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Responding to challenge call for machine learning model development in diagnosing respiratory disease sounds

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Abstract. The normal and abnormal sounds from the respiratory system shed great light on medical science by revealing the quality, diseases and changes in people's lungs. In medicine, this easy and old method, realized by the stethoscope, facilitates the diagnosis of diseases by specialists. This manual method can sometimes lead to wrong decisions in terms of sound detection due to different audibility. Detailed sound analysis is crucial for accurately detecting lung diseases with high mortality rates. As technology advances, the development of automated approaches based on machine learning is of great interest as they provide modern and highly accurate analysis. In today's most popular topic, i.e., the COVID-19 disaster, the conflict between early detection of respiratory disease and machine learning for sound signal processing is extremely important. In this study, a machine learning model was developed to detect respiratory system sounds such as sneezing/coughing in disease diagnosis. The automatic model and approach development of breath sounds, which carry valuable information, results in early diagnosis and treatment. A successful machine learning model was developed in this study, which was a strong response to the challenge called the "Pfizer digital medicine challenge" on the "OSFHOME" open access platform. In the database provided in this challenge, which consists of 3 parts, features that effectively showed coughing/sneezing sound analysis were extracted from training, testing and validating samples. Based on the Mel frequency cepstral coefficients (MFCC) feature extraction method, mathematical and statistical features were prepared. The sequential forward selection (SFS) feature selection method was used to select the relevant and dominant variables among the obtained features to represent the model fully and accurately. Three different classification techniques were considered for successful respiratory sound classification in the dataset containing more than 3800 sounds. Support vector machine (SVM) with radial basis function (RBF) kernels, decision tree and ensemble aggregation classification methods were used as classification techniques. In an attempt to classify coughing/sneezing sounds from other sounds, SVM with RBF kernels was achieved with 83% success.

Keywords: respiratory sounds, COVID-19, coughing/sneezing, feature extraction, classification

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1. Introduction

This paper is dedicated to the memory of the late Jalal and Behzad Manshouri, who passed away from COVID-19 in September 2021.

The respiratory system, the most important feature of being alive, helps us breathe by including the airways, blood vessels and lungs. Owing to the cooperation of the muscles that strengthen the lungs and the respiratory system, gas exchange takes place in the body [38]. It is surprising that the respiratory system has many important functions besides helping with breathing, which include the ability to speak and smell, balance air temperature and body temperature as well and remove harmful substances and waste gases from the body. By considering the factors affecting this vital organ, great success can be achieved in the early diagnosis of respiratory tract infections and diseases. The sounds emerging from the lungs have a great role in the early diagnosis of respiratory system diseases [39, 43]. Intensity, frequency, and quality, which are the characteristics of these sounds, are the considerations for distinguishing similar sounds.

The presence of cough symptoms in different types of respiratory diseases and the point that this symptom is a useful tool in diagnosing the disease have been the favourite subject of many studies [3]. The reflex that defends the lungs against any irritant in the respiratory system is coughing. Most of the time, a self-healing cough can sometimes be a sign of an important disease. Cough, which is a symptom of many diseases such as COVID-19, bronchitis, lung cancer and asthma, has different characteristics in every disease in terms of sound and provides great convenience to doctors as to diagnosis [6]. In addition to the field of medical science, automatic sound analysis of coughs and early diagnosis of respiratory diseases have been the main targets of much research. Thus, automatic analysis and classification of cough or sneezing, a symptom of deadly diseases such as COVID-19 in respiratory diseases, has become important today. Artificial intelligence provides great convenience and prosperity in people's lives and has become a technology that gives promising results in many studies.

Studies in the early diagnosis of cough-based disease can generally be categorized into two groups. While the first group is the cough sound classification in a dataset containing different sound types, the second group is to classify the cough types.

Sputum in the lung in the dry and wet cough type classification was extensively detected in [34]. Sputum detection should be considered the first sign of many diseases, such as pneumonia, cancer and infection. In clinical settings, sputum detection examinations are performed individually. This study, which increases the accuracy of these tests and facilitates this detection, proposes a different way according to the characteristics of cough sounds. A dry and wet cough sound from 131 participants was analyzed as a multi-layer labelling platform. As a result, 88% sensitivity and 86% specificity were achieved in dry and wet cough classification.

In 2013, a valuable and pioneering study developed an automatic and early detection model for pediatric pneumonia based on the analysis of respiratory system sounds [2]. This disease, which has a high mortality rate due to the lack of laboratories and the small number of health teams in poor areas, has led to promising results owing to not requiring any physical contact. Successful decisions were obtained by extracting effective features from cough sounds and applying a logistic regression classifier. Based on these effective features, the targeted disease could be differentiated from other diseases with 94% and 75% sensitivity and specificity, respectively.

A major advantage of automatic cough sound classification studies is to minimize the error rate in detecting dry or wet cough type, which is based only on the subjective judgments of doctors [48]. To largely solve this problem, a model for sound type analysis has been developed. After the signal processing steps were passed, the results obtained by automatic classification were compared with the decisions determined by the two experts. As a result of this comparison, it was concluded that the proposed model is a useful tool for cough-based remote disease monitoring and diagnosis.

In the literature review, studies based on different cough classifications are found. The main goal of these studies is to distinguish the cough sound from among several sounds. Detailed analysis of cough frequency and severity in patients suffering from cough as the result of chronic diseases provides valuable information. Based on this issue, automatic cough sound detection is made from the recordings taken via mobile using the hidden Markov model [30]. Based on the results of the proposed model, the feasibility of the hidden Markov method in detecting cough in mobile patients is demonstrated.

In another study conducted in 2019, information about preprocessing in cough sound detection, especially in noisy environments, was presented. This study showed that a preprocessing step was necessary to suppress the noise in cough sounds to minimize the margin of error in diagnosing respiratory disorders [8].

A model proposal that detected abnormal situations by examining cough sound information was made in [44]. The main purpose of this real-time model was to provide remote monitoring of older and lonely individuals and early intervention in critical situations. Two models in the dataset were used for cough sound classification, including different environmental sounds and cough. One was a neural network, and the other was a hidden Markov model. This model was shown to provide high performance at a low signal-to-noise ratio. It is noteworthy that presenting a simple prototype of the proposed model provided great convenience to the user candidate due to its use of the wireless microphone.

To detect different patterns in the flow of cough sound, a system using an acoustic detector was presented in [45]. The study focused on the classification process to distinguish the impulse patterns in the cough sound from other impulsive sounds. This system, which is strong against noise and reverberation, showed 90% and 99% sensitivity and specificity, respectively, due to having short-term architecture used in the field of deep neural networks.

The difficulties and advantages of studies with artificial intelligence methods in cough sound detection and early disease diagnosis were presented in [3] as a review study. In this comprehensive review based on the cough sound classification, different methods were compared. The most commonly used method in cough-based disease diagnosis studies was logistic regression and SVM. On the other hand, compared with random forest algorithms and deep learning architecture, artificial intelligence algorithms were widely preferred.

In our machine learning model, proposed as a solution to the COVID-19 disaster in 2021, spectral analysis of voice recordings was taken into account using a dataset consisting of cough sounds only. In the dataset of 16 individuals, a small sample pool obtained from 121 samples was prepared to lay the foundation for the model design. In this model, which gives very successful classification results, features obtained from cough sound samples are obtained by short-term Fourier transform (STFT) and Mel-frequency cepstral coefficients (MFCC) methods. Then, the COVID-19 diagnosis was performed using the SVM classifier. The disadvantages of this study are the small size of the dataset and the absence of the feature selection step, which is one of the signal processing steps.

In a study conducted in 2021 [1], diagnosing patients with Coronavirus in smart hospitals was possible thanks to the cooperation of the Internet of Things (IoT) and machine learning technology. In the presented model, diagnosis performance was achieved as 95% using the support vector machine algorithm. This successful model is also extremely effective in reducing the mortality rate by minimizing crowding in hospitals and greatly reducing the workload of healthcare personnel.

Within the scope of automatic diagnosis models based on machine learning, a real-time patient monitoring system was designed by analyzing data from Canada Health Infoway and different organizations. Thanks to the remote monitoring method, a great step has been taken in the biomedical field, and promising results have been obtained to detect COVID-19 [47].

In machine learning models, model optimization is very important in the trial process and model development. In this context, the adequacy and control of the physical system have been the main target of many studies [52, 54]. Effective stability is provided in the analysis of non-linear random sound signals and in online model design. Different studies have been carried out on fault detection in machine learning model design. Thanks to the asynchronous filters proposed in the study, fault detection was carried out without error alarms [55]. At the signal processing stage, randomly selected audio signal lengths can be called with an effective iterative learning control (ILC) method [56]. This method, which is based on a numerical basis, has been verified to be successful in terms of performance.

Detailed sound analysis is crucial for accurately detecting lung diseases with high mortality rates. As technology advances, the development of automated approaches based on machine learning is of great interest as they provide modern and highly accurate analysis. In this study, an automatic early detection system based on coughing/sneezing sound classification was tried to be modelled. In our work, we focused on designing a new machine learning model, paying close attention to the invitation of the open Science Center "OSFHOME" platform [35]. The three-part dataset created by this platform for the "Pfizer digital medicine challenge" consists of training, validating and testing sets. As the result of the efficient feature extraction method from this dataset, the classification stage was entered to complete the designed machine learning model. The validation dataset was analyzed to obtain the parameters of the used classifier algorithms.

In this dataset, the class covering coughing/sneezing sounds could be distinguished from those comprising other sounds. The designed machine learning model could be useful in the early diagnosis of the current widespread COVID-19 disaster and other diseases caused by viruses that spread through coughing/sneezing in crowded places.

2. Methods and test protocol

2.1. Dataset

The dataset of the proposed article was made up of signal from ESC-50 [36] and AudioSet [16] audio files. The general introduction of these datasets can be presented briefly and concisely in the following sentences:

The ESC-50 dataset is a collection of approximately 2000 types of labelled sounds suitable for sound classification studies. This dataset includes five major categories: the sounds of animals, natural sounds/water sounds, human sounds excluding speech, domestic sounds, and city noise sounds. ESC-50, one of the popular datasets since 2016, has many studies regarding audio signal analysis and classification [15].

Regarding data usability, OSF's fast access, up-to-date, and reliability create a solid basis for researchers to conduct projects. The open-access dataset in the presented article can be accessed from the link: https://osf.io/tmkud/.

By using artificial intelligence algorithms based on machine learning in the age of technology, this dataset can play an important role in the early detection of respiratory tract infections and in the analysis of different respiratory sound-induced diseases.

The AudioSet dataset, consisting of YouTube videos, comprises 10-second human-labeled audio clips. A detailed study has been made on the AudioSet dataset to open the door to acoustic sound event detection [14].

The proposed coughing/sneezing sound classification analysis presents the graph representing the training, validating and testing sample number in the three-part dataset consisting of ESC-50 and AudioSet audio files in figure 1. As can be seen, there were 3718, 1221 and 1654 samples, respectively, for training, validating and testing. The rough block diagram of the main work is shown in figure 2.

The study divided the dataset into two groups: patients and healthy individuals. The class containing the patient labels included respiratory diseases such as sneezing and coughing, while the healthy class included common human-induced sounds such as laughing and singing. Any sound except sneezing and coughing was included in the data set. Sound recordings with

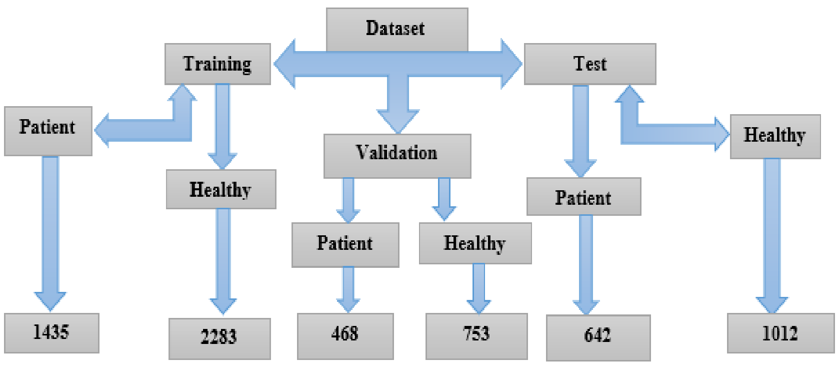

Figure 1: Sample distribution of the three-part dataset.

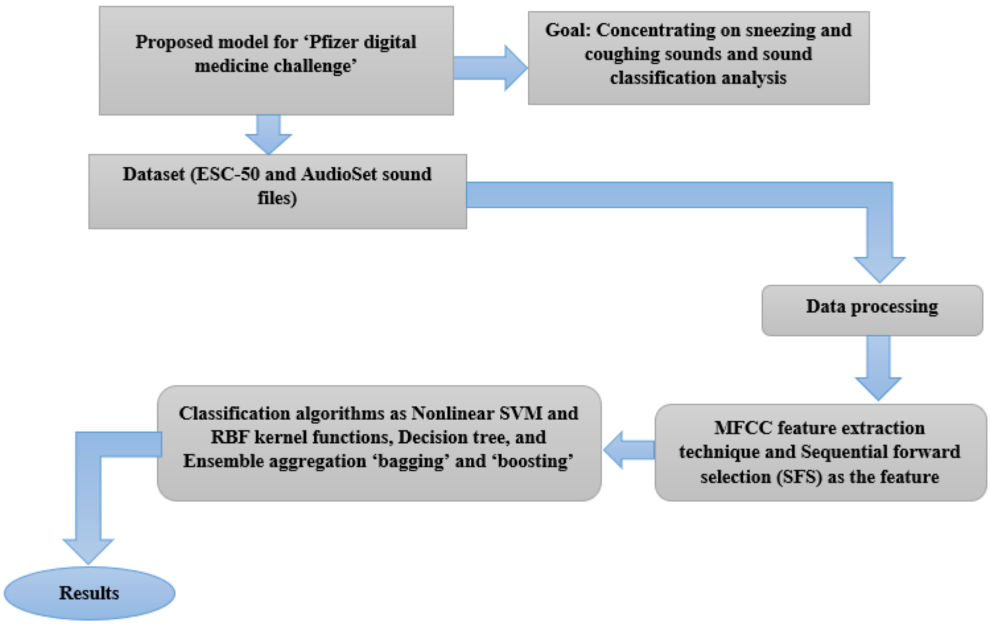

Figure 2: A rough block diagram of the main work.

a length of 4.98 seconds were sampled at 44100 Hz. All the data analyses in the study were performed using the Matlab 2019b application.

In the dataset used, figure 3 is given as an example to obtain information about the behaviour of different sound signals in addition to coughing/sneezing sound signals. This figure presents time, frequency, and MFCC representation for raw signals in the validation dataset in healthy and patient individuals.

2.2. Data processing

2.2.1. MFCC feature extraction technique

MFCC feature extraction is an efficient and common method for analyzing audio signals. Different techniques, such as linear prediction coefficients (LPC) and perceptual linear prediction (PLP) coefficients, are also used as feature extraction methods. MFCC has proven more successful than other methods in speech recognition systems.

This technique generally consists of five basic parts. These are, respectively, pre-emphasis, signal framing and windowing, applying the discrete Fourier transform, calculating the logarithm of the magnitude and multiplying the frequencies to the Mel scale (called the Mel filter bank step) and, finally, computing the inverse discrete cosine transform. The first stage, pre-emphasis, is actually a process that compensates for the rapidly distorting spectrum of the audio signal. Framing is the other step in dividing the audio signal into smaller compartments. The most important task of the windowing process is to prevent discontinuity of the obtained audio signal [19]. This study performed the windowing process by selecting the Hamming window. The

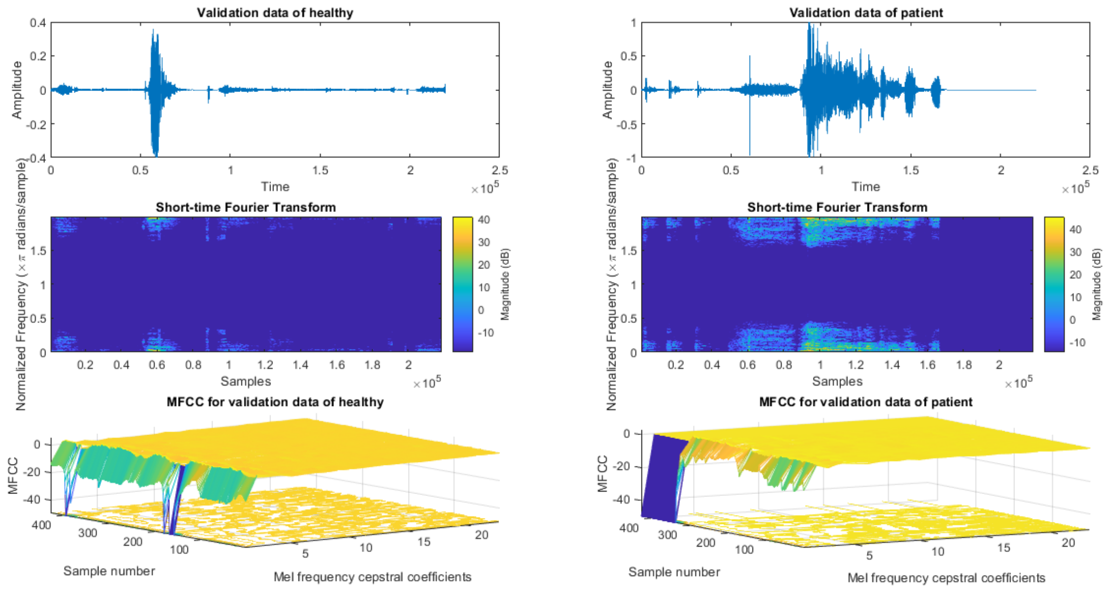

Figure 3: Time, time-frequency, and MFCC representation for raw signals in the validation dataset of healthy and patient individuals.

working principle of this window is shown in equation (1):

$$W[n] = 0.54 - 0.46\cos\left[\frac{2\pi n}{N-1}\right] \tag{1}$$

where $W[n]$ and N are the n-th coefficient of the Hamming window and the number of samples per frame, respectively [19]. Following the windowing process, the Fourier transform moves the audio signal from the time domain to the frequency domain. The other stage, the Mel filter bank, consists of overlapping filters. There was a relationship between the actual frequency and the perceived frequency known as Mel, as presented in equation (2):

$$f_{Mel} = 2595\log_{10}\left(1+\frac{f}{700}\right) \tag{2}$$

In this equation, f_{Mel} is the output of the filter bank, and f is its input. 2595 and 700 in the equation are constant numbers.

In the MFCC algorithm, which is used as a feature extraction step in the data analysis phase, priority is given to calculating the Mel frequency cepstral coefficients for each classifier. In the $M \times N$ matrix obtained from the MFCC application, the M and N parameters showed the Mel frequency coefficients and the number of windows, respectively. This coefficient was evaluated between 2 and 39 for each classifier in the present study. A hamming window, similar to a raised cosine structure and without zero ends, was used in the study. Using trial-and-error theory, the length of this window and the window overlap were selected as (4×512) and (1024+512), respectively. As the result of the evaluation between 2 and 39, the effective Mel coefficient value was determined as 23. After selecting the appropriate coefficient, seven statistical values for each coefficient index were considered as features: mean, standard deviation (SD), root means square (RMS), entropy, kurtosis (KUR), skewness (SKW) and variance (VAR). Thus, the size of the feature vector was calculated as M*7 (23*7=161). MFCC feature extraction process flowchart is shown in figure 4.

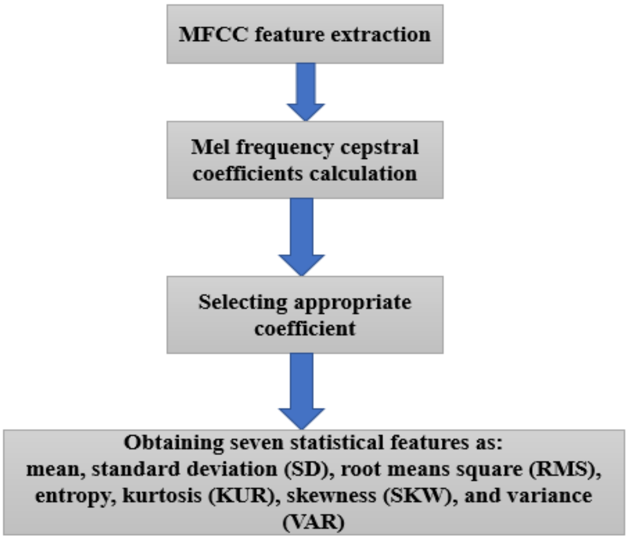

Figure 4: MFCC feature extraction process flowchart.

2.3. Sequential forward selection (SFS) as feature selection method

Feature selection (FS) is a useful process used to reduce the number of obtained features and select more efficient ones. In the problem-solving phase, some unnecessary features cause confusion and cluttered feature space, decreasing classification performance. FS is greatly beneficial in machine learning studies as it is simple to operate, accurate, and fast.

Many methods exist for reducing the feature set size and selecting dominant features. The sequential forward selection (SFS) technique is successful in terms of speed and ease of understanding.

This algorithm is based on sequential feature selection. Working as a bottom-up search tool, it gradually adds features that seem suitable due to the computational functions from an empty set. An important advantage of this algorithm is that the newly chosen feature is selected from the remaining feature set, so the newly designed and expanded set will have a minimum error in terms of the classification process compared to other additions.

2.4. Classification algorithms

2.4.1. Nonlinear SVM and RBF kernel functions

The SVM classification method is frequently preferred in regression analysis and classification-based research. In machine learning and signal processing, this supervised model is known as a robust method in the prediction field due to its strong statistical basis and ability to minimize the probable risk ratio. The easiest and most understandable definition of the SVM method can be expressed as follows: it reveals a decision hyperplane by considering the optimum support vectors and then performs the most appropriate data classification in the dataset. Thus, it is ideal for two-class problems [31]. This algorithm was first shown to be capable of linearly separating samples in a dataset with a linear format. Thus, in this case, it is responsible for choosing the hyperplane that maximizes the margin between the two classes with linearly distributed samples.

A nonlinear SVM classifier can be obtained from a nonlinear operator application called 'kernel trick'. Owing to this trick, data analysis can be moved to the multidimensional feature space [50]. One of the important factors affecting the classification result is the selection of kernels and effective parameters related to these kernels [42]. The most common RBF kernel in the SVM classification method was used in the study. The parameters that directly affect the performance of this nonlinear SVM type are C and γ. Parameter C is actually defined as a regulation criterion in SVM. For the sake of maximizing the margin of the decision function, this parameter sometimes prevents the correct classification of the samples. In the hyperplane representation, a limited number of selected points result from a small C value in determining the critical boundary between the classes. This wrong choice may result in obtaining incomplete information [10]. On the other hand, with a large C value, wrong decisions can be made again by obtaining a large decision limit due to the selection of more sample points. As a result, choosing the optimum value of C can minimize the error in the training phase [42]. Another important parameter in the designed training model is γ. This parameter actually shows the desired degree of curvature in the decision boundary. For two classes, the optimal selection of the gamma value, which shows the distance between the decision boundary and the nearest support vectors, is important.

A high γ value means choosing the ones closest to the decision boundary in terms of samples, and a low γ means choosing the farthest points on the decision boundary. RBF, one of the kernel varieties selected in the study, is presented in equation (3). In the presented formula, σ shows the standard deviation (SD) of the samples and is chosen as 1 in this study.

$$K_{RBF} = \exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right) \tag{3}$$

2.4.2. Decision tree

Decision tree, one of the important classifiers in artificial intelligence based on machine learning, has high speed, powerful learning model, and an easy structure [7]. This algorithm, which falls under the category of supervised classifier, is used to solve regression and classification problems. The purpose is to create a model to predict the class of an unknown sample based on the decision rules learned from the training data. This method, which subdivides the analysis dataset, consists of the root nodes and internal nodes. Each node comprises a single main part and two or more sub-parts called descendants. Based on Magerman's view, the decision tree is applied to the model to support the decision process at the classification stage. Thus, it creates possibilities for each choice in the different states of the decision.

The first node in the decision tree is the root node. As the result of the root state evaluation, the observation process that results in "Yes" or "No" is classified. Internal nodes representing attributes are located below the root node. As the number of nodes increases, the complexity of the designed model will increase. In this tree-like flowchart, the part that presents the result is the leaves, which are the lowest nodes [51]. This method, compatible with different variables, has great advantages in machine learning because it is easy to understand and can be classified with optimum calculation. The "fitctree" command was selected to set the maximum branch divisions of the decision tree. At this stage, the division criterion was considered as "gdi". In terms of the parameter of this algorithm, the maximum number of splitting ("MaxNumSplits") was chosen as 20 according to node splitting rules [12].

2.4.3. Ensemble aggregation "bagging" and "boosting"

In data analysis, the problem that classification studies often encounter is class irregularity and imbalance. Different methods have been developed to eliminate this problem, which occurs in disease diagnosis, face recognition, fluid leak diagnosis, and many other areas. Three different ways are followed to solve this problem. In the first way, by emphasizing the importance of positive samples, the new algorithm is obtained by correcting or changing the existing algorithms (i.e., algorithm level). In the second way, a pre-processing step is added. The aim is to minimize the effect of class distributions that suddenly change direction and decision (i.e., data level). The third method reinforces cost-sensitive methods by combining algorithm and data-level approaches. In addition to the three approaches mentioned above, the ensemble technique is used in the class imbalance problem [37]. This algorithm, which is used in classification and regression in the field of artificial intelligence based on machine learning [53], is designed to increase the stability and accuracy of the existing algorithms [17].

Bagging and boosting are the most common ensemble techniques that make big changes in a low-performance and powerless classification algorithm. The biggest advantage of these techniques is that they prepare the classifiers in advance, depending on the desired variety, while considering the training set. The bootstrapping concept presented by Breiman for the bagging technique creates a new dataset for training classifiers by randomly drawing class samples. The basis of the method is to gain variety by re-sampling using data subsets. After obtaining this variety, the class of an unknown guest sample is determined by voting [13]. The boosting technique, recognized by Schapire in 1990, has proven authoritative in producing a powerful classifier model [40]. AdaBoost, one of the most effective and powerful members of the boosting family, is used as a representative approach in data mining [51]. Minimizing variance and deviation, it performs well by increasing the margin between the classes, similar to the working principle of the SVM. The working logic of AdaBoost can be summarized as follows: using the whole dataset; it makes a focus and effort to correctly guide the hard-to-separated samples by considering the samples misclassified in each iteration. It reduces the weights of the correctly classified samples and increases the weights of the wrong samples by playing with the sample weights in each iteration. Different weights are assigned to each classifier during the testing phase. This process gives more credit and confidence to efficient classifiers. Thus, the choice of the class label for a guest instance is determined by the majority voting per classifier.

In this study, "AdaBoost.M1", a derivative of the boosting algorithm, and the "bagging" technique were used to smooth out the class imbalance. The maximum number of splittings for the "bagging" and "AdaBoost.M1" algorithms was chosen as 3715 and 100, respectively.

The numerical values of the classification algorithms were selected using the trial-and-error method. The parameters selected by this method are numerical values that adjust the algorithm to work optimally.

3. Results

After the features were obtained, the accuracy rates of the classifiers on the validation set using different MFCC coefficients are presented in figure 5. The reason the Mel coefficient was chosen as 23 was the maximum accuracy rate of the SVM algorithm, which provided successful performance at this value.

To increase the study's performance, classification algorithms' efficiency was focused on by applying SFS feature selection. By performing the SFS method to each classifier and considering 23 effective Mel coefficients, the improved accuracy rates for SVM, decision tree, "AdaBoost.M1" and "bagging" are shown in figures 6, 7, 8, and 9, respectively. Owing to the feature selection used to optimize the number of features in the dataset, omit unnecessary data, reduce the training time and, most importantly, increase the accuracy rate, 80 outstanding and effective features specific to each classification were selected from among 161 features. A closer look at figure 5 shows that, among the classifiers, the SVM provided successful performance and the decision tree yielded less. In the SVM algorithm, which exhibited successful accuracy, the highest percentage of accuracy was shown as 80.31% in the Mel coefficient, which is 23, as seen in figure 5.

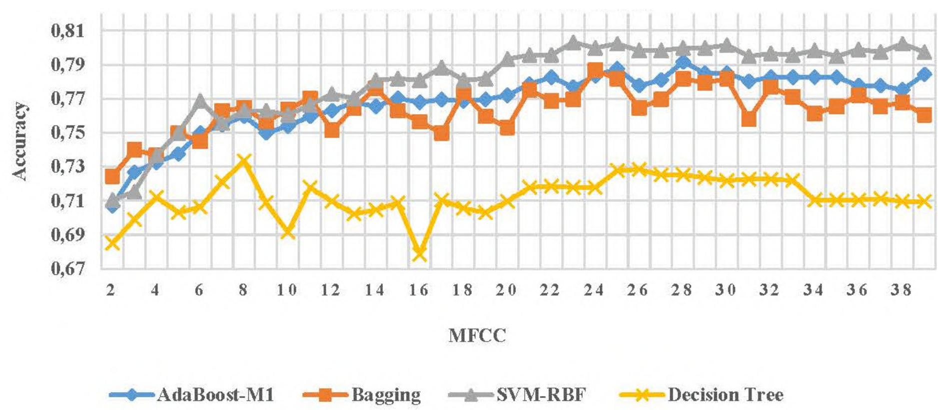

Figure 5: Accuracy rates of the classifiers on the validation set using different MFCC coefficients.

Considering the success of each classifier in figures 6, 7, 8, and 9, the effective number of features was chosen as 74, considering the behaviour of the successful SVM classifier. As a result of this selection, according to Figure 6, the accuracy success rate of SVM reached 83.18%. In other words, owing to the approximately 50% decrease in the number of total features (161), the classifier success percentage increased by 2.87%. This success was determined as 75.22%, 78.5% and 78.99% for the other three classifiers, as presented in figures 7, 8, and 9. On the other hand, when the graph of accuracy success according to 80 features in the SVM classifier was taken into visual analysis, the 83.01% success of this classifier in the number of 45 features cannot be overlooked. Also, it was observed that the ensemble aggregation derivatives "bagging" and "AdaBoost-M1" showed similar behaviours.

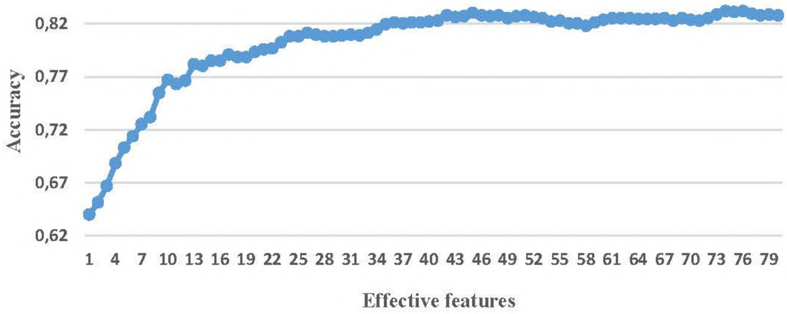

Figure 6: Accuracy rates of the SVM classifier after applying SFS.

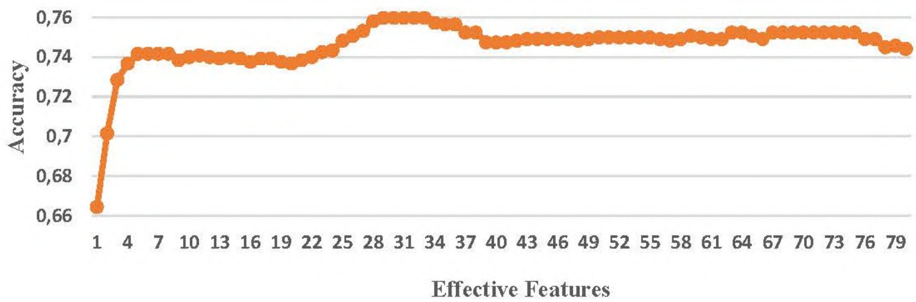

Figure 7: Accuracy rates of the decision tree classifier after applying SFS.

The interpretation and final result of this analysis on the validation data are presented in table 1. Based on the presented graphs, the successful accuracy rate in the selected effective 80 features was more pronounced for the first 74 features. Likewise, the accuracy, sensitivity, specificity, recall, precision, and area under the curve (AUC) values of the testing data for the proposed classifier algorithms after selecting effective features are presented in table 2. As seen in these tables, in the cough and sneeze analysis early diagnosis study, the SVM algorithm appeared successful in the validation and test data, while the second successful algorithm was the "AdaBoost.M1" algorithm.

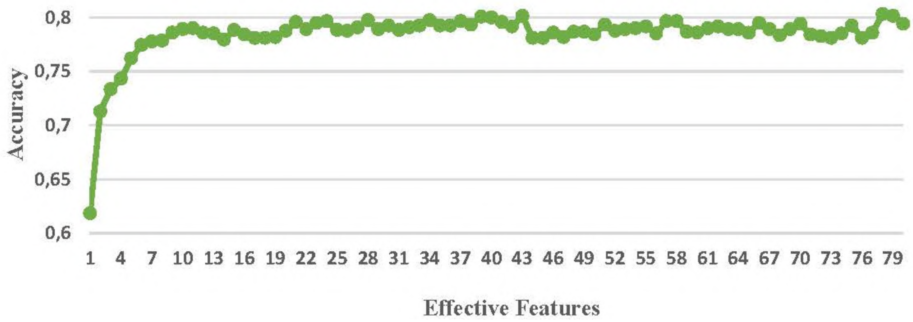

Figure 8: Accuracy rates of the "Bagging" classifier after applying SFS.

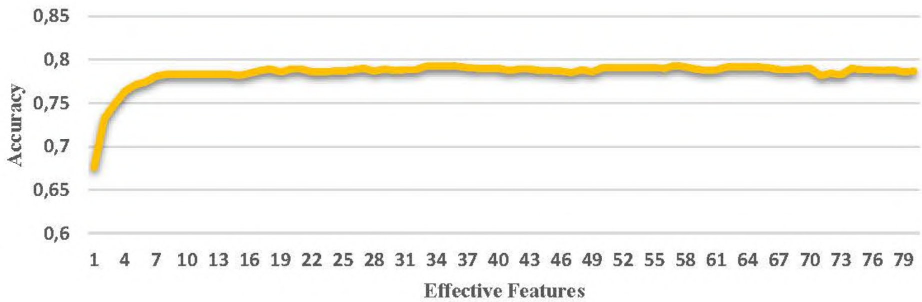

Figure 9: Accuracy rates of the "AdaBoost.M1" classifier after applying SFS.

Table 1
Validation data classification accuracies and sensitivity, specificity values for 74 effective features and Mel coefficient = 23.

	Classification parameters	Accuracy	Sensitivity	Specificity
Decision tree	"MaxNumSplits"=100	0.7596	0.7752	0.7344
AdaBoost.M1	"MaxNumSplits"=20	0.8022	0.8603	0.7087
Bagging	"MaxNumSplits"=3715	0.8014	0.8484	0.7259
SVM	δ=1	0.8318	0.8776	0.7580

As a result of the selection of active features and Mel coefficient 23, the SVM classifier in the validation data represents accuracy, patient sensitivity, and specificity with 83%, 87.76%, and 75.8%, respectively. Keeping the conditions constant, i.e., 74 features and Mel coefficient of 23, these classification performance values in the test dataset were determined as 77.60%, 81.58%, and 71.27% for accuracy, sensitivity, and specificity, respectively. As expected, the SVM algorithm is the best-performing classifier in both validation and test data analysis.

Table 2
Classification performance measures after selecting 74 effective features and Mel coefficient = 23 in the test data.

	Classification parameters	Accuracy	Sensitivity	Specificity	Recall	Precision	AUC
Decision tree	"MaxNumSplits"=100	0.7034	0.7810	0.6041	0.7810	0.7161	0.6926
AdaBoost.M1	"MaxNumSplits"=20	0.7621	0.7764	0.7322	0.7764	0.8586	0.7543
Bagging	"MaxNumSplits"=3715	0.7603	0.7808	0.7199	0.7808	0.8457	0.7504
SVM	δ=1	0.7760	0.8158	0.7127	0.8158	0.8190	0.7642

4. Discussion

Detailed analysis of respiratory sounds opens up great possibilities in the medical world. Advances in technology and the reflection of this development on the medical world have led to the design of digital recording and advanced instruments. The recording and visualization of respiratory sounds, which have different characteristics, can be an early harbinger of some diseases that harm people's lives [5]. For this reason, a comprehensive classification study based on sneezing/coughing sounds has been conducted to analyze the diversity of sounds originating from the respiratory system and to think this analysis will be useful for the early diagnosis of diseases.

We found no comprehensive studies on the presented dataset that responded to the "Pfizer digital medicine challenge" invitation. As mentioned, since there is no study on this dataset, it was not considered appropriate to compare the results of the presented model with studies on different datasets. However, explaining the results of some cough-based studies generally seems useful. It has been known for many years that coughing sounds are a symptom of many diseases and are of medical importance. Based on this information, a compilation study was made by Korbas et al. [26]. In a 2006 study, healthcare professionals analyzed cough sounds, showing that these analyses would help them identify cough sound characteristics. However, it is seen that the analyses made in those years were insufficient in terms of diagnosis [46]. Wavelet analysis of volunteers with cough-based disease originating from the respiratory system was the main target of another study [25]. Using the discriminant analysis method, nearly 90% success was achieved by separating the cough sounds of healthy subjects from the cough sound characteristics of volunteers with asthma bronchial and chronic lung diseases. Irregular and abnormal pulmonary function detection was performed by classifying cough sound and airflow patterns. In this successful study, a new model for cough sound classification was developed. In this system, a bright light was shed in the medical world by diagnosing abnormal lung functions [18] by considering the acoustic properties of airflow and coughing sound. The advantages and difficulties of cough sound-based studies regarding disease diagnosis were examined in a comprehensive current review study [3]. Finally, we emphasized the importance of cough while considering the different studies reviewed over the last 25 years or so. From the early diagnosis of respiratory system diseases, we found that cough is a strong candidate as it exhibits variable patterns. Only the passage of years and the advancement of technology seem to have the potential to turn this cough candidate into a more powerful and rapid diagnostic tool.

Table 3
Comparison of several important studies regarding cough sound analysis.

Studies	Advantages	Disadvantages
[22]	Presenting a successful diagnosis of pulmonary diseases	Small dataset
[20]	Convenient and easy-to-use mobile app	Low efficiency as a result of small datasets
[23]	Acceptable accuracy	Poor quality sound samples due to Raspberry Pi device usage
[49]	Convenient and easy-to-use mobile app	Need for individual coughs on recording process
[9]	Low-cost	Small dataset size
[32]	High accuracy, using a single cough sound to COVID-19 recognition	Small dataset size
[31]	Diagnosis COVID-19 patients by classifying only a single cough sound, high accuracy	Small dataset size
[41]	Ability to classify five different cough sounds with high success, computationally simple and explainable	Including only cough, breath, and speech classification
[24, 29]	The same dataset, Deep learning model design for COVID-19 diagnosis by cough sound analysis, High classification success	Hardware dependency, complex architectures
Proposed study	The first machine learning study conducted on this dataset, acceptable dataset size and accuracy, powerful model design in the diagnosis of respiratory diseases by sneezing and coughing sound classification in the dataset containing different sounds, largely overlapping with results of related studies in terms of cough sound classification	Application not ready and under construction to switch to real-time implementation

COVID-19, which has formed the blind years of our lives since 2019, continues. Promising studies have been revealed with the cooperation of artificial intelligence/machine learning technologies and cough sound diagnosis, which are important in the fight against many respiratory diseases such as COVID-19. A summary of some of these studies is presented in table 3.

As a result, this study invites researchers working in this field by giving fruitful results as a proposed pioneering response to the challenge call for machine learning model development for the diagnosis of respiratory tract diseases.

This study answered a challenge posed by the "OSFHOME" platform, proving that this dataset has sufficient potential for disease early detection model design. A machine learning model was developed to detect sounds such as coughing/sneezing in this dataset, a combination of ESC-50 and AudioSet audio files. Since 2016, different studies have been carried out on the ESC-50 dataset. These studies with different objectives have generally focused on sound event recognition, sound classification with neural networks and environmental sound classification [27, 33]. Statistical features were obtained by applying the MFCC feature extraction method, common in sound analysis studies [32] in this three-stage dataset. Contrary to the previous study [32], this machine learning model trained on a large number of samples shows good and successful classification performance in terms of dataset samples. Using the SFS method aimed to increase the performance of classification techniques by reducing the number of features to about half and selecting effective features. Coughing/sneezing sounds were successfully classified from other sounds in this mixed and crowded dataset using three classification algorithms. As a result of selecting effective features, the SVM-RBF classifier was ahead of other classifiers with 83.18% success in the validation data. On the other hand, in the testing data, this classifier achieved successful performance by distinguishing coughing/sneezing sounds from other sounds with 77.60% success. It caused great sway that the results of the algorithms used in this study largely overlapped with the respiratory cough sound diagnosis studies. Widespread active use of the SVM classifier has been discovered in cough sound diagnostic research [3].

This machine learning model based on coughing/sneezing sound analysis seems useful for early diagnosing diseases such as COVID-19 [21, 28]. The system can be used as an effective and distinctive tool in crowded environments by allowing it to be installed on smartphones as an application. Since these models depend on automatic machine learning technology, they can minimize the risk of virus transmission regarding human interaction in infectious diseases [11].

The machine learning-based model proposed in our dataset, consisting of the combination of AudioSet and ESC-50, shows a great advantage in preventing the spread of infection by providing timely and remote diagnosis. This benefit automatically satisfies the requirement to comply with legal duties from communicable disease diagnosis limitations [3]. The existence of some factors that affect the quality of the audio recordings and cause them to deteriorate directly affects the sample quality of the training dataset in the detection of respiratory diseases. To combat this issue, identifying and eliminating uncontrolled factors as much as possible is important in improving model performance. The sound recordings used in our study are clean enough to be called noiseless.

One of the important goals of this pioneering work is to enable the ordinary algorithms used in many cough sound analyses to progress in parallel with modern technology to deeply understand the disease spread and virus structure [4]. We are curious to see where the results will lead, using the deep learning application as an example.

5. Conclusion

A detailed analysis of respiratory system sounds, such as coughing/sneezing, was considered to accelerate the disease diagnosis. Owing to the design of the proposed automatic model, diagnosing and treating respiratory system diseases that can lead to fatal consequences can accelerate. In this case, in crowded environments, a portable application or smart model design based on machine or deep learning is indispensable. The study discusses various methods such as SVM, decision tree, and ensemble aggregation to distinguish cough and sneezing sounds from different sounds. The proposed study was presented as a strong response to an invitation called the “Pfizer digital medicine challenge”. The three-stage dataset consists of ESC-50 and AudioSet audio files, and the features that best represent coughing/sneezing sounds were extracted using the MFCC method. After obtaining the statistically appropriate features based on this feature extraction method, the coughing/sneezing sound classification process was successfully performed for three different classifiers. Considering the results, SVM was the most successful algorithm among the SVM, decision tree, and ensemble aggregation classifiers. Based on the results of deep-rooted and detailed studies based on cough sound diagnosis, it is not overlooked that the algorithm results match the proposed study. Widespread active use of the SVM classifier has been discovered in cough sound diagnostic research. Although there was no detailed machine learning study on this dataset, the proposed model was useful in automatically detecting coughing/sneezing sounds regarding classification accuracy. This pioneering research on the described dataset sheds a bright light on the field of medicine by enabling early detection of more serious and deadly viruses and infections, greatly preventing major catastrophes from occurring. As a result of this study, the best classifier in the training dataset was the SVM algorithm with 83.18% accuracy, while the same algorithm was successful with 77.60% accuracy in the test dataset.

It is hoped that other feature selection methods, one of the study's shortcomings, will be added to the machine learning steps, and even more successful results will be obtained for future studies. By designing a deep learning model, a successful comparison study between machine learning and deep learning can be presented. Additionally, classification performance success evaluation can be analyzed using different metrics. Future development of the study was planned as follows: tuning a larger dataset using different datasets, developing method comparison-based work by applying other feature extraction techniques and classification algorithms and testing up-to-date analytical tools applicable to large datasets. On the other hand, in the comprehensive research that we are working on, we apply our proposed machine learning model to different datasets and comprehensively analyze the suitability of this model in detecting COVID-19.

In addition, the proposed model can be used for early diagnosis and treatment of COVID-19 within the scope of smart health applications and tools. This successful model, which is being prepared for the use of smart hospitals as a future target, is extremely effective in reducing the mortality rate by reducing the crowding in healthcare institutions and greatly reducing the workload of healthcare personnel.

6. Conflict of interest statement

The author has no financial or personal relationships with others or organizations that could inappropriately influence their work.

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