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COVID-19 DETECTION USING VARIATIONAL MODE DECOMPOSITION OF COUGH SOUNDS

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Highlights

- The diagnosis of COVID-19 was performed by distinguishing the cough sounds of COVID-19 positive people from those of COVID-19 negative ones.
- The study was carried out on the "Virufy"open access cough sound dataset.
- Variational Mode Decomposition (VMD) method produced new features for the discrimination of cough sounds.
- Data balancing performed with the oversampling technique has significantly increased the performance.
- Ensemble machine learning methods showed high performances to identify cough sounds as COVID-19 and Non-COVID-19 through classification.

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ABSTRACT: According to the World Health Organization, cough is one of the most prominent symptoms of the COVID-19 disease declared as a global pandemic. The symptom is seen in 68% to 83% of people with COVID-19 who come to the clinic for medical examination. Therefore, during the pandemic, cough plays an important role in diagnosing of COVID-19 and distinguishing patients from healthy individuals. This study aims to distinguish the cough sounds of COVID-19 positive people from those of COVID-19 negative, thus providing automatic detection and support for the diagnosis of COVID-19. For this aim, "Virufy" dataset containing cough sounds labeled as COVID-19 and Non COVID-19 was included. After using the ADASYN technique to balance the data, independent modes were obtained for each sound by utilizing the Variational Mode Decomposition (VMD) method and various features were extracted from every mode. Afterward, the most effective features were selected by ReliefF algorithm. Following, ensemble machine learning methods, namely Random Forest, Gradient Boosting Machine and Adaboost were prepared to identify cough sounds as COVID-19 and Non COVID-19 through classification. As a result, the best performance was obtained with the Gradient Boosting Machine as 94.19% accuracy, 87.67% sensitivity, 100% specificity, 100% precision, 93.43% F-score, 0.88 kappa and 93.87% area under the ROC curve.

Keywords: *ADASYN, Cough Sound, COVID-19, Ensemble Machine Learning, ReliefF, Variational Mode Decomposition (VMD)*

1. INTRODUCTION

The coronavirus disease called as COVID-19 emerged in Wuhan, China, in December 2019. It triggers what doctors call a respiratory infection and it is declared a global pandemic in 2020 by the World Health Organization (WHO) [1, 2]. There have been 622.389.418 confirmed cases of COVID-19, including 6.548.492 deaths, reported to WHO (as of October 18, 2022). COVID-19 is spreading rapidly and related deaths are increasing day by day. Therefore, early diagnosis of this disease is very important in terms of taking early precautions, reducing deaths and better management of a pandemic.

The WHO states that coughing, high fever, fatigue, headache, muscle, sore throat and shortness of breath are common symptoms of COVID-19 [3, 4]. Cough is the predominant of them since it is one of the early symptoms of respiratory tract infections. Also it occurs in 68% to 83% of people with COVID-19 who come for a medical examination [2, 3]. Therefore, automatic detection of COVID-19 from coughing by using cough sound signals and machine learning has recently been one of the popular and important fields of study for early diagnosis.

When the literature studies were evaluated in terms of early diagnosis of patients with and without COVID-19, it was seen that some researchers classified only a single cough sound signal with different machine learning methods. Bagad, et al. [5] benefited from cough sounds and CNN-based framework to find COVID-19. They obtained area under of ROC curve (AUC) of 72%. Chaudhari, et al. [6] detected COVID-19 and Non COVID-19 with AUC of 77.1% using cough sounds and Ensemble Deep Learning Model. Imran, et al. [7] distinguished COVID-19 coughs and several types of Non COVID-19 coughs through classical machine learning and deep learning methods. Accuracy of 92.85% was accessed in the

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study. Fakhry, et al. [8] utilized cough sounds and Multi-Branch Deep Learning Network for diagnosis of COVID-19. Researchers acquired average AUC of 91.0%. Melek Manshouri [9] defined the coughs of subjects with COVID-19 and Non COVID-19 using Support Vector Machine method. As a result of their study, accuracy of 95.86% was reached. Pahar, et al. [2] discriminated coughs of patients with COVID-19 from both COVID-19 negative and healthy coughs by means of different machine learning classifiers. 98% and 94% AUC values were obtained with Resnet50 and LSTM respectively. Kamble, et al. [10] developed several systems using cough sounds and machine learning methods. Their best system obtained AUC of 76.31% employing light gradient boosting machine (LightGBM) backend. Rao, et al. [11] developed a model using VGG13 deep learning architecture for detection of COVID-19 cough sound. Their model achieved an average AUC of 78.3%. Erdoğan and Narin [12] detected COVID-19 patients from cough data. The highest accuracy in the study was found to be 98.4%. Tena, et al. [13] diagnosed COVID-19 with accuracy of 90% using cough sounds and supervised machine-learning algorithm. Islam, et al. [14] used cough sounds and a deep neural network. Thus, they developed an algorithm for automated diagnosis of COVID-19. The researchers automatically detected COVID-19 cough sounds with accuracies of 89.2%, 97.5%, and 93.8% using different feature vectors. In addition to these studies, some researchers classified different biological signals such as breathing and speech sounds along with cough sounds for the same purpose. Aly, et al. [15] studied the diagnosis of COVID-19 using cough, breathing and speech sounds together with Deep Model and Shallow classifiers. Average AUC of 96.4% performance was obtained in their study. Coppock, et al. [16] studied with cough and breathing sounds. They used ResNet and accessed AUC of 84.6%. Khriji, et al. [17] recognized positive COVID-19 cases via a deep learning technique-based COVID-19 cough and breathe analysis. In their study, Deep LSTM framework achieved up to accuracy of 80%. Grant, et al. [18] used crowd-sourced database consisted of cough, speech and breath sounds of COVID-19 and Non COVID-19 subjects. Random forests (RF) and deep neural networks (DNN) classifiers were utilized and AUC of 68.36% for cough sounds was obtained. Lella and Pja [19] prefered to classify voice, dry cough, and breath sounds with multi-channeled Deep Convolutional Neural Network. They obtained accuracy of 95.45% for the detection of COVID-19 disease from these sounds.

As a result of all literature studies, it has been concluded that cough sound are of great importance in the diagnosis of COVID-19 and in most cases, it achieves high success even when used alone. Based on this inference, the aim of this study was established and the automatic detection of COVID-19 was carried out for early diagnosis. For this aim signal processing method, appropriate machine learning methods and ''GitHub'' open source cough dataset ''Virufy'' were used. In this study, diagnosis is based on distinguishing of COVID-19 and Non COVID-19 cough sounds by classification.

It has been a difficult task to determine features that will enable characterize the signals. Researchers in literature have often used mel frequency cepstral coefficients (MFCC), mel spectrogram, short time fourier transform (STFT) signal processing methods and similar features such as log frame energies, zero crossing rate (ZCR), skewness, kurtosis to extract characteristic features from sound signals. Within the scope of this study, unlike the previous ones, Variational Mode Decomposition (VMD) method has been used to search new features used in distinguishing COVID-19 coughs from those of Non COVID-19. VMD is a new modal decomposition method proposed in recent years and can effectively solve the shortcomings of the conventional Empirical Mode Decomposition (EMD) such as sensitive to noise and mathematical expression. VMD decomposes signal into a number of sub-signals in other words independent modes [20]. Since VMD independent modes can capture the distinctive features of signals at different frequencies, the features extracted from these modes will be effective for the analysis and discrimination of cough sounds and therefore for the diagnosis of COVID-19 disease [21]. For this reason, in this study, after the data augmentation process with ADASYN technique, cough sound signals have been decomposed into independent modes by 5-layer VMD method and features have been extracted from each mode. Then, the most effective features have been determined through ReliefF feature selection algorithm [22]. By using these features with different ensemble machine learning methods, namely Random Forest (RF), Adaboost and Gradient Boosting Machine (GBM), the cough sounds of COVID-19 patients were separated from those of Non COVID-19. The findings of the study indicate that COVID-19 cough sound signals can be identified with acceptable classification accuracy and AUC.

As a result of the study, it was concluded that automatic detection of COVID-19 from cough sounds were achieved with high success thanks to data augmentation, VMD-based features and ensemble machine learning methods. Thus, early diagnosis of COVID-19 can be possible.

2. MATERIALS AND METHODS

2.1. Dataset

Virufy COVID-19 open-access Cough Dataset [6] available on ''GitHub''was used in this study. Collection of the cough sound data from subjects were carried out in a hospital under supervision by physicians, following standard operating procedures (SOPs) and informed patient consent. Cough sounds were recorded from 16 subjects using the smartphone app upon the request of Stanford University as seen in Figure 1 [6]. Some of the subjects have various symptoms such as fever chills etc., while others have no symptoms. These subjects were labeled as COVID-19 and Non COVID-19 according to PCR test status. Information about the subjects is shown in Table 1 [9].

Cough sounds records of the patients are in mp3 format with a 48000 Hz of sampling rate in a single channel (mono). After the preprocessing steps were carefully done on the cough sounds, dataset consisted of these coughs is available on ''GitHub''. Also, in the dataset, there are 121 cough sound segments resulting from the segmentation of these sounds. 73 of the segments are Non COVID-19 and 48 are COVID-19. Following the segmentation process, the each subject's cough time was 1640 ms (ms). The segmentation step makes a major contribution to the analysis by emphasizing the significance and dominance of infected regions [23]. Therefore, segmented forms of cough sounds were used in this study.

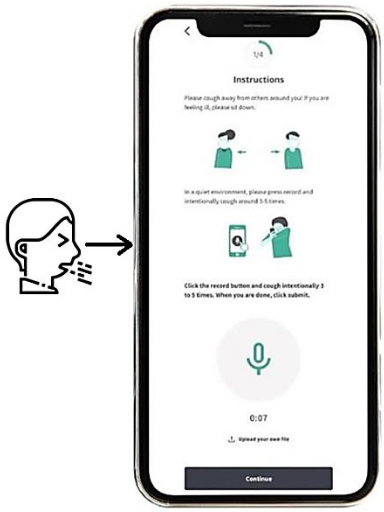

Figure 1. Recording of cough sounds [6]

Table 1. Information of 16 subjects

Patient No	Age	Gender	Any chronic illness	Complaints and symptoms	PCR result
1	53	M	None	None	N
2	50	M	Congestive heart failure	Shortness of breath	P
3	43	M	None	Sore throat	N
4	65	M	Asthma or lung disease	Shortness of breath, worsening cough	P
5	40	F	None	Sore throat, Loss of taste, Loss of smell	P
6	66	F	Diabetes	None	N
7	20	F	None	None	N
8	17	F	None	Shortness of breath, Sore throat, Body aches	N
9	47	M	None	Worsening cough	N
10	53	M	None	Fever, chills, or sweating, Shortness of breath, worsening cough, Sore throat, Loss of taste, Loss of smell	P
11	24	F	None	None	P
12	51	M	Diabetes	Fever, chills, or sweating, worsening cough, Sore throat	P
13	53	M	None	None	N
14	31	M	None	Shortness of breath, worsening cough	P
15	37	M	None	None	N
16	24	F	None	Worsening cough	N

*M: Male, F: Female, N: Negative, P: Positive

2.2 Pre-processing

COVID-19 positive and negative cough sounds in the Virufy dataset are unbalanced (73 Non COVID-19 and 48 COVID-19). The number of positive labeled coughs is very small and this insufficiency may result in failed COVID-19 and Non COVID-19 classification results. To effectively identify COVID-19 coughs, in the pre-processing step, the ADASYN [24] oversampling technique is applied to sound signals. The ADASYN technique is derived from Synthetic Minority Over Sampling Technique (SMOTE). The SMOTE technique creates synthetic samples based on the location of the data. Firstly, it randomly selects a point belong to minority class, then search the k nearest neighbors of the same class [25]. A new point is created in the vector between them for each of these pairs, this new point is located in a random percent of the way from the original point [25]. The ADASYN technique, on the other hand, adds a small random bias to the points after generating the samples, not making them linearly related to their parents. Although this is a small change, it causes an increase of the variance in synthetic data [25].

The parameters determined for the ADASYN technique were the cough data, labels, the number of k-nearest neighbors and beta value. The number of k-nearest neighbors was set to 5. Beta value is the desired level of balance, where 0 means that the size of the minority class will not be changed, and 1 means that the minority class will be ADASYNed to have (approximately, due to rounding) the same size as the majority class [26]. This value was chosen as 1. In this study, thanks to the use of the ADASYN oversampling technique, 34 synthetic positive samples were generated. Thus, 82 positive cough sounds have been available. In total,155 cough sounds were reached, of which 73 were Non-

COVID-19 and 82 were COVID-19. As a result of the pre-processing, the number of cough data in the dataset was augmented.

2.3 Feature Extraction

Dragomiretskiy and Zosso in 2014 [20] has proposed VMD model. It is a non-recursive optimization signal decomposition method that employs the Hilbert transform and Wiener filtering. The method decompases the real valued signal into a finite number of independent modes (IMFs) [20]. In the VMD method, it is considered that each mode has a limited bandwidth of center frequency. In this method, the sum of each mode's predicted bandwidth is also minimized under the constraint that the sum of each mode equals the original signal [27]. Detailed description of the technique and mathematical formulas can be found in the reference [20].

Before the decomposition process, values of VMD parameters should be determined. In this study, decomposition number of modes (k), data fidelity constrained (α) and tolerance convergence criteria (tol) were determined as 5, 120 and 10^{-7} respectively. These parameters were determined according to literature studies associated with sound signals [21, 28].

Choosing the decomposition number of modes (k) as 5 was also supported by correlation analysis. This analysis was carried out utilizing the study of Yang, et al. [29]. Researchers proposed the analysis of the Spearman correlation coefficient between the reconstructed signal from IMFs and the original signal. According to them, if the correlation coefficient reaches the determined threshold value, the VMD is considered to be sufficiently decomposed. Otherwise, k is incremented. In this study, this principle was adopted. The threshold value was determined as 0.80 because it represents very high correlation between sequences. k value was set to 2 initially. Then, VMD decomposition was carried out on each of COVID-19 and Non COVID-19 cough sounds to obtain k IMFs. After that, Spearman correlation coefficient was calculated between reconstructed and original cough sounds. The k value was increased as long as correlation coefficient was less than 0.80. As a result of this process, the k value was found to be 4 for some cough sounds and 5 for others. Choosing a k value of 4 causes insufficient decomposition for cough sounds where this value is found as 5. In the end, it was decided to have a k value of 5 since it included all sounds in the study.

The 5-layer VMD method used in cough sound signals of Non COVID-19 subjects (a) and COVID-19 patients (b) is shown in Figure 2.

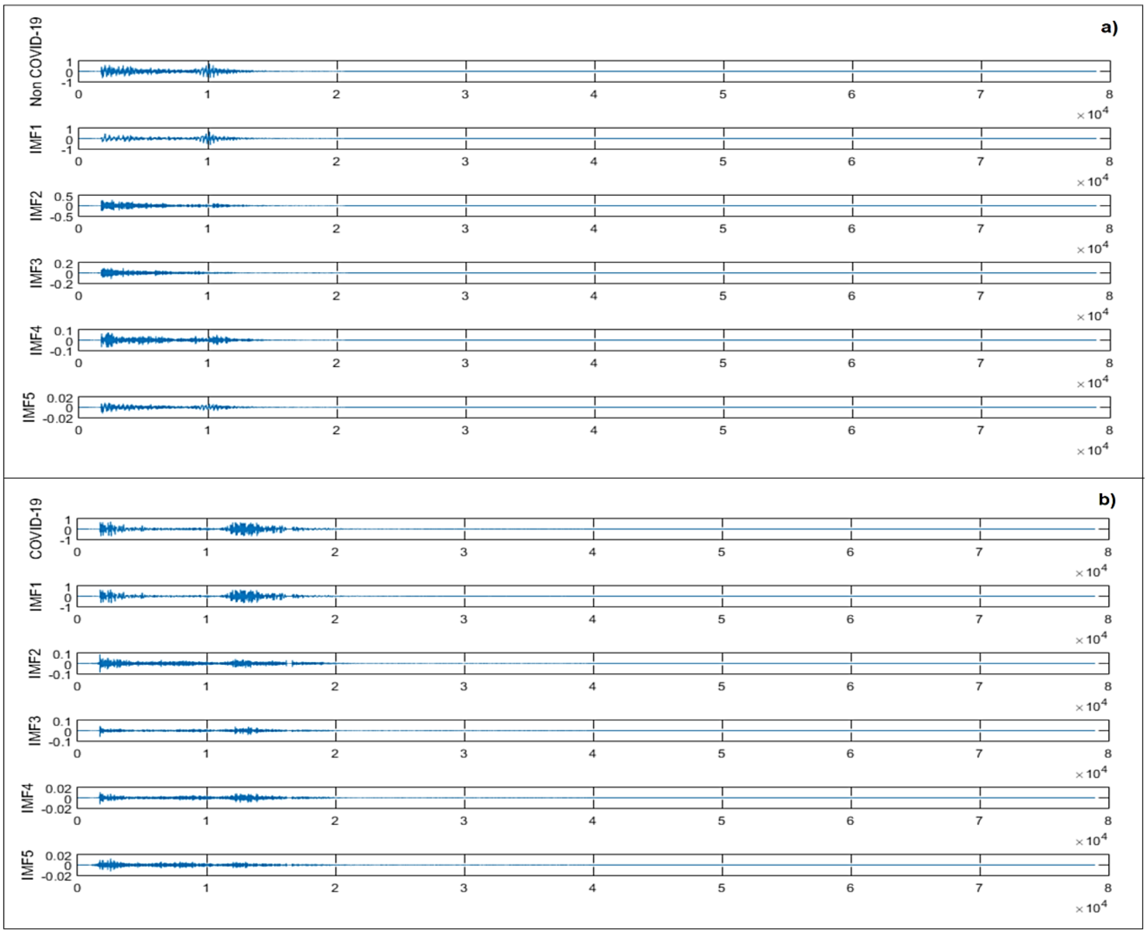

Figure 2. 5-Layer VMD decomposition a) of Non COVID-19 cough sound b) of COVID-19 cough sound

VMD independent modes can capture the distinctive features of signals at different frequencies. Therefore, following features was extracted from each of the modes (IMFs) such that will be effective for the analysis and discrimination of cough sounds.

i.Statistical features

Cough sounds of COVID-19 patients have different signal characteristics than healthy people. COVID-19 coughs may have different statistical characteristics than non-COVID-19 coughs. The variations can be evaluated using the mean, variance, skewness, and kurtosis properties of the time-domain signals at the independent modes. Hence, the mean, variance, skewness and kurtosis statistical values belong to time domain signal of each mode were used as features for COVID 19 disease analysis.

ii.Frequency corresponding to the peak in the spectrum

Figure 3 shows independent modes of Non COVID-19 cough sounds and their associated spectra. As can be seen from this figure, different frequency values correspond to the peak values in each mode. Figure 4 shows independent modes of COVID-19 cough sounds and their associated spectra. Here, too, different frequency values correspond to the peak values in each mode. The frequency values corresponding to the peaks differ not only according to the modes, but also according to the cough sounds of COVID-19 and Non-COVID-19. Therefore, the frequency corresponding to the peak in the spectrum was used as feature in the analysis.

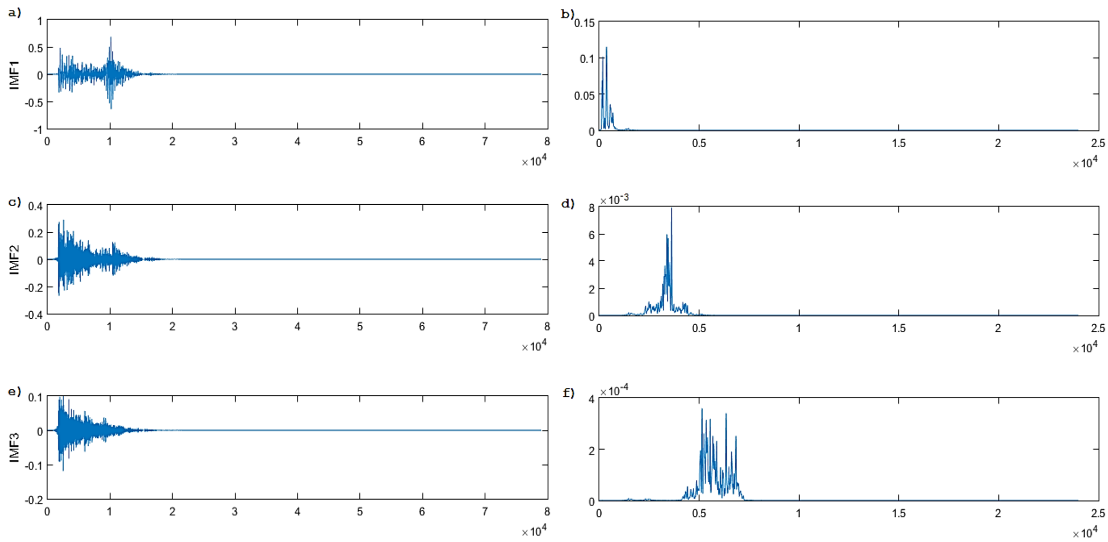

Figure 3. Independent 3 modes of Non COVID-19 cough sound signal and their spectrums (a) IMF1 signal (b) IMF1 signal spectrum (c) IMF2 signal (d) IMF2 signal spectrum (e) IMF3 signal (f) IMF3 signal spectrum

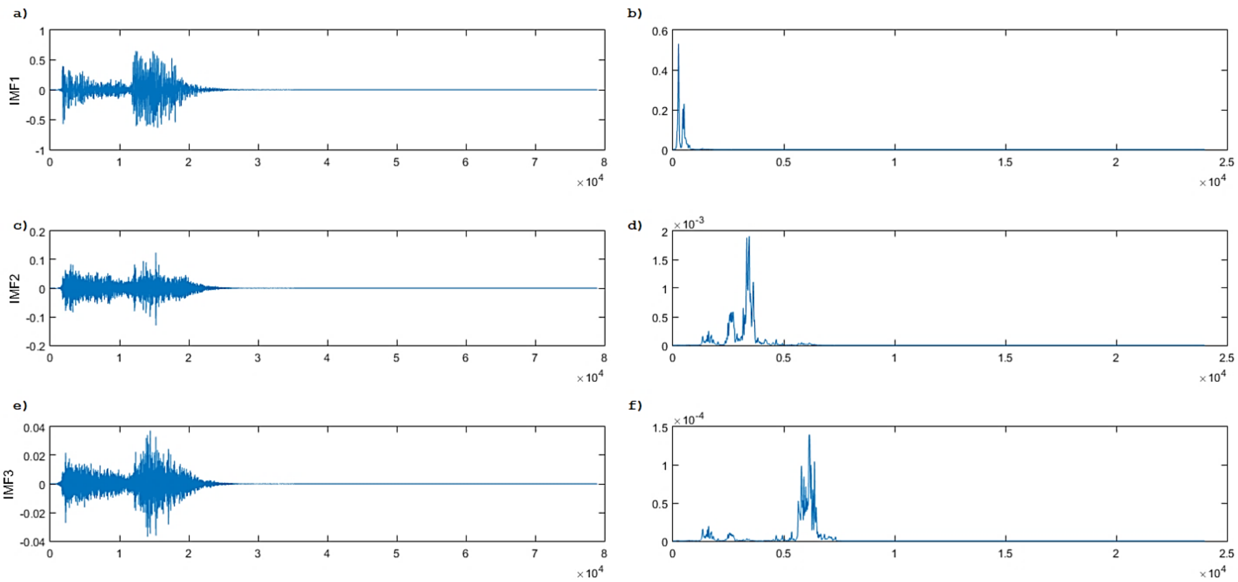

Figure 4. Independent 3 modes of COVID-19 cough sound signal and their spectrums (a) IMF1 signal (b) IMF1 signal spectrum (c) IMF2 signal (d) IMF2 signal spectrum (e) IMF3 signal (f) IMF3 signal spectrum

iii.Peak amplitude

Time-domain peak amplitudes of coughs belong to Non COVID-19 subjects and COVID-19 patients varies. This has led us to use this value as feature for COVID-19 disease analysis.

iv.Energy

In this study, energy of time domain signal at each mode was calculated as seen in Eq. 1 and it was used as a feature for analysis of COVID-19 disease. In the Eq. 1, N denotes the total number k^{th} mode's time domain signal samples, $x_k\ (n)$ is the k^{th} mode's time domain signal.

$$E_k = \sum_{n=1}^{N} |x_k(n)|^2 \quad \text{Eq. 1}$$

v.Entropy measures

Entropies are mathematical algorithms developed to measure repeatability, predictability, and complexity in a signals [30]. In this study, Permutation Entropy, Renyi's Entropy and Spectral Entropy measures were calculated for time domain signal of each mode as features for analysis of COVID-19.

Permutation entropy (PerEnt) measures the randomness of a signal [31]. A high PerEnt value indicates that the signal is more random. It is considered that the randomness of Non-COVID-19 cough sound is different from that of the COVID-19 cough sound. This measure is calculated as stated in the reference [21].

Renyi's entropy (ReEnt) gives information about the spectral complexity of the signal [32]. It is calculated as in referance [21].

Spectral entropy (SpecEnt) presents the regularity of signal [32]. The regularity of independent modes' signals of Non-COVID-19 cough sounds may differ from those of the COVID-19 patients' coughs. It is computed as in reference [21].

Taking these features from each of the 5 Modes into account, it can be stated that the feature vector of each cough sound signal is obtained by combining the statistical features (mean, variance, skewness, and kurtosis), the frequency corresponding to the peak in the spectrum, peak amplitude, energy, PerEnt, ReEnt, and SpecEnt. Therefore, dimension of resulting feature vector for each cough sound will be 50.

2.4 Feature Selection

In this study, dimension of features for each cough sound signal is too much. Using all of these features can both reduce performance and require more time. However, not all features may be effective in differentiating COVID-19 and Non COVID-19 cough sounds for the purpose of the study. Therefore, it is necessary to determine the most effective ones among the extracted features. This process will reduce the processing time of the next step, the classification process, and will contribute to high performance by eliminating the redundant features.

ReliefF algorithm gives positive weights to features in the same class that are close to each other, and negative weights to features in the other class that are close to each other [33]. In this way, it calculates a relevancy index for each feature. A high relevance index will be assigned to features that result in the best class separation across all observations in the training set [33]. In this study, ReliefF feature selection algorithm was chosen to determine the most effective features for separating of COVID-19 and Non COVID-19 cough sounds. With this algorithm, 9 features were selected among 50 features as effective. These features are listed below.

- ✓ IMF1-Skewness
- ✓ IMF1-Energy
- ✓ IMF1- ReEnt
- ✓ IMF2-Kurtosis
- ✓ IMF2-Frequency corresponding to the peak in the spectrum
- ✓ IMF2-Peak Amplitude
- ✓ IMF2-ReEnt
- ✓ IMF3-Frequency corresponding to the peak in the spectrum
- ✓ IMF5-Kurtosis

Considering the selected features, it can be said that Mode-1 (IMF1) and Mode-2 (IMF2) are the best modes to characterize the signals. Moreover, it is seen that kurtosis among the statistical features, frequency corresponding to the peak in the spectrum and RenEnt among the entropies more effective than others.

2.5 Classification Using Ensemble Machine Learning Methods

Ensemble learning technique puts together a group of independent learners to improve the model's performance [34]. Because its variance is decreased, the combined estimator is often superior than any single-based estimator [35]. The most well-known of these ensemble methods and used also in this study are Random Forests (RF), Gradient Boosting Machines (GBM) and Adaboost.

Random Forest was declared by Tin Kam Ho [36] in 1995. It's frequently used for classification as well as regression. The RF method uses the bagging technique to build an ensemble of decision trees. It is based on the developing of many decision trees depending on random data and random variable selection. Thus, the forest's bias usually increases slightly (in comparison to the bias of a single non-random tree), but its variance drops as well, frequently more than compensating for the bias increase, resulting in a superior overall model [37].

Yoav Freund and Robert Schapire [38] introduced Adaboost. It focuses on instances that were classified incorrectly. To begin, weights are assigned to the samples in the training set to establish the focus level [39]. During the first iteration, all samples in the training set are assigned the same weight. With the increase in the number of iterations, the weights of the misclassified samples increase. In the same time, the weights of correctly classified samples are gradually reduced. Additionally, when using the produced ensemble to make a prediction, weights are applied to individual baseline learners based on their aggregate prediction performance [40]. Variance reduction occurs since the models are built iteratively on randomly sampled but re-weighted training samples [40].

Gradient Boosting Machines is the ensemble method based on boosting. This method, like the adaboost method, iteratively builds base learners by reweighting misclassified observations. GBMs, on the other hand, vary from AdaBoost in that they calculate weights using the loss function's negative partial derivatives at each training observation [40].

Evaluation of the COVID-19 and Non COVID-19 cough classifications performed with the mentioned ensemble learning methods was carried out with the k cross validation technique. Classically, the value of k was determined as 10. Performance assessment was made with classification accuracy (CA) in Eq. (2), sensitivity in Eq. (3), specificity in Eq. (4), precision in Eq. (5), F-score in Eq. (6), Kappa statistic in Eq. (7) and AUC metrics by benefitting the confusion matrix obtained at the end of each classification. Table 2 represents the confusion matrix structure in the classifications of this study.

Table 2. Confusion matrix structure

		Predicted Class	
		Non-COVID19	***COVID-19***
True Class	***Non-COVID19***	TP	FN
	COVID-19	FP	TN

$$\text{CA} = \frac{TP+TN}{TP+TN+FP+FN} \quad \text{Eq. 2}$$

$$Sensitivity(Sens.) = \frac{TP}{TP+FN} \quad \text{Eq. 3}$$

$$Specificity(Spec.) = \frac{TN}{TN+FP} \quad \text{Eq. 4}$$

$$\text{Precision (P)} = \frac{TP}{TP+FP} \quad \text{Eq. 5}$$

$$\text{F-score} = 2 \text{ x } \frac{precision \ x \ sensitivity}{precision + sensitivity} \quad \text{Eq. 6}$$

$$Kappa\ statistics\left(K\right)=\frac{P_o - P_e}{1 - P_e} \qquad \text{Eq. 7}$$

Pe in Eq. (7) is calculated as in Eq. (8).

$$P_e=\frac{[(TP+FP)\times(TP+FN)]+[(FN+TN)\times(FP+TN)]}{(TP+TN+FP+FN)^2} \qquad \text{Eq. 8}$$

3 RESULTS AND DISCUSSION

In this study, for the distinguishing of COVID-19 and Non COVID-19 cough sounds, 50 features were extracted from them using VMD method. After that, most effective 9 features were selected by ReliefF algorithm. The results obtained by using these effective features with RF, GBM and Adaboost methods are shown in Table 3. Table 4, Table 5 and Table 6 show the confusion matrices from which these results were achieved by the RF, GBM and Adaboost methods, respectively.

Table 3. Performance of Ensemble Learning Methods for classification of 155 cough sounds

Ensemble Learning Method	CA (%)	Sens. (%)	Spec. (%)	P (%)	F-score	K	AUC (%)
RF (number of trees: 85, Number of attributes considered each split: 2)	92.26	83.56	100.00	100.00	91.04	0.84	91.78
GBM (Scikit-learn, the number of trees: 270, learning rate: 0.899)	**94.19**	**87.67**	**100.00**	**100.00**	**93.43**	**0.88**	**93.84**
Adaboost (the number of estimators: 100, learning rate: 1)	81.94	79.45	84.15	81.69	80.50	0.64	81.80

Table 4. Confusion matrix obtained by effective features and RF

	Non COVID-19	COVID-19
Non COVID-19	61	12
COVID-19	0	82

Table 5. Confusion matrix obtained by effective features and GBM

	Non COVID-19	COVID-19
Non COVID-19	64	9
COVID-19	0	82

Table 6. Confusion matrix obtained by effective features and Adaboost

	Non COVID-19	COVID-19
Non COVID-19	58	15
COVID-19	13	69

As presented in Table 3, the highest performance was obtained using the GBM ensemble method. By this method, all of the COVID-19 cough sounds were detected correctly, as seen in Table 5. In other words, 100% specificity and precision measures could be obtained. Only 9 cough sounds of subjects diagnosed with Non COVID-19 were misclassified, so 87.67% sensitivity was obtained. This method also produced F-score of 93.43% and AUC of 93.84% values. Also, 0.88 kappa statistics value was reached by this method. As can be seen from Table 3, Table 4 and Table 5, although the RF method recognized all COVID-19 cough sounds like GBM, it was able to recognize fewer Non COVID-19 cough sounds than GBM. Therefore, other performance metrics of RF except for specificity were lower than GBM method. On the other hand, the Adaboost ensemble method provided the lowest performance in terms of all performance measures.

To emphasize the number of data and legitimacy of ADASYN technique, original 121 cough sounds (73 Non COVID-19 and 48 COVID-19) before the augmentation process were also classified using 9 effective features and ensemble learning methods. The results of the classifications are shown in Table 7.

Table 7. Performance of Ensemble Learning Methods for classification of 121 cough sounds

Ensemble Learning Method	CA (%)	Sens. (%)	Spec. (%)	P (%)	F-score	K	AUC (%)
RF (number of trees: 100, Number of attributes considered each split: 2)	80.17	86.30	70.83	81.82	84.00	0.58	78.6
GBM (Scikit-learn, the number of trees: 200, learning rate: 0.921)	**81.82**	**86.30**	**75.00**	**84.00**	**85.14**	**0.62**	**80.65**
Adaboost (the number of estimators: 100, learning rate: 1)	71.07	78.08	60.42	75.00	76.51	0.39	69.25

Table 7 showed that the highest performance was again obtained with the GBM method. However, if both Table 3 and Table 7 are examined together, it can be seen that although there was no significant change in the recognition success (sensitivity) of Non COVID-19 cough sounds, the recognition success (specificity) of the minority class i.e. COVID-19 coughs were reduced considerably. Because most machine learning algorithms are designed around the assumption of an equal number of samples for each class, the imbalance in the dataset poses a challenge for predictive modelling. This results in models with poor predictive performance, especially for the minority class. The data balancing process performed on a data set with such unbalanced classes has an improving effect on the performance. In this study, this process was carried out using the ADASYN oversampling technique, and the data set was balanced by producing synthetic data belonging to the minority class. Thus cough data were augmented. According to results seen in Table 3 and Table 7, it was concluded that augmentation using ADASYN helps in increasing the performance of classifiers significantly.

There are many studies in the literature to automatically detect COVID-19 by analyzing both COVID-19 and Non COVID-19 cough sounds for early diagnosis. The comparison of this study with only few studies using the "Virufy" dataset as one of the datasets is given in Table 8.

Table 8. Comparison of this study with literature.

Study	Dataset	Type of Sound	Features	Classifiers	Results
[6]	Coswara Coughvid **Virufy**	Cough	Mel- spectrogram MFCC	Ensemble Deep Learning Model	77.1% AUC
[15]	Coswara **Virufy**	Cough Breathing Speech	MFCC – RMS – ZCR Spectral Rolloff / Centroid/etc.	Deep Model Shallow classifiers	96.4% AUC 96% CA
[9]	**Virufy**	Cough	STFT – MFCC	SVM classifier with RBF kernel	95.8% CA 98.6% sens. 91.7% spec.
This study	**Virufy**	**Cough**	**VMD-based features**	RF **GBM** Adaboost	**94.19% CA** **87.67% Sens.** **100% Spec.** **100% Precision** **93.43% F-score** **0.88% Kappa** **93.84% AUC**

As it can be seen in Table 8, this study is competitive with other studies that use the Virufy dataset as one of their sets in terms of different performance measures. Moreover, this study produced highest specificity performance metric throughout VMD-based features and GBM ensemble learning method. Despite all this, it should be noted that most of the studies in Table 8 considered not only the Virufy data set, but also different data sets, as well as sounds other than cough sounds. As a result, studies gave the performance criteria seen in Table 8 as average values. For this reason, it would not be right to compare this study with other studies in Table 8 exactly.

Most of the studies in this field in the literature have used different cough sound datasets. Despite the different datasets, this study is also comparable to other studies focusing on the automatic detection of COVID-19. Some of these studies using only cough sound signals gave the AUC value as a measure of success. This study found the AUC success criterion for detection of COVID-19 to be 93.84%. In terms of this metric, this study outperformed Bagad, et al. [5], Chaudhari, et al. [6], Fakhry, et al. [8], Kamble, et al. [10] and Rao, et al. [11] which achieved AUC of 72%, 77.1%, 91.0%, 76.31% and 78.3% respectively. If this study is compared with studies using only cough sounds and showing CA as a measure of success, it outperformed Imran, et al. [7] and Tena, et al. [13] which achieved CA of 92.85% and 90% respectively. Although this study showed lower performance in terms of CA metric than that of Erdoğan and Narin [12] with CA of 98.4%, it provided a higher performance in terms of specificity obtaining 100% success. If we compare with studies using different signals along with cough sounds, this study is better than Coppock, et al. [16] with AUC of 84.6%, Grant, et al. [18] with AUC of 68.36% and Khriji, et al. [17] with CA of 80.0%. Apart from these, this study is comparable to Melek Manshouri [9], Islam, et al. [14], Aly, et al. [15] and Lella and Pja [19] which accessed CA of 95.86%, CA of 89.2%, 97.5, 93.8%, CA of 96.4% and CA of 95.45%.

Among the studies focused on the automatic detection of COVID-19, there have also been those that used only the lung/breath sounds without including the cough sounds. Raj, et al. [41] performed nonlinear time series and principal component analyses to diagnose the COVID-19 through lung sounds. Tuncer, et al. [42] detect COVID-19 with CA of 95.43% using lung sound, Novel Local Feature Generation Technique and SVM. TUNCER, et al. [43] carried out automated Covid-19 respiratory sound classification with CA of 91.02% by utilizing lung sounds.

Considering the literature studies and their results, it can be said that; Although a detailed comparison cannot be made due to different feature sets, this study can compete with the studies in the literature. Also, it shows the use of cough sounds alone may be sufficient for COVID-19 detection without the need for other signals.

When the literature studies are evaluated from another perspective, it has been seen that generally similar feature extraction methods, especially MFCC, were used for the analysis of cough sound signals. This study, unlike other studies, examined the VMD method and decompose the each cough sound signal into different independent modes. Then, it extracted several features from these modes to characterize COVID-19 and Non COVID-19 coughs. As a result of using these features with the GBM method, which is one of the ensemble learning methods, the study achieved its purpose and was able to detect COVID-19 with high success by identifying positive and negative cough sounds.

4 CONCLUSION

This study aimed to detect COVID-19 by distinguishing cough sounds of people with the COVID-19 from coughs of healthy people, thus contributing to the diagnosis of COVID-19 disease. For this aim, it used the public Virufy cough sounds dataset, ADASYN oversampling technique, VMD feature extraction method and ensemble machine learning methods namely RF, GBM and Adaboost.

Firstly, the cough sounds included in the study were pre-processed in order to eliminate the imbalance between the classes. In this way, the number of COVID-19 cough sound signals, which were few in number, was increased with the ADASYN technique. Then, 5-layer VMD technique was applied to each cough sound and the sounds were separated into 5 independent modes (IMFs). Since VMD discrimination modes can capture the distinctive features of signals at different frequencies, several features (mean, variance, skewness and kurtosis statistical features, frequency corresponding to the peak in the spectrum, peak amplitude, energy, PerEnt, ReEnt and SpecEnt) were extracted from each mode of every sound. However, it has resulted in the emergence of a large number of features that will force the next step, discrimination of COVID-19 coughs and Non COVID-19 coughs by classification via RF, GBM and Adaboost. Therefore, ReliefF algorithm was used and 9 features were selected as the most effective features for the purpose of this study. Finally, cough sounds were recognized through classification by using 9 active features and RF, GBM, and Adaboost methods. The best performance was obtained by GBM ensemble learning method. All COVID-19 cough sounds were identified correctly and fewer Non COVID-19 sounds were misidentified. So, the diagnosis of COVID-19 from cough sounds were performed with acceptable accuracy.

As a result of the study, it can be said that the cough sound is one of the most prominent symptoms of COVID-19, and even this sound alone can indicate the presence of COVID-19. Just like in this study, with the analysis of cough sounds in digital environments automatically, negativities such as one-to-one interaction and crowded environment in hospitals that accelerate the spread of COVID-19 can be prevented. According to the results of the study, it can also be said that VMD method chosen different from those used in the literature is convenient for cough sound analysis by capturing the distinctive features of signals at different frequencies. Moreover, the augmentation performed to balance the different classes is very important in terms of improving the performance. Also, based on the working principle of ensemble methods by combining multiple models, successful results have been produced for the detection of COVID-19 in the study. Even, the GBM ensemble learning method outperformed the RF and Adaboost methods as each tree corrected the classification error of the previous tree and grew trees sequentially, increasing overall performance.

Although the performed study also requires validation on a larger dataset, the obtained results are very promising and show that detection of COVID-19 based on the automatic classification of only cough sounds is feasible.

Declaration of Ethical Standards

The author declares to comply with all ethical guidelines, including authorship, citation, data reporting, and original research publication.

Credit Authorship Contribution Statement

The author contributed to the all stages of the work, namely, preprocessing, feature extraction, feature selection, classification using ensemble machine learning methods, the analysis of the results and also the writing of the manuscript.

Declaration of Competing Interest

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Availability

The dataset used in the study is open-access Cough Dataset available on ''GitHub''(Virufy COVID 19 Open Cough Dataset, GitHub, https://github.com/virufy/virufy-data).

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