IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.021 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 12, Issue 1, January 2024

DOI: 10.17148/IJIREEICE.2024.12101

Detection of Respiratory Diseases Through Cough Analysis

Aseel Wadeea Shukri Aldoori[1], Begüm Korunur Engiz[2]

Department of Electrical and Electronics Engineering, Ondokuz Mayıs University, Samsun, Türkiye[1,2]

Abstract: Since cough is a common symptom of many respiratory diseases, cough analysis is a crucial aspect in diagnosing various respiratory illnesses. This paper introduces an algorithm designed for the automatic diagnosis of specific respiratory diseases based on acoustic signals. The proposed algorithm extracts the features of the patient’s cough sound, including MFCC, pitch, spectral centroid. These features are then compared with those stored in a database, aiding in the diagnosis of the disease. The algorithm’s functionality involves a comprehensive comparison that calculates the similarity percentage for each potential respiratory disease using Dynamic Time Warping (DTW). The results are subsequently sorted in descending order, highlighting the two diseases with the highest similarity. These top two matches are then displayed in the user interface. By employing this automated approach, the algorithm provides valuable insights into the type of respiratory disease a patient may be experiencing. The user interface enhances accessibility, offering medical professionals a clear and organized presentation of the most likely diagnoses based on the acoustic features of the patient’s cough.

Keywords: Cough analysis, respiratory diseases, MFCC, DTW.

I. INTRODUCTION

Cough is a prevalent symptom of respiratory diseases, and its characteristics can aid in the early diagnosing illnesses such as asthma, Chronic Obstructive Pulmonary Disease (COPD), pulmonary fibrosis, pneumonia, influenza, tuberculosis etc. Because cough sounds provide crucial information about the condition of the respiratory system, the type, and the progress of the disease, several researchers have focused on developing automatic methods for the detection and/or classification of cough sounds. In [1], a model was proposed that was trained using a combined dataset to detect cough events from cough audio signals. Three feature selection algorithms were used to build several models with different numbers of features. It was shown that the model with 20 features, selected by uninformative variable elimination, achieved the best performance. In [2], various acoustic features were evaluated for cough detection. Deep neural networks, convolutional neural networks, and long-short term models were used to evaluate Short-time Fourier transform (STFT), mel-frequency cepstral coefficients (MFCC), and mel-scaled filter banks (MFB), and the length of the analysis window frame was discussed. In [3], an algorithm was proposed to detect cough events from acoustic signals, and this algorithm uses a logistic regression model and only three spectral features to classify acoustic sound segments as either cough or non-cough events. [4] used audio recordings for automatic cough detection, a wide range of features describing various aspects of the audio signal were suggested, and their efficacy was confirmed using Artificial Neural Network (ANN), Gaussian Mixture Model (GMM), and Support Vector Machine (SVM).

Since dry cough is one of the most common symptoms of COVID-19, many studies have been conducted since 2020 for the detection and automatic diagnosis of COVID-19. A database of respiratory sounds (including coughs, breaths, and voices) was created in [5] to facilitate sound-based technological solutions for the diagnosis of respiratory infections, including COVID-19. Study [6] also created a dataset that contributes a wealth of cough recordings for training machine learning models. In [7], voice and cough sounds were collected through a mobile application, and the dataset of respiratory sounds was used to aid in the diagnosis of COVID-19. An audio classifier based on Convolutional Neural Networks (CNN) was proposed in [8] using the open cough dataset that was manually labeled into COVID and non-COVID classes for the assessment of COVID-19. A review [9] on cough sound acquisition, detection, and classification has shown that approximately 50% to 66% of the 144 research studies reviewed focus on detecting coughs, while roughly 33% concentrate solely on classifying coughs. Furthermore, classification studies aim to diagnose a specific disorder, while detection studies mainly focus on providing an objective or clinical-free method for cough monitoring or assessing a disorder. Mostly used features are cepstral coefficients, preferred classifiers are the neural networks.

Most of the aforementioned works either employ large datasets or utilize machine learning methods to detect coughs or identify specific diseases. The aim of this paper is to develop an automated algorithm for detecting the type of coughs, which extracts fundamental features from cough sounds, utilizes them to identify similarities, and subsequently

DOI: 10.17148/IJIREEICE.2024.12101

categorizes the type of respiratory diseases. To achieve this goal, 100 categorized cough sounds were obtained from open databases, and manually labeled as asthma, allergy, COPD etc. An algorithm has been developed in MATLAB that extracts essential features from the data, calculates the similarity between the sound features to be examined and those in the database, determines the percentage of similarity, and assists in the diagnosis of respiratory diseases. The paper is organized as follows. Section II provides an explanation of the features and database used, the processing steps involved, and the details of the proposed algorithm. Section III presents the experimental results, and the paper concludes with Section IV.

II. MATERIAL AND METHOD

In this study, a total of 100 labeled cough recordings from various respiratory diseases such as asthma, allergy, bronchitis and COPD were obtained from open databases. Since the recordings were obtained from different sources, there were differences in properties like sampling frequencies, recording length. The variations were removed by applying processing like filtering, resampling, and normalization. Furthermore, a tool has been developed that allows the patient to record their cough and evaluate it with the proposed program. The overview of the proposed algorithm is shown in Fig. 1.

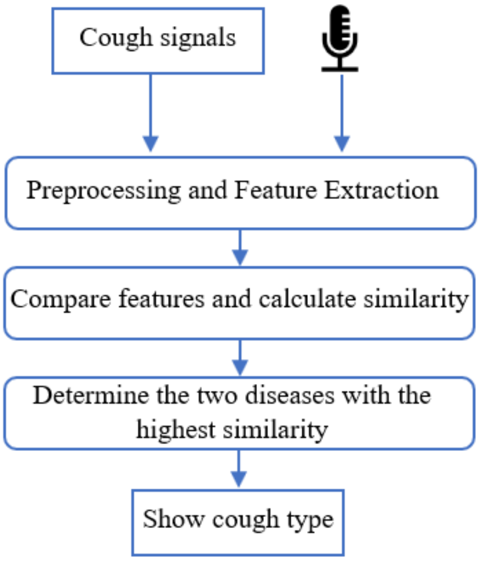

Fig. 1 Overview of the proposed algorithm

The user interface of the cough analysis program is shown in Fig. 2. The first step of the proposed algorithm can be observed in the interface, allowing the user to choose or record the cough signal to be tested.

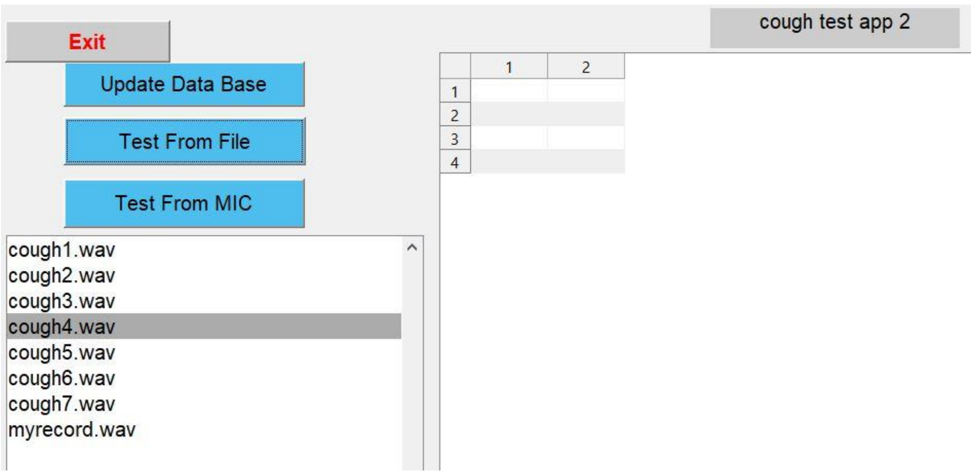

Fig. 2 Cough analysis program user interface

ISSN (O) 2321-2004, ISSN (P) 2321-5526
International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
Impact Factor 8.021 ⁑ Peer-reviewed & Refereed journal ⁑ Vol. 12, Issue 1, January 2024
DOI: 10.17148/IJIREEICE.2024.12101

After selecting the cough signal to be tested, the “Test From File” button is pressed. The preprocessing and feature extraction, comparison of features, calculation of similarity, and determination of diseases with the highest similarity are performed through the created cough analysis program. After the completion of these processes, the cough type with the highest similarity is shown on the user interface. Details of the proposed algorithm are given in the following sections.

A. Feature Extraction

This section explains the details of the features used in the study.

1) Mel-Frequency Cepstrum Coefficients (MFCC)

MFCC is commonly used for extracting the features from the audio signal. In MFCC calculation several steps are involved. First, the signal is windowed, then the discrete Fourier transform (DFT) is applied. Next, Mel filter banks are used to extract relevant frequency components. The logarithm of the filter bank energies is then taken, followed by the application of discrete cosine transform (DCT) to obtain the final MFCCs. This process is shown in Fig. 3.

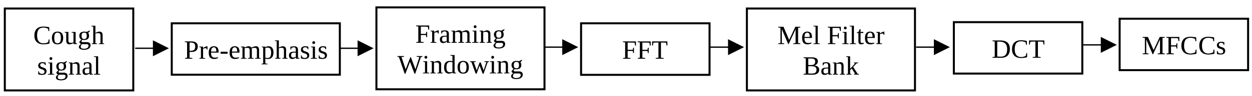

Fig. 3 Extracting process of MFCC

2) Pitch

Pitch is an important feature that can provide useful information about the characteristics of an audio signal. Pitch can be calculated from an audio signal using several different methods, depending on the application and the characteristics of the signal. In this study, pitch was calculated using normalized correlation function method in which the audio input is segmented according to the window length and overlap length arguments, then fundamental frequency is estimated for each frame based on normalized correlation coefficients.

3) Spectral centroid

The Spectral Centroid serves as a metric indicating the weighted center of the frequency content within an audio signal. This feature aids in identifying the frequencies where the audio signal exhibits greater concentration. Notably, Spectral Centroid exhibits correlation with brightness, a perceptual characteristic of sound. The calculation of Spectral Centroid, denoted as Eq. 1, involves determining the weighted central point within the frequency spectrum of an audio signal.

$$Spectral\ Centroid = \frac{\sum_{n=0}^{N-1} f(n)X(n)}{\sum_{n=0}^{N-1} X(n)} \quad (1)$$

where, N is audio signal’s length, $f(n)$ is n^{th} sample of the frequency, $X(n)$ is magnitude of the n^{th} frequency component.

B. Cough Comparison Algorithm

After extracting features from cough sounds, we apply the Dynamic Time Warping (DTW) algorithm to assess the similarity between the cough under examination and the dataset. The similarity of the cough sound is then evaluated based on the obtained results.

DTW is a widely employed algorithm for measuring the similarity between two sequences that may exhibit variations in time. It finds applications in automatic speech recognition, pattern recognition, and time-series analysis [10]. The similarity between sequences is quantified by the cumulative distance, where a smaller distance corresponds to a higher degree of similarity. The pairwise distances between each element in the two sequences with the Euclidian distance metric is calculated as in Eq. 2.

$$d_{mn}(X,Y) = \sqrt{\sum_{k=1}^{K} (x_{k,m} - y_{k,n}) * (x_{k,m} - y_{k,n})} \quad (2)$$

where, X and Y represent K-dimensional signals, $d_{mn}(X,Y)$ present the Euclidian distance between m^{th} sample of X and n^{th} sample of Y.

ISSN (O) 2321-2004, ISSN (P) 2321-5526
International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
Impact Factor 8.021 ⫶ Peer-reviewed & Refereed journal ⫶ Vol. 12, Issue 1, January 2024
DOI: 10.17148/IJIREEICE.2024.12101

III. RESULTS AND DISCUSSIONS

In this study, we extracted MFCC, pitch, and spectral centroid features to characterize cough signals. The extracted features served as key input parameters for the subsequent DTW analysis. The cough analysis program successfully processed a set of cough signals. Features for a large number of cough sounds were determined using the program, and their characteristics were compared with cough recordings from various respiratory diseases stored in the database. The similarity ratio was determined using DTW. For the sake of brevity, results for one cough sound example are provided. Figure 4 illustrates an example of a cough sound to be tested along with four cough sound examples from the database.

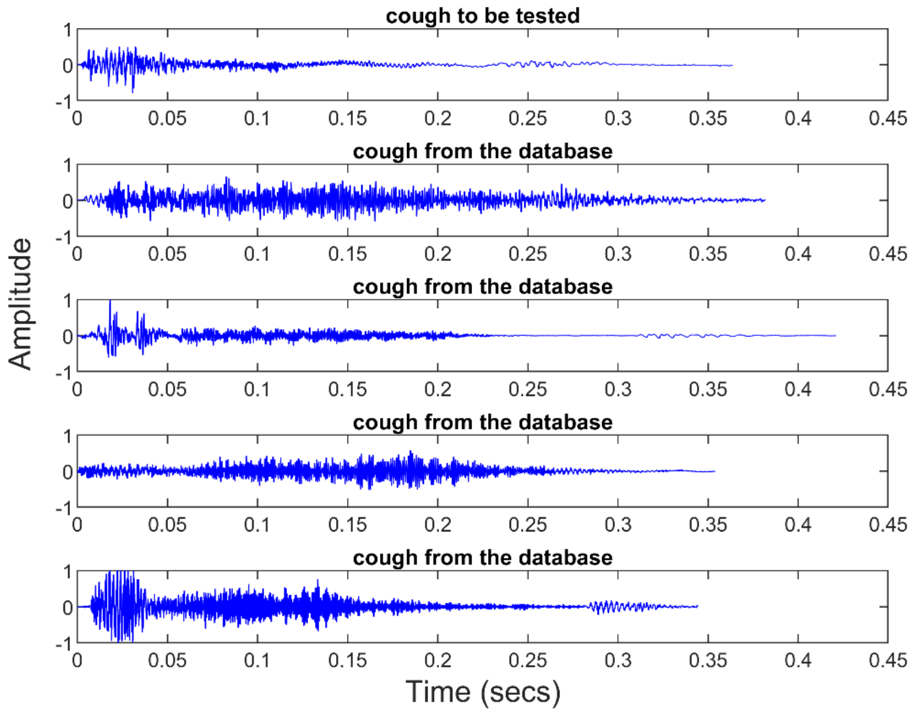

Fig. 4 Cough sound examples

The MFCC matrix of the test cough sound is presented in Fig. 5, while a sample MFCC matrix from the database is depicted in Fig. 6. The pitches for the test cough sound and the cough sample from the database are displayed in Figs. 7 and 8, respectively. The spectral centroids for the same cough samples are illustrated in Figs. 9 and 10.

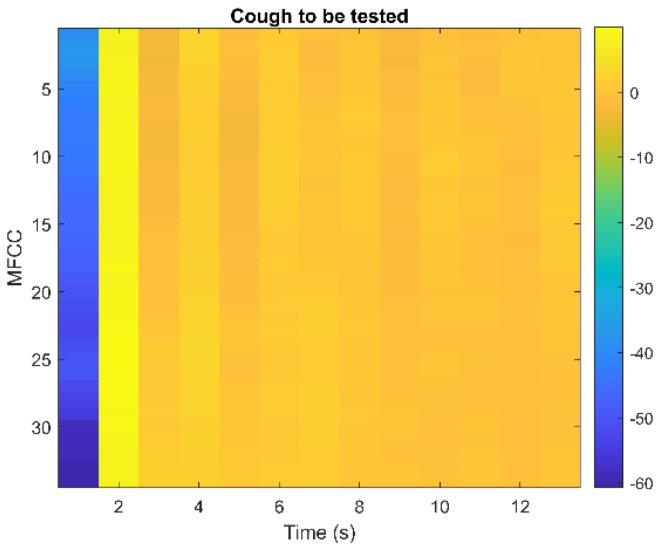

Fig. 5 MFCC matrix of cough to be tested

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
Impact Factor 8.021 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 12, Issue 1, January 2024
DOI: 10.17148/IJIREEICE.2024.12101

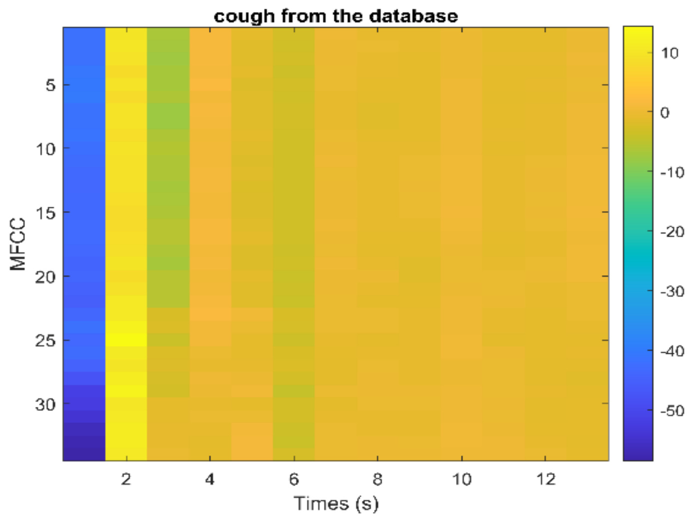

Fig. 6 MFCC matrix of cough from the database (an example)

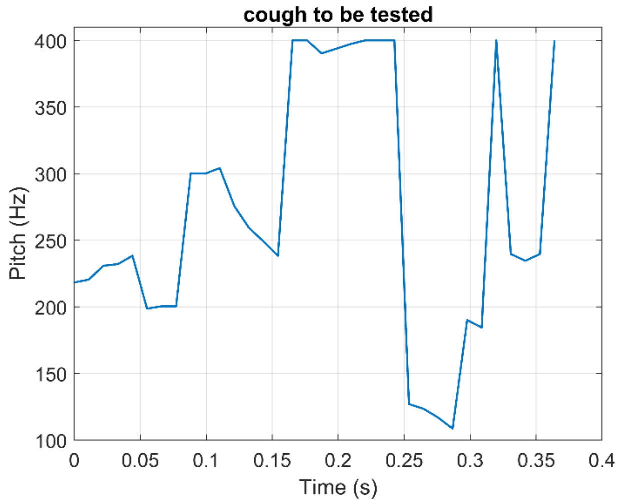

Fig. 7 Pitch contour of cough to be tested

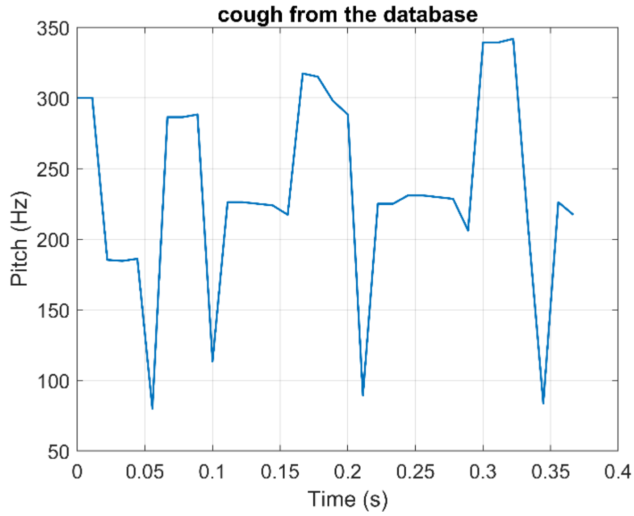

Fig. 8 Pitch contour of cough from the database (an example)

DOI: 10.17148/IJIREEICE.2024.12101

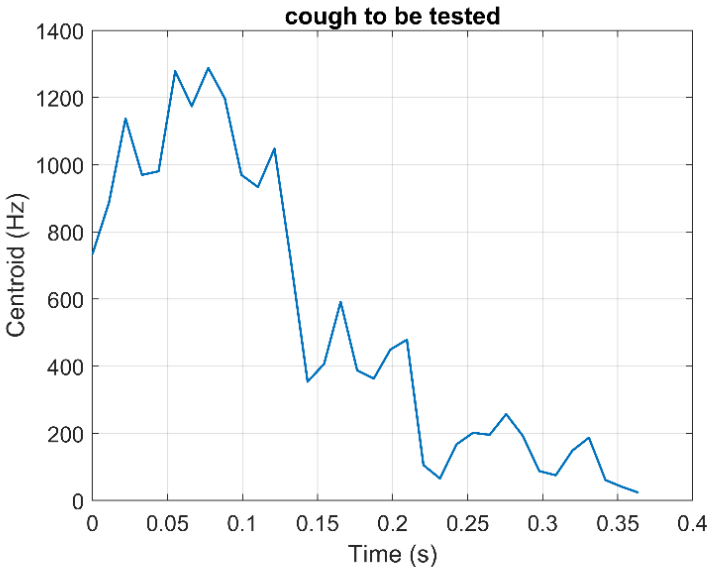

Fig. 9 Spectral centroid of cough to be tested

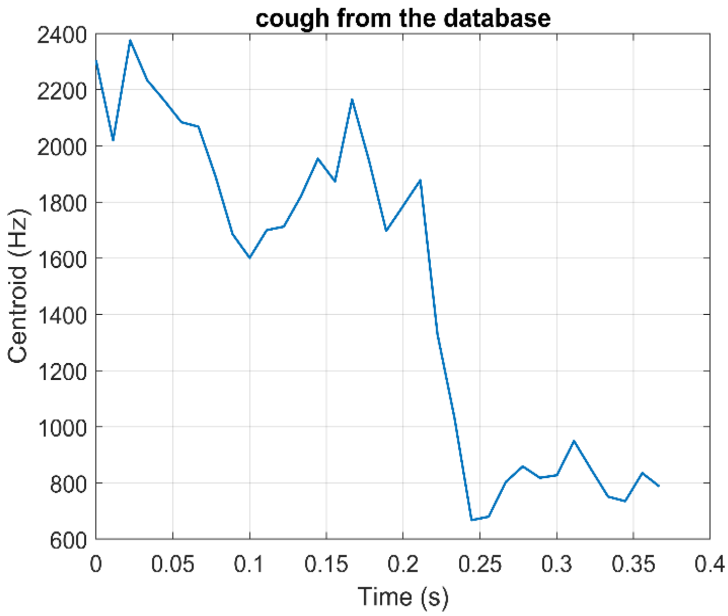

Fig. 10 Spectral centroid of cough from the database (an example)

After obtaining MFCC, pitch, and spectral centroid values as features for the test cough and all cough sounds in the database, the DTW algorithm is used to determine the similarities of these features. The overall similarity is calculated as the sum of the similarity percentages for each feature, with equal weights assigned to each feature.

The label of the cough sound with the highest similarity is displayed on the screen as shown in Fig. 11. This label, using the similarity percentage of the features, assists in determining the disease.

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.021 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 12, Issue 1, January 2024

DOI: 10.17148/IJIREEICE.2024.12101

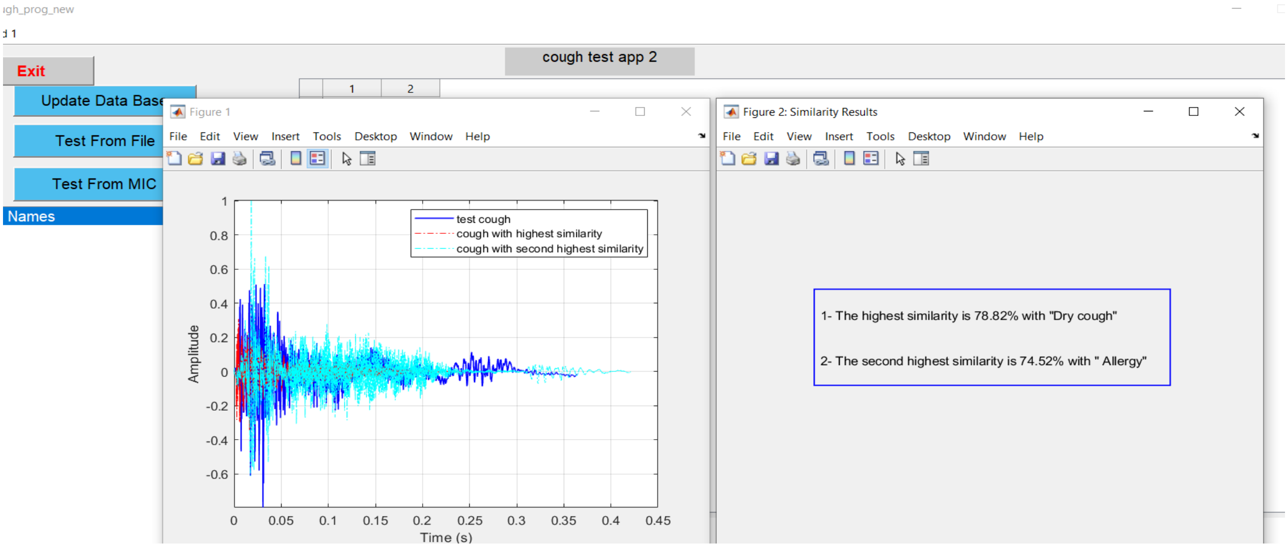

Fig. 11 Cough analysis program similarity results screen

IV. CONCLUSION

In this paper, we have presented an algorithm for the automatic diagnosis of respiratory diseases based on the analysis of acoustic signals, with a particular focus on cough sounds. The proposed algorithm utilizes advanced signal processing techniques, including the extraction of Mel-Frequency Cepstral Coefficients (MFCC), pitch, and spectral centroid from patient cough sounds. Then similarity percentages between patient cough features and those in the database were calculated using Dynamic Time Warping. The top two diseases with the highest similarity are highlighted and displayed on the user interface, facilitating efficient clinical decision-making. This study aims to fill the gap between advanced signal processing techniques and practical clinical applications, providing a user-friendly tool for healthcare professionals in diagnosing respiratory diseases. Future work may involve expanding the database, refining feature extraction methods, and exploring additional signal processing techniques to further enhance the algorithm's diagnostic accuracy.

REFERENCES

[1]. X. Chen, M. Hu and G. Zhai, "Cough Detection Using Selected Informative Features from Audio Signals", In 2021 14th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI) pp. 1-6, 2021.

[2]. I. D. Miranda, A. H. Diacon and T. R. Niesler, "A comparative study of features for acoustic cough detection using deep architectures", In 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 2601-2605, 2019.

[3]. R. X. A. Pramono, S. A. Imtiaz and E. Rodriguez-Villegas, "Automatic cough detection in acoustic signal using spectral features", In 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 7153-7156, 2019.

[4]. T. Drugman, J. Urbain and T. Dutoit, "Assessment of audio features for automatic cough detection", In 2011 19th European Signal Processing Conference, pp. 1289-1293, 2011.

[5]. N. Sharma, P. Krishnan, R. Kumar, S. Ramoji, S. R. Chetupalli, P. K. Ghosh and S. Ganapathy, "Coswara--a database of breathing, cough, and voice sounds for COVID-19 diagnosis", arXiv preprint arXiv:2005.10548, 2020.

[6]. L. Orlandic, T. Teijeiro and D. Atienza, "The COUGHVID crowdsourcing dataset, a corpus for the study of large-scale cough analysis algorithms", Scientific Data, 8(1), 156, 2021.

[7]. C. Brown et al., "Exploring automatic diagnosis of COVID-19 from crowdsourced respiratory sound data", In Proceedings of the 26th ACM SIGKDD international conference on knowledge discovery & data mining, pp. 3474-3484, 2020.

[8]. V. Bansal, G. Pahwa and N. Kannan, "Cough Classification for COVID-19 based on audio MFCC features using Convolutional Neural Networks", In 2020 IEEE international conference on computing, power and communication technologies (GUCON), pp. 604-608, 2020.

[9]. A. Serrurier, C. Neuschaefer-Rube and R. Röhrig, "Past and trends in cough sound acquisition, automatic detection and automatic classification: A comparative review", Sensors, 22(8), 2896, 2022.

[10]. Dynamic Time Warping, "In: Information Retrieval for Music and Motion", Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-74048-3_4, 2007.