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.

1 Introduction

Corona virus (Covid-19) is one of the common viruses that causes upper respiratory infections, sinuses, and sore...
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

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] Studying 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% |
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
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 follow 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
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 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% and 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
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 people 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)
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%

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.

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Declarations

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

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