Classification of COVID-19 Using Temporal and Spectral Features of Cough Sounds

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Abstract: *Chest X-ray and computed tomography scan play a major role in the diagnosis of lung diseases, including coronavirus disease (COVID-19). However, their cost, the obstacles to their implementation in health facilities in small settlements of developing countries, and the limitations of their use for daily assessment due to the risk of repeated radiation dose, greatly limit their application. In response to the search for safe, simple, rapid, non-invasive, and cost-effective promising alternatives for the diagnosis of COVID-19, researchers in the field are increasingly turning to the analysis of human respiratory sound signals, including cough, breathing, and voice sounds. This is due to the direct connection of the respiratory sound signals with the lungs. Despite the detection efficiency obtained in earlier related works, further studies are still needed on the ability of breath sounds to provide meaningful information about COVID-19. This study used 2660 samples of cough sounds (1 330 recordings from healthy subjects and 1 330 recordings from subjects infected with COVID-19) from the CoughVid dataset, to train models for the classification of the COVID-19 disease. An attempt has been made to classify COVID-19 using different machine-learning models. Temporal and spectral features were extracted from the amplitude spectrum of cough sound signals, and evaluated using a periodogram, and those with higher discriminative power were selected. 1862 cough sound recordings were used for training and 798 cough sound recordings were used to test the model. On the test set, the final optimized model achieved classification accuracy, sensitivity, and specificity of 97.87%, 97.90%, and 97.85%, respectively. The experimental results of the study showed that the proposed method provides significant accuracy for classifying the COVID-19 disease, making it a reliable decision-support tool in healthcare settings where reverse transcription polymerase chain reaction is not available and test kits are scarce.*

Keywords: *Coronavirus, COVID-19, Feature extraction, Hyperparameter optimization.*

Introduction

Coronavirus disease (COVID-19) is an infectious disease caused by a novel coronavirus called severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). The disease has been identified as the cause of an outbreak of respiratory illness in Wuhan, Hubei Province, China in the beginning of December 2019 [2, 30]. COVID-19 disease now become one of the biggest killers with a total of 754 816 715 confirmed cases and 6 830 232 deaths reported by the World Health Organization (WHO) in February 2023 [31]. The numbers are still kept increasing. The symptoms can range from mild (or no symptoms) to severe illness. The most common symptoms include fever, dry cough and tiredness while the less common symptoms include aches and pains, sore throat, diarrhea, conjunctivitis, headache, loss of taste or smell, skin rash. The most serious symptoms include shortness of breath, chest pain or pressure, loss of speech or movement [17].

Many diagnostic tests are available for the diagnosis of COVID-19. These diagnostic tests are largely based on four different techniques such as reverse transcription polymerase chain reaction (RT-PCR), loop-mediated isothermal amplification (LAMP), lateral flow-hand-held single-use assay (LFA) and enzyme-linked immunosorbent assay (ELISA) [4, 19, 21, 23, 27]. Including all these and a range of molecular techniques are under development for the diagnosis and management of COVID-19 patients. However, the current molecular techniques for COVID-19 diagnosis have certain limitations such as the scarcity of RT-PCR test kits, the long wait for results, the low sensitivity, and they require high cost. Therefore, following the outbreak of COVID-19 disease, different scholars did and are in doing lots of contributions for early diagnosis of the disease using Chest X-ray (CXR) and computed tomography (CT) scan images processing along with machine learning and deep learning models. Belman-Lopez [7] performed detection of COVID-19 and other pneumonia cases. He performed a binary classification using X-ray images and convolutional neural networks (CNN), and claimed a classification accuracy of 99.17%. Mahesh et al. [18] also developed an optimal CNN model that can automatically detect COVID-19 and normal X-rays. They performed a binary case classification (COVID-19 or normal) and found a validation and training accuracies of 98.00% and 95.00%, respectively. Similarly, Saxena and Singh [25] followed a deep learning approach for the detection of COVID-19 from CXR images using CNN. They suggested a deep CNN that was trained on five open access datasets and had binary output (normal and COVID-19). Maximum detection accuracy of 97.00% was attained using the dataset of 9 472 CXR images from more than 13 870 patients.

Besides to CXR images, CT scan images were also used for detection of COVID-19 disease [9, 13, 16, 29]. Kogilavani et al. [16] detected COVID-19 using lung CT scan images and various CNN architectures. They trained six different CNN models (Vgg16, DeseNet21, MobileNet, NASNet, Xception and EfficentNet) using a total of 3 873 CT scan images. Their experimental results showed that the Vgg16 architecture outperformed the others, with an accuracy of 97.68%. Rao et al. [24], on the other hand, used deep learning techniques on CT and CXR images to classify COVID-19. For classification, they used pre-trained deep CNN (ResNet50, InceptionV3, VGGNet-19 and Xception). When using CT scan images alone, the VGGNet-19 model outperformed the others, while Xception performed best when using CXR images alone, with accuracy of 87.00% and 98.00%, respectively. They obtained the best score through VGGNet-19 network which is 90.05% accuracy when using the average of the two modalities (CXR and CT images). Additionally, He et al. [13] developed simple-efficient deep learning methods for COVID-19 diagnosis using CT scan images. They performed a binary case classification (COVID-19 and non-COVID-19) and claimed F1 score of 0.85 and an area under the curve (AUC) of 0.94. Furthermore, Walvekar and Shinde [29] performed classification of COVID-19 from pneumonia and other medical conditions using ResNet50. They obtained 96.23%, 97.15% and 95.60% of accuracy, sensitivity and precision values, respectively.

Generally, CXR and CT scan provide a major role in the diagnosis of novel COVID-19 as other lung diseases. Moreover, chest CT outperformed lab testing in the diagnosis of COVID-19 confirmed in a study of more than 1 000 patients published in the journal radiology [3]. However, it is difficult to deploy these imaging modalities in many rural healthcare settings of developing nations, and their cost provides a high barrier for many patients of the third world countries with certain financial limitations. Moreover, it is difficult to use them for a day-to-day assessment of COVID-19 patients due to the risk of repeated dose of radiation which will prone patients for other harmful hazards. Hence, searching for safe, simple, fast, non-invasive, and cost-effective promising alternatives for COVID-19 diagnosis is still the ultimate goal of researchers. Human respiratory sound signals including coughing, breathing, and voice sounds could be another promising tool for COVID-19 detection. Thesis is due to the fact that these signals have a direct connection with lungs. As a result, researchers have made significant contributions to COVID-19 detection through the processing of voice, cough, and breath sound data as well as various deep learning architectures and machine learning models [5, 8, 11, 23, 26]. A pre-screening deep learning approach for COVID-19 classification utilizing a smartphone-based breathing recording was proposed by Alkhodari and Khandoker [5]. They used CNN and bi-directional long short-term memory (BiLSTM) units which perform classification using features extracted from the original recordings and from the mel-frequency cepstral coefficients (MFCC) as well as deep-activated features. Finally, their proposed deep learning approach claimed an overall classification accuracy of 94.58% and 92.08% using shallow and deep recordings, respectively. Rahman et al. [23] developed an intelligent application which can detect COVID-19 patients using cough and breath sounds. By using cough sound spectrogram images, accuracy, sensitivity and specificity for symptomatic and asymptomatic patients were found 96.50%, 96.42%, 95.40% and 98.85%, 97.01%, 99.60%, respectively. While by using the breath sound spectrogram images, the accuracy, sensitivity, and specificity for symptomatic and asymptomatic patients were found 91.03%, 88.90%, 91.50% and 80.01%, 72.04%, 82.67%, respectively. Similarly, Evangeline et al. [11] used breath and cough sounds for the detection of COVID-19 using CNN. They pre-processed and converted audio samples into mel-spectrograms so that they used MFCC as input to the model. Final classification was performed using an ensemble CNN which reported accuracy and AUC values of 88.75% and 71.42%, respectively. Additionally, Schuller et al. [26] used deep neural networks (DNN) to identify COVID-19 from sounds of coughing and breathing. Similarly, Brown et al. [8], implemented an audio based-machine learning approach for automated diagnosis of COVID-19 using breath and cough sounds. They used cough and breath sounds for COVID-19 classification, and claimed an AUC of above 80.00% across all tasks. Furthermore, Despotovic et al. [10] performed detection of COVID-19 from breath, cough, and voice sound patterns. They obtained a preliminary result for binary case classification from cough sound patterns using wavelet scattering features, standard acoustic features and deep audio embeddings extracted from low-level representations, and achieved an accuracy, sensitivity and specificity of 88.52%, 88.75%, and 90.87%, respectively.

Regardless of the classification or detection performances achieved in the earlier works discussed above, further investigations on the ability of respiratory sounds in providing useful information about COVID-19 are still needed, especially when dealing with comparison of various machine learning models. Most importantly, given the alarming increase in the number of confirmed positive COVID-19 cases worldwide, it is critical to develop a system capable of recognizing the disease from recorded sound signals. These are the motivating factors towards developing a system which can classify COVID-19 disease from the cough sound signals using machine learning techniques. Therefore, a cough sound-based binary classification (healthy or COVID-19) has been done in the study.

Materials and methods

For the successful classification of COVID-19 disease from cough sounds, we followed the procedure presented in Fig. 1. Dataset collection, signal pre-processing, feature extraction, feature selection and normalization, model training and hyperparameter optimization, and final data classification are all steps in the procedure.

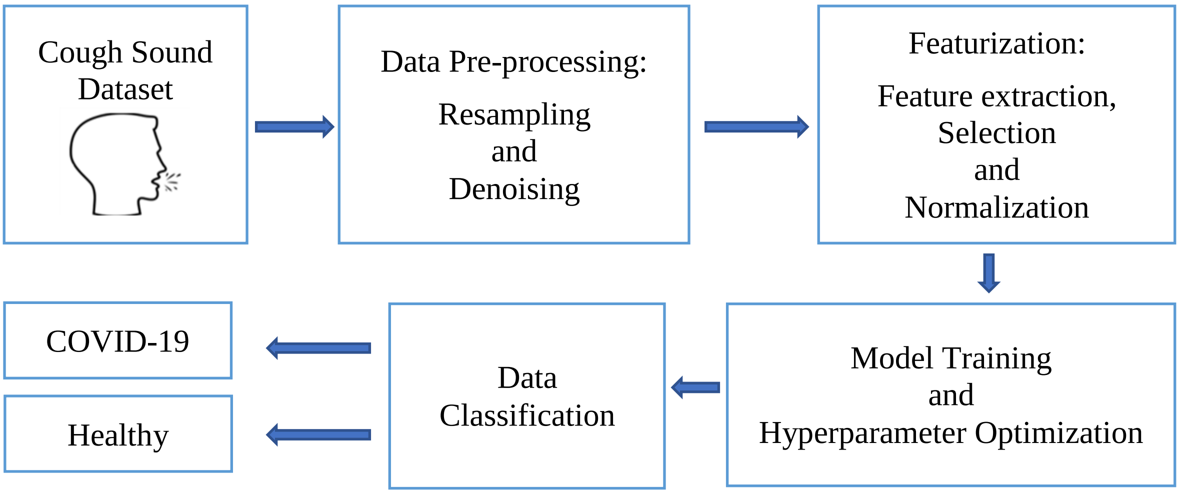

Fig. 1 A general procedure for classification of COVID-19 disease from cough sounds

Dataset collection

Cough audio signal classification along with machine learning techniques have been successfully used for COVID-19 screening. Hence, different public datasets such as CoughVid, Coswara and Cambridge datasets are available for this purpose [23].

In this study, we used the cough sound samples found in CoughVid dataset [22] to train our models and to perform classification of COVID-19 disease. The CoughVid dataset contains a wealth of cough recordings obtained from health and COVID-19 subjects that can be used to train machine learning models for detecting the current global pandemic issue (i.e. COVID-19). Therefore, we took a total of 2 660 cough sound samples (1 330 records from healthy subjects and 1 330 records from COVID-19 infected subjects) to train the selected machine learning models.

Data pre-processing

All audio samples used in the study were converted into WAV audio format using a standard sampling rate and bit-depth. Sampling rate is the number of samples per second in a piece of audio measured in Hertz (Hz) or Kilohertz (KHz) while bit-depth relates to the dynamic range in audio, also called the dynamic range of the signal. It is the number of bits of information in every single sample. Therefore, in this study, all audio samples were converted to WAV audio format by resampling them at 22 KHz sampling frequency and 16-bit floating point bit-depth, a standard value for audio tasks [8]. Moreover, stereo recordings were converted to mono before further processing. In addition, we reduced ambient noise or non-cough sound segments using the spectral noise gating feature of audacity software (audacity v2.4.2.).

Featurization

Following the pre-processing step, some feature-related activities were carried out, including feature extraction, feature selection and feature normalization. One of the most important steps in the machine learning process, feature extraction, converts the input data into a set of discriminatory characteristics. Hence, a set of discriminatory time-domain and spectral-domain features of cough sound signals were extracted and used as inputs to train the machine learning models. All the temporal and spectral features were extracted or computed from the cough sound signals either by using the syntax or by implementing the required formula.

In this study a total of 16 features were extracted from the pre-processed cough sound signals. These features include *mean*, variance (*VAR*), standard deviation (σ), root mean square (*RMS*), skewness (*skew*), kurtosis (*kurt*), peak amplitude, average amplitude change (*AAC*), entropy, mean absolute value (*MAV*), zero crossing (*ZC*), mean frequency (*MF*), median frequency (*MDF*), band power, signal to noise ratio (*SNR*), signal to noise and distortion ratio (*SINDR*). The mathematical descriptions presented using Eqs. (1)-(12) demonstrate the formulae of some of the extracted features. In each of the equations, X indicates the input signal, N represents the number of signals, and P indicates the probability distribution of the signal.

$$X_{mean} = \frac{\sum_{i=1}^{N} X_i}{N} \tag{1}$$

$$VAR = \frac{1}{N-1} \sum_{i=0}^{n} (\mathrm{Xi})^2 \tag{2}$$

$$\sigma = \frac{\sqrt{(\sum (X_i - X_{mean})^2)}}{N} \tag{3}$$

$$X_{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} X_i^2} \tag{4}$$

$$X_{skew} = \frac{\frac{1}{N} \sum_{i=1}^{N} (X_i - X_{mean})^3}{(\frac{1}{N} \sum_{i=1}^{N} (X_i - X_{mean})^2)^{3/2}} \tag{5}$$

$$X_{kurt} = \frac{\frac{1}{N} \sum_{i=1}^{N} (X_i - X_{mean})^4}{(\frac{1}{N} \sum_{i=1}^{N} (X_i - X_{mean})^2)^2} \tag{6}$$

$$X_{AAC} = \frac{1}{N} \sum_{i=1}^{N-1} \left| X_{i+1} - X_i \right| \tag{7}$$

$$Entropy = \sum_{i=1}^{N} (P_i \log_2 P_i) \tag{8}$$

$$MAV = \frac{1}{N} \sum_{i=1}^{N} \left| X_i \right| \tag{9}$$

$$ZC = \sum_{i=1}^{N-1} [sgn(-X_i * X_{i+1}) \cap \left| Xi - X_{i+1} \right| \geq threshold] \tag{10}$$

$$MF = \frac{\sum_{i=1}^{N} X_i}{N} \tag{11}$$

$$MDF = \frac{1}{2} \sum_{i=1}^{N} X_i \tag{12}$$

Furthermore, feature selection was carried out prior to training models with the extracted features. This aids in the selection of the most useful features for classifying cough sound signals from healthy and COVID-19 diseased subjects. Statistical filter feature selection methods reduce highly correlated features in classification with no weights [1]. They are used to assess the significance of features using univariate statistics. As a result, the T-test filter method was used to rank all of the extracted features based on the final weight calculated for each feature. For binary case classification, the T-test feature selection method is the preferred statistical filter feature selection method. Furthermore, normalization of features was performed to avoid the possible occurrence of bias during final data training and classification. Generally, the feature extraction, selection and normalization steps were carried out using MATLAB software (MATLAB R2109b).

Model training and hyperparameter optimization

Before training the machine learning models, data splitting into training and testing sets was done using the hold-out method. Next, a common 10-fold cross-validation was applied and 30% of the data were used for testing and the remaining 70% were used for training.

Following the data splitting, 10 supervised machine learning models (4 K-nearest neighbor (KNN), 3 ensemble CNN, and 3 support vector machine (SVM) models) were trained for classification of COVID-19 disease. KNN models classify the data based on the distance between the new object and the defined objects, while SVM models represent the training data as points using a flat separated space and mapped the new objects into space with the forecast category based on which side of the gap they fall [6]. Moreover, decision tree algorithms are used to classify the new tuples based on its values by traversing the tree until reaching the leaf that contains the class [6]. Following relevant model training, hyperparameter optimization was performed to improve model classification accuracies. The fundamental goal of machine learning is to develop a model that predicts a specific set of cases well and with high classification accuracy [12]. To obtain a more accurate model, we must use the model optimization technique. Optimization is the process of adjusting hyperparameters to minimize the cost function and achieve maximum performance [12]. This is because hyperparameters can have a direct impact on machine learning model training.

As a result, the Bayesian optimization technique was used to optimize the trained machine learning models, resulting in improved classification performance. It is the most important optimization technique for hyperparameter optimization. We can use *fitcauto*, *fitrauto*, classification learner app, regression learner app, fit function, and *bayesopt* to implement Bayesian optimization. Following optimization, the classification accuracies of the optimized models were compared and a model that outperformed the others was chosen for further testing using the new dataset. Finally, the classification performances including sensitivity, specificity and accuracy of the selected optimized model were calculated using true positive (TP), false negative (FN), true negative (TN), and false positive (FP) rates through Eqs. (13)-(15).

$$Sensitivity = \frac{TP}{TP+FN} \tag{13}$$

$$Specificty = \frac{TN}{TN+FP} \tag{14}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{15}$$

Results

Data pre-processing

Signal denoising is an important step in signal processing that involves removing artifacts that can corrupt the acquired or recorded signals. Therefore, we used the spectral noise gating available in audacity v2.4.2 to remove the unwanted signals. A sample of denoised cough sound signals of healthy and COVID-19 subjects are illustrated using Fig. 2.

Feature selection, and normalization

The extraction, selection and normalization of features were performed following the pre-processing step. Feature selection is used to select and retain only the most relevant features used for discriminating between the distinct classes (healthy and COVID-19). This prevents overfitting and makes the model more time-efficient while also cutting down on training time and computational costs. Only 12 features were chosen after using the T-test algorithm for feature selection, as is shown in Table 1 along with their rank. Furthermore, normalization of features has been done by subtracting each mean from the value of the feature and dividing it by the standard deviation.

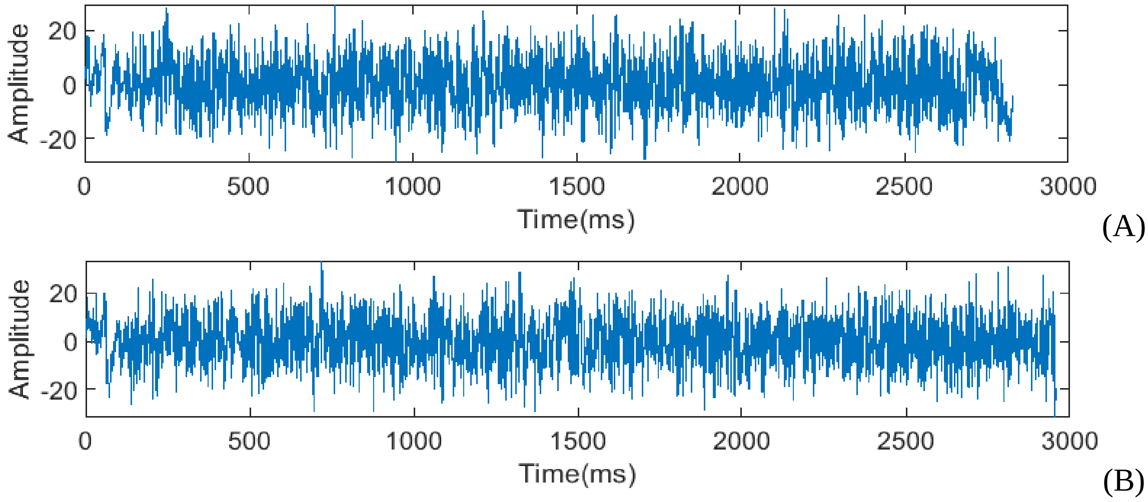

Fig. 2 Denoised cough sound signals of (A) healthy subjects, and (B) COVID-19 subjects

Table 1. List of selected features after applying feature ranking using T-test algorithm

Feature	Feature-domain	T-test score	Rank
Entropy	Time	13.1056	1
Peak amplitude	Time	12.0963	2
Variance	Time	12.0334	3
Standard deviation	Time	8.1304	4
Root mean square	Time	6.4103	5
Signal to noise and distortion ratio	Time	5.1056	6
Signal to noise ratio	Time	5.0321	7
Band power	Spectral	4.1932	8
Skewness	Time	4.0876	9
Kurtosis	Time	4.0031	10
Mean frequency	Spectral	3.1389	11
Median frequency	Spectral	3.1204	12

Data splitting and model training

Data has been split so that 70% of the data will be used for training and the remaining 30% will be used for testing. As a result, a total of 1 862 cough sound signals were used to train various machine learning models, with 798 cough sound signals used to test the final optimized model. Fig. 3 depicts the classification performances of the 10 previously mentioned machine learning algorithms trained on the same data. An ensemble subspace KNN classifier provided the highest classification accuracy of 96.20% among all trained models. Fig. 4 also shows the number of correctly and incorrectly classified observations during the training of an ensemble subspace KNN classifier.

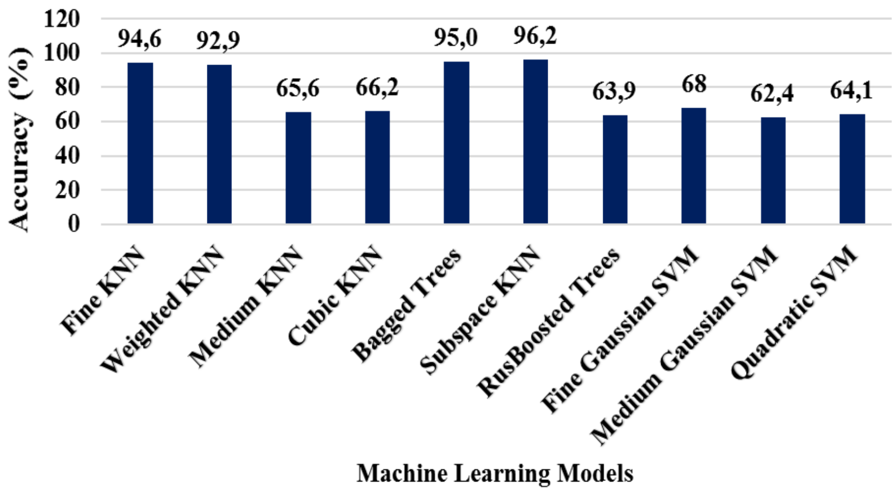

Fig. 3 Accuracy achieved on different machine learning models before optimization

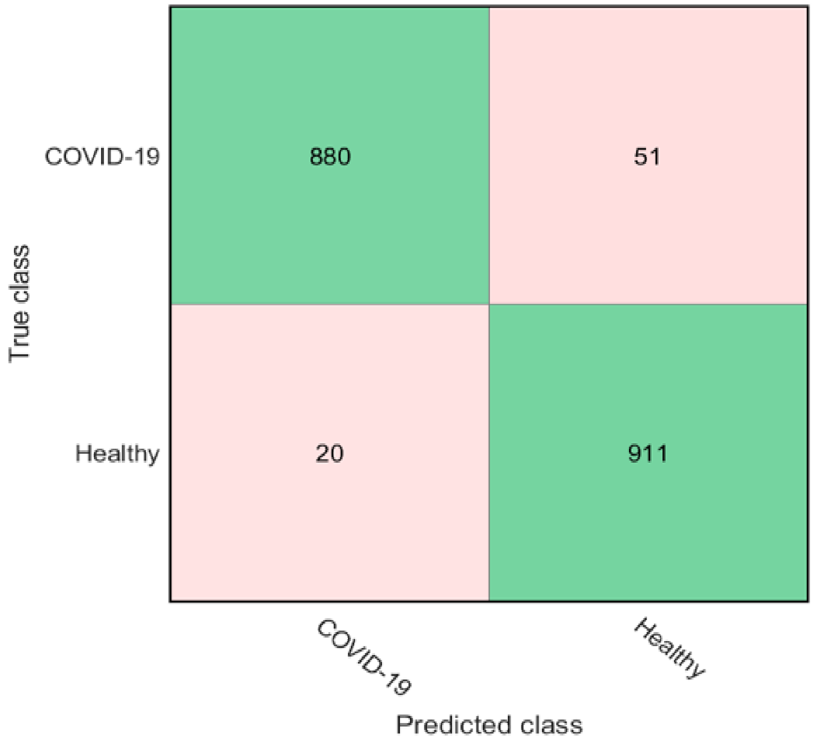

Fig. 4 The number of observations correctly and incorrectly classified by an unoptimized ensemble subspace KNN classifier

Model optimization and evaluation

Following the completion of the preceding steps, model optimization using the Bayesian optimization technique was performed to improve the accuracy of each model. The classification performances of the optimized machine learning models are shown in Fig. 5. After the optimization process, an ensemble subspace KNN classifier outperformed the others and still provided the best performance, with an accuracy of 96.60%. As a result, an ensemble subspace KNN model was chosen for further testing with the new data. Fig. 6 also shows the classification performance of the selected model after optimization.

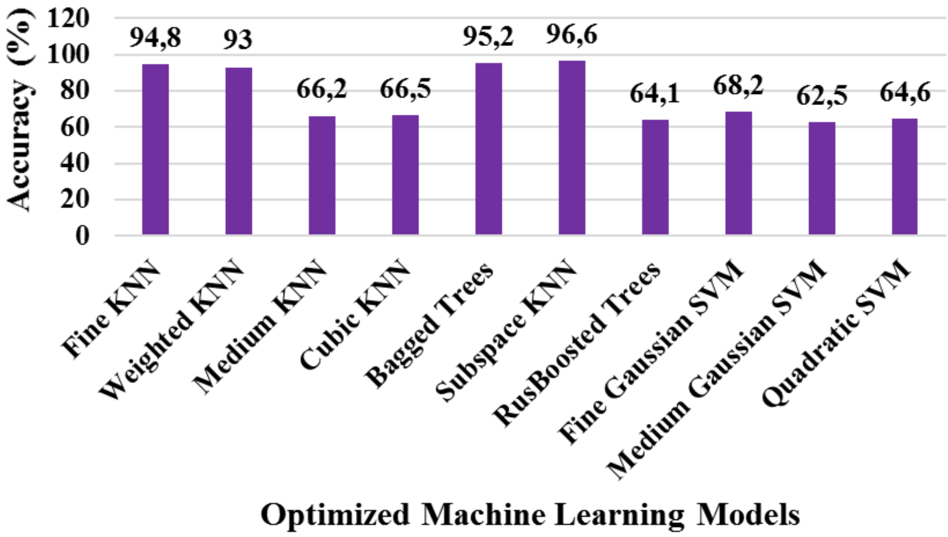

Fig. 5 Accuracy achieved after optimization of different machine learning models

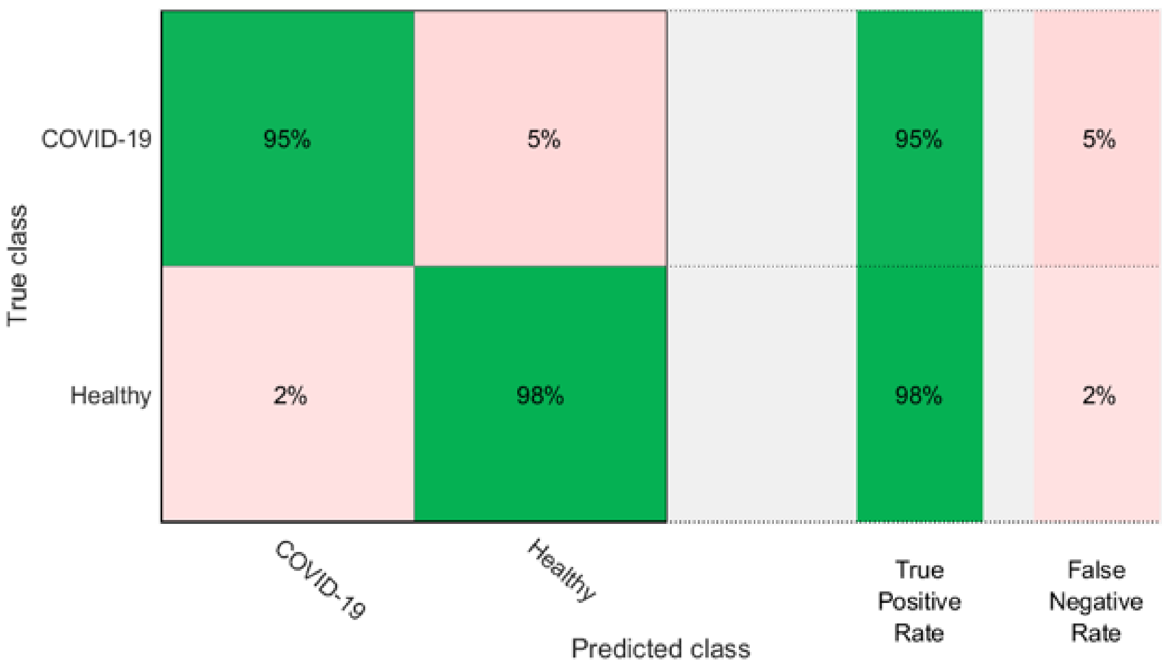

Fig. 6 Confusion matrix demonstrating the performance of optimized ensemble subspace KNN classifier per each true class

Model testing

The final optimized model was tested for final evaluation using new or previously unseen data. The final optimized model was tested using 798 cough sound signals. During testing with the new dataset, the optimized model achieves the highest classification accuracy of 97.87%. Fig. 7 depicts the classification performance of the final optimized model using a confusion matrix. Therefore, the highest average classification accuracy of 97.87%, specificity of 97.85%, and sensitivity of 97.90% were obtained using the unseen dataset.

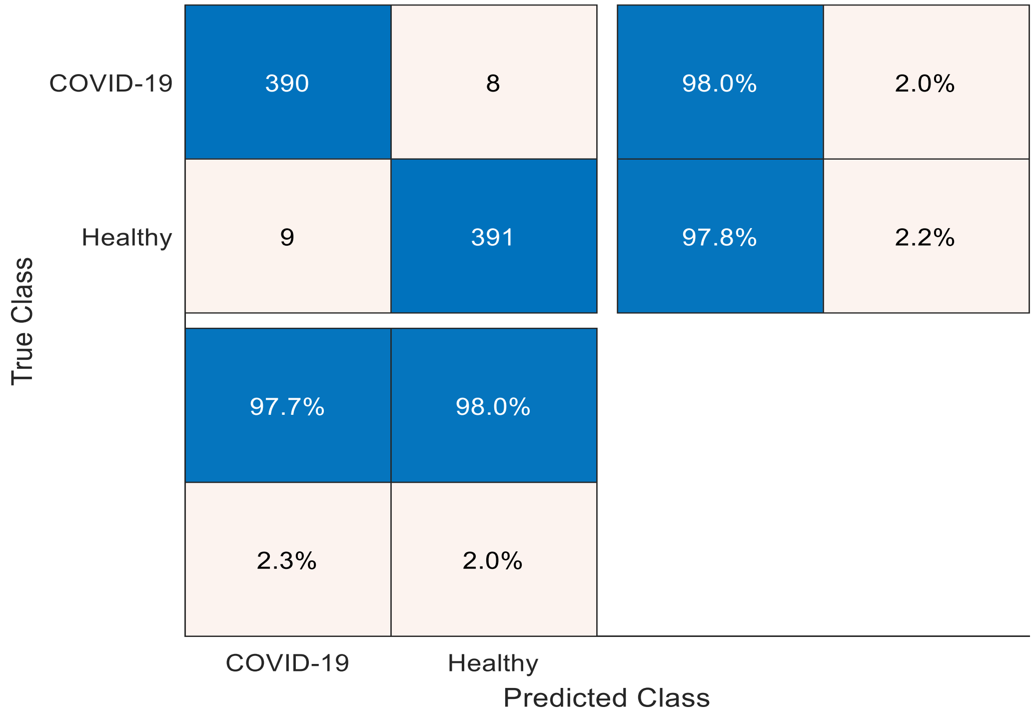

Fig. 7 Confusion matrix demonstrating test result of the final optimized model using unseen dataset

Discussion

Aside from standard molecular techniques, many researchers are attempting to develop robust techniques for early detection of COVID-19 disease by utilizing various image and signal processing techniques, as well as machine learning and deep learning models. Some challenges to getting imaging diagnostic approaches include the risk of repeated doses of harmful radiation, the cost of machines, and the inconvenient deployment in many healthcare settings. As a result, many researchers are investigating the use of respiratory sound signals in conjunction with artificial intelligence (AI) applications for COVID-19 detection. This is because respiratory sound signals have been identified as a promising tool for COVID-19 screening due to their direct association with the lungs [5]. As a result of the dramatic increase in the number of confirmed positive COVID-19 cases worldwide, it is highly encouraged to develop a system capable of detecting the disease based on respiratory sounds. Despite of the detection performances obtained in the earlier related works summarized using Table 2, further studies on the ability of respiratory sounds in providing essential information about COVID-19 are still needed.

In this study, an incredible attempt has been done for classification of COVID-19 from the cough sound signals using different machine learning models. A total of 2 660 cough sound records where used: 1 330 healthy and 1 330 COVID-19 records were collected from dataset [22] and used in the study. The collected cough sound records were normalized at a standard sampling rate of 22 KHz and 16-bit floating point bit-depth. Moreover, cancellation of the non-cough sound segments was performed using the spectral noise gating found in audacity software. Following signal collection and pre-processing, extraction of temporal and spectral features was performed. The spectral features were extracted from the amplitude spectrum of the cough sound signals being estimated using the periodogram function available in MATLAB.

Table 2. Comparison of the proposed study with related references

Authors	Applied techniques	Accuracy, %
Proposed method	Ensemble subspace KNN optimized using Bayesian optimization	97.87
Rahman et al., 2022 [23]	Stacking CNN model based on logistic regression classifier meta-learner	96.50
Manshouri, 2021 [20]	SVM using power spectral density	95.86
Imran et al., 2020 [14]	Deep transfer learning-based CNN	95.60
Alkhodari and Khandoker, 2020 [5]	CNN using BiLSTM units	94.58
Tena et al., 2022 [28]	Random forest using features extracted by Autoencoder	90.00
Islam et al., 2022 [15]	DNN consisting of three hidden layers	89.20
Evangeline et al., 2021 [11]	CNN using Mel spectrograms	88.75
Despotovic et al., 2021 [10]	Multi-layer perceptron (MLP) using wavelet scattering features	88.52
Brown et al., 2020 [8]	Audio-based machine learning using logistic regression classifier	80.00
Rao et al., 2021 [24]	VGG-13 architecture trained using a combination of binary cross entropy and focal losses	78.30
Schuller et al., 2020 [26]	DNN via Bayesian optimization combined with Hyper Band	73.70

Following feature extraction, feature selection was performed to select features with higher discriminatory power. The T-test feature selection method was used and 12 of 16 features were chosen to train machine learning models. Prior to model training and classification, features were normalized to make them nearly on the same scale. Next, splitting the whole dataset into training (70%) and testing (30%) has been performed. Hence, 1 862 cough sound records were used for training and 798 cough sound records were used for testing the model. Moreover, a common cross-validation (10-fold cross-validation) was performed to overcome the possible occurrence of overfitting. Finally, 10 machine learning algorithms from 3 families were trained for final classification of the data. The classification performances of each trained machine learning models have been shown in Fig. 3.

Furthermore, each of the models was optimized for classification accuracy using the Bayesian optimization technique. Fig. 5 also shows the classification performance of each of the optimized models. An ensemble subspace KNN model outperformed all other models in both experiments before and after optimization. It has an accuracy value of 96.20% before optimization and 96.60% after optimization. Finally, when tested with new data, the optimized ensemble subspace KNN model achieves an overall accuracy of 97.87%, specificity of 97.85% and sensitivity of 97.90%. In general, the proposed study yielded promising results for COVID-19 classification using important temporal and spectral features extracted from cough sound signals.

The proposed study used only machine learning techniques to perform binary case classification of COVID-19 from cough sound signals. In the future, multiclass classification of COVID-19 using respiratory sounds will be investigated. Furthermore, the classification performances of today's state-of-the-art deep learning techniques will be addressed in the future.

Conclusion

One of the main current research hotspots is improving a respiratory sound-based diagnosis of COVID-19 by combining signal processing and AI applications. An attempt was made in this study to analyze cough sound signals for further binary case classification of COVID-19 disease.

Cough sounds from the CoughVid dataset were collected and converted to WAV audio format by resampling them at 22 KHz sampling frequency and 16-bit floating point bit-depth. Following pre-processing, the most discriminative features were chosen using the T-test method, and a total of 12 features were chosen to train different machine learning models. During classification, an ensemble subspace KNN model achieved the highest classification accuracy of 96.20%. In addition, the Bayesian optimization technique was used to improve the accuracy of trained models. The accuracy of an ensemble subspace KNN model has been increased to 96.60% after optimization. Finally, the accuracy of the optimized ensemble subspace KNN model in making predictions of new data was 97.87% with specificity of 97.85% and sensitivity of 97.90%. Overall, experimental results demonstrated that the proposed method provides a significant performance for the classification of COVID-19 disease, and thus it can be used as a decision support system in healthcare settings where RT-PCR is unavailable and test kits are scarce.

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