Int. j. inf. tecnol.
https://doi.org/10.1007/s41870-022-01120-7

ORIGINAL RESEARCH

# COVID-19 assessment using HMM cough recognition system

**Mohamed Hamidi[1,2] · Ouissam Zealouk[3] · Hassan Satori[3] · Naouar Laaidi[3] · Amine Salek[4]**

Received: 30 May 2022 / Accepted: 13 October 2022


**Abstract** This paper is a part of our contributions to research on the ongoing COVID-19 pandemic around the world. This research aims to use Hidden Markov Model (HMM) based automatic speech recognition system to analyze the cough signal and determine whether the signal belongs to a sick or healthy speaker. We built a configurable model by using HMMs, Gaussian Mixture Models (GMMs), Mel frequency spectral coefficients (MFCCs) and a cough corpus collected from healthy and sick voluntary speakers. Our proposed method is able to classify dry cough with sensitivity from 85.86% to 91.57%, differentiate the dry cough, and cough COVID-19 symptom with specificity from 5 to 10%. The obtained results are very encouraging to enrich our corpus with more data and increase the performance of our diagnostic system.

**Keywords** COVID-19 · Diagnostic · HMMs · ASR system · GMM

## 1 Introduction

Corona virus (Covid-19) is one of the common viruses that causes upper respiratory infections, sinuses, and sore throat. The most common symptoms are fever, dry cough, and shortness of breath [1]. The epidemic has spread rapidly around the world, which caused researchers to make efforts to better understand and combat this phenomenon from a medical and interdisciplinary point of view. Among these efforts, we find computer science researchers who aim to achieve solutions using scientific approaches and available achievable methods. In particular, artificial intelligence and mathematical modeling that are being exploited to predict the spread of COVID-19. [2–4].

In this paper, we concentrate on analysis and investigation of the difference between dry cough and cough caused by COVID-19 infection based on HMMs-GMMs combination and MFCC feature extraction technique.

The rest of the paper is organized as follows: Sect. 2 presents the related works. Section 3 presents the cough production process. Section 4 shows the cough ASR system preparation. Section 5 shows the system performances. Finally, and Sect. 6 concludes the paper.

## 2 Related works

Table 1 presents some Covid 19 studies and diagnostic methods based on machine learning and deep learning approaches. On the other hand, automated speech recognition (ASR) systems have been exploited in both detection and diagnosis stages [5, 6]. Botha et al. [7] showed that disaggregation of cough data may be an effective, low-cost and low-complexity method for detecting tuberculosis. Their system can realize a sensitivity of 95% with a specificity of approximately 72%. Pramono et al. [8] have presented a pertussis automated diagnostic study based on cough and whoop sounds analysis. Their system permits to detect individual cough sounds with an accuracy of 92%

✉ Mohamed Hamidi
mohamed.hamidi.5@gmail.com

1 Advanced Systems Engineering Laboratory, ENSA-UIT, Kenitra, Morocco

2 Multimedia and Arts Department, FLLA, UIT, Kenitra, Morocco

3 LISAC, Department of Mathematics and Computer Science, FSDM, USMBA, Fez, Morocco

4 Faculty of Medicine and Pharmacy, UMP, Oujda, Morocco

Published online: 25 October 2022

**Table 1** COVID-19 studies based on artificial intelligence methods

| | Description | Results |
|---|---|---|
| [10] | Use of symbolic frequency scales with MFCC functions for automatic detection of COVID-19 based on the cough sounds of healthy and sick individuals | 97% and 99% |
| [11] | Exploiting automated extraction of cough and temporal frequency features and selecting the most important ones for COVID-19 diagnosis using a supervised machine-learning algorithm | The best accuracy is 90% was obtained by using the Random Forest method |
| [12] | Implementing a nested set model by exploiting deep learning approaches based on long-term memory (LSTM) | 97.59% and 98.88% |
| [13] | Studding the cough sound of infected people based on formants frequency and pitch analysis | The formant analysis variation is clearly observed with F1, F3, and F4 |
| [14] | Exploiting cough sound features and deep learning algorithms to develop a COVID-19 automated diagnostic tool | 82.23% average validation and a test of 78.3% with a sensitivity of 80.49% |

and a PPV with 97%. In [9] researchers have Introduced a remote patient monitoring system based on a method for automatically identifying cough events using audio cues. The achieved results show that the obtained sensitivity is 86.78%, specificity is 99.42% and F1 score is 88.74%.

## 3 Cough production

The Cough is defined as a defense reflex reaction mechanism that can help clear the respiratory passages (larynx, trachea, and large bronchi) of fluids, unwanted irritants, foreign particles and microbes by an air expulsion from the lungs via the epiglottis with fast speed. Figure 1 presents the cough reflex schematic description with receptors location, the afferent pathways, the nerve centers, the efferent pathways and the effectors [15]

In our work, we will investigate the cough sound based on the cough of healthy and Covid-19 infected people by exploiting the ASR technology [16] through the HMM-GMM combined system and MFCC Features extraction method.

## 4 Cough ASR system preparation

### 4.1 System architecture

In this paper, a cough recognition system is proposed based on Hidden Markov Models [17] and the Mel-Frequency

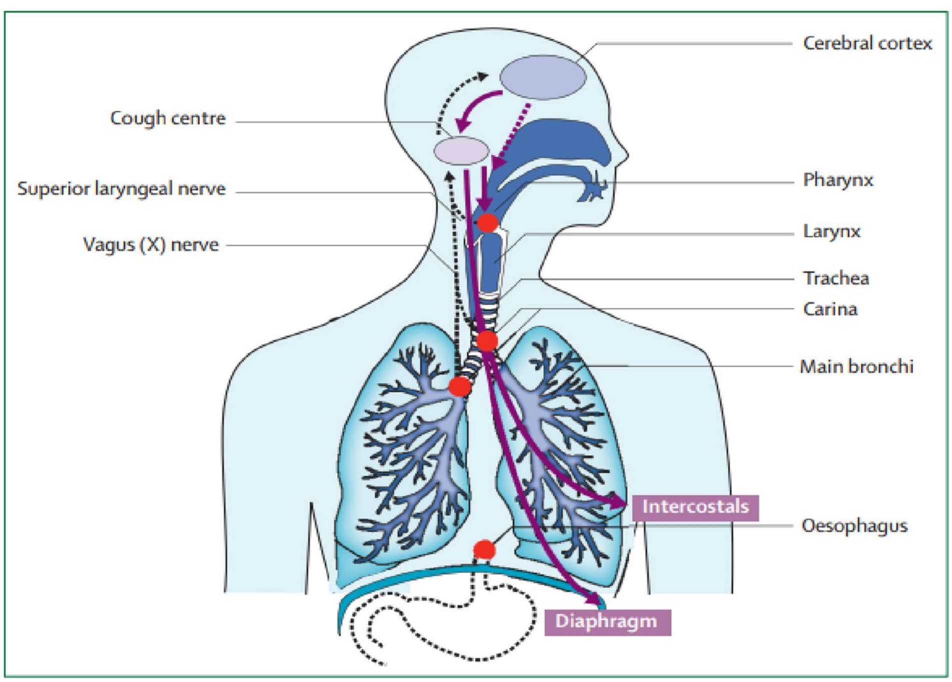


**Fig. 1** Anatomical representation of the airway innervation [6]: cough receptors (red) located in the larynx, carina, bronchi, distal part of the esophagus; afferent pathways: vagus nerve and superior laryngeal nerve; cough center and cerebral cortex; efferent pathways arriving at effectors

Cepstrum Coefficients [18]. In this study, we aim to classify the dry cough among other spoken words. In addition, we address the issue of speech recognition for separating dry cough from produced cough by a COVID-19 infection in people diagnosed with respiratory diseases.

In the HMM-based approach the used digits or cough are modeled as a sequence phoneme, while each phoneme is modeled as a sequence of HMM states (see Fig. 2).

As presented in the Fig. 3, the system cuts the captured speech into different parts. Then, it generates feature vectors representing the characteristics of the speech signal. After, the decoder processes the received information, and it analyzes it and compares it with the knowledge base to give the application a result.

### 4.2 Corpus preparation

This phase consists of preparing the data for training and testing steps. Our database includes samples of dry cough collected from 14 volunteers in good health who do not suffer from any respiratory diseases (7 males and 7 females) aged between 18 and 65 years-old. Each volunteer speaker is asked to cough 10 times (by producing cough not spontaneously) in detached data files each file includes one cough sample. The audio data are recorded in the normal environment in wave format with the help of a microphone by using the audacity-recording tool.

In the case of COVID-19 volunteers' patients, we have recorded the sound data in the quarantine rooms. The samples of infected volunteers' speakers collected from 5 speakers (2 males and 3 females) aged between 40 and

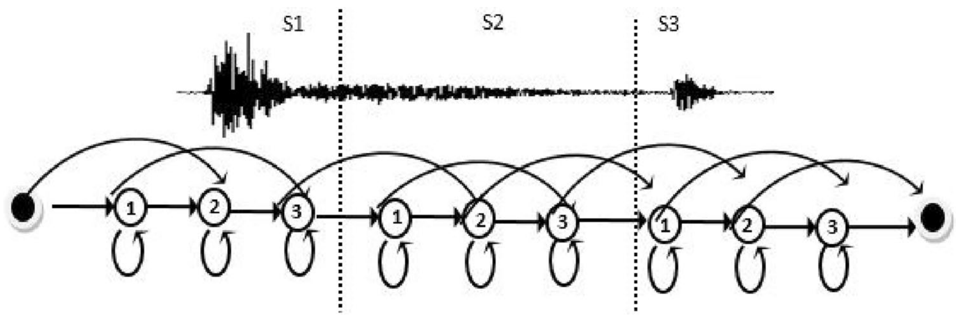


Fig. 2 Cough signal modilisation based on HMM states

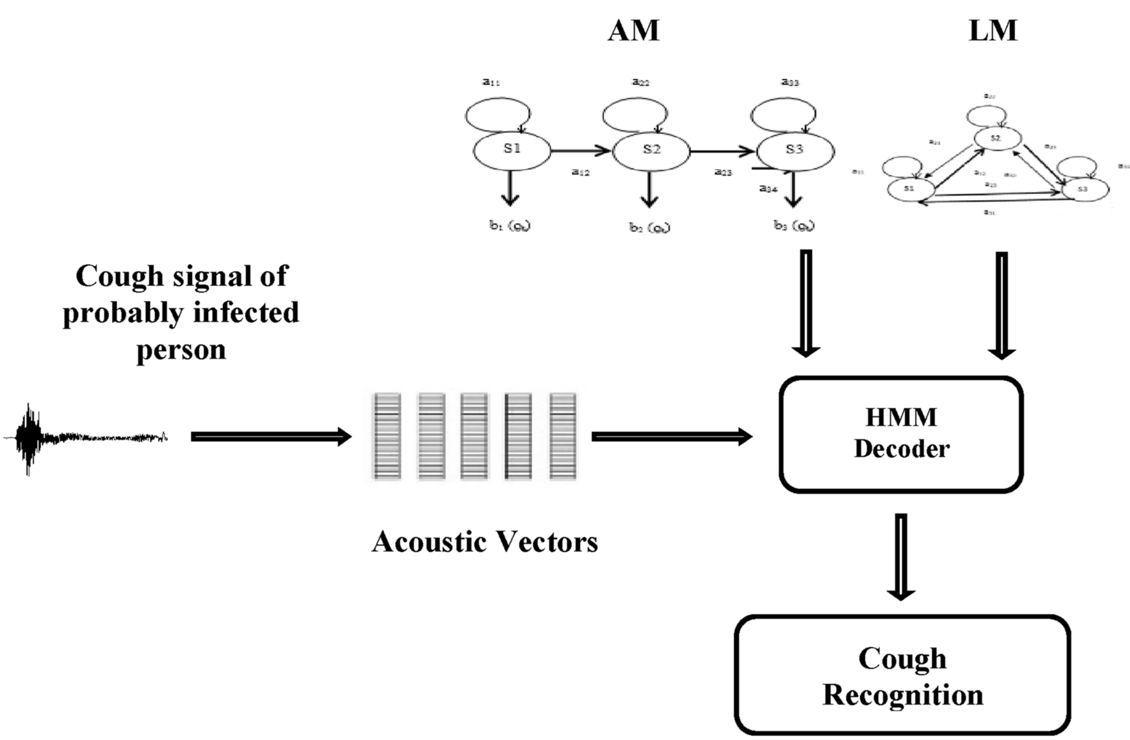


Fig. 3 Cough recognition system architecture

**Table 2** Corpus information

| Parameter | Value | Parameter | Value |
|---|---|---|---|
| Sex | males and females | Others symptoms | Difficulty breathing, fever or others |
| Illness stage | Diagnostic or treatment | Cough symptom | Yes–no |

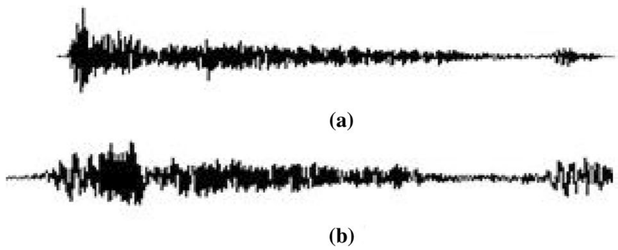

**Fig. 4** Waveform of cough samples obtained from an infected male (**a**) and non-infected (**b**)

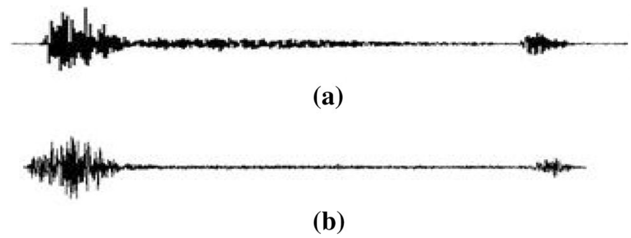

**Fig. 5** Waveform of cough sample obtained from an infected female (**a**) and non-infected (**b**)

60 years-old where we focus on recording the resulting natural cough of volunteer patients in the diagnosis or treatment stages. At this step, we have faced several difficulties, most notably reaching people affected during the onset of symptoms, as well as recording the resulting spontaneous cough from volunteer patients. The sampling rate of the recording is 16 kHz, with 16 bits resolution. Table 2 presents more information about the collecting phase. In addition to coughing data, our database includes ten Amazigh spoken digits (0–9) collected from Moroccan Amazigh native speakers aged between 18 and 50 years-old. Each digit is pronounced ten times in detached data files each file includes one pronounced word. These digits are exploited in our previous works [19–24].

### 4.3 Acoustic model

An acoustic model is a file that includes sounds data statistical representations designed in the training phase by using Hidden Markov Models. To prepare our acoustic models based on different sound (digits and coughs) we have we have clustered a set of input data and treat them by using the SphinxTrain. The followed list presents the used inputs.

### 4.4 Feature extraction parameterization

In our work, the MFCC method is exploited to obtain the speech features in the training and testing phases. Figure 4 shows samples of cough sounds obtained from two males (non-infected and patients). Figure 5 shows samples of cough sounds obtained from two females (non-infected and patients). The decoder to produce the best recognition result uses the extracted feature vectors, language model, Lexicon file and acoustic model. In this work, we have based on the CMU Sphinx 4 [25] and Pocketsphinx [26] decoders.

### 4.5 Cough recognition performances

In order to efficiently use of ASR technology in the diagnosis of COVID-19 cough, we have proposed two experimental parts. On the first one, we have tried to detect the cough sound from normal speech; this technique can be exploited in the corpus collection by detecting and isolating cough sounds in continuous speech or conversations. In the second part, several scenarios and experiments are realized by trained the system with patients cough and tested with healthy cough sounds and inverse in order to select the best technique for an effective diagnosis. In all of our experiments (see Table 3), the vocal database was separated and segmented for 70% training and 30% testing in order to ensure the speaker-independent aspect. In addition, the different Gaussian mixture models are exploited.

### 4.6 Cough detection

In this part, we describe our conducted experiments to detect and recognize cough from normal speech based on the cough of non-infected and infected people and the ten first Amazigh digits. In the first experiment, we aim to recognize the cough among the spoken words that is a positive thing to use in the cough recognition system, all digits and cough sounds are combined in order to use the maximum available and mixed data set.

Figure 6 shows the cough and total digits recognition rates using 700 digits samples and 40 cough sounds. For the cough recognition system performances, the obtained

**Table 3** All experiments description

| Part | Experiment | Training set | Testing set |
|---|---|---|---|
| 1 | Exp-1 | Digits: 14 speakers<br>Cough: 10 healthy speakers | Digits: 7 speakers<br>Cough: 4 speakers |
| | Exp-2 | Digits: 14 speakers<br>Cough: 6 speakers (3 healthy and 3 patients) | Digits: 7 speakers<br>Cough:4 speakers (2 healthy and 2 patients) |
| 2 | Exp-3 | Dry cough of 3 non-infected speakers | Dry cough of 2 non-infected speakers |
| | Exp-4 | Dry cough of 3 non-infected speakers | cough of 2 infected speakers |
| | Exp-5 | Dry cough of 3 infected speakers | Dry cough of 2 non-infected speakers |
| | Exp-6 | Dry cough of 3 infected speakers | cough of 2 infected speakers |

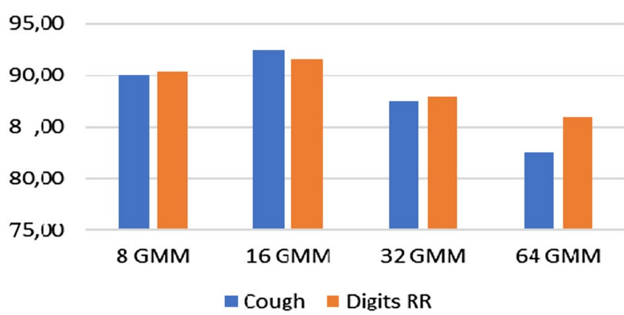


**Fig. 6** The cough and digits recognition rates

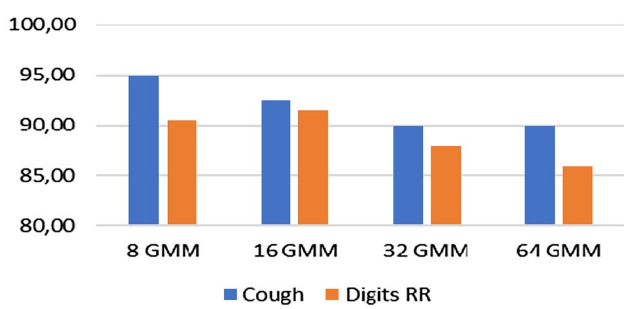


**Fig. 7** The mixed cough and digits recognition rates

recognition rates are 92.50, 90.00, 87.50 and 82.50% and for total digits recognition rates the achieved findings are 90.43, 91.57, 88.00 and 85.86% were found for using 8, 16, 32 and 64 Gaussian mixture distributions, respectively. It is found that 8 GMMs obtained the best cough recognition rate. Our system is able to recognize cough among speech with a recognition rate greater than 90%.

In the second experiment, the system was trained with digits and mixed cough of infected and healthy people. Figure 7 presents the mixed cough sounds and total digits recognition rates using 700 digits and 40 cough sound samples. The achieved findings are as follows; 95, 92.5, 90 and 90% were found for using 8, 16, 32 and 64 GMMs, respectively. The best result is found with 8 Gaussian mixture distributions.

**Table 4** Related works performances comparison

| Reference | Method | Accuracy (%) |
|---|---|---|
| [10] | Symbolic frequency scales with MFCC | 91 and 89 |
| [11] | Random forest method | 90 |
| [14] | Deep learning | 82.23 |
| [6] | LRM | 86.78 |
| [7] | Logistic regression | 95 |
| [30] | LRM | 95 |
| [27] | HMM | 90 |
| [28] | DNN | 86.82 |
| Proposed work | HMMs-GMMs-MFCC | 91.57 |

Table 4 presents the cough detection performance comparison between our proposed dry cough recognition system and other related works. In [27] the authors use the HMM approach with the MFCC feature extraction method and their obtained results are 82% 90%, respectively A cough detection system is proposed in [28] by using deep neural networks for the classification phase with 13 MFCC features. In [29] authors have presented an approach that allows diagnosis of the preliminary condition of a patient even without visiting a hospital and without the help of any medical staff as it serves as an automatic detection tool. Based on The Mel Frequency Cepstral Coefficient (MFCC)), they proposed a new audio feature called C-19CC that issued for the detection of COVID-19. In contrast, our proposed method is based on the GMM-HMM system combination and the Mel frequency spectral coefficients technique and it achieves a comparable detection performance.

### 4.7 Covid-19 cough diagnostic

In this part, we realize several experiments to choose the best scenario for an efficient diagnostic system. In the third experiment, the systems try to recognize 20 dry cough

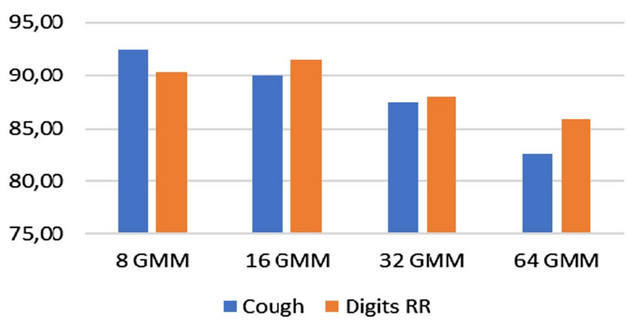


**Fig. 8** The recognition rates of non-infected people based on non-infected acoustic model for the two decoders

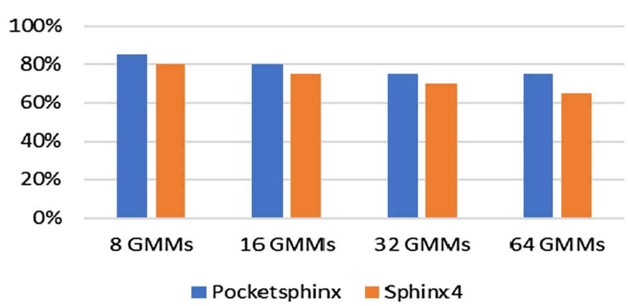


**Fig. 9** The recognition rates of infected people based on non-infected acoustic model for the two decoders

samples of two non-infected speakers based on two different decoders that are Sphinx 4 and Pocketsphinx. Figure 8 illustrates the cough recognition rates. For the first decoder, the system accuracies are 90, 85, 80 and 80% concerning the second decoder the obtained results are 95, 90, 85 and 80% for using 8, 16, 32 and 64 GMMs, respectively. In addition, in the case the best results were found with 8 GMMs based on Pocketsphinx decoder.

In the fourth experiment, we change the kind of data between the training and testing phases where the system was trained by using the cough sounds of non-infected people and we test it with coughing data of people with symptoms COVID-19. We aim to analyze the difference in the audio signal of the cough caused by COVID-19 and respiratory dry cough. The system correct rates, in this case, were 85, 80, 75 and 75% found by using Pocketsphinx decoder, whereas 80, 75, 70 and 65% found by using sphinx 4 decoder for 8, 16, 32 and 64 GMMs, respectively. This confirms our previous observation that 8 GMMs perform better as compared to 16, 32 and 64 GMMs (see Fig. 9).

Figure 10 illustrates the recognition rate variation of cough data based on Pocketsphinx. In general, the best rates are obtained when the system trained by using the cough data of non-infected speakers. The test data of non-infected speakers reaches the highest rate of 95% with 8 GMMs in comparison to the test with infected people cough data

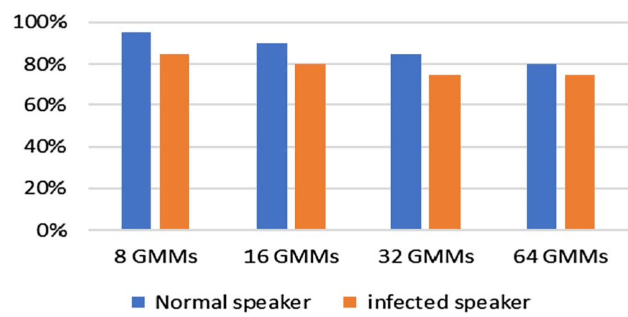


**Fig. 10** The cough recogniton rates of non-infected and infected people based on non-infected acoustic model and pocketsphinx decoder

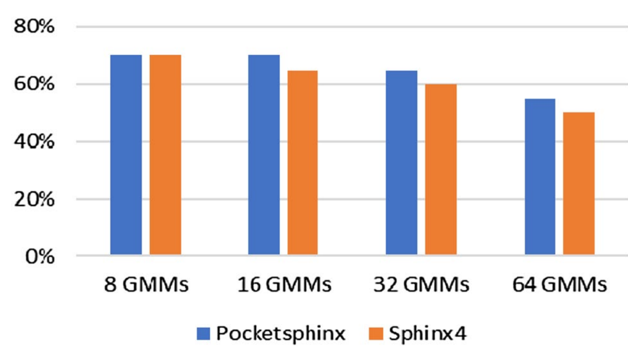


**Fig. 11** Cough recogniton rates of non-infected people based on infected acoustic model for both decoders

which is lower by 10% with the same GMM value. The same difference was observed with Sphinx 4. Generally, the obtained results have witnessed a decrease with the rest of GMM values. The differences between the rates of cases are 10% for both 16 and 32 GMMs, respectively and 5% for 64 GMM. The lower recognition rates are obtained with the infected speaker's data compared to the non-infected people data. That may be due to the change in the cough signal caused by COVID-19 infection.

Concerning the fifth experiment, we train the system with the cough of infected speakers and we test it with coughing data of non-infected people. This experience gives us a view on the difference between the recognition rates based on the cough sounds of patients and healthy people. In this experiment, the highest rate is 70% found with 8 GMMs for both decoders, and the lowest obtained rates are 55% and 50% found with 64 GMMs for Pocketsphinx and sphinx 4 respectively. On the other hand, the best rate is 70% obtained with 8 GMMs and 16 GMM based on Pocketsphinx and 8 GMM based on Sphinx 4. Figure 11 presents the recognition rates of experience 4 with different GMM values.

For the last experiment, the system was trained with cough of infected speakers and tested with cough sounds of infected people. The system recognition rates (see Fig. 12)

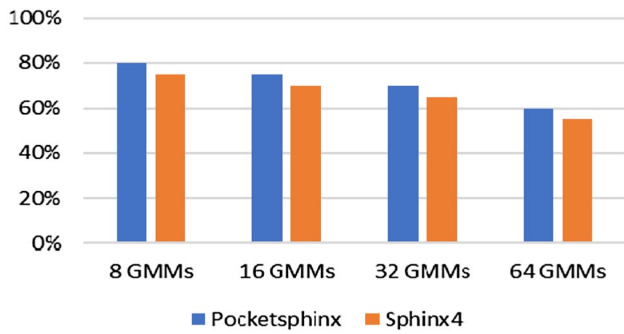


**Fig. 12** Cough recogniton rates of infected people based on infected acoustic model found with the two decoders

are 80, 75, 70, 60% for Pocketsphinx and 75, 70, 65, 55% for Sphinx 4 were found for using 8, 16, 32 and 64 Gaussian mixture distributions, respectively. In this experience, it is found that 8 GMMs obtained the best recognition rate for the two decoders.

Figure 13 appears the variation in the recognition rate between the fifth and Sixth experiments. The difference between recognition rates for 16, 32 and 64 GMMs is about 5% and it increases to 10% % for 8 GMMs. So, the higher difference was observed with Pocketsphinx decoder based on 8 GMMS.

Figure 14: boxplot of the test rates of non-infected (healthy) and infected people based on infected data trained acoustic model with 8 GMMs. As a comparison of the lowest and highest recognition rates among the non-infected and infected people, we conclude that the cough sounds of the patients (P) were recognized better than the healthy (H) people by using an infected data based acoustic model. This conclusion appears to follow since the lowest rate of 70% for P is greater in value than the lowest rate of 60% for H. In addition, the highest rate of 80% for P is greater in value than the highest rate of 70 for H. These box-and-whisker plots show that the difference between the lowest and highest rates of infected and non-infected people is 10%

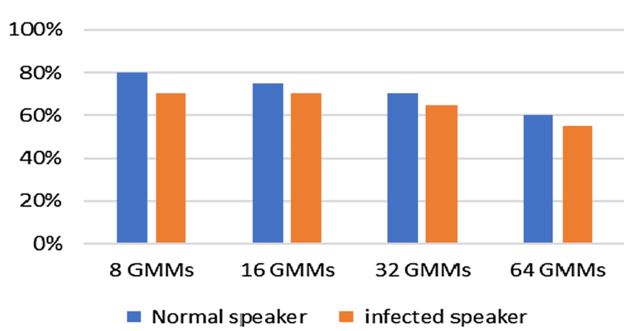


**Fig. 13** Cough recogniton rates of non-infected and infected people based on infected acoustic model

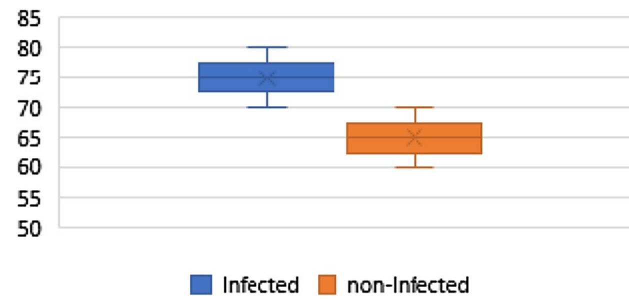


**Fig. 14** The peak rate of the two classes of recognized cough sounds

However, the box portion of the representation shows information that is more detailed. The middle bar in each box presents the median rate of 75 with P sounds that is greater in value than the median rate of 65 with H data. The difference between the medians is 10%. By considering the upper one-fourth, upper half, and upper three fourths instead of just the lowest and highest rates, we conclude that the recognition rates are better with patient data and the system recognizes the cough of patient's more than healthy people by 10%.

Based on our obtained results, we believe that a few changes in cough sounds can be a clear sign of an infection indication. If we train and test our system with large data, maybe we will get better results and more differences between the cough of infected and non-infected people. On the other hand, our proposed system does not specify if a person is infected with the Coronavirus. However, it can reveal if a laboratory COVID-19 test for infection should be performed. In the case where promising results are achieved with the large data, we will take the test to the next level, which is clinical. In addition, the designed system allows optimizing the medical resources by filtering the people that need the medical COVID-19 test. In the current context of the epidemic, to develop and give more reliability to our system we will combine speech and image technologies in order to produce an audiovisual system that consists of two phases. The first phase is the detection of the cough by the use of ASR methods and the second phase is the use of the thermal camera for temperature measurement. Integrating decisions from two systems will produce a final decision with high precision.

## 5 Conclusion

In this paper, we have presented the diagnosis of the COVID-19 patients and healthy people based on the speaker-independent ASR technology. Our conducted experiments have provided a performance evaluation of the cough train system in three HMM states and several Gaussian mixture distributions. The obtained results showed that when the system was trained with cough sounds of infected people the recognition rate of COVID-19 infected speakers was higher by 5% to 10% than non-infected speakers' rate. In addition, when we train the system by cough sounds of non-infected people the rate of COVID-19 infected people was lower by 5% to 10% than non-infected speakers' rate. In the best case, the classification sensitivity and specificity values of 90% and 10% were achieved respectively.

In our future work, we will be focused on the development of our COVID-19 detection system by adopting the visual speech recognition system based on large data through HMM and deep learning approaches.

**Acknowledgements** We would like to thank the volunteer patients and speakers, who have, help us to collect the Digits-Cough corpus, wishing patients speedy and full recovery. In addition, we would like to extend our appreciation to D. El Ayoubi Fahd, D. Lachkar Azzeddine, D. Eabdenbi Adil Tsen and D. Hamaz Siham professors at the Faculty of Medicine and Pharmacy of Oujda, Morocco.

**Funding** The authors declare they have no financial interests.

**Declarations**

**Conflict of interest** All authors declare that there is no conflict of interest.

## References

1. Rothan HA, Byrareddy SN (2020) The epidemiology and pathogenesis of coronavirus disease (COVID-19) outbreak. J Autoimmun 109:102433
2. Senapati A, Nag A, Mondal A, Maji S (2021) A novel framework for COVID-19 case prediction through piecewise regression in India. Int J Inf Technol 13(1):41–48
3. Hasan I, Dhawan P, Rizvi SAM, Dhir S (2022) Data analytics and knowledge management approach for COVID-19 prediction and control. Int J Inf Technol 11:1–18
4. Alafif T, Etaiwi A, Hawsawi Y, Alrefaei A, Albassam A, Althobaiti H (2022) DISCOVID: discovering patterns of COVID-19 infection from recovered patients: a case study in Saudi Arabia. Int J Inf Technol 4:1–14
5. Pramono RXA, Imtiaz SA, Rodriguez-Villegas E (2016) A cough-based algorithm for automatic diagnosis of pertussis. PLoS ONE 11(9):162128
6. Pramono RXA, Imtiaz SA, Rodriguez-Villegas E (2019) Automatic identification of cough events from acoustic signals. In: 2019 41st annual international conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp 217–220. IEEE, New York (2019)
7. Botha GHR, Theron G, Warren RM, Klopper M, Dheda K, Van Helden PD, Niesler TR (2018) Detection of tuberculosis by automatic cough sound analysis. Physiol Meas 39(4):045005
8. Satori H, Zealouk O, Satori K, Elhaoussi F (2017) Voice comparison between smokers and non-smokers using HMM speech recognition system. Int J Speech Technol 20(4):771–777
9. Zealouk O, Satori H, Hamidi M, Satori K (2020) Pathological detection using HMM speech recognition-based Amazigh digits. In: Embedded systems and artificial intelligence, pp 281–289. Springer, Singapore
10. Mouawad P, Dubnov T, Dubnov S (2021) Robust detection of COVID-19 in cough sounds. SN Comput Sci 2(1):1–13
11. Tena A, Clarià F, Solsona F (2022) Automated detection of COVID-19 cough. Biomed Signal Process Control 71:103175
12. Shastri S, Singh K, Kumar S, Kour P, Mansotra V (2021) Deep-LSTM ensemble framework to forecast Covid-19: an insight to the global pandemic. Int J Inf Technol 13(4):1291–1301
13. Zealouk O, Satori H, Hamidi M, Laaidi N, Salek A, Satori K (2021) Analysis of COVID-19 resulting cough using formants and automatic speech recognition system. J Voice
14. Rao S, Narayanaswamy V, Esposito M, Thiagarajan JJ, Spanias A (2021) COVID-19 detection using cough sound analysis and deep learning algorithms. Intell Decis Technol 2021:1–11
15. Chung KF, Pavord ID (2008) Prevalence, pathogenesis, and causes of chronic cough. Lancet 371(9621):1364–1374
16. Huang X, Acero A, Hon HW, Foreword By-Reddy R (2001) Spoken language processing: a guide to theory, algorithm, and system development. Prentice Hall PTR, London
17. Rabiner LR (1989) A tutorial on hidden Markov models and selected applications in speech recognition. In: Proceedings of the IEEE, vol 77(no. 2), pp 257–286 (1989)
18. Muda L, Begam M, Elamvazuthi I (2010) Voice recognition algorithms using mel frequency cepstral coefficient (MFCC) and dynamic time warping (DTW) techniques. arXiv preprint arXiv:1003.4083
19. Hamidi M, Satori H, Zealouk O, Satori K (2020) Amazigh digits through interactive speech recognition system in noisy environment. Int J Speech Technol 23(1):101–109
20. Zealouk O, Satori H, Hamidi M, Laaidi N, Satori K (2018) Vocal parameters analysis of smoker using Amazigh language. Int J Speech Technol 21(1):85–91
21. Barkani F, Satori H, Hamidi M, Zealouk O, Laaidi N (2020) Amazigh speech recognition embedded system. In: 1st international conference on innovative research in applied science, engineering and technology (IRASET), pp 1–5
22. Zealouk O, Satori H, Hamidi M, Satori K (2018) Voice pathology assessment based on automatic speech recognition using Amazigh digits. In: Proceedings of the 2nd international conference on smart digital environment. ACM, New York, pp 100–105
23. Hamidi M, Satori H, Zealouk O, Satori K (2020) Interactive voice application-based amazigh speech recognition. In: Embedded systems and artificial intelligence. Springer, Singapore, pp 271–279
24. Hamidi M, Satori H, Zealouk O, Satori K (2019) Speech coding effect on Amazigh alphabet speech recognition performance. J Adv Res Dyn Control Syst 11(2):1392–1400
25. Lamere P, Kwok P, Gouvea E, Raj B, Singh R, Walker W, Wolf P (2003) The CMU SPHINX-4 speech recognition system. In: IEEE international conference on acoustics, speech and signal processing (ICASSP 2003), Hong Kong, vol 1, pp 2–5
26. Huggins-Daines D, Kumar M, Chan A, Black A, Ravishankar M, Rudnicky A (2006) Pocketsphinx: a free, real-time continuous speech recognition system for handheld devices. In: 2006 IEEE international conference on acoustics speed and signal processing proceedings
27. Amrulloh YA, Abeyratne UR, Swarnkar V, Herath D, Triasih R, Setyati A (2017) HMM based cough sound analysis for classifying pneumonia and asthma in pediatric population. In: EMBEC & NBC 2017. Springer, Singapore, pp 852–855
28. Liu JM, You M, Wang Z, Li GZ, Xu X, Qiu Z (2014) Cough detection using deep neural networks. In: 2014 IEEE international conference on bioinformatics and biomedicine (BIBM), pp 560–563
29. Dash TK, Mishra S, Panda G, Satapathy SC (2021) Detection of COVID-19 from speech signal using bio-inspired based cepstral features. Pattern Recogn 117:107999

30. Swarnkar V, Abeyratne U, Chang A, Amrulloh Y, Setyati A, Triasih R (2013) Automatic identification of wet and dry cough in pediatric patients with respiratory diseases. Ann Biomed Eng 41(5):1016–1028