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Performance analysis of deep learning algorithms for classifying chronic obstructive pulmonary disease

Pinal J. Patel,[1] Dhanashree Yelve,[1] Daksha Diwan,[2] Shashi Ranga,[3] Kinjal Gandhi,[4] Samay Dumasia,[1] Rutu Nayak[5]

[1]Computer Engineering Department, Government Engineering College, Sector-28, Gandhinagar, Gujarat, India. [2]General Department - Mathematics, Government Engineering College, Sector-28, Gandhinagar, Gujarat, India, [3]Chemical Engineering Department, Government Engineering College, Valsad, Gujarat, India, [4]Computer Science Engineering Department, ITM(SLS) Baroda University, Vadodara, Gujarat, India. [5]Biomedical Engineering, Government Engineering College, Sector-28, Gandhinagar, Gujarat, India

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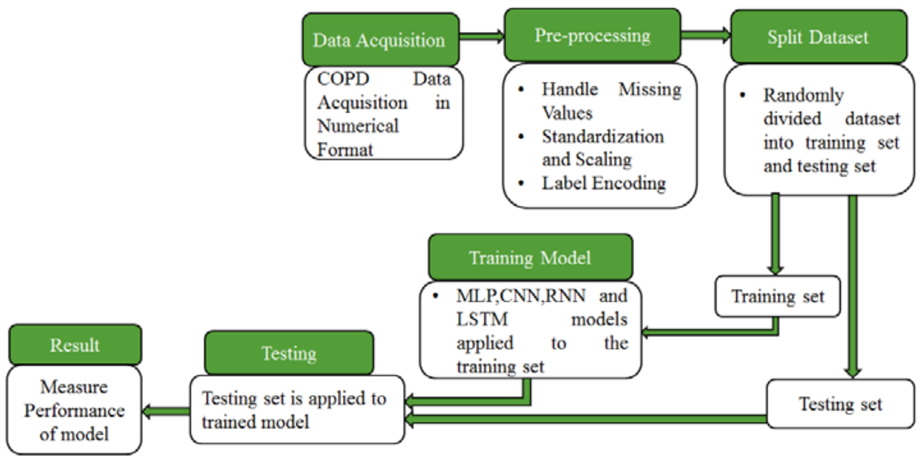
ABSTRACT

Nowadays, Deep learning (DL) and machine learning (ML) play a vital role in furnishing solutions to the medical problems. Owing to their accurate and timely forecasting models and results, ML and DL algorithms are being embraced by the medical professionals for early detection and prompt treatment of different diseases. The respiratory diseases like Chronic Obstructive Pulmonary Disease (COPD) are emerging and need an early diagnosis. The major methods for diagnosing COPD involve expensive and unsuitable spirometer and imaging equipment. In this paper, an analysis of cough sound of the patients and identification of COPD severity levels using ML and DL algorithms has been reported. The study includes experiments conducted using Librosa library and used CNN, RNN, LSTM, and MLP algorithms for detecting COPD severity levels.



Keywords: COPD, Deep Learning, Machine Learning, Algorithms, Classification

INTRODUCTION

Apart from severe health diseases like cancer,[1] respiratory disease such as COPD is gradually increasing and endangering the society survival. According to the prediction made by the World Health Organization, COPD will be the third-leading cause of the death and the seventh-leading cause of morbidity globally by 2030. According to the World Health Organization, the disease affects 64 million people and results in an estimated 3.2 million deaths annually.[2] Nearly 90% of deaths due to COPD are found in nations with low or middle incomes, where accessible or consistently applied effective prevention and control techniques are frequently lacking.[3] Airflow to the lungs becomes restricted due to the chronic inflammatory lung disease COPD. Wheezing, breathing difficulties and coughing up (sputum) are among the early warning signs and symptoms. It occurs because of frequent exposure to irritant chemicals or particles, primarily from cigarette smoke.[4] Heart disease, lung cancer, and a number of other diseases are more likely to occur in people with COPD. COPD is a catch-all term for a variety of progressive lung diseases. COPD may result from emphysema and chronic bronchitis. Figure 1 depicts the healthy lungs and COPD condition.

Emphysema is a lung ailment carried by damage to the lungs' alveolar walls. There's a chance that a clog can be formed and air can be trapped. If there is too much air trapped in the lungs, the chest can seem bigger or barrel-chested. Less oxygen gets supplied to the bloodstream when there are fewer alveoli.[5] Finally, patient

*Dr. Pinal J. Patel, CE Department, Government Engineering College, Gandhinagar, Gujarat, India
Email: pinalpatel@gecg28.ac.in

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unable to expel it. Chronic bronchitis is a condition marked by constant coughing that lasts longer than three months and appears more than twice in a two-year period. Smoking is a substantial cause for it and is frequently a contributing factor in chronic obstructive pulmonary disease.[6] Inflammation forms in the lining of the bronchial tubes, which transport oxygen to and from the lungs.

Early detection of COPD is essential for the better and complete treatment. The application of machine learning, CNN, deep learning is at frontier area of research for development of diagnostic methods for diseases in healthcare.[7–10] Herein, we have studied the use of machine learning and deep learning for detection of COPD based on the applied analysis of patient datasets.

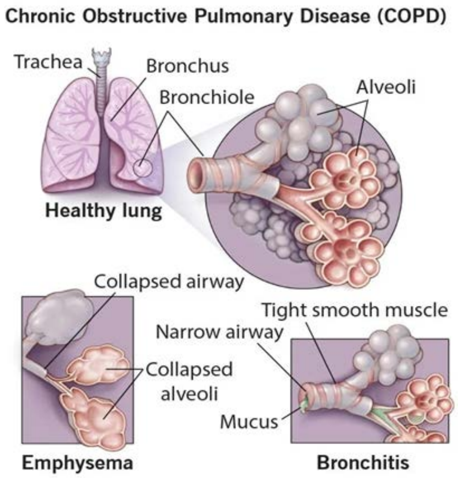


Figure 1: Emphysema and Bronchitis illness of COPD [3]

LITERATURE SURVEY

Multi-Layer Perceptron (MLP) with back propagation algorithm was used to detect peak demand days of Chronic Respiratory Diseases.[11] Machine learning approaches were used for detecting the disposition of asthma and COPD exacerbations in the emergency department (ED).[12] A 3D Convolutional Neural Network has been used to classify COPD in CT images.[13] COPD has been identified by utilizing deep CNN to generate 3D lung airway trees from CT images.[14] Deep learning algorithms have been used to analyze respiratory sounds with the purpose of detecting chronic obstructive pulmonary disease.[15] Different stages of COPD patients were detected using ML Techniques.[16] Analysis of the effect of cardiac color ultrasound on COPD under mask region is done using deep learning methods.[17] The literature approaches, particularly those that don't use CNNs use extremely complicated analysis networks that need a lot of resources. This suggests that it needs advanced processing capability, which can result in significant infrastructure expenses. To determine whether a patient has COPD or not, current approaches like manual diagnosis by a doctor also require a lot of time and multiple hospital visits. We have analyzed the performance of the deep learning methods for detecting the severity level of COPD diseases by considering various training parameters. We have used numerical and audio datasets of COPD patients to carry out the research. Below is a description of the dataset.

DATABASE DESCRIPTION

We have worked on two different types of datasets: 1) kaggle's COPD patient dataset that contains numerical values, 2) An audio collection of lung sound recordings. Dataset1 consists details of 101 patients with different 24 variables. The details contains patient's characteristics like age, Gender, smoking etc. It also has information about diseases severity, and co-morbidities. Apart from it, dataset contains measures of patient's walking ability, quality of life, and anxiety and depression. There are four different COPD severities represented in the dataset: Mild, Moderate, Severe, and Very Severe. Each severity level represents a different stage of COPD progression. Table 1 shows the no. of samples / COPD severity levels.

Table 1: COPD Numerical dataset : Dataset1

Sr.no	COPD Level	No. of data samples
1	Mild	23
2	Moderate	43
3	Severe	27
4	Very Severe	8

Dataset2 is a collection of lung sounds recorded from patients with varying degrees of COPD. The dataset2 consists of 12-channel lung sounds for each patient, providing a multi-channel analysis opportunity. Dataset2 contain 504 .wav files and labels for it. Two pulmonologists used a Littmann3200 digital stethoscope to concurrently record the left (L) and right (R) channels in each lung region to gather the respiratory data.

There are five different COPD severities represented in the dataset2: COPD0, COPD1, COPD2, COPD3, and COPD4. Each severity level represents a different stage of COPD progression, with COPD0 representing no COPD and COPD4 representing the most severe stage. The lung sound recordings are short-term, lasting at least 17 seconds each. The recordings were captured using electronic stethoscopes and were collected from a diverse population of patients from around the world. The database includes lung sounds from 42 COPD patients, aged 38 to 68, with varied degrees of severity, including 34 men and 8 women. This dataset is intended to be used for the development and evaluation of deep learning models for COPD severity analysis, particularly for the classification of COPD severity levels using lung sound recordings. The dataset is publicly available and can be accessed for research purposes. Table 2 depicts the no. of COPD recording per COPD severity levels.

Table 2: COPD audio dataset: Dataset2

Sr.no	COPD levels	Total number of recordings / level
1	COPD0	6
2	COPD1	5
3	COPD2	7
4	COPD3	7
5	COPD4	17

DESIGNED SYSTEM

We have trained CNN, RNN, MLP and LSTM deep learning models for both the datasets: numerical and audio. Figure 2 depicts the steps for training and testing numerical dataset while figure 3 demonstrates the flow of training and testing models for audio dataset. Each stage is discussed below.

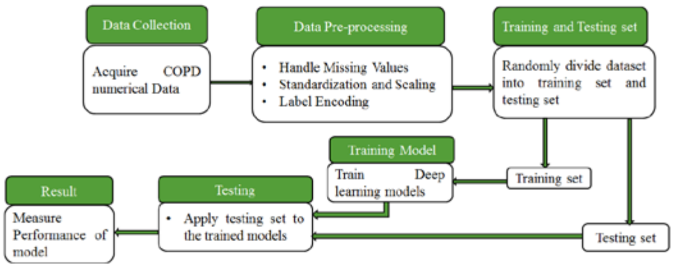


Figure 2: Proposed system for numerical dataset

Dataset 1:

Data is acquired in the format of .csv file. File contains numerical values for all the variables (columns) like age, gender etc. In a data preprocessing step, we have removee the insignificant variables form the files like age. It's a critical to fill the missing values with mean, median of the column. We simply drop it. In standardization and scaling steps, all values are normalized in the range of [-1, 1]. We used one hot encoding method for label encoding. Finally, dataset is divided into train and test sets. We have trained four models CNN, RNN, MLP and LSTM using train dataset. Test data is used to find the accuracy of the trained models. We have performed various experiments by considering ADAM, SGD and RMSProp as an optimizer functions, categorical cross entropy as a loss function, batch size to 16 and 32 and epoch's value to 50,100 and 200 for the trained and test models. If we use only one epoch, it leads to the under fitting. So, it's necessary to choose the appropriate no of epochs for learning models. Table 3 shows the result of trained models for the different no of epochs. Table 4 shows the performance of all the models. Figure 4 depicts the results in the graphical representation.

Dataset2:

.Wav files representing audio files are used as an input during the data acquisition phase. Using the librosa library, we have extracted various features from it, including MFCC. A mel-frequency cepstrum (MFC) is made up of MFCCs. The short-term power spectrum of a sound is represented by an MFC, which is based on a linear cosine transform of a log power spectrogram on a non-linear mel scale of frequency. Due to the vocal tract's form, which matters for sound elaboration, these characteristics serve as representations of phonemes, the discrete units of sound. We have used the time stretching strategy in the Data Augmentation stage to handle the imbalanced class issue.

RESULTS

As a result, MFCC is an ideal element to take into account for. In standardization and scaling steps, all values are normalized

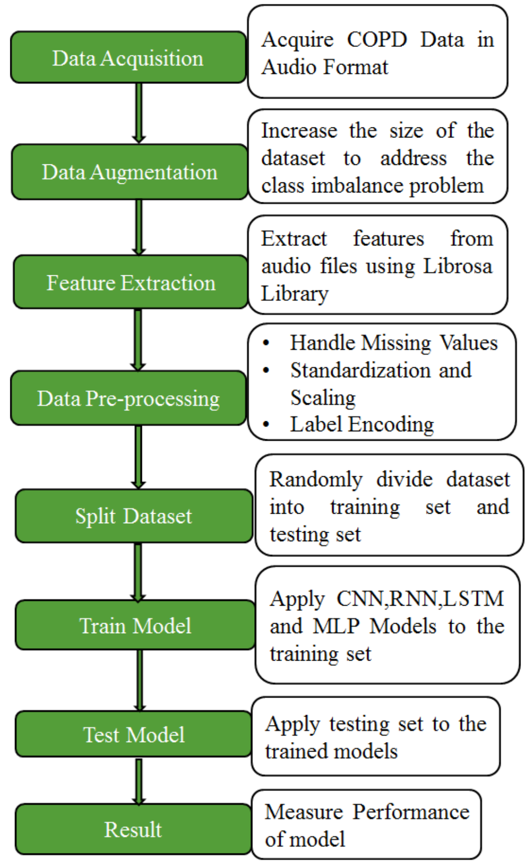


Figure 3: Proposed system for audio dataset

in the range of [-1, 1]. We have used one hot encoding method for label encoding. Finally, dataset is divided into train and test sets. We have trained four models CNN, RNN, MLP and LSTM using train dataset. Test data is used to find the accuracy of the trained models. Result is shown in Table 5. Table 6 shows the result of trained models for the different no of epochs. The objective for considering different epoch values for the trained models is to determine its impact on the performance of detecting COPD levels.

Table 3: Performance of DL algorithms for different no of epochs

Sr. No	Model	No. of Epochs	Training Accuracy	Validation Accuracy
1	CNN	50	0.8974	0.9048
2	CNN	100	1.0000	0.8095
3	CNN	200	1.00	0.9048
4	RNN	50	1.00	0.7143
5	RNN	100	1.0000	0.7143
6	RNN	200	1.0000	0.6667
7	LSTM	50	0.7692	0.7143
8	LSTM	100	0.9103	0.7619
9	LSTM	200	0.8974	0.7143
10	MLP	50	0.9103	0.7143
11	MLP	100	0.8974	0.8095
12	MLP	200	0.9744	0.9524

Table 4: Performance of the DL algorithms for using 1000 epoch, Loss function categorical cross entropy

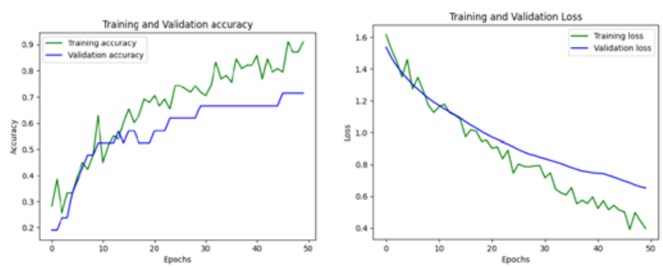
Model Name	Optimizer	Batch Size	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
MLP	Adam	32	0.9487	0.8571	0.18	0.42
CNN			1.00	0.9048	0.02	0.23
RNN			1.00	0.8095	0.03	0.59
LSTM			0.9872	0.7143	0.8	0.10
MLP	Adam	16	1.00	0.8571	0.04	0.28
CNN			1.00	0.8571	0.01	0.67
RNN			1.00	0.8095	0.03	0.65
LSTM			1.00	0.7619	0.01	0.10
MLP	SGD	32	0.8846	0.7146	0.49	0.56
CNN			0.8462	0.7143	0.48	0.57
RNN			1.00	0.8571	0.07	0.41
LSTM			0.4744	0.5714	0.11	0.10
MLP	SGD	16	0.8205	0.7619	0.44	0.54
CNN			0.9744	0.8571	0.21	0.38
RNN			1.00	0.8571	0.02	0.44
LSTM			0.6410	0.7143	0.90	0.89
MLP	RMS prop	32	0.9744	0.9524	0.6	0.22
CNN			1.00	0.8571	0.03	0.34
RNN			1.00	0.8095	0.06	0.76
LSTM			0.9615	0.6190	0.11	0.95
MLP	RMS prop	16	0.9615	0.8095	0.09	0.36
CNN			1.00	0.8095	0.11	0.47
RNN			1.00	0.8095	0.001	0.88
LSTM			0.9744	0.6190	0.15	0.88

Table 5: Performance of the DL algorithms for using 1000 epoch, Loss function categorical cross entropy

Model Name	Optimizer	Batch Size	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
CNN	Adam	32	0.9271	0.8701	0.20	0.41
RNN			0.9583	0.7598	0.14	0.79
LSTM			0.8842	0.6348	0.34	0.63
MLP			0.9338	0.7990	0.2575	0.6321
CNN	Adam	16	0.9124	0.8480	0.24	0.47
RNN			0.9203	0.7010	0.22	0.99
LSTM			0.9167	0.6691	0.25	1.03
MLP			0.9743	0.8578	0.1304	0.5511
CNN	SGD	32	0.8732	0.8431	0.34	0.49
RNN			0.8113	0.6299	0.52	0.1
LSTM			0.3125	0.2892	1.5	1.5
MLP			0.7181	0.6765	0.7931	0.8961
CNN	SGD	16	0.9277	0.8578	0.21	0.43
RNN			0.8480	0.6299	0.46	0.98
LSTM			0.2800	0.2517	1.55	1.55
MLP			0.8235	0.7402	0.5664	0.7170
CNN	RMSprop	32	0.9148	0.8627	0.24	0.50
RNN			0.9145	0.7721	0.24	0.73
LSTM			0.8205	0.6544	0.52	0.99
MLP			0.9179	0.7794	0.2798	0.6155
CNN		16	0.8793	0.8824	0.35	0.40
RNN	RMSprop		0.9222	0.7304	0.24	0.91
LSTM			0.8456	0.6936	0.44	1.01
MLP			0.9547	0.8333	0.1572	0.5931

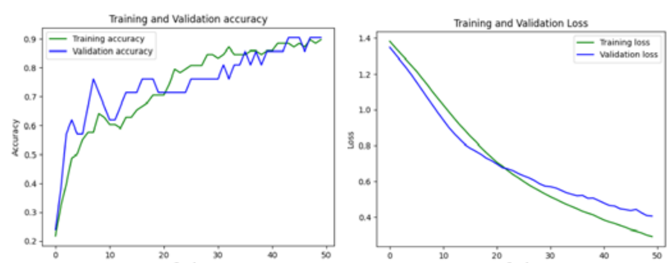
Table 6: Performance of DL algorithms for different no of epochs

Sr. No.	Model	Number of Epochs	Training Accuracy	Validation Accuracy
1	CNN	50	0.7034	0.7206
2	CNN	100	0.9277	0.8578
3	CNN	200	0.9271	0.8701
4	RNN	50	0.9988	0.7941
5	RNN	100	1.0000	0.8571
6	RNN	200	1.0000	0.9048
7	LSTM	50	0.9081	0.6373
8	LSTM	100	0.9872	0.7143
9	LSTM	200	1.0000	0.6667
10	MLP	50	0.9779	0.7941
11	MLP	100	1.0000	0.8725
12	MLP	200	0.9510	0.7990



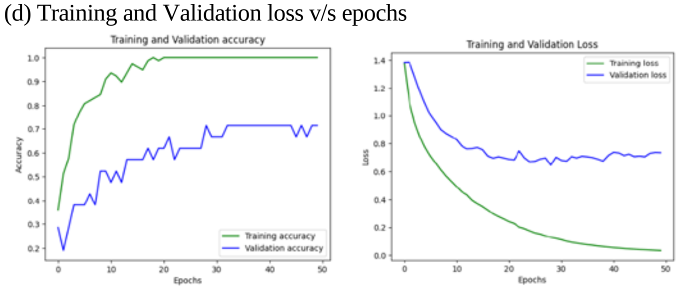
(a) (b)

MLP Model: (a) Training and Validation accuracy v/s epochs (b) Training and Validation loss v/s epochs



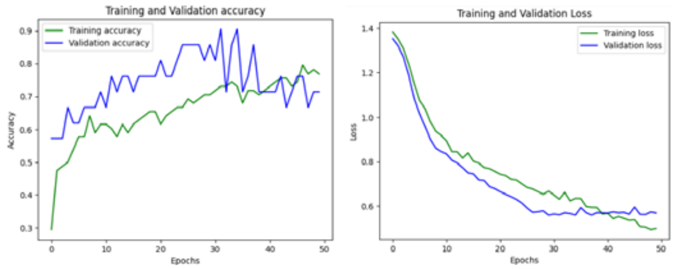
(c) (d)

CNN Model: (c) Training and Validation accuracy v/s epochs (d) Training and Validation loss v/s epochs



(e) (f)

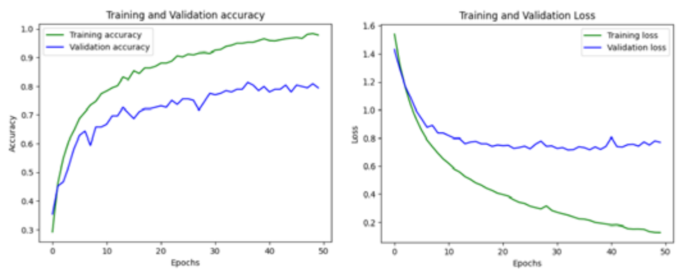
RNN model: (e) Training and Validation accuracy v/s epochs (f) Training and Validation loss v/s epochs



(g) (h)

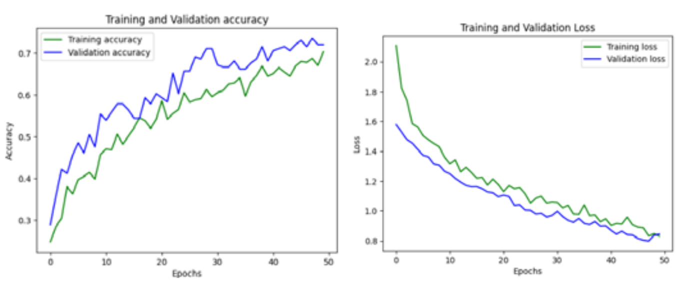
LSTM model: (g) Training and Validation accuracy v/s epochs
(h) Training and Validation loss v/s epochs

Figure 4: Accuracy and Loss curves of DL algorithms for COPD numerical dataset



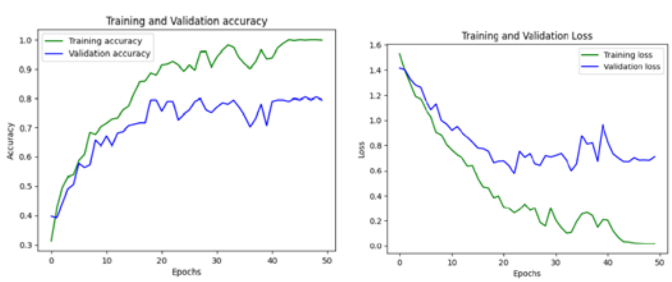
(a) (b)

MLP Model: (a) Training and Validation accuracy v/s epochs
(b) Training and Validation loss v/s epochs



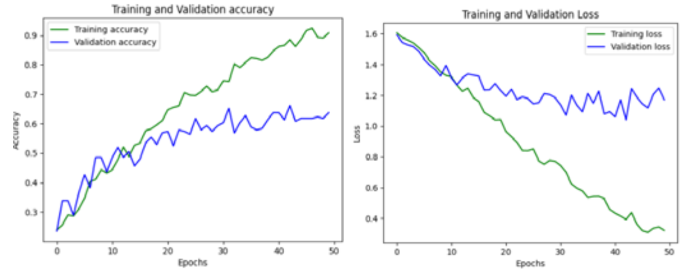
(c) (d)

CNN Model: (c) Training and Validation accuracy v/s epochs
(d) Training and Validation loss v/s epochs



(e) (f)

RNN model: (e) Training and Validation accuracy v/s epochs
(f) Training and Validation loss v/s epochs



(g) (h)

LSTM model: (g) Training and Validation accuracy v/s epochs
(h) Training and Validation loss v/s epochs

Figure 5: Accuracy and Loss curves of DL algorithms for COPD audio dataset

Using ML and DL algorithms, we have identified the severity levels of COPD and examined the cough sounds of patients using the Librosa library. To examine the effectiveness of the various deep learning algorithms,[18–21] including CNN, RNN, LSTM, and MLP, for categorizing COPD severity levels for both numerical and audio datasets, several experiments have been conducted by considering different values for the learning parameters such as epochs, batch size, etc. To handle the issue of an imbalanced dataset, we have used data augmentation during the learning of the models.

The result indicates that CNN and RNN models with Adam as an optimization function provide higher accuracy values for COPD classification than MLP and LSTM models. Examining different epoch values is done to determine how they affect the performance parameters for various DL models. For the audio dataset, the RNN model performs better at epoch value 100, while the CNN model works better for the numerical dataset. Training models obtain accurate results while learning with a batch size of 32.

Conclusion

We have conducted numerous experiments by taking different values for the learning parameters like epochs, batch size, optimization functions etc. to analyze the performance of the various DL algorithms such as CNN, RNN, LSTM, and MLP for classifying COPD severity levels for both types of the datasets, numerical and audio. Result of experiments suggests that CNN and RNN models with adam as an optimization function give better accuracy values for COPD classification than MLP and LSTM. Training models provide accurate result when they are learnt with batch size 32.

Conflict of Interest

Authors have no conflict of interest, academic or financial, for publication of this work.

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