} \quad (4)$$

$$\text{F1score} = \frac{TP}{\sum TP + \frac{1}{2}(FP + FN)} \quad (5)$$

Where True Positive (TP) indicates the amount of CA that has been reliably measured, True Negative (TN) notes that CA does not truly have the disease but is forecasted as yes, False Negative (FN) shows that CA truly has pulmonary diseases but is predicted no, and False Positive (FP) indicates the falsely CA envisioned by the deep learning model.

TABLE V. CLASSIFICATION PARAMETERS

Class	Accuracy	Precision	Recall	F1-Score
COVID-19	1.00	0.99	1.00	0.99
Pneumonia	0.99	1.00	0.99	1.00

We randomly inferenced each class sample to our system and got the right class label against each sample as shown in Fig. 8. Pneumonia spectrogram is predicted with a confidence of 98.87%. and Covid-cough is predicted with 99.04% confidence.

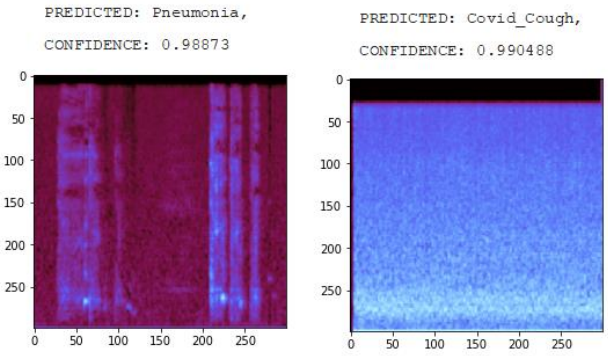

Fig. 9. Random Prediction During Inference.

V. CONCLUSION

COVID-19 is a dangerous disease that emerged in December 2019. Some of its symptoms overlap with pneumonia so we designed a cough auscultation sensor and collected dataset 1353 COVID-19 and 5404 Pneumonia cough samples that could accurately classify the pneumonia-cough and the covid-cough. Our system achieved 99.98% accuracy. As an extended version of this article, we are aiming to explore more deep learning models and provide a comprehensive analysis between all. We are also aiming to implement the best deep learning model in the NVIDIA jetson nano as an end device solution for the detection and classification of pulmonary diseases. We will also analyze our system in the medical environment and engage with clinicians to learn how they utilize it and what they think about the simulations. As a result, we can enhance the models in our future work.

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