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Analysis of COVID-19 Coughs: From the Mildest to the Most Severe Form, a Realistic Classification Using Deep Learning

Fabien Mouoméne Moffo[*1], **Auguste Noumsi**[1], **Joseph Mvogo Ngono**[2], **Samuel Bowong**[1]

[1]Douala University, FS, Department of Mathematics and Computer Science, Cameroon
[2]Douala University, IUT, Department of Computer Science, Cameroon

*E-mail : Fabien MOUOMENE fmouomene@yahoo.fr

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Abstract

Cough is the most common symptom of lung disease. COVID-19, a respiratory illness, has caused over 700 million positive cases and 7 million deaths worldwide. An effective, affordable, and widely available diagnostic tool is crucial in combating lung disease and the COVID-19 pandemic. Deep learning and machine learning algorithms could be used to analyze the cough sounds of infected patients and make predictions. Our research lab and the COUGHVID research lab provide the cough data. This diagnostic approach can distinguish cough sounds from COVID-19 patients and people suffering from other ailments as well as healthy people using deep learning and feature extraction from Mel spectrograms. The model used is a variant of ConvNet. This ConvNet model can easily capture features in MFCC Vectors and enable convolution parallelism, which increases processing speed. ConvNet attains translational invariance in features through the sharing of weights between layers. During data acquisition for model training, it is important to consider quiet environments to reduce errors in audio quality. The architecture of the convolutional neural networks gives an F1-score of 89%, an accuracy of 90.33% and sensitivity of 87.3%. This system has the potential to significantly impact society by reducing virus transmission, expediting patient treatment, and freeing up hospital resources. Early detection of COVID-19 can prevent disease progression and enhance screening effectiveness.

Keywords

Diagnosis ; Cough ; Deep learning ; MFCC features ; ConvNet

I INTRODUCTION

Cough is the most common symptom of lung disease. COVID-19 is a significant lung disease, and the pandemic has resulted in over 700 million positive cases and 7 million deaths worldwide, with numbers still rising [30, 33]. The viruses responsible for respiratory diseases are present in the respiratory secretions of patients, which can be projected as droplets around the patient during coughing [18]. These droplets are the main sources of contamination.

COVID-19 contamination can be direct or indirect [13]. Direct contamination occurs during the patient's cough, while indirect contamination can occur after the patient's cough through infected surfaces [23]. Medical and clinical solutions, such as nucleic acid testing (NAT) and polymerase chain reaction (PCR) testing, have been used to stop the spread of the disease. The diagnosis of COVID-19 is confirmed by RT-PCR testing of nasopharyngeal and oropharyngeal swabs. Test results are typically available within four hours. The samples collected for the initial detection of COVID-19 include nasopharyngeal swabs, lower respiratory tract swabs (sputum, BAL) in cases with parenchymal involvement, and blood samples (Respiratory Syndrome) [32]. The interpretation of the RT-PCR test carries significant weight due to its higher specificity and sensitivity. Other scientific methods in epidemiology have been published for the prevention of COVID-19 [14, 20].

However, RT-PCR tests for SARS-CoV-2 pose some challenges. These include the requirement of health care personnel, the risk of contamination during collection, and the high cost of testing due to the need for expensive reagents (viral RNA, and reverse transcriptase) and tools [26]. Reagents are defined as chemicals or substances employed in laboratory tests, such as those used for the detection of the SARS-CoV-2 virus, to facilitate the identification of the virus's presence in a sample obtained from a patient. These reagents are indispensable for the accurate and reliable diagnosis of the disease. In addition, the processing of the collected samples is not in real-time. These issues prevent RT-PCR tests from being used as large-scale screening tools. Although some countries have achieved high vaccination rates necessary for herd immunity, many continents affected by the COVID-19 pandemic still have very low rates due to vaccine backlogs and failures. Experts are uncertain about the achievement of herd immunity, especially with the unpredictability of viral variants. Therefore, an effective, inexpensive, and widely available diagnostic tool is essential to address the lung disease and COVID-19 crisis.

One of the most common symptoms of COVID-19 is a cough [10, 12, 25, 27]. Convolutional neural networks, a revolution in artificial intelligence (AI), show promise in creating a solution. Deep learning and machine learning algorithms can be used to analyze the cough sounds of infected patients and make predictions. Deep learning refers to the application of learning methods to networks or graphs of interconnected parameterized modules [17]. The parameters of these modules are modified through learning using gradient descent, with the gradient typically obtained through backpropagation. An example of deep learning is the training of multilayer neural networks. Research labs need to collect sound recordings for COVID-19 patients of all ages, in changing environments, symptomatic or asymptomatic. This data provides an opportunity for AI algorithms to learn pandemic-specific patient audio patterns. Cough recordings are commonly collected to detect COVID-19 by laboratories such as COUGHVID and COSWARA. However, the sound quality and format of this recorded data are not always objective and can vary depending on the tool used and the environment. Additionally, missing donor data can render some metadata unsuitable for learning algorithms.

In this study, a deep-learning network based on cough sounds is discussed. The model is a variant of ConvNet and has been successful in learning from cough audio submissions, categorizing them into four groups: severe and non-severe COVID-19-positive individuals, healthy patients, and patients with lung conditions unrelated to COVID-19.

The paper is structured as follows: Section I presents the materials and methods, while Section II presents the results and discussions.

II MATERIALS AND METHODS

We are conducting a cross-sectional study with a descriptive, exploratory and diagnostic approach. Our work has implications for the world's population. This research is being carried out in our laboratory before the COVID-19 pandemic. In collaboration with healthcare professionals, we collect cough samples from healthy patients and patients suffering from respiratory diseases. The dataset was later updated with data on patients who tested positive for COVID-19. The participants' recordings are made in a quiet environment [9]. Any recording with excessive ambient noise is excluded. Patients consented to participate in sound recordings with the probity of the team. The subjects are geographically dispersed worldwide to ensure sample diversity. The geographic dispersion of individuals or objects across a given geographic area is a measure of their spatial distribution. While statistical measures such as range, standard deviation, and interquartile range provide numerical insights, the visualization of this dispersion through maps and spatial analysis techniques offers a more intuitive and comprehensive understanding. This decision was made because lung disease and COVID-19 are not limited to a single country or continent.

Figure 1 shows the impact of the COVID-19 pandemic on populations: a geographical visualisation, this impact is marked by the color blue [31]. The map illustrates that COVID-19 is most prevalent in America, Asia, and Europe, with the most affected areas having an incidence rate of over 70 million cases. While there is a downward trend in COVID-19 infections in most regions, the disease remains a significant public health concern in many countries.

Figure 2 illustrates the methodology used in this study. The methodology of this study involves collecting data, preprocessing it using appropriate techniques, transforming it into a spectrum, and using the spectrum to train the CNN model.

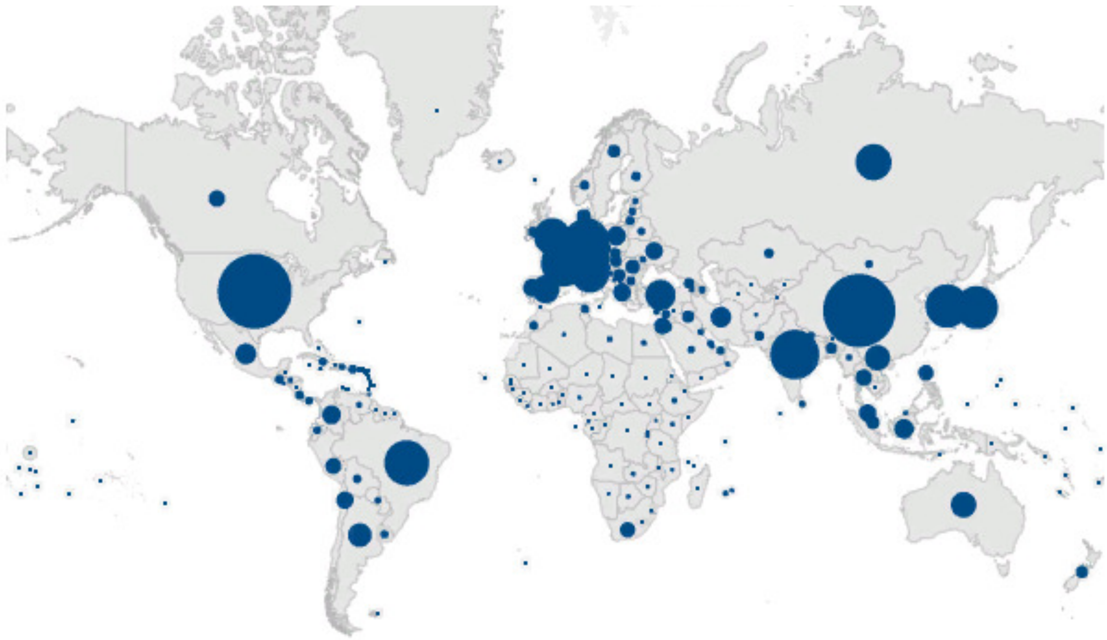

Figure 1: The Geographical Overview of the Impact of the COVID-19 Pandemic on Populations.

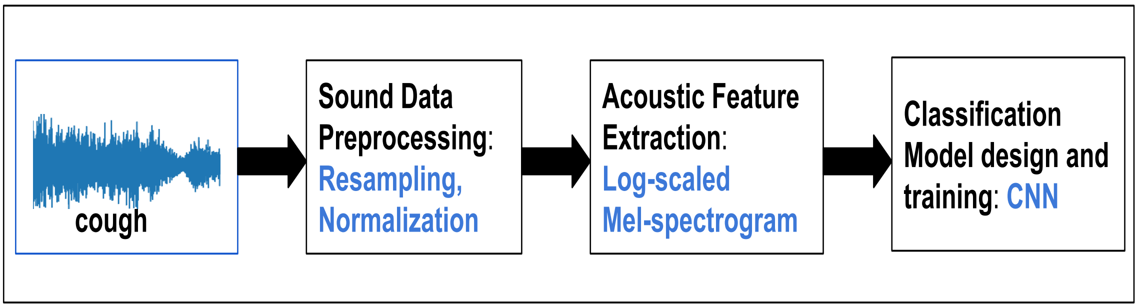

Figure 2: Methodology of this study.

2.1 Data Collection

The analyzed data pertains to audio recordings of coughing patients. These audio recordings were collected randomly from the microphones of cell phones and computers. Our dataset comprises 3300 entries, describing coughs of healthy patients, patients with a negative COVID-19 test, and patients with severe and non-severe COVID-19. Samples from 258 healthy patients and patients with a negative COVID-19 test were recorded pre-pandemic. The remaining data, recorded during the pandemic through the COUGHVID laboratory, are public. The COUGHVID dataset provides over 20,000 crowdsourced cough recordings representing a wide range of subject ages, genders, geographic locations, and COVID-19 statuses [29]. Crowdsourcing enables the rapid and cost-effective collection of a substantial amount of data, as well as the utilisation of the expertise and diversity of contributors from various continents. COUGHVID issues calls for contributions via online platforms, which are then responded to by participants, who carry out tasks related to cough sound recording. Once the data has been collected, it is subjected to a verification and validation process by COUGHVID before being employed for research projects. The metadata provides the patients' condition, age, gender, and geographic location. Recurrent COVID-19 symptoms include cough, fever, and fatigue, with high fever being the most prominent symptom of severe cases[1, 19]. Severe COVID-19 is characterized by the presence of hemoptysis, decreased white blood cells, and renal failure [15, 22].
Figure 3 illustrates the geographical sources of all collected cough sounds, indicating an almost equal distribution across continents. Socio-economic factors and intercontinental travel are contributing factors to the pandemic's spread.
Figure 4 presents the statistical clinical forms of the dataset, showing a much higher frequency of healthy individuals, potentially due to respiratory illnesses leading to coughing and isolation from loved ones.

2.2 Preprocessing

First, the audio signal, like any other incoming signal, must be digitized into a sequence of numbers called samples, each of which represents the air pressure on the microphone at a given time. The raw data collected is in Ogg, Webm, and MP3 formats. We first developed an algorithm to automatically convert the data set from each compressing audio format to the WAV format. The WAV format provides superior audio quality compared to Ogg and WebM formats, as it does not compress the audio file. The data is divided into four categories: samples of sick patients without COVID-19 (Sick, 1000 cough sound data), samples of healthy patients (Healthy, 1340 cough sound data), samples of patients with severe COVID-19 (Severe, 280 cough sound data), and samples of patients with non-severe COVID-19 (Mild , 680 cough sound data). Normalization to a frequency of 22 kHz was applied to samples with different frequencies. A second algorithm is developed to segment the audio samples into equal 3-second

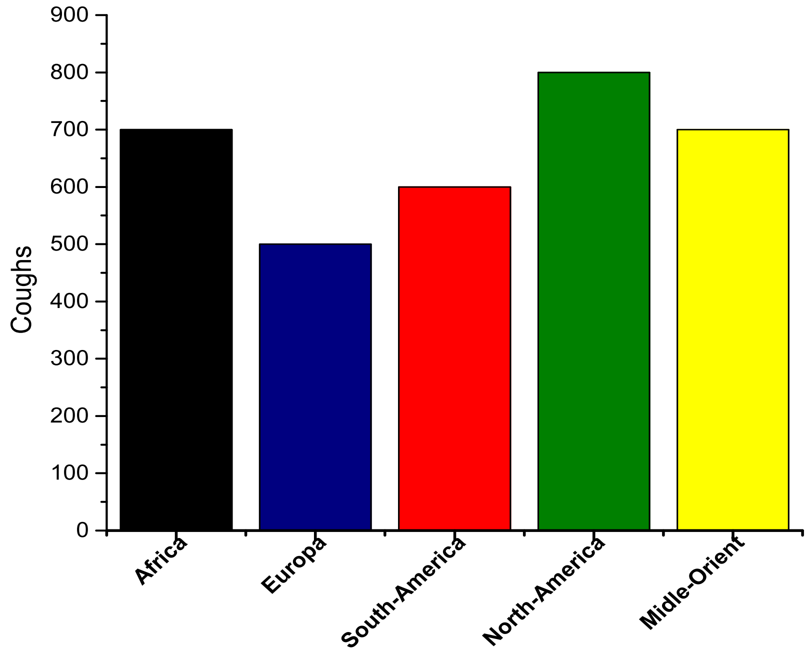

Figure 3: Geographical sources of the dataset collected.

durations for input into the 2D CNN. The dataset is resampled and normalized in order to mitigate the challenge of data imbalance. Figure 5 illustrates the nature of Waveform for each cough category. According to scientific literature, coughing is a three-phase motor act [3]. The first phase is the inspiratory phase, during which air is drawn into the lungs with the glottis fully open. The second phase is the compressive phase, where respiratory muscles contract and compress the air against the glottis with the glottis fully closed, increasing the pressure. Finally, during the expulsive phase, the glottis suddenly reopens and air is rapidly expelled, generating the cough sound.
Figure 5 presents an example of each waveform from one of the four cough categories studied. The waveforms of the Heath category show fewer significant expulsive phases compared to those of the sick patients. The most significant expulsive phases are found in the (Sick) and (Severe) COVID-19 categories.

2.3 Feature Extraction

The audio data's acoustic characteristics are extracted using the log-scale mixing spectrogram method. This method allows for the representation and differentiation of various sound events. Logarithmic spectrograms offer detailed acoustic information from short audio recordings. It enables efficient detection of sound events occurring within a short period. In order to create the log-scale spectrogram of the original sounds, three steps are necessary. Firstly, the sound clips must be converted from the time domain to the frequency domain by applying the short-time Fourier transform. Then, a Hann window of 23 ms with a jump length of 256 is used [8]. The audio sequence is transformed into a spectrogram with 120 graduated frequency bands and magnitudes that represent the characteristics of the human audible range, including the decibel scale. Each speech signal is represented by a sequence of vectors with dimensions 120x40, with one vector every 10 milliseconds, resulting in 100 vectors per second [2]. The convolutional network analyzes a 120x40 window of vectors representing sound. It then classi-

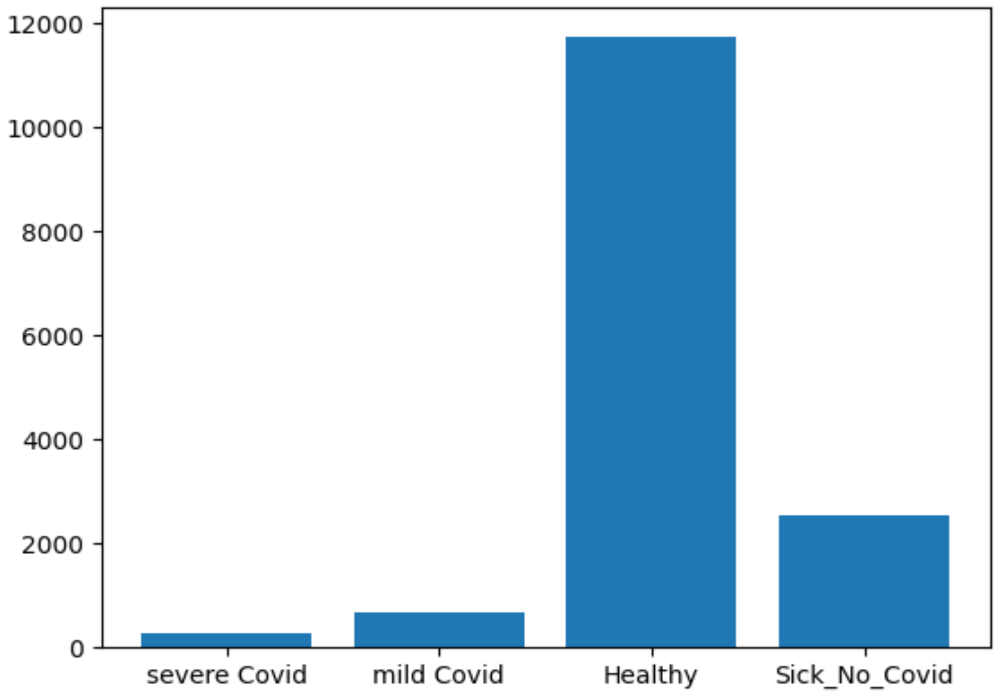

Figure 4: Statistics: Clinical forms of the dataset.

fies the elementary sound present in the middle of the window. Additionally, the derivative of the log-scaled hybrid spectrogram was used to create additional channels, enhancing the comprehension and discrimination of acoustic features.
Figure 6 shows a flowchart that describes the algorithm for converting cough audio signals into MFCC feature vectors [7]. Converting an audio signal into MFCC (Mel-Frequency Cepstral Coefficients) spectrum follows this path: The audio signal is divided into fixed-length segments, and the discrete Fourier transform is applied to each segment to obtain the power spectrum. The power spectrum is then filtered using a Mel filter bank, which distributes the frequencies according to the Mel scale. Finally, normalized cepstral coefficients are calculated to reduce variations caused by the global level of the audio signal [4].

2.4 Architecture

Architecture refers to the interconnected structure of parameterized modules. This structure can be seen as a mathematical function with its parameters or as a computational graph consisting of nodes representing operations and links symbolizing variables or parameters. The architecture for cough recognition involves several parameters. In deep learning, a multilayer network is built by arranging and connecting modules, and then training this architecture using gradient descent after computing the gradient by backpropagation [6]. Our deep learning architecture is based on convolutional feed-forward neural networks, which use all connected layers, also known as ConvNet. Feed-forward neural networks are indispensable tools in the domain of deep learning, offering a plethora of advantages that elucidate their surging popularity. Their universality of approximation allows them to model complex relationships between inputs and outputs, making them flexible and suitable for a variety of problems. In other words, the choice of a feed-forward network depends on various factors, including the nature of the data, the sample size, and the modelling objectives. In this study, The choice of this tool is a result of the nature of the dataset, which is imbalanced. It is preferable to use a feed-forward

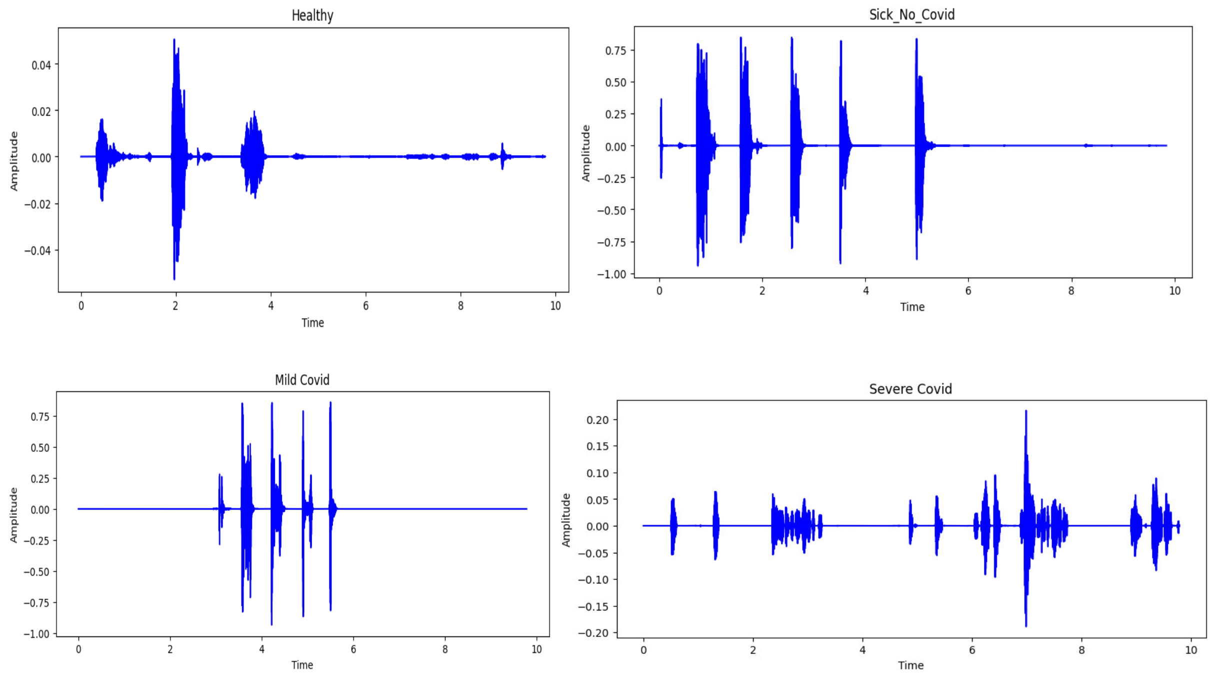

Figure 5: Waveform for each cough category.

network in order to minimise the risk of overfitting. Convolutional networks use the discrete convolution operation, a mathematical filtering process that involves computing a weighted sum over a window of an image or signal and sliding this window across the entire input signal while recording the results in the output signal. The weights of the sum are uniform for all windows. The output signal is translated if the input signal is translated; otherwise, it remains unchanged. Convolution allows for the detection of patterns regardless of their position in the input signal. The ConvNet includes 3 convolutional layers of 3x3 and max-pooling of 4x2. The last two layers consist of two fully connected layers with dimensions of 1024x1024, followed by a fully connected layer with a dimension of 1024. Dropout is applied to the fully connected layers.
Figure 7 illustrates the connection between the three layers. The convolution produces a feature map with both positive and negative values, as the weights can be negative. When passing through the ReLU layer, negative values are set to zero, while positive values remain unchanged. The resulting arrays are referred to as feature maps. This non-linear operation enables the system to identify patterns in the image. The ReLU layer is then followed by a pooling layer, which divides the feature map output into non-overlapping tiles or windows. Each neuron in the pooling layer takes a window of 8 numbers and calculates its maximum value, resulting in a process called max pooling. This technique is used to create an image representation that is invariant to small pattern shifts. The max-pooling operation selects the highest value from its input, which corresponds to the most prominent pattern in its receptive field. The convolutional network is composed of a series of layers consisting of convolutions, ReLU activations, and pooling.

2.5 Training and Build

Learning involves gradually reducing errors in the system by trying, making mistakes, and readjusting. Each parameter readjustment overwrites the previous parameter values. For a given training example, where an MFCC x feature vectors is associated with output y, the error

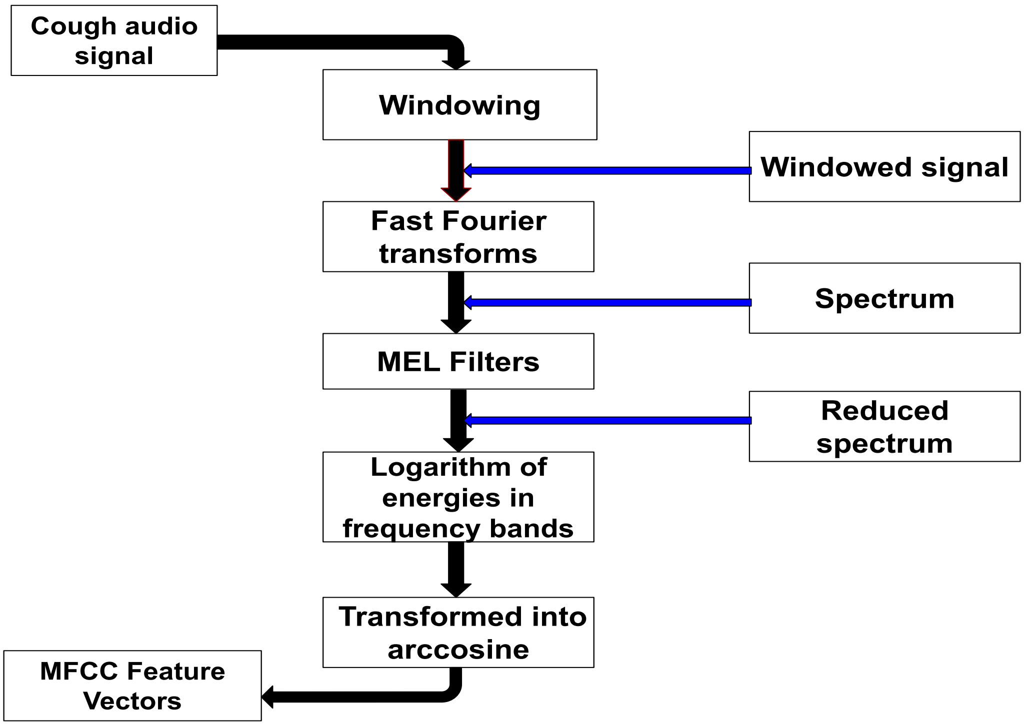

Figure 6: Flowchart: Converting cough audio signals into MFCC feature vectors.

is measured by a simple number indicating the distance between the output produced by the machine (ys = f(x,w)) and the desired output y. The parameter vector is represented by w. The error for each learning example, each pair (x,y), is measured by a cost function C(x,y,w). The cost function measures the difference between the behavior of a model and the desired behavior. Learning involves adapting the system to reduce errors and minimize the cost function.

To train our model, the data is first grouped based on its dependence and then labeled into four classes ranging from 1 to 4, based on the expected model outputs. The dataset is then split into training and test sets in an 80:20 ratio. The loss function employed is cross-entropy, while accuracy is measured using the accuracy score and the F1-score obtained after this calculation. The F1 score is a metric that combines a model's precision and recall scores.

The Adam method is used as the learning optimizer. It is used for gradient backpropagation [5], which computes the gradient of a cost function. This backpropagation of gradients is the adjoint state applied to multi-layer networks, allowing the calculation of the gradient of a cost function. The principle consists of propagating a signal backward in the network, thus propagating the partial derivatives (gradients). The model is trained for 100 epochs with a batch size of 30 to adjust the weights or variables of the cost function. The algorithmic model is developed by our laboratory using the Python programming language. The complete experimental dataset, including all relevant source code, is stored in our internal repository, thus facilitating reproduction of the reported results.

III RESULTS AND DISCUSSIONS

3.1 Results

The sample studied is a short sequence or excerpt from a human voice recording. These recordings are coughing sounds of patients and are classified into four categories: Healthy, Sick without COVID-19, Sick with Severe COVID-19, and Not Severe. It is important to consider

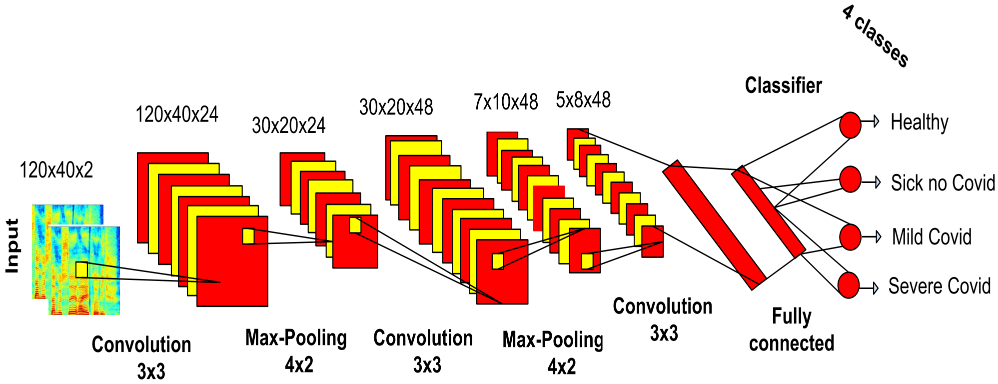

Figure 7: Architecture for the classification of cough sounds in the context of COVID-19, a variant of ConvNet designed by our laboratory.

quiet environments during data acquisition for model training to reduce systematic and random errors in audio quality. Statistical measures used to estimate the numerical results of the algorithms include Sensitivity (or recall), which measures correctly identified true positives; Specificity (or selectivity, precision), which measures correctly identified true negatives; Accuracy, which measures the total number of samples correctly classified; and F1 score, which is the harmonic mean of precision and recall.

$$Sensitivity = \frac{TP}{TP + FN} \tag{1}$$

$$Specificity = \frac{TN}{TN + FP} \tag{2}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

Where: TP (true positive) = correctly identified; TN (true negative) = correctly rejected; FN (false negative) = incorrectly rejected; FP (false positive) = incorrectly identified [24].

$$F1 = \frac{2 * Sensitivity * Specificity}{Sensitivity + Specificity} \tag{4}$$

The convolutional neural network architecture provides an F1-score of 89%, an accuracy of 90.33% and sensitivity of 87.3%. The feature extraction process involves converting cough sounds into MFCC spectrograms, demonstrating a strong correlation between the cepstral characteristics of images within the same class, and significant differences for images from different classes.

Figure 8 displays four MFCC spectrums, each representing a sample from a different class. The spectrum of severe COVID-19 is brighter, indicating higher energy and the four spectrums are visibly distinct, making classification by CNN easy.

Figure 9 shows the outcome of the model compilation, presenting the learning curve illustrating the progression of loss and validation loss values throughout 100 training epochs of the convolutional neural network model. This curve is used to analyze the model's performance and adjust hyperparameters for better results. The algorithmic model was developed by our laboratory using the Python programming language. The complete experimental dataset, including all relevant source code, is stored in our internal repository, thus facilitating reproduction of the reported results.

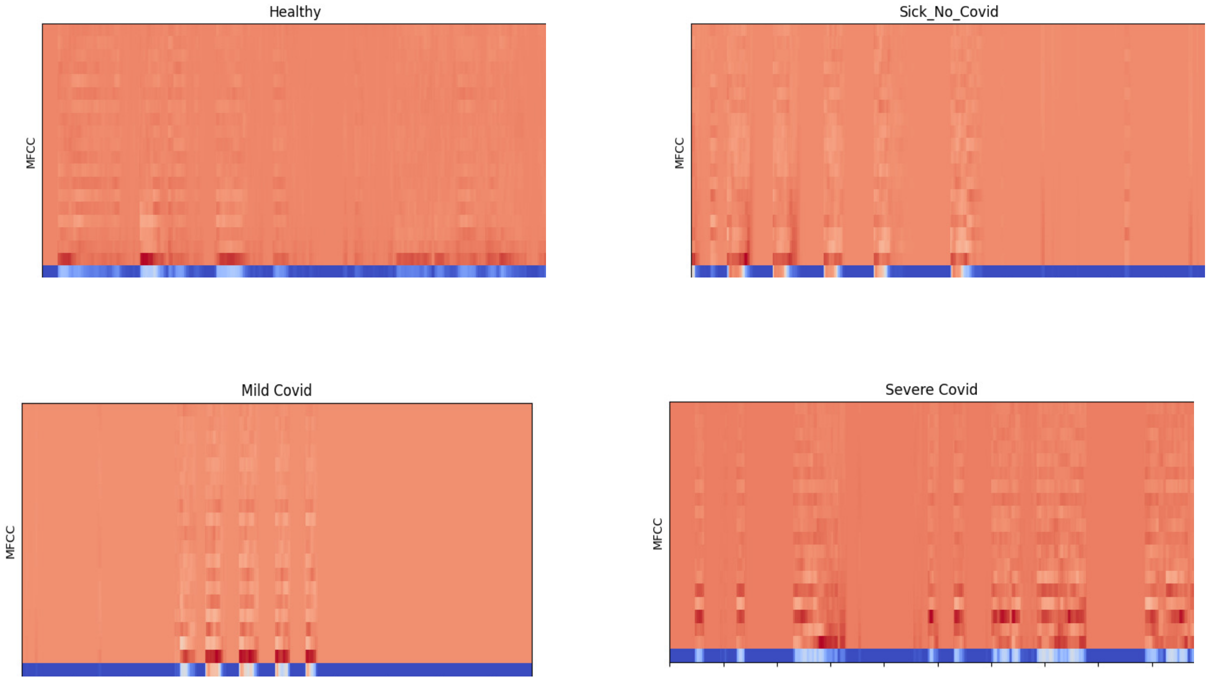

Figure 8: Results of feature extraction: The Mel Frequency Cepstral Coefficients (MFCCs) to explore the fundamental characteristics of coughing sounds associated with COVID-19.

3.2 Discussions

Our study reveals three key findings. The initial finding pertains to the categorization of four types of cough sounds.: cough of sick patients without COVID-19, cough of healthy patients, and cough of sick patients with severe and non-severe COVID-19 The second result relates to the learning process using the Adams method, and the third result focuses on extracting characteristics for each cough category.

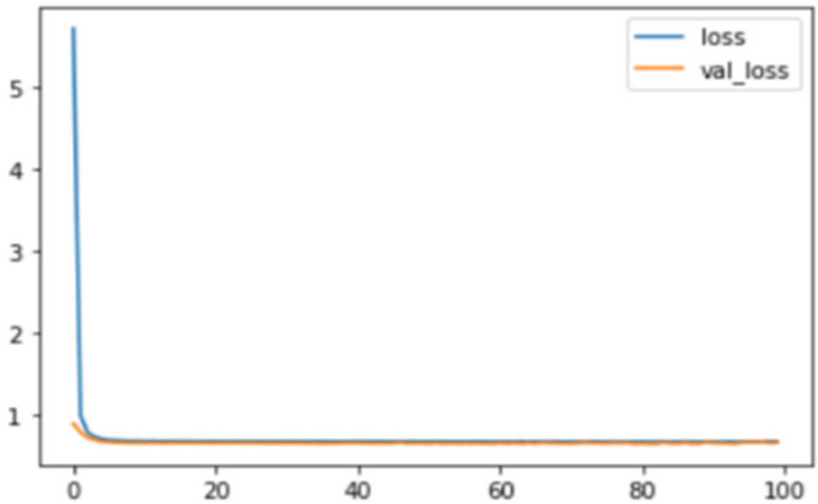

Figure 9: The graph, derived from the model Compilation, presents the optimisation of ConvNet model parameters by gradient backpropagation.

References	Methods	Dataset size	Metrics
Schuller et al. [21]	CNN	1427 cough sound	80.7% Accuracy
Ali Imran et al. [16]	Method of MFCCs and CNN	317 cough sound	92.6% Accuracy
Bansal et al. [11]	CNN	871 cough sound	70.5% Accuracy
Mohamed and Seyedali [28]	binary machine DL transfer model	1457 cough sound	94.9% Accuracy
This Work	method of MFCCs ConvNet	3300 cough sound	90.33% accuracy

Table 1: Positioning the Work in the Field.

This study presents a thorough analysis of COVID-19 diagnosis by classifying it into four groups, focusing specifically on the severity of the illness. Ali Imran et al.'s study focuses on diagnosing bronchitis, pertussis, COVID-19, and Normal using AI [16]. However, the study does not address the severity of COVID-19, although it is alluded to in the clinical information on disease states. Accurate diagnosis of the severity of COVID-19 allows for appropriate follow-up and monitoring of patients to prevent complications. This initial diagnosis will aid in the effective management of hospital resources by directing them toward the most severely affected patients.

It's worth noting that our CNN model, with a 90.33% accuracy rate, outperforms the models of Schuller et al., whose CNN model for cough detection had an accuracy of 80.7%, and also surpasses the work of C. Bansal et al. on COVID-19 detection with an accuracy of 70.5% [11, 21].

The reasons for selecting CNNs for MFCC feature vectors classification are as follows: In this study, convolutional neural networks (CNNs) are employed to accommodate data imbalance. This is performed through the use of techniques such as class weighting and oversampling of minority classes, which enable CNNs to effectively learn from imbalanced dataset. CNN architecture specializes in image classification due to the mathematical convolution and pooling operator. In contrast, RNNs are designed more for signals, so the inputs are 1D. CNNs can easily capture features in images and enable convolution parallelism, which increases processing speed. CNN achieves translational invariance in images by sharing weights between layers, while RNNs are sensitive to the position of data in signal sequences. Deep transfer models such as ResNet, DenseNet, LeNet-5, AlexNet, GoogleNet, VGG 16 and NasNetmobile are extremely powerful and can be a quick solution to many automatic classification tasks, but building this ConvNet model offers significant advantages in terms of the specificity of this particular four-class classification task and control over the learning process. By training this model from scratch, we can better control the learning process and adapt the network architecture to this specific classification task. This leads to fine tuning of the network.

The cepstral characteristics of MFCC feature vectors make CNNs suitable for classification. This technique enables the correlation of images in each class category. In the work of Ali Imran et al., the MFCC method was also used as an extractor. Table 1 shows the positioning of the paper to other papers in the field.

IV CONCLUSION

This study discusses the development of an intelligent tool for early diagnosis of respiratory diseases, specifically using cough sounds to detect conditions such as COVID-19. The diagnostic approach, employing deep learning, can identify cough sounds from individuals with no COVID-19, as well as those with mild and severe cases, and healthy individuals. A CNN model was created and trained on data collected by our team and other research groups. The experimental results, following validation of the model on the data, demonstrate the CNN model's robust ability to detect all four categories. Based on the favorable results achieved with the metrics employed, this proposed model demonstrates considerable scientific merit. It enables rapid vocal diagnosis of respiratory problems and effectively differentiates between mild and severe COVID-19 for improved patient management in healthcare settings.

In order to facilitate the provision of real-time diagnostics by our system, we are currently developing a pipeline comprising this model and an adaptive filter. The filter in question analyses the input signal in real time, adjusting its parameters in accordance with the background noise present in order to minimise its impact on the recording. Furthermore, the performance of the model is to be enhanced through the investigation of additional data standardisation techniques.

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