EMDL: Ensemble Multimodal Deep Learning Framework For Early Diagnosis and Classification of COVID-19

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EMDL: Ensemble Multimodal Deep Learning Framework For Early Diagnosis and Classification of COVID-19

Santosh Kumar, Shivang Tiwari, Sameep Kadu, Chanchal Saytode, Mithilesh Kumar Chaube

***Abstract*—Recently, COVID-19 has emerged as a fatal infection over the past years. Cost-effective screening of coronavirus disease cases has been growing essential to alleviate and prevent the fast spread of the infection during the current period of the COVID-19 pandemic worldwide. Traditional clinical testing methods are used for the diagnosis of infected people. However, these methods are primarily physical and time-consuming, which means that physical contact between patients and doctors is needed. In this work, a novel multimodal learning framework is proposed for the early diagnosis and accurate classification of COVID-19 patients using deep learning techniques and speech signal processing techniques. The proposed framework consists of a chest X-ray-based model and cough (audio) model to extract features from the chest X-ray and cough database using a deep U-Net and convolutional neural network. Extracted features are used fused using the weighted sum-rule fusion method and ensemble deep learning techniques to predict COVID-19 cases accurately. The proposed framework is based on collected samples of chest X-ray images and cough (audio). We are using a publicly available coswra cough (audio) dataset that contains 92 COVID-19 positives and 1079 healthy subjects for early classification. The proposed framework provides the accuracy of 98.67% and 86.53% for chest X-ray images and the cough samples for early diagnosis of patients.**

***Impact Statement*—The requirement of adequate screening of COVID-19 cases is becoming much necessary to decrease and prevent the fast spread of the disease in pandemics. This article presents a multimodal system for early diagnosis and accurate prediction of covid cases. The proposed framework consists of a chest X-ray-based model and cough (audio) model to extract features from the chest X-ray images and cough (audio) database using a convolutional neural network. The ensemble model is generated by integrating multiple COVID-Net and CNN-based cough models with the deep neural network. The system processed chest X-ray images and cough samples using the weighted sum-rule ensembling method. The results represented that the proposed system gives an accuracy of 98.67% for COVID-19 cases for early classification. It can provide practical screening solutions for COVID-19 case detection.**

***Index Terms*—Deep learning, Ensemble learning, Feature extraction, Mulltimodal Fusion.**

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I. Introduction

Recently, the COVID-19 pandemic has been caused by infection of SARS-CoV-2 virus and proceeded to pose an essential threat to global health [2]. The infection in the human respiratory system, such as chest infection, Tuberculosis (TB), and other infections, is significant and spread out globally. The pandemic recapitulates to medical-related difficulties in several aspects, including salient advances in requirements for medical facilities, hospital resources, diagnosis kits, and significant deficiencies [3]. In contrast, worriers and various healthcare staff and workers have been contaminated and died due to this infection.

However, most existing statistical learning models and unimodal systems cannot perform for early diagnosis of patients based on extracted features from scanned images of a different body of infected people. It needs colossal computation to preprocess unlabelled data for extracting prominent features for further analysis of symptoms for infected people. Therefore, statistical learning models and unimodal systems are not effectively used for the early diagnosis of COVID-19 patients in the general population[26]. Moreover, the statistical learning models and unimodal learning systems also need to annotate the lesions, especially for disease diagnosis in CT volumes, for accurate prediction of COVID-19 [20].

For predicting the chest infection, we need the annotated lesions on chest scan images for early diagnosis. It needs much effort and associated maximum costs for experts such as radiologists and another medical COVID-19 testing department, which is unacceptable when COVID-19 is spreading fast. Significant shortages for radiologists and medical staff members. Therefore, there is a need to design and develop a multimodal framework for early diagnosis and accurate prediction of COVID-19 patients [2]-[4].

The deep multimodal learning techniques are gaining proliferation due to wide applications and solutions for early diagnosis for COVID-19. Thus, performing COVID-19 diagnosis in a multimodal framework is of great importance to improve the system's overall performance for accurate prediction of COVID-19. One of the most straightforward labels for COVID-19 diagnosis is the patient label based on cough and chest X-rays image database.

A. Motivation

The traditional clinical procural method is used for the early diagnosis of infected people. However, it takes more time to diagnosis the COVID-19 patients [13]. The pathological testing methods also are a very time-consuming process for the diagnosis of patients. To overcome this problem, the real-time-PCR method is used to diagnose infected people. However, these approaches take a couple of weeks to predict the diagnosis results for COVID-19.

To solve the early diagnosis of COVID-19, several researchers contributed to significantly alleviate early diagnostic procedures for COVID-19 patients using deep learning techniques. Due to the availability of a massive amount of large-scale annotated image datasets, deep learning techniques are gaining more proliferation due to great success for different applications. The deep convolutional neural networks (CNNs) and other deep models have been achieved using for image classification, and object recognition [23]. However, annotated image data for medical analysis, the classification of medical images for early diagnosis, and accurate prediction of COVID-19 patients remain the biggest challenge in medical diagnosis. Interdisciplinary researchers have recently proposed a framework for efficient solutions for detecting COVID-19 [2]-[4].

Among the proposed framework-based solutions, deep multimodal-based learning-based and Artificial Intelligence (AI) learning models are getting proliferation due to broad applications. It plays an essential role in fighting the COVID-19 pandemic based on several datasets such as chest-X-rays and cough sound-based datasets for better analysis [17]-[22]. No literature has yet been published to the best of our knowledge based on multimodal based early diagnosis of the spread of COVID-19. Therefore, we hypothesize that the cough, chest-X-rays, and another diagnostic model can be used for early diagnosis of the COVID-19 patient [15]. Hence, integrating multimodal's discriminatory features and their possible interactions is essential for an accurate prediction model of disease spread.

In this paper, we address the problem: *how to early diagnosis and accurate classification of COVID-19 patients?* To solve this problem, we propose a novel multimodal learning framework for accurate classification of COVID-19 patients based on chest- X-ray images and cough (audio) datasets using deep multimodal learning techniques. The multimodal framework extracts discriminatory features from chest X-ray images and cough (audio) samples of COVID-19 patients using convolutional neural network and speech signal processing techniques. The framework builds a classification model to classify COVID-19 and Non-COVID-19 based on combined extracted features from chest X-ray and cough datasets using the weighted sum rule fusion method and deep multimodal learning techniques.

B. Major Contributions

The contributions of the work are as follows:

1) We propose a novel multimodal framework that consists of chest-X-ray images and cough (voice) sample, classification-based models using deep multimodal fusion techniques for early diagnosis of patients.
2) In the proposed framework, a chest X-ray-based model and cough (audio) model are used to extract texture and holistic features from the X-ray image dataset. The cough model processes the cough (audio) sample to extract discriminatory features such as Mel-frequency Cepstral Coefficient (MFCC) features using speech signal processing techniques.
3) The extracted features from the chest X-ray image model and cough modal are fused using the weighted sum rule method to predict COVID-19 patients accurately. The framework provides a better representation of extracted features using structured latent representation learning technique provides robustness, generalization, and stability into the proposed framework.
4) To improve system performance, coughs of infected patients have distinct latent features from distinct respiratory syndromes. These discriminant features of cough samples are extracted by speech signal processing and the cough sound's transformation techniques to train a learning model for performing the preliminary diagnosis solely based on the cough to differentiate COVID-19 cough from non-COVID-19 cough.

II. Literature work

In this section, the literature work is divided into different subsections describing the literature survey of each part of the system separately.

A. Chest-X Ray based Model

Various works done for COVID-19 detection using chest X-Ray or similar inputs are mentioned in this subsection. Wang, Linda et al. [2] proposed a deep learning-based model named Covid-net with which they claimed 93.30% accuracy. They have used a projection-expansion-projection-extension (PEPX) pattern.

Tulin et al. [3] proposed the classification techniques to classify diseases into multi classes without transfer learning. The proposed model provided good accuracy without an over-fitting problem. They have implemented two kinds of classifier binary for COVID-19 and no-findings and tertiary for COVID-19, Pneumonia, and no-findings.

Cascella et al. [24] have mentioned an intense and comprehensive study for the work done so far for COVID-19. They have mentioned the deep learning techniques and frameworks, especially defining various components of the works and comparing using various existing pre-trained models and the datasets used in different studies. According to this work, Resnet -50 is the most used learning model used for COVID-19 detection [17]-[22].

Yujin.et.at [4] proposed a deep learning algorithm for lung segmentation to early diagnosis of COVID-19 and achieved better results. The lung segmentation is done using the FC-DenseNet technique and then provided the segmented images to the deep learning-based CNN classification network using ResNet and achieved 88.9% with segmentation and 79.8% without segmentation for accurate prediction COVD-19.

In this work also the mentioned accuracy is not enough to predict the COVID patient. In [19] a well-known CheXNet model is used to develop the COVID-CXNet classification model. The model detected coronavirus pneumonia based

TABLE I
LITERATURE WORK BASED ON COUGH(AUDIO) MODALITY SYSTEM/FRAMEWORKS

Ref.	Ad	AD	Tech.
[2]	NA	LA	VG
[4]	Lung segmentation	LA	FC-DenseNet
[3]	Effective	NS	DarkNet
CheXNet [22]	Precise localisation	LA	CNN
VP [19]	RL	SL	CAAD model

Abreviation: Ref.=Reference, Ad.=Advantages, AD=Disadvantages, Tech.=Techniques, LA=Low Accuarcy(%), VG=VGG-19, ResNet-50,NA= Not Available, VP=Viral pneumonia screening, RL=Reinforces one-class model, SL=Singular class, so non-useful in covid detection, NS=No segmentation techniue used

on chest features for localization of crucial segmented lung images.

B. Cough based Model

In this subsection, cough-based COVID-19 diagnosis has been reported in the literature, several researchers have proposed different types of the framework for classification of COVID-19 patients. Imran et al.[10] collected cough samples from COVID-19, bronchitis, and pertussis patients along with healthy individuals and created an Artificial Intelligent (AI) engine/system [28].

The AI-based system consists of a cough detector and classifiers that use deep transfer learning and classical machine learning approaches. They developed a working prototype as an app renders the results with three outcomes, namely; (i) COVID-19 likely, (ii) COVID-19 unlikely, and (iii) Test inconclusive with an overall accuracy of 92.64% The major shortcoming of this method is that it is time-consuming to process the cough sample datasets.

Brown et al.[11] proposed a framework using machine learning techniques for classifying COVID-19 patients. They have used a crowd-sourced dataset of 4352 cough samples, out of which 235 declared having tested positive for COVID-19. They analyzed handcrafted as well as features obtained through transfer learning. They tested classifiers such as Logistic Regression (LR), Gradient Boosting Trees (GBT), and Support Vector Machine (SVM), performing various classification, namely, Covid-positive vs. not-declared positive, Covid positive cough vs. Covid-positive without cough, and achieved an accuracy under area (AUC) of 80% for early diagnosis.

In a similar direction, Laguarta et al. [12] author collected variable length, cough audio recordings with bit-rate 16kbps. It consists of 2660 COVID-19 positive samples with a 1:10 ratio of positive to control subjects sample is split into 6 seconds audio chunks and processed with an MFCC feature extraction technique.

III. PROPOSED FRAMEWORK

The proposed framework consists of various steps: (1) data collection and pre-processing, (2) Extraction of features and matching, and (3) classification (shown in Fig. 2). In the test phase, the unThe brief description is illustrated in the following subsections.

TABLE II
LITERATURE WORK BASED ON COUGH SOUND MODALITY SYSTEM/FRAMEWORKS

Ref.	Advantage	Dis	Tech.
[10]	MD	HSR	CNN
[11]	HF	A	DL
[12]	Bio	Low-D	Bio-Model
[13]	TM	Not implemented	ML
[14]	EA	FD	DL

Abreviation: AD=Advantages, Dis=Disadvantages, Tech=Technique used, MD=Mediator based architecture, HSR=High sample rate & Mel-spectrogram, CNN=Convolutional Neural Network, Low-D Require more dataset, Bio= Use of multiple Biomarkers,Bio-model=Bio Marker Model,TM= Simple theoretical model and proof methods, FD=Fault way of data collection, DL=deep/machine learning & pattern recognition, A=Low AUC , EA=Easy availability ,HF=Easy availability

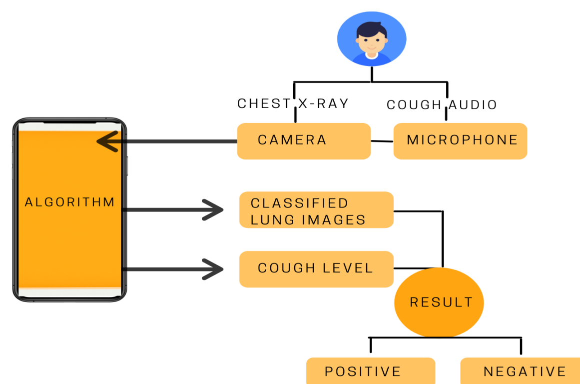


Fig. 1. Shows working of proposed framework using deep learning model.

A. Cough based COVID-19 detection

The cough-based model consists of several steps:(1) input cough sample collection, (2) pre-processing and normalization of collected data, (3) cough burst detection, (4) segmentation, (5) feature extraction and classification.

1) Data Collection: For the detection of COVID-19 patients, we considered cough, breathing, and speech sound samples of individual patients (speaker/users) to train the proposed framework. We have used several datasets from different sources available in open source platforms. The Coswara cough database is used provided by IISc Bangalore, India under Coswara[28] project for diagnosis of covid-19 patients (shown in Table III. The cough audio recordings have been collected via worldwide crowd-sourcing using web applications from different speakers. The dataset comprises categories cough (two kinds; heavy and shallow), breathing (two kinds; heavy and shallow). It sustained vowel phonation (three kinds: a, e, o) and digit counting (two

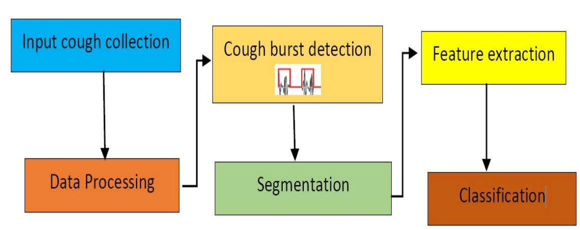


Fig. 2. Shows the ipeline for cough based model.

TABLE III
ILLUSTRATES DATA SET DESCRIPTION OF COUGH SAMPLES

Database	Size	Class ratio	Data types
Coswara[28]	8000	10:1	C+B+S
Coughvid[32]	20000	7:3	Cough sounds
DetectNow[33]	6500	8:5	Cough sounds
Virufy[18]	16	9:7	Cough sounds

Abreviation:C+B+S= Cough, breathing and speech sounds

kinds: fast and regular) along with metadata information. Namely- age, gender, location (country, state), presence of co-morbidity (pre-existing medical conditions and current health status(healthy/cured/infected/exposed) from healthy and those who have identified as COVID-19 positive.

The Coughvid [32], DetectNow [33] and Virufy[18] datasets are publicly available. Each month's audio recordings of cough samples were collected in a separate folder and compressed along with its metadata information in multiple files. The files were then uncompressed, and folders equal to the number of users were extracted, consisting of audio recordings in .wav file format (44.1KHz). We used all the positive samples from the dataset, and the same number of negative samples were randomly chosen for balanced distribution.

2) Processing of audio cough data: The collected audio sample of the cough is taken into consideration by down-sampled at 44.10 kHz. The audio sample used the pulse-code modulation technique for transferring audio format in the mono channel. The audio sample is processed to remove noises by the filtering method—the artifacts and noises by low pass filter techniques. Chebyshev filter technique is used with a transition frequency of cough audio at 10Hz to maintain the high pitch of audio while attenuating environment sounds simultaneous. The low-pass filter method is used to smoothing of spectrogram images. The short-term frequency is analyzed and used with the filtered audio signals by utilizing the empirical mode decomposition [29] [30]. It splits the cough audio sequence into more minor sequences or simple modes. Each mode contains the energy associated with different vowels and digits utterances at a particular scale.

We used the down-sample technique to performe smoothing on the cough sample which is the recorded at a 16kHz sample rate. The significant challenges we faced with these collected datasets were that it consists of lots of dead space and the recordings were variable in length. To deal with the former problem, we created an amplitude envelope with a threshold of 100 to get rid of dead spaces and tiny background noises which fall below the amplitude of value 100, leaving only the desired recordings. After getting the proper audio recordings, we divided the cough audio sample database into chunks of four seconds each, and we padded as needed. We used the 80% of the datasets for training the proposed cough model, and the remaining 20% of the complete database was used to test and validate the proposed model. Figure 4 shows a wide-band spectrogram of a heavy cough sample.

3) Feature extraction: Coughing is one of the most significant symptoms for early diagnosis of COVID-19. The cough (audio) signal is represented as a sequence of spectral vectors. The representation of cough sample in the time vs. frequency representation depicted that cough signal consists of high energy band, referred to as spectrogram. The spectrogram of the cough sample provides information about the signal strength of cough overtime at various frequencies, which may be presented in a particular waveform of high-energy bands of spectrograms. We computed the Mel-Frequency Cepstral Coefficients (MFCCs) feature of the IMFs, and windowed cough signal sample from spectrograms used as MFCC features to classify cough using a deep convolutional neural network model. The computation of MFCC features is illustrated in Algorithm 2.

Algorithm 1: Pre-possessing cough audio samples

1) **Initialization**: A variable length audio signal of sample rate 44.1KHz as input audio signal .
2) **Resampling**: Mono-downsampled at 16KHz.
3) **Thresholding**: Passed through an amplitude envelope of threshold value 100 to trim off background noise.
4) **Splitting**: Variable length audio signal was splitted into audio chunks of 4secs each.

Algorithm 2: Feature Extraction

1) Initialization: Let y(n) = Input data: cough (voice signal): y[n] = x[n]-ax[n].
2) Processing and filtering noise of the input signal y[n] (shown in Eq. 1):

$$y[n] = \frac{1}{n}\sum_{i=0}^{n-1} y[n-i] \tag{1}$$

3) **Segmentation using Hamming Window:** The hamming window reduces the ripple and provide accurate voice signal's frequency spectrum.
4) **Mel frequency cepstral coefficients features:**
5) **Frame the signal into short frames:** For each frame calculate the period gram estimate of the power spectrum. Apply the mel filter bank and take logarithm of all filter bank energies.
6) **Computation of Discrete Cosine Transformation (DCT:** We computed DCT of the log filter bank energies and keep DCT coefficients 2-13, discarding the rest.
7) The formula for converting from frequency to MeI scale is (shown in eq.2):

$$M(f) = 1125ln(1 + f/700) \tag{2}$$

1) The Discrete Fourier Transform (DFT) technique is applied to get the signal in the time interval from the frequency domain after dividing the speech signal into a small number of speech frames.
2) Ultimately, the power spectrum has been obtained for mapping it onto the Mel scale. Figure 4 depicts the power spectrum of a cough audio input volume.
3) Next, log outputs are found using Discrete Cosine Transform technique.

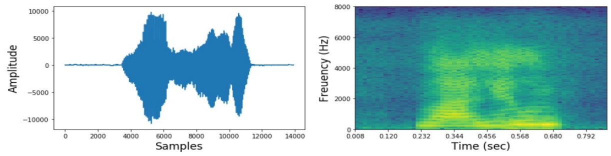


Fig. 3. Illustration of cough (speech) signal for volume and its power spec

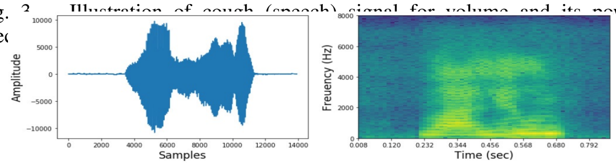


Fig. 4. Illustration of cough (speech) signal for volume and its power spectrum.

4) Finally, delta (△) and delta-delta (△) (△) coefficients are calculated as follows:
5) Let us consider the MFCC of a window frame (t) is denoted by C_t. The delta coefficient $(\triangle_t)$ is computed as (shown in Eq. 3):

$$\triangle_t = \frac{\sum_{i=1}^{I} i \times (C_{t+i} - C_{t-i})}{2 \times \sum_{i=1}^{I} i^2} \tag{3}$$

Where I, is a delta window is usually set to 6 to 10 frames, as the consumer devices' speech input may have different signal duration, the MFCC feature vector will also be of various lengths. Therefore, the proposed system normalizes the feature vector by constructing MFCCs with no sound for shorter signals.

The MFCC feature extraction includes windowing the signal, Taking the Fourier Transform, Wrapping the spectrum's powers into the Mel scale, and taking the powers' logs. The Mel log powers list is a signal applying discrete cosine transform to signals and amplitudes known as MFCCs. The steps involved in this process are further explained and shown in Fig. IV.

After windowing and frame blocking cough audio signal, Discrete Fourier Transform (DFT) technique is applied. To each windowed frame to convert the audio signal to power spectrum moving from the time domain to frequency domain where the values we have for each frequency tells us how much each frequency component is present in the original waveform (shown in Eqs. 5).

$$X(k) = \sum_{n=0}^{N-1} x(n) e \frac{-j2\pi nk}{N} \tag{4}$$

N is a number of feature points. It is used to compute the DFT and k range between 0 and N-1. After getting the spectrum, we apply logarithm to the spectrum to obtain the log power spectrum, which gives us the magnitudes in decibels.

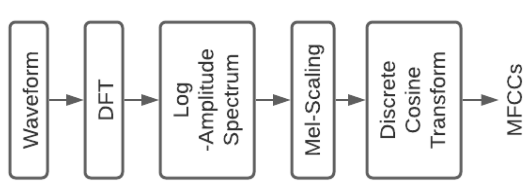


Fig. 5. Illustrates feature extraction from the cough (voice) samples for MFCC extraction.

The cepstrum represents how these quefrencies are present in the log power spectrum. The mathematical equation to obtain a cepstrum is mentioned below (shown in Eqs.4).

$$C[x(t)] = F^{-1}[log(F[x(t)])] \tag{5}$$

Where (C) is the obtained cepstrum and F^{-1} is the inverse discrete Fourier transform, and F is the Discrete Fourier transform technique. The next step is the computation Mel spectrum. Mel is a unit of measure based on how the human ear perceives a frequency. Human auditory systems do not perceive pitch linearly in a physical frequency scale. The Mel approximation from physical frequency is expressed as (shown in Eq. 6).

$$f_{Mel} = 2595 log_{10}(1 + \frac{f}{700}) \tag{6}$$

Where f_{Mel} denotes the perceived frequency and (f) denotes the physical frequency and partition the physical frequency scale into bins and, using overlapping triangular filters, transform each bin into the corresponding bin in the Mel scale. A Mel spectrogram can be computed by multiplying each triangular Mel weighing filter with the magnitude spectrum.

We have considered the first 13 MFCC coefficients truncating the high order DCT coefficients to make the system more robust. The zeroth coefficient was excluded since it represents the average log-energy of the signal and holds little information about the signal. MFCC features are computed by using the following mathematical expression (shown in Eq. 7):

$$c(n) = \sum_{m=0}^{M-1} log_{10}(s(m)) cos(\frac{\pi n(m-0.5)}{M}), n = 0, 1 \cdots, C-1 \tag{7}$$

C is the number of MFCCs of cough samples, M and c (n), the number of cough samples, and cepstral coefficients.

4) Classification: This step creates a classification model using the extracted MFCCs feature vectors Δ and Δ-Δ. The proposed system applies a deep CNN technique to classify the cough audio signal. The basic structure of the CNN model comprises convolution, pooling, and fully connected layers. The CNN model begins with an initial layer, applies a spectrogram of the captured MFCC features/ feature map), and gives it to the convolution layer.

The ReLU non-linear activation method is used in the convolution layer to create feature maps. As the input, the extracted MFCC features are used for training the CNN learning model. The model consists of two blocks of block layer. It comprises two convolutional layers followed by 2 × 2 max-pooling layers: the batch normalization layer and a 0.20 dropout is used to prevent the model from overfitting problem. The next step is to apply the max-pooling layer to mitigate the feature maps using down-sampling methods by summing the extracted features.

The batch normalization layer is used to standardize the input to layer and stabilizing the learning process. The convolutional layers in the first block use a kernel size of 5× 5 with 100 filters. The second block uses a kernel size of 3× 3

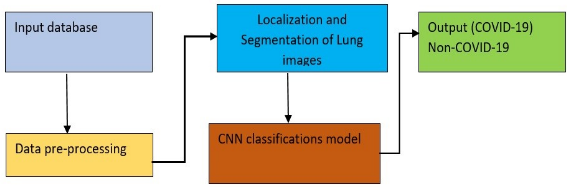


Fig. 6. Shows the working of chest X-ray model.

with 100 filters from each convolutional layer to learn complex features from these four convolutional layers.

Finally, the output and softmax activation functions classify COVID-19 cases for the given input chest X-ray images. In this model, for all the convolutional layers, the ReLU activation function is used. We used the Adam optimizer technique with a learning rate of 0.0001. It is used due to its relatively better flexibility and efficiency. In the proposed framework, the cross-entropy loss function is used and the softmax activation function to measure the loss rates.

B. Chest X-Ray based COVID-19 detection model

We collected the chest X-ray image database for extracting rich and distinct information. We focus on conducting diagnosis for COVID-19 patient and community-acquired pneumonia for characterizing the relationships between multiple types of discriminatory features from captured Chest X-ray images and these diseases, which caters to a possible pipeline for automatic diagnosis and investigation of COVID-19 using deep learning techniques.

In the proposed multimodal system for COVID-19 detection, the system performed the prediction for infected and non-infected persons based on the collected chest X ray database. The chest-X-ray-based working model consists of several steps: (1) pre-processing, (2) segmentation of images, (3) extraction and mapping, and (4) classification.

1) Pre-processing: As mentioned earlier, we have obtained a database from online available open-source platforms (Kaggle & Github). We separated them into 500 COVID positives and 1600 COVID negative images from the collected database using the available chest X-ray images. After data collection, the chest X-ray image database, the model pre-processed images using image processing techniques. It includes image interpolation methods to downsample images to remove noises and other artifacts from images before providing it as an input image sample to the chest-X-ray-based classification model.

2) Segmentation of Chest X-Ray Image: It is the process of dividing the given image into distinct regions of interest. In this model, we are concerned with lungs, so we performed lung segmentation. The main objective of segmentation in collected data is proper extraction of information from this database, as is essential for classifying COVID-19 and No-findings. The chest X-ray dataset is segmented to mark lungs and regions of interest to identify the COVID-19 infected parts in the given image.

This algorithm helps localize the lungs, which is the primary part of studying in this chest X-ray model. To improve the accuracy of the proposed system, we are using a deep learning

Algorithm 3: Prepossessing of Chest X-Ray samples

1) **Initialization:** Input chest X-ray images $I[M \times N] = [I_1, \cdots, I_N]$
2) **Resize:**Input images [I] are resized from their original size to 256 $\times$256.
3) **Coloring:** Chest images are transferred to RGB color format.
4) **Labelling:** The data is labelled as COVID-19 or No-findings.
5) Perform sanity check for verifying the data pre-processing & labelling.

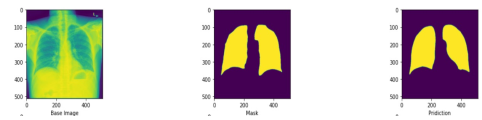


Fig. 7. Shows the segmentation of chest X-ray images using proposed model.

U-Net-based segmentation model. It is a CNN [23] used for the segmentation of the medical image. It consists of a contracting & an expansion path. The contraction path is used to capture the data from the image. In this path, we have convolutional layers followed by ReLU and max-pooling layers. After this, the expansion path is used, which localizes the data to be segmented. In expansion, path transposed convolution operation is used.

3) Classification model: In classification model, we have used 14 convolution layers and 3 max pooling layers. Each convolutional layer has a different number of filters and the number of filters increases as we go deeper into the architecture. The convolutional operation$(*)$mathematically defined as (shown in in Eq. 8):

$$(X * Ki, j) = \sum_{m}^{\infty} \sum_{n}^{\infty} K(m, n) \cdot (i - m, j - n) \qquad (8)$$

The classification model based on CNN [23] model compares chest X-ray images based on the patch by patch (piece by piece) matching technique. The pieces that it looks for are called features. Features are chosen and put on the input image. If it matches, then the image is classified correctly. The Max-pooling layer is used to shrink the image stack into a smaller size. A window of some specific size is chosen with some stride. Pick the maximum value in the window and replace the whole window with that max value. Move the window across the filtered image by the value of stride.

After convolution layers, pooling and softmax activation functions are used. For pooling, we have used the max-pooling method, a down-sampling technique in the CNN framework that uses the maximum value from each cluster of neurons at the last layer. Since it is a binary classification, the proposed architecture has two classes, "Covid-19" and "No-findings" prediction.

IV. Experimental Results and Discussion

In this section, we present the experimental results of the proposed system. First, experimental results are computed

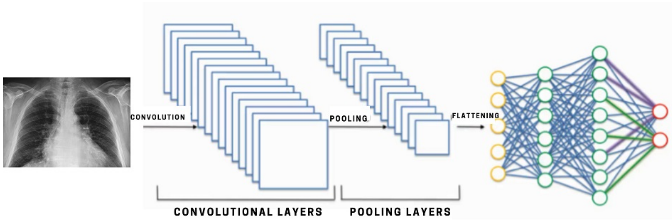


Fig. 8. Schematic presentation of convolution& max pooling layer operations.

TABLE IV
SHOWS PERFORMANCE METRICES OF PROPOSED CHEST X-RAY MODEL OF 5 FOLD CROSS VALIDATION RESULTS.

Folds	Sensitivity	Specificity	Precision	Accuracy	F1
1	0.9459	1.0000	1.0000	0.9890	0.9722
2	1.00009	1.0000	1.0000	1.0000	1.0000
3	0.9453	0.91235	0.9367	0.9578	0.9646
4	0.9354	0.94285	0.9669	0.9677	0.9879
5	0.9891	0.97685	0.9556	0.9576	0.9789

based on different benchmark settings and protocols we conducted to evaluate the performance of classification models using the CNN model on Chest X rays images.

The overall results of the proposed chest X-ray classification model are mentioned in Table IV. It depicts 5-fold cross-validation performance matrices of the classification model with the segmented images. The overall accuracy of the proposed chest X-ray classification model is 98.35%, which is higher than other approaches in the current state of art methods listed in Table VI.

A. Cough Analysis

The experimental results demonstrated that our cough detection algorithm could classify COVID-19 positive and no findings with an accuracy of 86.53%. Figure 11 shows an accuracy error graph of mean loss versus epochs. It also shows the accuracy vs. epochs for both training and testing data sets shown in Table V.

TABLE V
SHOWS THE MATRICES OF PROPOSED COUGH CLASSIFICATION MODEL.

Sensitivity	Specificity	Precision	Accuracy	F1-Score
0.8345	0.8126	0.8141	0.8461	0.8653

V. COMPARISON WITH EXISTING WORK

In this section, we have done a comparative analysis of the existing methodologies for COVID-19 detection. Each

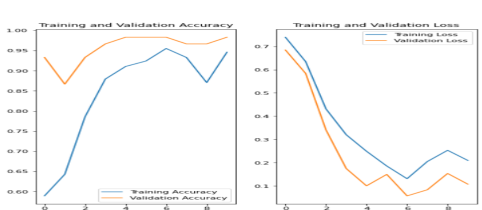
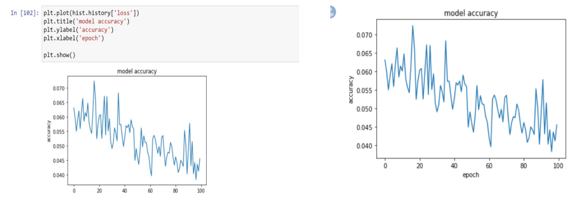


Fig. 9. shows training accuracy vs validation accuracy for chest X-ray classification

(a) (b)

Fig. 10. Confusion Matrix for (a) chest X- ray images and (b) cough based di



(a) (b)

Fig. 11. Shows (a) accuracy vs epoch graph for cough classification and (b) loss vs epoch for cough classification.

learning-based modality in multimodal, chest X-ray-based, and cough sound-based, is considered to validate the accuracy of the proposed multimodal-based framework with current state-of-the-art methods discussed.

1) **Chest X-ray Model** To demonstrate the importance of our proposed model for processing the chest X-ray images for early classification, we have compared the chest X-ray model with the existing works done so far, shown in Table VI. We have compared the experiments of different X-ray models Covid-19 diagnosis based on different data sets and current state-of-the-art methods. In Table VI, we compared the existing works with proposed work based on different benchmark settings and datasets.
2) **Cough (audio) Detection Model**
We compared the performance of the existing method with the cough (audio) model for classifying COVID-19 patients. The comparative analysis of proposed cough model-based work with various work done so far in this field. We have compared the experiments of different cough-based models covid-19 diagnosis based on different datasets. In Table VII we have mentioned various works and proposed works with the type of data used and results.

VI. WEIGHTED SUM-RULE BASED FUSION METHOD

In the past few years, much attention has been devoted to multimedia indexing by fusing multimodal information.

TABLE VI
SHOWS COMPARISONS WITH EXISTING TECHNIQUES FOR COVID-19 DETECTION

Ref.	Data	Tech.	A
[2]	CXR	COVID-Net	92.4%
[5]	CXR	ResNet50	95.4%
[3]	CXR	DarkCovidNet	98
[7]	Chest CT-Scan	ResNet	86.7%
[8]	CXR	VGG-19	93.48%
[9]	CT	M-Inception	82.90%
[31]	CXR	COVIDX-N	90
Prop.	CXR	Deep fusion+CNN+U-net	98.33%

Ref.=Reference, CXR=Chest images, Data=database used, Tech.=Techniques, A=Acuarcy(%), Prop.=Proposed

TABLE VII
SHOWS COMPARISONS WITH EXISTING TECHNIQUES BASED ON COUGH FOR COVID-19 DETECTION

Ref.	Data	Tech.	A
[7]	chest-CT	Res-A	86.7%
[9]	Chest CT	MI	82.90%
[10]	Xray	DTL	92.1%
[18]	CC	ED	77.1%
[22]	audioset/ ESC-50	TL	70.58 %
Prop.	Coswara	CNN	84%%

abreviation: Ref.=Reference, Data=database used, Tech.=Techniques, A=Acuarcy(%), Prop.=Proposed, DLT= DLT-based classifier, ED=Ensembled DNN, TL=Transfer Learning with VGGish, chest-CT=Chest CT Scan ,REs-A=ResNet and Location Attention,MI=M-Inception techniues, CNN=Convolutional neural Network , Coswara=Coswara cough audio database, CC=Coswara/ Coughvid

TABLE VIII
SHOWS THE CLASSIFICATION ACCURACY (%) OF 5-FOLD CROSS VALIDATION OF PROPOSED FRAMEWORK.

Fold	Chest X-Ray	Cough
1	0.9890	0.7776
2	0.9778	0.8278
3	0.9833	0.8116
4	1.000	0.7926
5	0.9832	0.8453

There are two kinds of ensemble fusion technique, (1) early fusion and (2) late fusion technique [19]. In this work, a late ensemble fusion technique is used based on weighted sum-rule method forcombining accuracy of chest and cough models for classification of COVID-19 cases. For analysis of fusion accyarcy, we used the 5-folds validation process to compute and validate model accuracy (shown in Table VIII of cough model and chest X-ray image-based modal for early diagnosis based on predicted cases.

The sum rule-based fusion has done in the following manner:

$$F_S = \Sigma_{n=1}^{i} W_i S_i \tag{9}$$

The notation W_i stands for the Weight of I the model, and S_i stand for mean accuracy of 5 cross-validations of I the modality.

A. Ensemble Techniques

Ensemble the learning paradigm is used to solve the problem as mentioned earlier. It is assumed to be a practical approach [37]. A hybrid learning paradigm produces reliable prediction results than the unimodal learning techniques by fusing multiple learners and models effectively.

In the past few years, much attention has been devoted to multimedia indexing by fusing multimodal information. There are two kinds of ensemble fusion techniques: (1) early fusion and (2) late fusion technique [19]. In this work, a late ensemble fusion method is used based on the weighted sum-rule method for combining the accuracy of chest and cough models for the classification of COVID-19 cases.

These ensemble strategies are applied using simple averaging, random forest [17], boosting [36], and stacking fusion techniques [35]. For making the ensemble computing effective, we must ensure that many learning models (e.g., chest X-ray models and cough (audio) models) for interacting are diverse. We study ensemble deep learning for detection and classification COVID-19 case in the proposed multimodal framework by combining multiple deep learning models for chest X-ray and cough (audio) processing using an ensemble strategy (weighted sum rule fusion method).

After creating many snapshots of the learning model in the initial phase, the chest X-ray and cough model are fused in the ensembling phase to build an ensemble fusion framework by combining accuracy from the chest X-ray and cough (audio) models. Therefore, many ensembling strategies are used for the model ensemble. We used averaging ensembling strategy to average the class probabilities for each class from all learning models for database and samples for snapshot-based ensemble learning, respectively.

Let M=[M_1, M_2, $\cdots$ M_N] defines the number of classification models for the chest-X rays model and cough (audio). $p_{m,k}(d_i)$ illustartes the probability of the k^th output of class by the m^th classifier concerning the input sample d_i. The average probability of class is given as follows:

$$\frac{\sum_{m=1}^{M} p_{m,k}(d_i}{M} \tag{10}$$

for (k) $\in$ [1, K] of the input data d_i, with (K) number of classes.

The weighted sum-rule-based ensembling approach is used in statistical machine techniques based on the solid hypothesis that all the models have the same weights.

Based on overall observation, it can be concluded that we cannot wholly consider each model equally for training models during the model ensembling of chest X-ray and cough (audio) model for early diagnosis and classification of COVID-19 cases. tely consider each model equally for training models during the model ensembling of chest X ray and cough (audio) model for early diagnosis and classification of COVID-19 cases.

B. Weights estimation for Weight Sum-rule Method

The weighted sum-rule-based fusion method is used to fuse them. Vora et al. [27], in particular, developed a brilliant way that accounts for error rates in different models and tries to give more weight to the model, which is less susceptible to errors. Referring to the same analogy, we calculated the mean deviation value on the 5-fold cross-validation accuracies for both X-Ray & Cough sound models, as mean deviation directly corresponds to the system's consistency. We calculated the 5-fold cross-validation accuracy over different datasets of training and testing sets; therefore, we made an inference that the mean deviation(Md) value gives an idea of the system's error rate. For analysis of fusion accuracy, we used the 5-folds validation process to compute and validate model accuracy (shown in Table VIII of cough model and chest X-ray image-based modal for early diagnosis based on predicted cases.

$$Md = \frac{1}{n} \Sigma_{n=1}^{i} |x_i - S| \tag{11}$$

TABLE IX
WEIGHTED SUM RULE FUSION METHOD BASED ACCURACY FOR CLASSIFICATION OF COVID-19 PATIENTS

Modality	Weight	Mean accuracy (S_i)	W_{sm} score
Chest X ray	0.54	98.67	53.35
Cough audio	0.46	86.53	39.80

S is the mean of the accuracies of the models of chest X-ray model and cough audio model for accurate prediction. For example, S_1 and S_2 are:-

$$S_1 = \sum_{i=1}^{5} \frac{chestx - rayaccuracies(A_i)}{5} \tag{12}$$

$$S_2 = \sum_{i=1}^{5} \frac{CoughA_i}{5} \tag{13}$$

Also, the computation of weights for each models are illustrated as follows:

$$W_2 = \frac{Md_1 \times Md_2}{sum(Md_1 + Md_2)} = 0.46 \tag{14}$$

$$W_1 = 1 - W_2 = 0.54 \tag{15}$$

The absolute accuracy for accurate prediction for classifying COVID-19 patients based on cough and chest X-ray is achieved using the weighted sum rule method. The final fusion-based classification accuracy of the multimodal framework is achieved as follows:

$$F_s = sum(W_{sm}Score) = 93.1538\% \tag{16}$$

VII. CONCLUSION AND FUTURE DIRECTIONS

In this paper, a novel multimodal learning framework is proposed for early diagnosis and accurate prediction of COVID-19. The proposed frameworks include two modalities, namely chest X-ray and cough sound models, to diagnose patients. We used different deep learning architectures such as the CNN and U-net model, deep learning-based segmentation methods to make different models for extracting features from chest X-ray images, and cough (audio) samples for accurate prediction.

To improve the performance of the proposed framework, we fuse extracted features from both models using the weighted sum-rule fusion technique for the accurate classification of patients. For chest X-ray, we achieved an accuracy of 98.67%, and for the cough sound mode (87.53%)l, the proposed model provided 79.50% accuracy for the classification of patients. Based on overall observations, the final accuracy of the proposed framework is 92.03% for the early diagnosis of patients. This system can be used remotely at different places, especially with no medical facilities, COVID-19 detection centers, monitoring systems, and other diagnosis centers. The limitations we faced for developing the framework for early diagnosis of the patient are: (1) there is no availability of sufficient database for training models for the COVID-19 positive class., (2) there is always room for improvement for analysis for cough samples-based diagnosis using deep multimodal fusion techniques.The future directions for the proposed multimodal are illustrated as follows:

1) We will collect the large databases for chest X-ray images and cough sound sample database to train our proposed model to analyze experimental results for accurate predictions.
2) Based on collected samples from several modalities, the accuracy of the proposed cough sound-based model can be increased using deep multimodal fusion techniques.
3) We are working on developing a smart system based on the android application for early diagnosis of common patients and users.
4) An android application will be developed for deploying the system for common patients and users.
5) We will include statistical machine learning techniques for computing significant features from several modalities and adding more testing features to improve the overall accuracy and make the system more robust.

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