Diagnosing and evaluating the severity of chronic obstructive pulmonary disease based on the time-frequency features of the S transform applied to the lung sound signal

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Abstract

Chronic Obstructive Pulmonary Disease (COPD) is a common respiratory disease characterized by chronic inflammation of the lung airways and destruction of lung tissue that leads to airflow limitation. Asthma and Chronic Obstructive Pulmonary Disease are the two most common respiratory diseases that together cause approximately 180,000 deaths worldwide every year. Moreover, the death rate of COPD is eight times higher than the death rate of asthma. COPD is the third leading cause of death worldwide. Time-frequency transform has been used to diagnose and evaluate the severity of this disease using recorded signals, which are dynamic and non-static. In this research, the S transform is used as a tool to extract features from the lung signal. S transform has a higher frequency resolution than wavelet transforms at low frequencies, and at high frequencies, it has a lower frequency resolution but a higher time resolution. After feature extraction using S transform, mathematical statistics were applied to reduce feature dimensions. The results indicate that with K-fold validation for K-Nearest Neighbors (KNN) classification, the accuracy, precision, and sensitivity values are 98.39%, 97.45%, and 93.88%, respectively. For Support Vector Machine (SVM), the results are 95.23%, 92.59%, and 83.33%, respectively.

Keywords: *Classification, COPD, Lung Sound, S Transform, Time-Frequency Features*

INTRODUCTION

Chronic obstructive pulmonary disease, abbreviated as COPD, is a disease that is both preventable and treatable. People with this disease usually struggle to breath more than healthy people, which causes shortness of breath. At the beginning of the disease, a person may experience symptoms such as shortness of breath during exercise. As the disease progresses, breathing, especially exhalation, becomes increasingly difficult [1]. Symptoms of COPD include shortness of breath, cough, and phlegm production. However, some patients may experience more severe symptoms such as frequent respiratory infections, chest pain, and fatigue. This disease is currently one of the leading causes of death in the world, and it is expected that the number of deaths will increase in the coming years [2]. The increasing severity of chronic obstructive pulmonary disease indicates worsening symptoms and significant adverse outcomes for patients. Exacerbations of this disease cause increased airway and systemic inflammation and physiological changes [3].

The increase in disease severity and airway inflammation is often caused by infections. Viral infections are a major cause of this disease, although bacterial infections and environmental factors such as air pollution, geographical conditions, and ambient temperature can also contribute to chronic obstructive pulmonary disease [4]. Chronic obstructive pulmonary disease affects more than 250 million people worldwide and has significant economic costs [5]. In early childhood, severe viral and bacterial lung infections have been associated with reduced lung function and increased respiratory symptoms in adulthood, contributing to COPD development [6]. Sound can be produced from a person's lungs during the breathing mechanism. These sounds are classified into two categories: natural breathing sounds and adventitious sounds. Normal breath sounds are produced with no lung problem, but wheezing and crackling sounds are usually associated with lung pathology [7]. This article presents a review of clinical auscultation as a diagnostic tool for lung diseases and the recent advances that have made it possible to obtain more objective observations compared to the past. Quantitative lung sounds are related to clinical, physiological, and radiological information. Accurate diagnosis of lung sounds and their correlation with clinical findings can be a powerful tool in diagnosing lung diseases [8].

This study involves the use of lung sounds to diagnose and classify chronic obstructive pulmonary disease (COPD) through machine learning techniques with high accuracy. This method can be an effective tool to assist doctors and specialists in the field of health. Machine learning (ML) is a suitable approach for disease prediction, decision-making, and diagnosis that does not require human intervention. This technique is rapidly growing in the medical industry, from disease diagnosis to medical imaging [9]. COPD is treated with lifestyle changes such as smoking cessation and breathing techniques, prescription medications such as bronchodilators and corticosteroids, supplemental oxygen therapy, and pulmonary therapy. For more severe cases, surgery is sometimes an option. Figure 1 shows a representation of the lung cycle for COPD patients.

This study aims to diagnose COPD and its severity by extracting appropriate features in the time-frequency domain resulting from S transform. The S transform has a higher frequency resolution at low frequencies and a lower frequency resolution at high frequencies but a higher time resolution. After extracting the feature using S transform, mathematical statistics have been applied to reduce the dimensions of the feature. The rest of the paper is organized as follows: Section II describes the literature reviews. Section III discusses the methods and materials. Section IV describes the results; after that, section V concludes.

Related works

In recent years, several clinical studies have explored the potential use of artificial intelligence in medicine. Examples include the assessment of changes in pulmonary function and their impact on the quality of life, the number of treatments performed on patients, the rate of hospitalization, mortality due to the disease, and patient satisfaction. In this context, special attention has been given to patients with COPD.

In 2020, Moll et al. used a random forest algorithm with 30 clinical features as input to predict disease progression in patients with COPD. The most informative features were then used in a Cox regression analysis to predict mortality. It should be noted that this method was compared to other statistical and machine-learning models. The models were trained on individuals with moderate-to-severe COPD from a subset of individuals in the COPD Genetic Epidemiology (COPDGene) study and their predictive performance was evaluated on the remainder of individuals with moderate-to-severe COPD in COPDGene and the Longitudinal COPD Assessment to identify surrogate endpoints for predictive testing. The Machine Learning Mortality Prediction COPD (MLMP-COPD) model resulted in a C index of ≥ 0.7 in COPDGene [10].

Levy et al. have presented their research on the possibility of automatic COPD diagnosis using continuous oximetry data analysis. Levy and colleagues hypothesize that patients apply specific COPD patterns or dynamics to their oximetry sets that, using given information, may act on these conditions. In this study, 350 patients were studied, were trained with the help of a random forest classifier and using the extracted features, and were evaluated using nested cross-validation. A total of 8 COPD subjects out of 70 were misclassified. No severe cases were detected. [11].

Spathis and colleagues investigated clinical decision support systems in diagnosing and treating chronic obstructive pulmonary disease. The results of the machine in this study showed that in the case of chronic obstructive pulmonary disease, the Random Forest classifier outperforms other techniques with an accuracy of 97.7%. At the same time, the most prominent features for diagnosis include smoking, forced expiratory volume, age, and vitals. Classification is mandatory [12].

Kandaswamy et al. have described in an article that since the sound signals of the lungs are not constant, the conventional frequency analysis method is not very successful in diagnostic classification. This article deals with a new method of analyzing lung sound signals using wavelet transform and classification using artificial neural network (ANN). Lung sound signals were analyzed into frequency sub-bands using wavelet transform, and a set of statistical features were extracted from the sub-bands to show the distribution of wavelet coefficients. An artificial neural network-based system, trained using a flexible backpropagation algorithm, was implemented to classify lung sounds into one of six categories: normal, wheeze, crackle, squawk, stridor, or rhonchus [13].

In the study by Chung. et al., a retrospective cohort study was used, which included 595. Checking the plan manually on a group to diagnose asthma based on PAC. Then, in the next step, half of the data, i.e., 298 data, were used as training data, and the rest of the samples were used as test data using the NLP-PAC algorithm. The data distribution was 160 men and 268 white women, and the average age was 2.3 years. Description, specificity, positive predictive value, and negative predictive value for the NP algorithm in predicting asthma status were 92%, 96%, 89%, and 97%, respectively [14].

Using machine-based algorithms by Lu et al., Such as regression, simple business decision-making, and the perceptron algorithm, were used to predict the onset of severe asthma in 2010 patients. However, the model based on logistic regression achieved 90% discovery and 83% specificity [15].

Prosperi et al. compared linear and non-linear models for predicting eczema and asthma. The method proposed in this study also follows this path and replaces eczema with chronic lung disease COPD. They suggested that more complex modeling is the appropriate solution to better understand the mechanisms of illness and personal health care. They argued that in addition to performance, the system must be interpreted in terms of complexity. The experiments considered the mentioned opinions and provided the ability to interpret them by ranking the features. In this study, several factors were found to overlap in the diagnosis of asthma and COPD. There was a higher level of sensitivity and specificity for non-linear models compared to other methods, particularly for asthma and wheezing, with an area under the receiver operating characteristic curve of 84%, 76%, and 64%, respectively [16].

In Liu et al.'s paper, automatic seizure detection is essential for diagnosing epilepsy and reducing the extensive workload of reviewing continuous EEGs. This work proposes a new approach, combining Stockwell transform (S-Transform) with deep Convolutional Neural Networks (CNN), to detect the onset of seizures in long-term intracranial EEG recordings. The sensitivity obtained is 97.01%, and the accuracy is 98.12% [17].

In the article by Melekoğlu et al., for faster diagnosis of COPD and easier prevention of the disease, the use of Photo Plethysmography signal (PPG) was applicable. This study aims to determine whether COPD can be diagnosed with PPG. Two groups of healthy and sick signals were investigated. Each group of signals was first cleaned with a numerical filter method of 0.1-20 Hz. Then 25 cases of feature extraction were performed in time domains. According to the results, the highest performance values were obtained with 2 seconds data group and 99% sensitivity, 99% specificity, and 98.99% accuracy [18].

Palaniappan et al. have described an article related to the analysis of lung sounds. At the beginning of the features, identifying the distinctive features of a decision plays a major role in the classification of lung sounds. The features can be extracted from the signals in the time, frequency, and time-frequency domains. The feature techniques commonly used in computer-based lung sound analysis are the regression model, Mel frequency coefficient, energy, entropy, generative features, and wavelet. The use of wavelet-based features in Kandasamy et al.'s work has been the basis for 100% classification accuracy for the training set using ANN [19].

Khan et al. objectively analyzed lung sound signals associated with COPD. Specifically, Empirical Mode Decomposition (EMD), a data-adaptive signal decomposition technique suitable for analyzing non-stationary signals, was employed to decompose non-stationary lung acoustic signals. Applying EMD to the lung sound signal results in intrinsic mode functions (IMFs) that are symmetric and band-limited. Analytical IMFs were then calculated through the Hilbert transform, which represents the instantaneous frequency content of each IMF. The Hilbert transform signal is analytic and has a complex representation including real and imaginary parts. Then, the Central Tendency Measure (CTM) was introduced to quantify the circular shape of the IMF analysis chart. The result was considered as a useful feature for the diagnosis of normal lung sound signal with ALS. The simulation results show that the analytical CTM IMFs have a strong ability to discriminate between normal and ALS lung sound signals [20].

In this study, we aimed to diagnose and evaluate the severity of chronic obstructive pulmonary disease based on the characteristics of the time and frequency of S transform applied to the pulmonary sound signal, which has not been widely studied for COPD diagnosis.

Material and Methods

The general block diagram of the research is presented in Figure 2. According to this block diagram, first, the necessary filters are applied to the lung sound signal, then the primary features are extracted using the proposed of combine the Discrete Cosine Transform and Discrete Orthogonal Stockwell Transform (DCT-DOST) algorithm, and finally, the features are reduced through mathematical statistics. Then, class label classification is applied to KNN and SVM classifiers.

DATABASE

In this study, two stethoscopes were used to collect data through a clinical method. A Computerized Medical Instrumentation (CMI) database has been created with lung and heart sounds from patients with different stages of COPD, respiratory disorders, such as asthma and chronic bronchitis, and healthy breathing recordings from various individuals. Voluntary acceptance was assessed through a voluntary form with minimal information. Patients aged 38 to 68 years are selected from different occupational groups, socio-economic statuses, and male and female genders for the analysis of disorders. The studied population consists of 13 female and 64 male. The distribution of diseases according to gender is shown in Table 1.

During the study, healthy subjects and those with asthma were excluded from the testing group, and only individuals with COPD were examined. As a result, the publicly available database only contained information on subjects with COPD, while the database for asthmatic and healthy cases was excluded.

The 16-channel database is acquired with lung and heart auscultatory sounds collected from 8 basic foci on both sides of every subject. Simultaneous recordings from 2 channels for the left and right body regions were made for the TR@ respiratory database. However, parallel recording of 2-channel hearing aid sounds can cause deviations in milliseconds. The coordinator needs a distinct point to separate the start of two adjacent recordings. In this study, the patient was asked to cough for the first 5 seconds before starting to breathe to provide a clear separation between recordings. Coughing during auscultation can cause an unexpected increase in the sound signal. Peaks in specific areas of sound can be automatically detected using the built-in CMI and marked with an annotation bar.

Khan et al. also discuss the advantages of electronic stethoscopes over traditional stethoscopes, such as the ability to record and analyze sounds, and the potential for telemedicine applications [21].

Despite the specifications of the digital stethoscope, which reduces 85% of ambient noise, artificial sounds such as room acoustics, contact noise from the doctor, and high-frequency movement can cause friction between the skin and the diaphragm, leading to unwanted noise. To remove any offset, lung sounds were filtered using a high-pass filter at 7.5 Hz (Butterworth first-order DC filter). In addition, a low-pass filter at 10 kHz (Butterworth 8th-order filter) was used to reduce aliasing and high-frequency noise during the analysis [22].

PRE-PROCESSING

In general, filtering is a necessary step before processing to remove noise and signal interference. In this database, filtering was done to remove unwanted noise and friction between the stethoscope's diaphragm and the skin. In this section, a secondary filter will be used to remove signal interference. The filter used in this research is a Butterworth filter.

In this database, the heart and lung signals can interfere with each other due to overlapping frequency ranges. The optimal frequency range of the lung signal is approximately 150 Hz to 2000 Hz, while the main frequency range of the heart signal is below 150 Hz [23]. To separate the two signals, a 4th-order Butterworth band-pass filter was used with a lower cut-off frequency of 150 Hz and an upper cut-off frequency of 1950 Hz.

The reason for using a 4th-order Butterworth filter is that increasing the order of the filter not only increases its sharpness but also causes a greater delay when applied. This results in increased computational requirements. Therefore, lower orders of the Butterworth filter are preferred, provided that the filter's cut-off frequency is appropriate. In this study, a suitable cut-off frequency has been obtained using a 4th-order filter, and therefore there is no need to increase the order of the filter.

Due to the small number of subjects studied, each signal was divided into 3 segments to artificially increase the dataset, while maintaining the same label. This increased the number of samples from 59328 to 19776 per segment, and the number of sample increased from 42 to 126.

Stockwell Transform

The lung signal is a dynamic and non-static signal. As a result, time-frequency transform is suitable for them. The transform studied in this research is the modified S transform. In the following, S transform and its modifications will be introduced.

The S transform retains the good properties of both the short-time Fourier transform (STFT) and wavelet transform. The S transform can be considered a wavelet transform that is phase-corrected, and from another point of view, it can be seen as a special mode of the STFT that uses a Gaussian window with a variable length. The length of this Gaussian function depends on the variance of the function, becoming wider as the variance increases and narrower as the variance decreases.

The S transform is defined by determining the local spectrum at a specific time point (t=τ) in a time series (x(t)). This is achieved by multiplying x(t) with a Gaussian window, centered at t=τ, and then taking the Fourier transform of the resulting product.

$$S(t,f,\sigma)=\int_{-\infty}^{+\infty} x(\tau)g(t-\tau,\sigma)e^{-j2\pi f\tau}d\tau \qquad (1)$$

In the original S transform, a scaled Gaussian window called $g(t-\tau,\sigma)$ is used, with its midpoint at $\tau = t$. For any given time, point t and frequency f, the S transform can be considered a collection of localized Fourier coefficients. These coefficients are obtained by analyzing only the part of the primary function that lies within a few cycles on either side of $\tau = t$. As the frequency f increases, the relevant range of τ becomes Morse localized around t due to the scaled narrowing of the Gaussian window $g(t-\tau,\sigma)$.

For this purpose, variance is considered as a function of frequency. The variable length of the window makes the resolution variable with the frequency. The scaled Gaussian window $g(t-\tau,\sigma)$ where the middle point of this window is located at the point τ=t, is in the form of equation 2:

$$g(t-\tau,\sigma)=\frac{1}{\sigma\sqrt{2\pi}}e^{\left(-\frac{(t-\tau)^2}{2\sigma^2}\right)} \qquad (2)$$

By choosing the variance as $\sigma=\frac{1}{|f|}$, the Gaussian window is calculated as equation 3. In equation 4, the Fourier transform of this Gaussian window is presented in terms of the variable τ.

$$g\left(t-\tau,\frac{1}{|f|}\right)=\frac{|f|}{\sqrt{2\pi}}e^{\left(-\frac{(t-\tau)^{2t}f^2}{2}\right)} \qquad (3)$$

When the Fourier transform of it is taken with respect to τ, which is also a Gaussian function, the resulting function is obtained.

$$G(v,f)=e^{\left(-\frac{2\pi^2 v^2}{f^2}\right)} \qquad (4)$$

Finally, S transform of $h(t)$ signal can be expressed as equation 5:

$$ST(\tau, f) = \int_{-\infty}^{+\infty} h(t) \frac{|f|}{\sqrt{2\pi}} e^{\left(-\frac{(\tau - t)^2 f^2}{2}\right)} e^{-j2\pi ft} dt \tag{5}$$

As the frequency increases, the length of the Gaussian window decreases and leads to an increase in the length of the window in the frequency domain. Thus, in the S transform, the frequency resolution is better at low frequencies and the frequency resolution is lower at high frequencies, but the time resolution is increased. This transform has a weaker performance in detecting high frequencies than lower frequencies. To solve this issue, amendments have been proposed, which can be mentioned as a change [24,25].

Discrete Orthonormal Stockwell Transform (DOST)

They provide an efficient method for computing the discrete canonical Stockwell transform, DOST. DOST is a modified version of S transform that solves many memory and computing issues, because Sin and Cos functions have been used [26]. In DOST, the input signal is displayed periodically. And while reducing the coefficients, it loses its shape.

For how to combine the transforms to obtain the DOST transform, we follow the path of Wang and Orchard. The following basis vector defined by Stockwell is a sum of the Fourier basis vector that is time-shifted and phase-corrected.

$$D_{\nu\beta\tau}[k] = \frac{e^{i\pi\tau}}{\sqrt{\beta}} \sum_{f=\nu-\beta/2}^{\nu+\beta/2-1} exp\left(-i\frac{2\pi}{N}kf\right) exp\left(+i\frac{2\pi}{\beta}\tau f\right) \tag{6}$$

In this context, f represents the frequency, while t and τ are both variables that correspond to time or space and ν is the center of the sub block in the overall matrix. DOST is an orthogonal transform and each coefficient is obtained by the inner product of the signal vector with a basis vector. At last, observe that the ultimate summation is an inverse Fourier transform applied to a sub band of the Fourier change of the signal. Finally, β_k, τ_k, Ω_k are the bandwidth, time index, and bandwidth of the base vector, respectively.

$$< h, D_{\nu\beta\tau} > \sum_{K=0}^{N-1} h[k] \frac{e^{i\pi\tau}}{\sqrt{\beta}} \sum_{f=\nu-\frac{\beta}{2}}^{\nu+\frac{\beta}{2}-1} exp\left(-i\frac{2\pi}{N}kf\right) exp(+i\frac{2\pi}{\beta}\tau f) =$$

$$\frac{e^{i\pi\tau}}{\sqrt{\beta}} \sum_{f=\nu-\frac{\beta}{2}}^{\nu+\frac{\beta}{2}-1} \exp\left(+i\frac{2\pi}{\beta}\tau f\right) \sum_{k=0}^{N-1} h[k] \exp\left(-i\frac{2\pi}{N}kf\right) \tag{7}$$

$$= \frac{e^{i\pi\tau}}{\sqrt{\beta}} \sum_{f=\nu-\frac{\beta}{2}}^{\nu+\beta/2-1} F(h)|f| exp\left(+i\frac{2\pi}{\beta}\tau f\right)$$

$$S[k] = \sqrt{\beta_k e^{i\pi\tau k}} \left(F_{\Omega_i}^{-1} Fh\right)[k] \tag{8}$$

The Discrete Orthonormal Stockwell Transform (DOST) is a variation of the general Fourier-family transform, but instead of a truncated Gaussian window, it uses a rectangular window. In (10), a fast algorithm for the DOST is introduced, which can be modified to produce the conjugate-symmetric DOST as noted in (10). Another way to analyze the DOST is to view it in the context of matrices. It can be expressed as a matrix product. And finally, DOST can be considered in the framework of matrices:

$$DOST = \left(\oplus_{i=1}^{K} D_i \right) DFT \tag{9}$$

$$D_i = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & -1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & (-1)^n \end{bmatrix} F^{-1} \tag{10}$$

The DOST transform is separable, so higher dimensional transforms can be performed by applying the transform on each axis one after the other.

The discrete cosine transform is a real-valued transform, which makes it more suitable for compression and filtering. The connection of DCT-DOST with Fourier transform makes it compatible with DOST algorithm. A DCT-based DOST (DCT-DOST) may be defined simply by replacing the DFT in Eqs. (9) with DCT:

$$DCT - DOST = \left(\oplus_{i=1}^{K} DCT_{ni}^{-1} \right) DCT \tag{11}$$

Due to the advantages that DCT transform has when compressing the initial coefficients and also its coefficients are real, these two transforms have been combined and DCT-DOST transform (Discrete Orthogonal Stockwell Transform using Discrete Cosine Transform) is presented. In DCT transform, it can maintain the shape of the input signal while reducing the coefficients [27].

$$DCT - DOST = (\oplus_{i=1}^{k} DCT_{n_i}^{-1})\ DCT \tag{12}$$

Finally, due to the higher calculation speed and the truth of the coefficients, S transform corrections (DCT-DOST) have been used.

FEATURE EXTRACTION

After applying the necessary filters and obtaining the raw signal, the desired transform is applied to the signal. In this research, the DCT-DOST transform was used, which was applied to the lung sound signals, and the resulting coefficients were obtained as shown in Figure 3.

In DCT-DOST transform, the number of coefficients is equal to the number of signal samples. the number of DCT-DOST transform, coefficients are equal to the number of samples and its value is 19776.

The number of features is 19776. To reduce the dimensionality of the feature space, mathematical parameters such as mean, mode, max, min, kurtosis, skewness, standard deviation, variance, range, rms, median, and mode were used. This reduced the number of features to 14, as shown in Figure 4, which illustrates the general process of feature selection.

Results

The validation method used in this study is K-fold, and we will discuss their properties below. The following results of validation using KNN and SVM methods are observed and evaluated.

Classification means labeling areas based on similar characteristics of signals. The purpose of this research is to implement KNN and SVM algorithm in order to compare the accuracy of feature classification. In this article, due to the strong features extracted from DCT-DOST, a classifier with high speed and less amount of mathematical calculations is used, which is the main point of the article.

KNN calculates the distance between a test data point and each training data point using a distance metric such as Euclidean or Manhattan distance. It then selects the k closest neighbors and assigns the test data point to the majority class or mean of their respective labels. The choice of distance metric can have a significant impact on the performance of the algorithm.

SVM stands for Support Vector Machine, a powerful machine learning algorithm used for classification or regression tasks. SVMs use a kernel function to transform the input data into a high-dimensional feature space, where a linear decision boundary can be used to separate the classes. The choice of kernel function can have a significant impact on the performance of the algorithm.

In KNN classification, which had better results compared to SVM, Hamming, Euclidean, Chebychev, correlation and Minkowski distances and the number of neighborhoods from 1 to 10 were used with trial and error. As the results show, the percentage of results decreased with the increase in the number of neighborhoods.

In the K-fold method, there is a single parameter called k, which refers to the number of groups into which a given data sample is to be divided. As a result, this method is often referred to as K-fold validation. The goal of K-fold validation is to achieve a model with optimal parameter values. Model parameters are estimated using training data, while model error estimation is calculated based on validation data. After designing and building a model or algorithm, one of the most important steps is to evaluate its performance, accuracy, and correctness. In this study, the criteria of sensitivity, specificity, precision and accuracy have been used to evaluate the classification and distinguish the classes, which are briefly:

$$Accuracy = \frac{True\ Psitive + True\ Negative}{True\ Positive + False\ Negative + False\ Positive + True\ Negative} \tag{13}$$

$$Sensitivity = \frac{True\ Positive}{True\ positive + False\ negative} \tag{14}$$

$$Specificity = \frac{True\ Negative}{True\ Negative + False\ Positive} \tag{15}$$

$$precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{16}$$

True Positive (TP): A test result that correctly indicates the presence of a condition or specificity.

True Negative (TN): A test result that correctly indicates the absence of a condition or specificity.

False Positive (FP): A test result which wrongly indicates that a particular condition or attribute is present.

False Negative (FN): A test result which wrongly indicates that a particular condition or attribute is absent

In the KNN classifier, the best number of neighbors and distance, as well as in the SVM classifier, the best kernel and number of neighbors were obtained experimentally using K-fold evaluation methods.

As shown in Figure 5, the percentages obtained from the KNN classification with 5 different distances and the number of neighbors are from 1 to 5. As Figure 5 shows, the results decrease with the increase in the number of neighbors. As a result, in all distances, the number of neighbors 1 shows the best result.

The results shown in figure 5, with the data used in this study, using the KNN classification, from neighborhood number 1 to neighborhood number 5, the results decrease respectively, and in all distances, the best result is for the Euclidean distance with neighborhood number 1.

Figure 6 shows the confusion matrix of the KNN classifier. Due to 10 repetitions, the confusion matrix exhibits slight changes, which are represented by the standard deviation (STD).

Table 2 displays the results of SVM classification performed using three different kernels: Linear, Polynomial and Radial Basis Function (RBF).

Table 2 indicates that the polynomial kernel achieved the highest performance, while the linear kernel obtained the lowest performance.

Figure 7 illustrates that the KNN classifier with Euclidean distance and neighborhood 1 achieved better results than the SVM classifier with the polynomial kernel

This research aims to diagnose and evaluate Chronic Obstructive Pulmonary Disease from the lung signal with 5 different severities from COPD0 to COPD4 using time-frequency transform of S transform. Several tests and methods have been done to improve the general and partial results to achieve the best classification accuracy. At first, after equalizing the length of the lung signal and performing the required pre-processing, including filtering the interference on the signal, S transform was applied to the data to extract features.

Due to a large number of signal samples and the same number of coefficients obtained from the samples, feature dimension reduction has been used using mathematical statistics, reducing the number of coefficients from 19776 to 14 features. Now, to diagnose and evaluate the different severity of this disease, the features have been applied to KNN and SVM classification, which was done in KNN using the K-fold validation method.

The main goal of this study is to use S transform to extract features from lung sound signals for COPD diagnosis. Using the KNN classifier with different distances and the number of neighbors from 1 to 10 and the SVM classifier with different kernels, the best results were obtained by trial and error, which shows the superiority of the KNN classifier compared to SVM. By using the KNN classifier, good results were obtained in the accuracy, sensitivity and precision evaluation criteria.

According to the investigations carried out in the KNN classifier with K-fold validation with k=10 and the number of neighbors 1 and the Euclidean distance with 97.45% accuracy, 98.39% accuracy, and 93.88% sensitivity, the best results among others have evaluation methods. Table 3 shows the proposed algorithm performed in this study with other performed methods.

Conclusion

In this study, real coefficients and primary features were extracted using Time-frequency S transform and its modification based on DCT-DOST transform. By applying the statistical features to the primary features, a very significant reduction in the dimensions of the features to 14 features was achieved. The results of the 5-class classification show the effective space of features in the classification of COPD disease severity.

Author Statement

Mahsa Amin Eskandari: Methodology, Software, Formal Analysis, Writing Original Draft, Review and Editing.

Saeid Rashidi: Supervision, the idea of the research, helping in Programming, Helping in editing paper.

Data availability the database used in this study was downloaded from the below site, that is available by link

(https://data.mendeley.com/datasets/p9z4h98s6j/1).

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Compliance with ethical standards

Research Involving Human Participants and/or Animals This paper does not contain any studies with human participants or animals performed by any of the authors.

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Conflict of Interest The authors declare that they have no conflict of interest.

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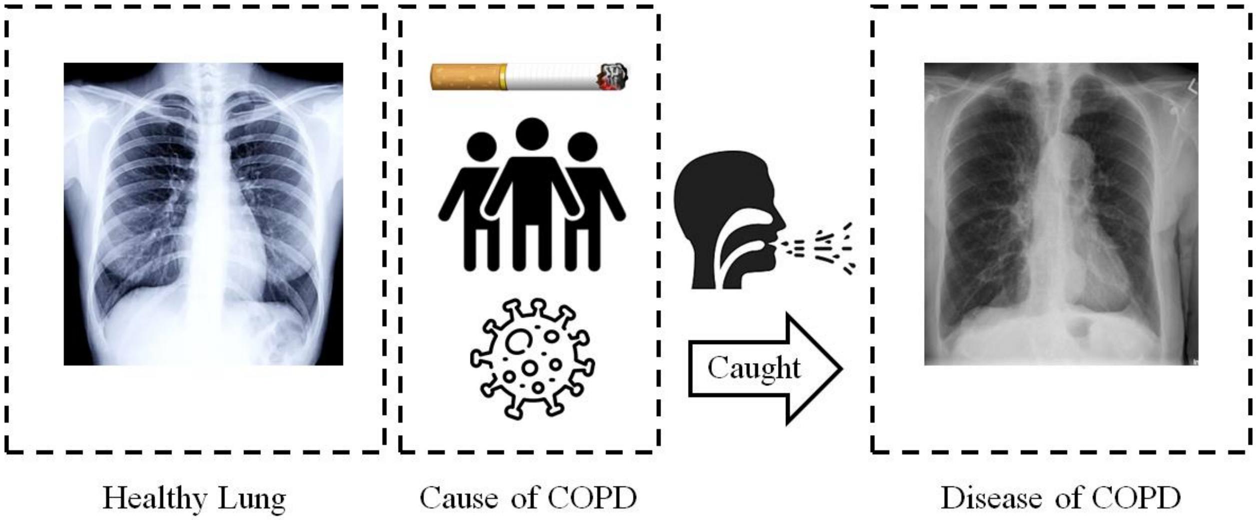


Figure 1

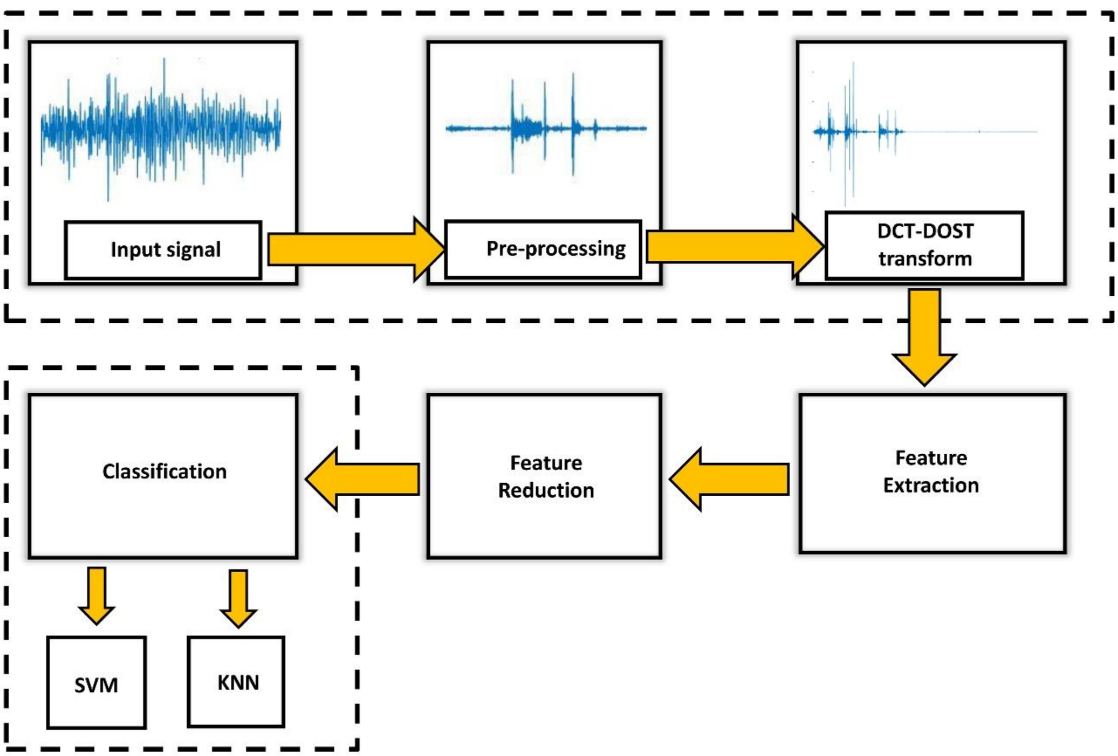
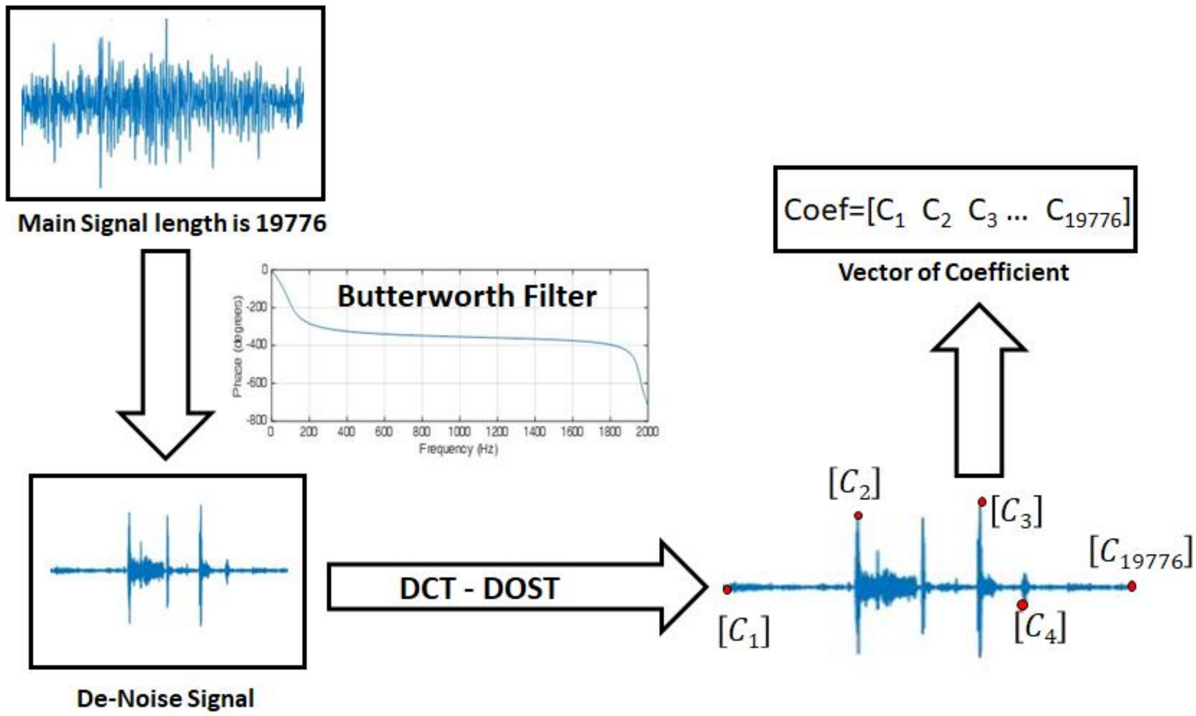


Figure 2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Butterworth Filter
Phase (degrees)
Frequency (Hz)
De-Noise Signal
DCT - DOST
[C_1]
[C_2]
[C_3]
[C_4]
[C_{19776}]
Coef=[C_1 C_2 C_3 ... C_{19776}]
Vector of Coefficient

Figure 3

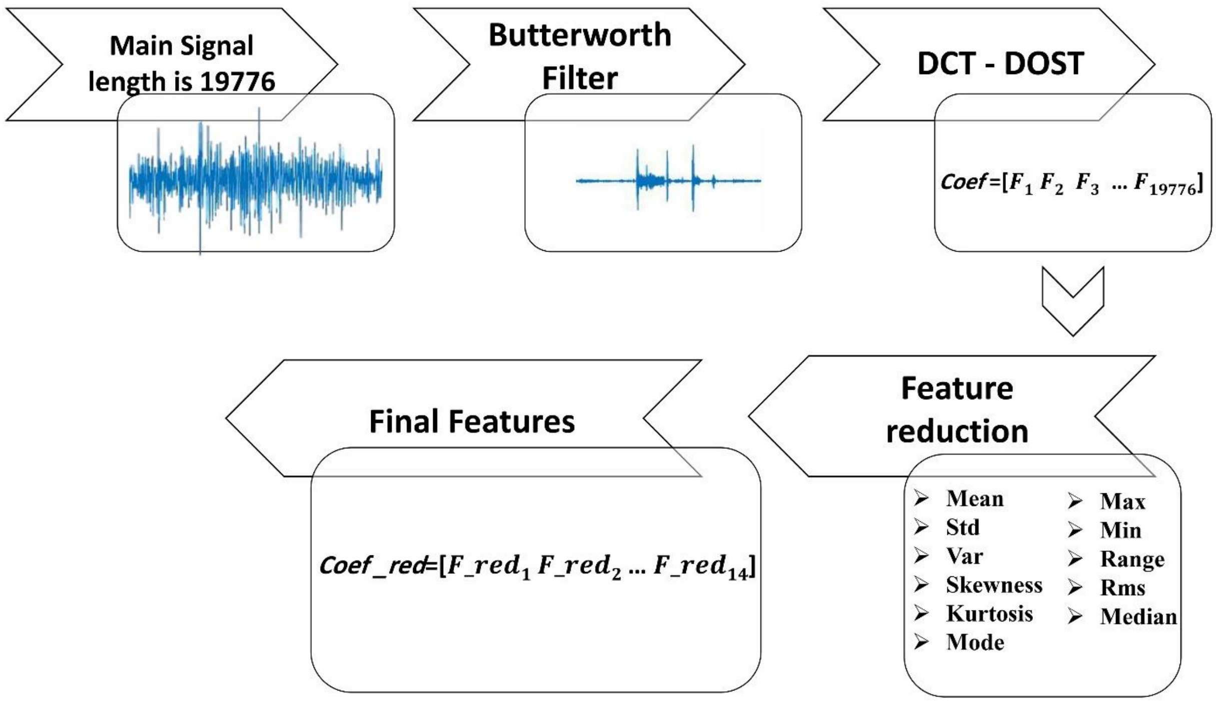
Main Signal
length is 19776
Butterworth
Filter
DCT - DOST
Coef =[F_1 F_2 F_3 ... F_19776]
Feature
reduction
Mean
Std
Var
Skewness
Kurtosis
Mode
Max
Min
Range
Rms
Median
Final Features
Coef_red=[F_red_1 F_red_2 ... F_red_14]

Figure 4

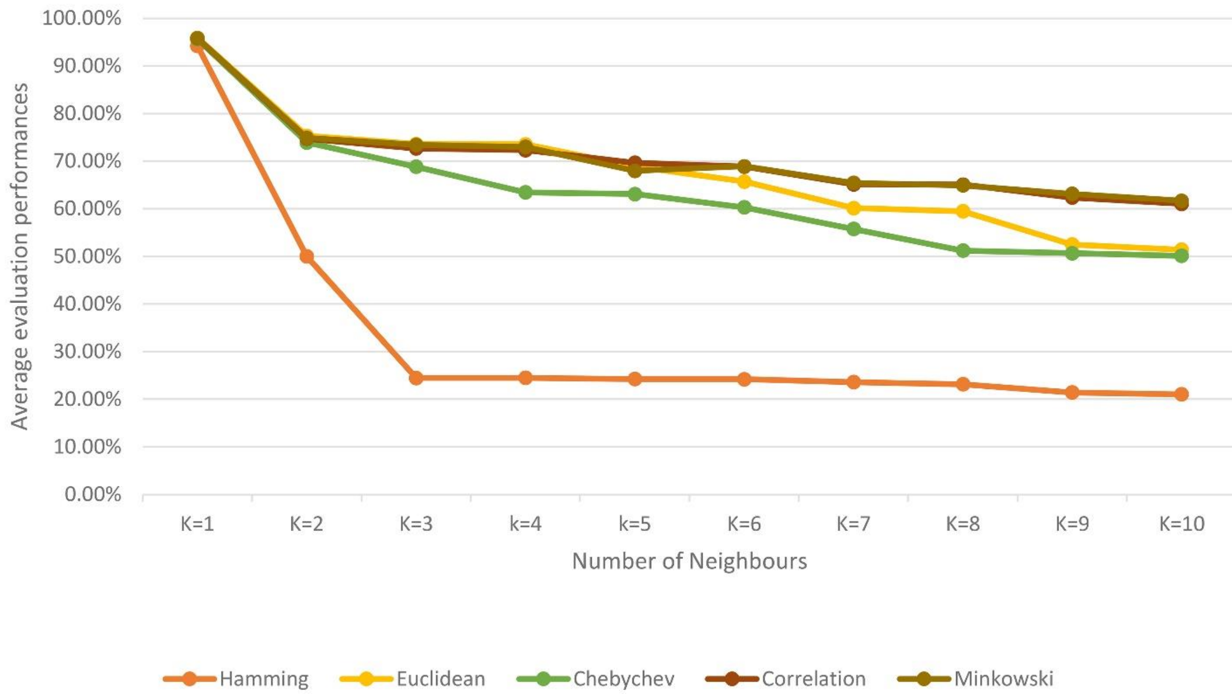
100.00%
90.00%
80.00%
70.00%
60.00%
50.00%
40.00%
30.00%
20.00%
10.00%
0.00%
Average evaluation performances
K=1
K=2
K=3
k=4
k=5
K=6
K=7
K=8
K=9
K=10
Number of Neighbours
Hamming
Euclidean
Chebychev
Correlation
Minkowski

Figure 5

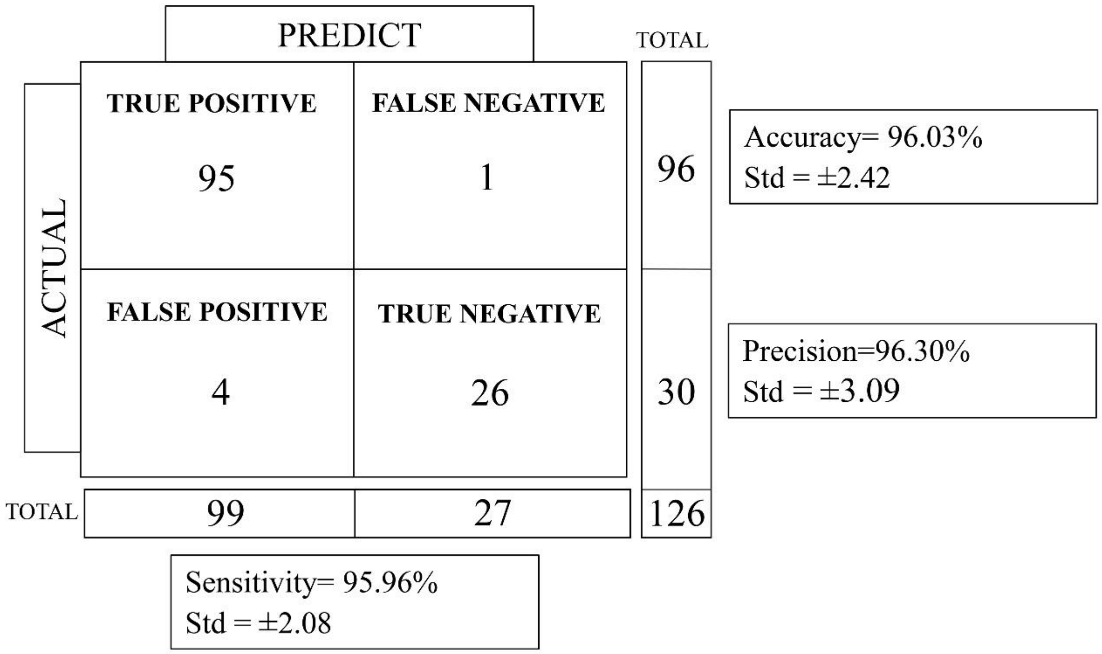

Figure 6

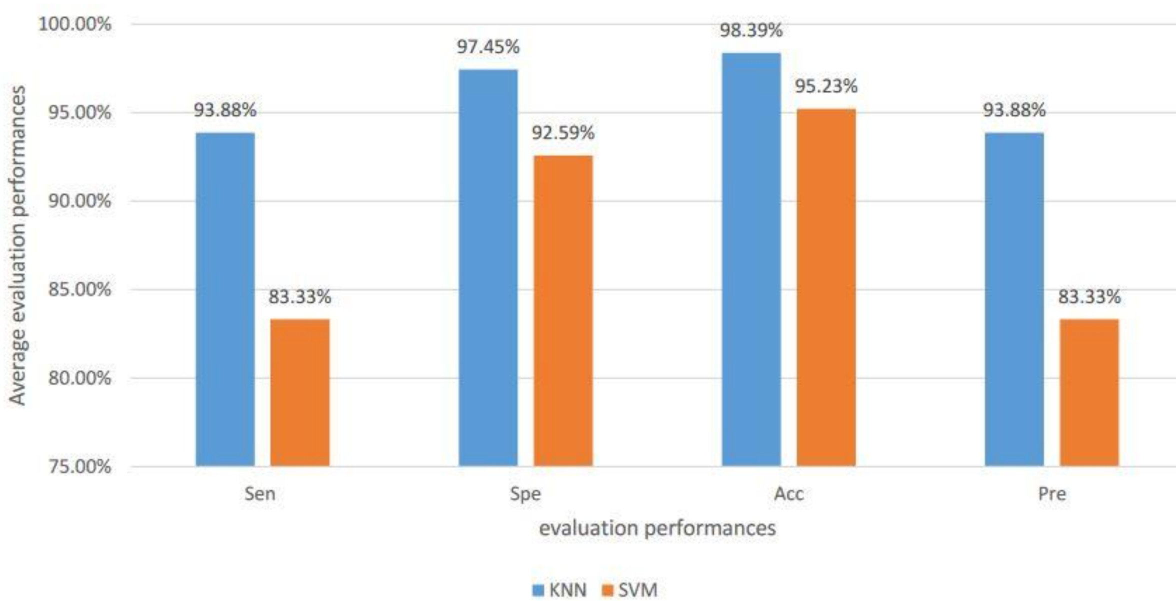

Figure 7

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Table 1

Diseases	Records	Gender	
		Male	Female
Asthma	6	4	2
COPD 0	5	4	1
COPD 1	5	4	1
COPD 2	7	7	-
COPD 3	7	6	1
COPD 4	17	13	4
Healthy	30	26	4
Total	**77**	**64**	**13**

Table 2

Kernel	SEN (%)	SPE (%)	ACC (%)	PRE (%)
Polynomial	83.33	95.23	92.59	83.33
Linear	67.46	89.23	83.82	67.46
RBF	76.98	93.04	89.31	76.98

Table 3

Authors	Signal Type	Channel	Method	Classifier	Spe (%)	Sen (%)	Acc (%)
Morillo et al. [28]	Tracheal Sound	1	STFT	NN	81.80	72.00	77.60
Altan et al. [29]	Lung Sound	12	3D-SODP	DBN	93.65	93.34	95.84
Kim et al. [30]	Lung sound	-	VGG16	SVM	85.70	82.30	82.40
Purpose Method	Lung Sound	12	DCT-DOCT	KNN	98.39	93.88	97.45