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Artificial Intelligence Against Virus Changes: A Long Term Detector of COVID-19 using the Clinical Symptoms and Respiratory Sounds.

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Abstract

In this research, we introduce our methods for creating a COVID-19 diagnostic tool based on the artificial intelligence to analyze the data of COVID-19 external symptoms such as cough, respiratory sounds, and other clinical symptoms such as fever, muscle pain, cold, sore throat, asthma, etc. to detect the virus without the need of any chemical or clinical tests which are expensive, slow and not available everywhere. Our diagnostic tool can be used publicly in crowded places such as shops, schools, or any human gatherings to detect the patients in their early stages, reduce the virus spread and forward the suspected people to clinical examination.
For creating our tool, we used deep learning-based models to analyze and learn from the collected sounds and the clinical features of confirmed COVID-19 cases and other normal cases. By using those models as classifiers they could distinguish the positive cases from the negatives. And we found that using simple binary classifiers trained with small samples of COVID-19 data collected early in 2021 can be trustworthy to detect COVID-19 in the recently collected samples regardless of the changes that occurred to the virus. And by testing the samples collected from 313 cases after several months of training our models, we could achieve an average accuracy of 91% to prove the proficiency of our tool in diagnosing COVID-19 and detecting the virus in the long term after several mutations.

Keywords: *COVID-19, AI, Machine Learning, Cough sounds, Clinical Information, Respiratory sounds.*

1 Introduction

By the end of March 2022, about 64.5% of the world population has received at least one dose of a COVID-19 vaccine, 11.29 billion doses have been administered globally, and about 18 million are now administered each day [1].
As Oxford AstraZeneca, Sinopharm, Sinovac-CoronaVac and Janssen Ad26.COV2.S vaccines have an efficacy of 63.09%, 79%, 51%, and 66.9% respectively against symptomatic SARS-CoV-2 infection [2–5], and while vaccination prevents serious illness and death, it will not keep you from being infected and passing the virus to others [6]. And the more we allow the virus to spread, the more opportunity the virus has to change [6]. So, public health practices such as mask-wearing and social distancing will continue to be important until a sufficient proportion of the population is immunized or achieves herd immunity [7, 8]. Therefore, the need for reliable and rapid pre-screening tools for COVID-19 detection and diagnosis will always remain for a longer time, especially because of the lack of interest in precautionary measures.

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Other than those who work in the medical field, many researchers studied the spread and the diagnostic methods of COVID-19 using statistical and mathematical models. In [9] they used a fractional mathematical model to study the effect of various parameters of the coronavirus and discussed the possibility to slow the speed of spreading of COVID-19 by social distancing and decreasing the contact rates. Also, Artificial Intelligence researchers had an important role, some studies worked on predicting the number of coming positive COVID-19 cases as discussed in [10]. While others used AI-based models to detect COVID-19 by classifying Chest images or X-Ray scans [11, 12]. While the dry cough was the most significant symptom of COVID-19, many studies discussed the possibility of detecting COVID-19 by classifying the cough and the respiratory sounds using machine learning models [13, 14].

In this research, we continue our efforts that have been started in [15] where we discussed the importance of using several COVID-19 sounds rather than cough sounds only for the sound-based COVID-19 diagnosis to create a fast and efficient pre-screening tool to detect the virus in the early stages. And now we aim to confirm the importance of using the clinical information that describes the suspected person's health condition such as fever, muscle pain, cold, sore throat, asthma, pneumonia, and chronic lung disease besides the cough and respiratory sounds for building more reliable COVID-19 classifiers based on the external symptoms.

2 Related Works

There are many former studies interested in the external symptoms of COVID-19 and worked to utilize them for distinguishing the infected persons from the healthy ones using Machine learning and Deep Learning-based models. Some studies trained their models using the COUGHVID dataset [16] which provides thousands of cough recordings obtained from positive and negative volunteers. Others preferred the Coswara dataset [17] in which each volunteer has recorded 9 types of sounds such as cough, breathing, and different voice patterns labeled with COVID-19 status besides metadata and clinical features that describe the health condition of the audio samples' owner.

For the sake of the sound-based diagnosis of COVID-19, we found some studies worked on the classification of cough sounds only [18, 19]. While [20] preferred detecting the presence of COVID-19 through speech and voice rather than using cough sounds. Others included both cough sounds and several respiratory sounds for training their models [21–23]. Whereas In [24–26], they used not only COVID-19 sounds but also the clinical features of patients to create an ensemble model with multiple inputs of features extracted from different symptoms of COVID-19 seeking to increase the classification accuracy.

In our previous research [15], besides using cough and respiratory sounds of COVID-19 to train our deep models, we introduced using special human voices such as recordings of counting and vowels, to train several models with a unique sound type for each model, then every separate model is used to detect the COVID-19 by testing samples of the same sound type used to train it, finally, the predictions of those models are averaged for voting the presence or absence of COVID-19 in the sounds collected from that suspected person. In Table 1. we present a comparison between some of the sound-based COVID-19 researches that used the Coswara dataset for training their shallow or deep models [17].

Table 1. The classification results of different studies used the Coswara dataset for training their models.

Research	Sound type/Features	Models /Classifiers	Results
Bagad et al., 2020 [27]	Cough	ResNet-18	AUC = 72%
Pahar et al., 2020 [19]	Cough	Resnet50 LSTM	AUC = 98% AUC = 94%
Verde et al. 2021[20]	Speech	SVM	Accuracy = 97%
Pahar et al., 2021 [28]	Cough or Breathing or Speech	Resnet50	AUC = 98% for coughs AUC = 94% for breaths AUC = 92% for speech
Aly et al., 2021 [15]	Cough and Breathing and Speech	Deep Learning Models	Averaged AUC = 96.4%
Fakhry, Ahmed, et al., 2021 [26]	Cough – Clinical Information	Multi-Branch Deep Learning Network	Averaged AUC = %91

3 Methods

In this study, we aim to emphasize the importance of using the clinical features that describe the health condition of COVID-19 patients besides the respiratory sounds and human voices for training more reliable COVID-19 classifiers that rely only on the external symptoms with no need for chemical or radiological tests. Also, we want to confirm that models trained with respiratory sounds collected early in the past year, could be knowledgeable enough to classify test samples of different COVID-19 sounds collected recently after many changes and mutations that had occurred to the virus.

3.1 Data Collection

Since the beginning of the pandemic, many efforts have been made to collect COVID-19 sounds and publish them publicly for research purposes. One of those projects was the Coswara dataset [17]. The Coswara dataset is a database of breathing, cough, and voice sounds for COVID-19 attached with other clinical features for the volunteers like fever, muscle pain, cold, sore throat, asthma, pneumonia, and chronic lung disease. We used this dataset for training our models.

3.1.1 Training Data

In this study, we used the same pre-trained sound models introduced in [15]. So, we could have 9 separate models that have been trained using 9 sound types of COVID-19 taken from the Coswara dataset [17]. Those models were (breathing-deep, breathing-shallow, cough-heavy, cough-shallow, counting-fast, counting-normal, vowel-a, vowel-e, vowel-o) as described in [15]. But now we want to use the clinical features attached to the COVID-19 sounds in the Coswara dataset to see their effect on the classification performance. Therefore, we have created a new dataset containing the clinical features of the volunteers who have recorded the sound samples. The selected features were (fever, muscle pain, cold, sore throat, asthma, pneumonia, and chronic lung disease). This dataset will be used to train a new clinical features-based model to be used besides the existing sound models for detecting COVID-19 as we will discuss in the next sections.

3.1.2 Testing Data

For testing our models and evaluating their performances in Coronavirus detection, we used more samples from the Coswara dataset [17]. Those samples were published in the following 5 months June, July, August, and September 2021 after training the models. We have selected all the samples that were labeled with covid_status (positive_mild, positive_asymp, positive_moderate) and considered them as (positive), in contrast, we have selected all samples with the status normal and labeled them as (negative). Finally, we have divided the data of the four months into 4 groups, each group containing 9 different types of COVID-19 sounds and the clinical symptoms dataset that describes the health condition of each volunteer. In Table 2, we describe the number of unique samples for each dataset in the testing groups.

Table 2. The number of samples in a testing group.

Test Group	Negative	Positive	Total
2021-06	38	70	108
2021-07	13	89	102
2021-08	11	4	15
2021-09	15	73	88
All Groups	77	236	313

The final result was four groups (2021-06, 2021-07, 2021-08, 2021-09) each group contains 10 datasets, where 9 of them represent COVID-19 sounds (breathing-deep, breathing-shallow, cough-heavy, cough-shallow, counting-fast, counting-normal, vowel-a, vowel-e, vowel-o) and the last dataset is the clinical symptoms data of the same volunteers who have recorded the sounds, and all samples were labeled with COVID-19 status positive or negative as described in Fig. 1.

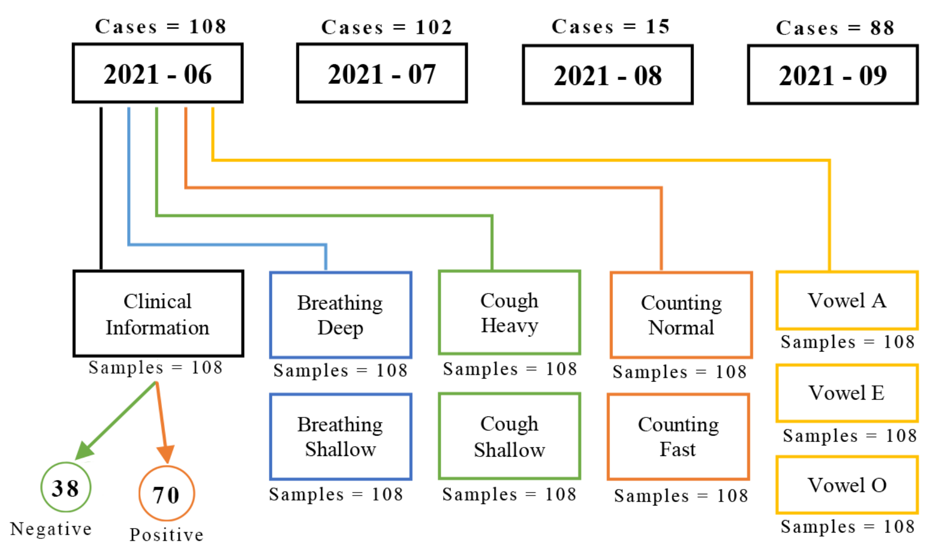


Fig. 1. A description of the testing groups

3.2 Feature Extraction

While our previous study [15] is based on the theory that confirms the existence of the Coronavirus signature in the cough and respiratory sounds of patients. This research is based on an assumption that emphasizes the necessity of using the data of the clinical symptoms alongside the COVID-19 sounds to build more accurate and reliable COVID-19 detectors. Therefore the feature extraction was an important step to extract the most significant features from the raw COVID-19 sounds and data to help our deep models learn and classify those samples correctly and detect the signature of COVID-19 if it was found.

And for the COVID-19 sound datasets, we extracted the same features described in [15] section 3.3. The main features are Mel Frequency Cepstral coefficients (MFCCs) which were used widely in many COVID-19 sound-based classification studies [15, 18, 21, 25, 26], besides other frequency, time domain, and statistical features as indicated in Fig. 2 below.

And for the clinical symptoms dataset, we have selected 9 features (pneumonia, asthma, breathing difficulties, diarrhea, fatigue, muscle pain, fever, cold, sore throat) labeled with COVID-19 status positive or negative. As not all those features are available for every case in the dataset and there are many missing features, we have merged those features into 3 groups containing similar features that were Feature_A (pneumonia or asthma or breathing difficulties), Feature_B (diarrhea or fatigue or muscle pain) and Feature_C (fever or cold or sore throat). For each feature set, if one symptom or more are available, then the feature will be (True) otherwise, it will be (False). Finally, we could have a dataset containing 3 features (Feature_A, Feature_B, Feature_C) labeled with COVID-19 status positive or negative.

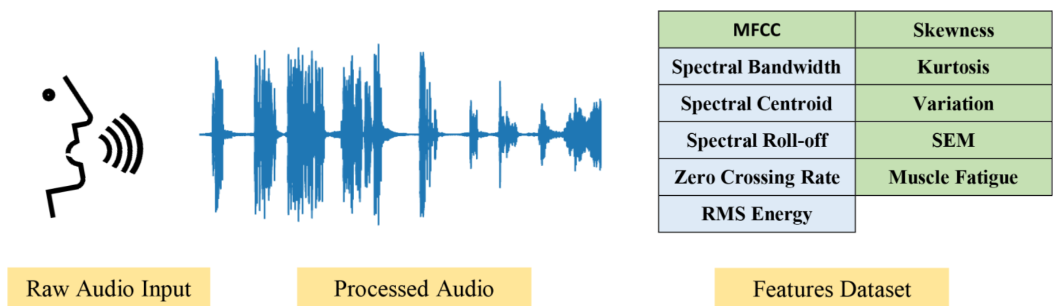


Fig. 2. The extracted features from a COVID-19 audio sample [15]

3.3 Classification

3.3.1 Model Architecture

As we will train a new model to classify the clinical features introduced in this research. We will use the same network architecture in [15] with minor changes in the input shape as indicated in Fig. 3. The clinical features selected for the training process mentioned in section 3.3 were oversampled to balance the positive samples with negatives using the Smote oversampling technique introduced in [15, 19]. The final features dataset contained 1173 positive samples versus 1173 negatives the same as every dataset used for training the sound models and were ready to train our new clinical features model.

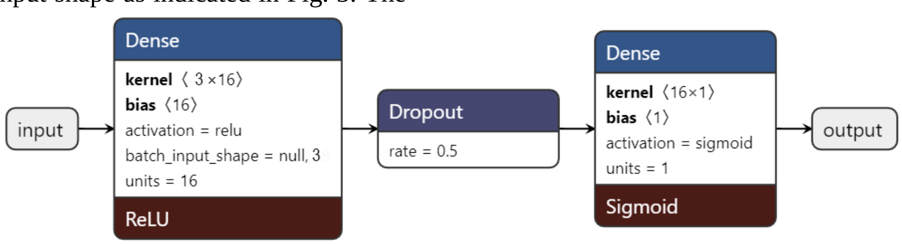


Fig. 3. The clinical features network architecture.

3.3.2 Multiple Classifiers

Now we have 10 models that have been trained with 10 datasets of COVID-19 sounds and clinical features extracted from the Coswara dataset [17]. The testing methodology that we introduced in [15] and proved its success, was to average the predictions of multiple models that have been trained and tested separately with unique data or a sound type. Here we continue using the same method with a small change, which is to add the newly created clinical features model to the sound models set to understand its effect on the overall classification performance as shown in Fig 4.

While we won't use all the 10 classifiers at the same time, we have to find the best models set that achieves the highest classification accuracy, and this can't be determined unless testing our data with all model combinations. As discussed in detail in [15] section 4.4, we will use the power set concept to determine all subsets of models in the set {clinical information, breathing-deep, breathing-shallow, cough-heavy, cough-shallow, counting-fast, counting-normal, vowel-a, vowel-e, vowel-o} which size is 10 and has $2^{10} = 1024$ combination of models. And for averaging the predictions of several models, we will use the mean statistical function.

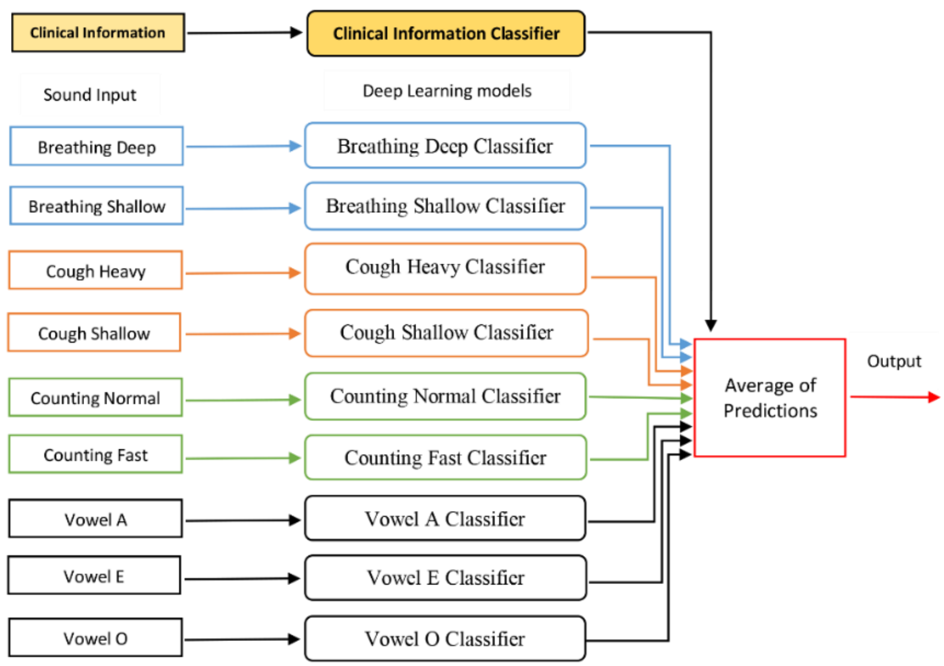


Fig. 4. The strategy of models training and evaluation with different types of COVID-19 sounds and the clinical information.

4 Results

In [15] we have tested all the combinations of models on the 24 samples taken from the Coswara dataset in May 2021 [17]. And we found that a combination of 6 models *{breathing-shallow, cough-heavy, cough-shallow, counting-fast, vowel-e, vowel-o}* achieved the highest classification accuracy and detected all the positive samples which were 10 samples. Although the testing dataset was small, the classification results have given us a rule about the importance of using multiple sound models rather than using a single model for diagnosing COVID-19 and this rule will be confirmed again here with larger testing datasets. And the question that is going to be answered now is: Will this models combination keep its high classification results with the testing data uploaded in the next months June, July, August, and September or it was just a coincidence that occurred with small samples of data selected from May's data. Also, we will know whether the newly introduced clinical features model would help to increase the overall classification performance or not.

So, in the next sections we will discuss our classification results for several testing datasets using:

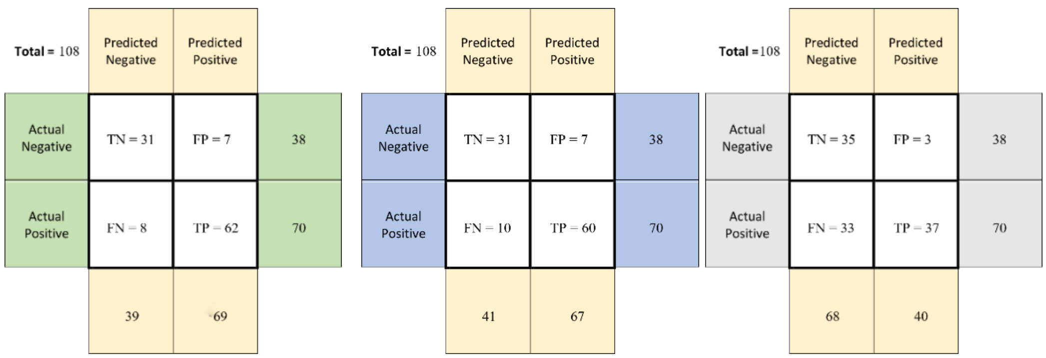
1) Hybrid models combination (It contains sound models and clinical features model together).
2) Sound models.
3) Clinical features model.

4.1 Group 2021-06

As mentioned in section 3.2, this group contained 108 samples for each sound type recorded in June 2021. After testing this group by all models combinations, we found that averaging the predictions of the models set *{breathing-deep, breathing-shallow, cough-heavy, cough-shallow, vowel-e, vowel-o, clinical information}* using the mean value of predictions, could detect (62) positive samples out of (70) as indicated in Fig 5.a. While using the same models set without the clinical features model decreased the accuracy by 2% and detected less positive samples (see Fig 5. b). Whereas, the clinical features model alone achieved the lowest accuracy as indicated in Table 3.

Table 3. The best classification results on testing group 2021-06 with Hybrid models combination, sound models combination, and the clinical model.

Type	Models	ACC	AUC
Hybrid	breathing-deep, breathing-shallow, cough-heavy, cough-shallow, vowel-e, vowel-o, clinical information	0.86	0.85
Sounds	breathing-deep, breathing-shallow, cough-heavy, cough-shallow, vowel-e, vowel-o	0.84	0.84
Clinical	clinical information	0.67	0.72



(a) **(b)** **(c)**

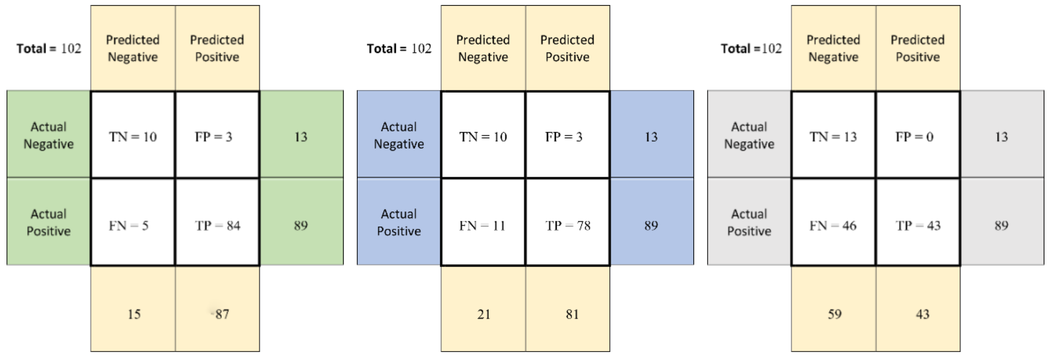
Fig. 5. The confusion matrix for testing group 2021-06 Using (a) hybrid models. (b) sound models. (c) clinical model.

4.2 Group 2021-07

The second group contained 102 samples for each sound type recorded in July 2021 including 89 positive samples. Our classifiers could achieve higher accuracy of about 92% and detected 84 positive samples out of 89 using the hybrid models set *{breathing-deep, breathing-shallow, cough-heavy, cough-shallow, counting-fast, vowel-o, vowel-e, clinical information}*. While excluding the clinical features model, dropped the accuracy by about 6%, but the clinical features model alone achieved the lowest accuracy as indicated in Table 4. and Fig. 6.

Table 4. The best classification results on testing group 2021-07 with Hybrid models combination, sound models combination, and the clinical model.

Type	Models	ACC	AUC
Hybrid	breathing-deep, breathing-shallow, cough-heavy, cough-shallow, counting-fast, vowel-o, vowel-e, clinical information	0.92	0.86
Sounds	breathing-deep, breathing-shallow, cough-heavy, cough-shallow, counting-fast, vowel-o, vowel-e	0.86	0.82
Clinical	clinical information	0.55	0.74



(a) (b) (c)

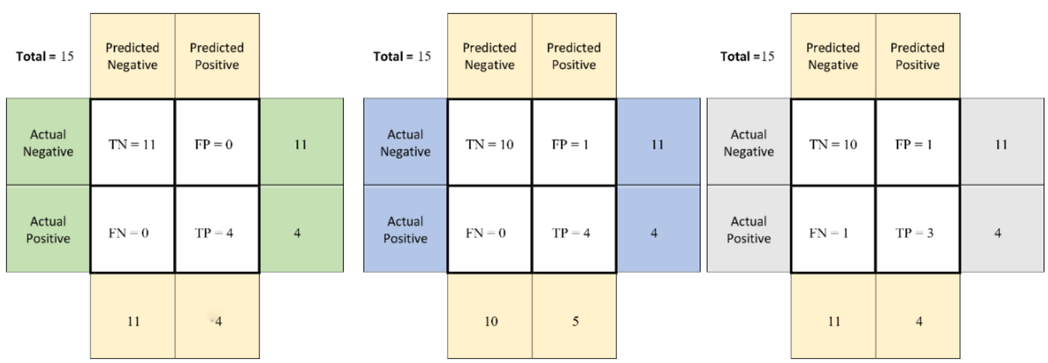
Fig. 6: The confusion matrix for testing group 2021-07 Using (a) hybrid models. (b) sound models. (c) clinical model.

4.3 Group 2021-08

The next testing group contained the samples uploaded in August 2021 and was the smallest group compared to other groups with 15 samples only. We found that averaging the predictions of hybrid combination *{breathing-deep, breathing-shallow, cough-heavy, vowel-o, clinical information}* could detect all the positive samples and the negatives correctly with an accuracy of 100%. While the sound models missed one negative sample to achieve an accuracy of 93%. Even the clinical features model alone has achieved an acceptable accuracy of 87%. We can see all results indicated in Fig. 7 and Table 5.

Table 5: The best classification results on testing group 2021-08 with Hybrid models combination, sound models combination, and the clinical model.

Type	Models	ACC	AUC
Hybrid	breathing-deep, breathing-shallow, cough-heavy, vowel-o, clinical information	1	1
Sounds	breathing-deep, breathing-shallow, cough-heavy, vowel-o	0.93	0.95
Clinical	clinical information	0.87	0.83



(a) (b) (c)

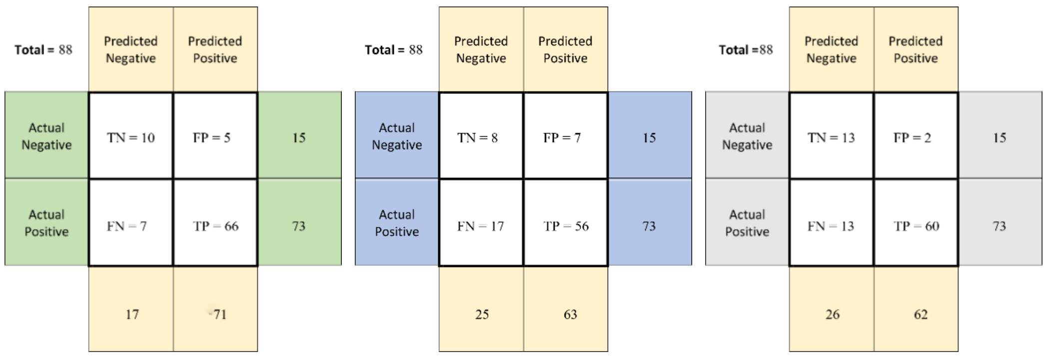
Fig. 7. The confusion matrix for testing group 2021-08 Using (a) hybrid models. (b) sound models. (c) clinical model.

4.4 Group 2021-09

The last testing group contained 88 samples for each sound type collected in September 2021. As expected the hybrid models set *{breathing-deep, cough-heavy, counting-normal, clinical information}* achieved the highest accuracy 86%, and detected 66 positive samples out of 73. While the clinical information model alone could achieve an accuracy of 83% and detected 60 positive samples out of 73 as indicated in Fig. 8 and Table 6 below.

Table 6. The best classification results on testing group 2021-09 with Hybrid models combination, sound models combination, and the clinical model.

Types	Models	ACC	AUC
Hybrid	breathing-deep, cough-heavy, counting-normal, clinical information	0.86	0.79
Sounds	breathing-deep, cough-heavy, counting-normal	0.73	0.65
Clinical	clinical information	0.83	0.84



(a) **(b)** **(c)**

Fig. 8. The confusion matrix for testing group 2021-09 Using (a) hybrid models. (b) sound models. (c) clinical model.

5 Discussion

In Tables 7 and 8 Below we summarize the classification results for different model types used for testing several datasets collected in four months from the Coswara dataset [17]. We can see that creating hybrid models combination of sounds and clinical symptoms could achieve the best performance with an average accuracy of 91% and an AUC of 88%. Although the clinical model improved the overall accuracy, this doesn't give him an advantage over the sound models, because the clinical information model alone achieved the lowest accuracy and AUC 73%, 78% respectively.

In Fig. 9 and 10 we can see the line plots comparing the accuracies and the AUCs of different models on testing the 4 test groups. We can realize that the hybrid combination of the sound and the clinical symptoms always achieves the best performance followed by the sound models.

Table 7. The averaged accuracy for all testing groups.

Models	2021-06	2021-07	2021-08	2021-09	Average Accuracy
Hybrid	0.86	0.92	1.0	0.86	**0.91**
Sounds	0.84	0.86	0.93	0.73	**0.84**
Clinical	0.67	0.55	0.87	0.83	**0.73**

Table 8. The averaged AUC for all testing groups.

Models	2021-06	2021-07	2021-08	2021-09	Average AUC
Hybrid	0.85	0.86	1	0.79	**0.88**
Sounds	0.84	0.82	0.95	0.65	**0.82**
Clinical	0.72	0.74	0.83	0.84	**0.78**

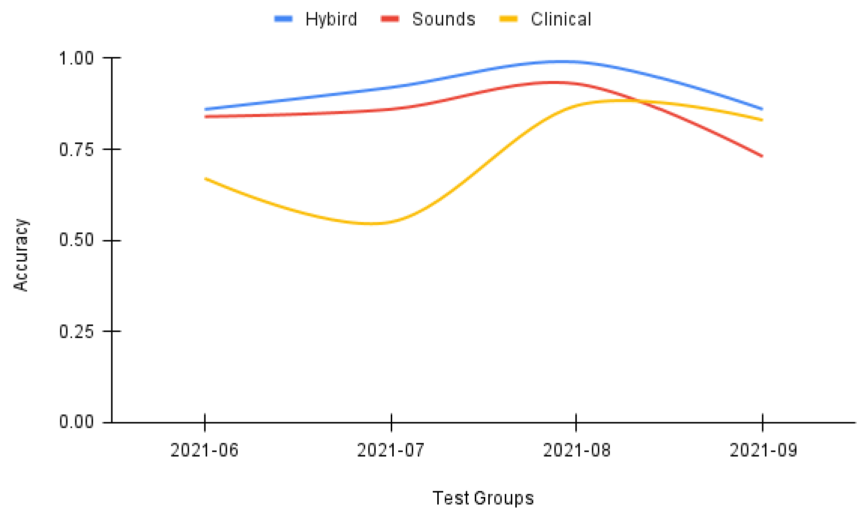


Fig. 9. A Comparison between the classification Accuracies achieved by different model combinations while testing the 4 test groups.

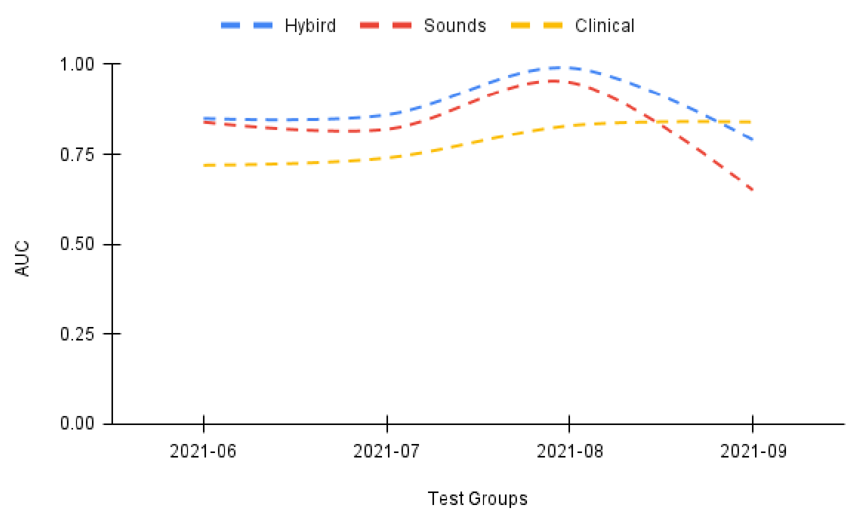


Fig. 10. A Comparison between the classification AUCs achieved by different model combinations while testing the 4 test groups

And based on our results in this study and in [15] We can confirm that analyzing the coughs, respiratory sounds, and the speech can be very useful to diagnose COVID-19 and detect the virus reliably without the need for chemical or radiological tests as the COVID-19 virus affects the respiratory system and the vocal cords. Also, we have introduced the importance of using the clinical symptoms besides the COVID-9 sounds for creating a more accurate COVID-19 detector and a diagnostic tool that relies on artificial intelligence and the external symptoms of the disease. In Fig. 11 we summarize the whole process and the steps that our COVID-19 detector uses to detect the virus instantly. At first, the user records his coughs, breathing, and speech. Also, he provides the clinical symptoms that he feels. Then our detector analyses every sound type separately by extracting the features from the raw sounds and classifying them to predict the COVID status. Finally, an ensemble model is used to average the predictions of several models and decides whether the case is positive or negative

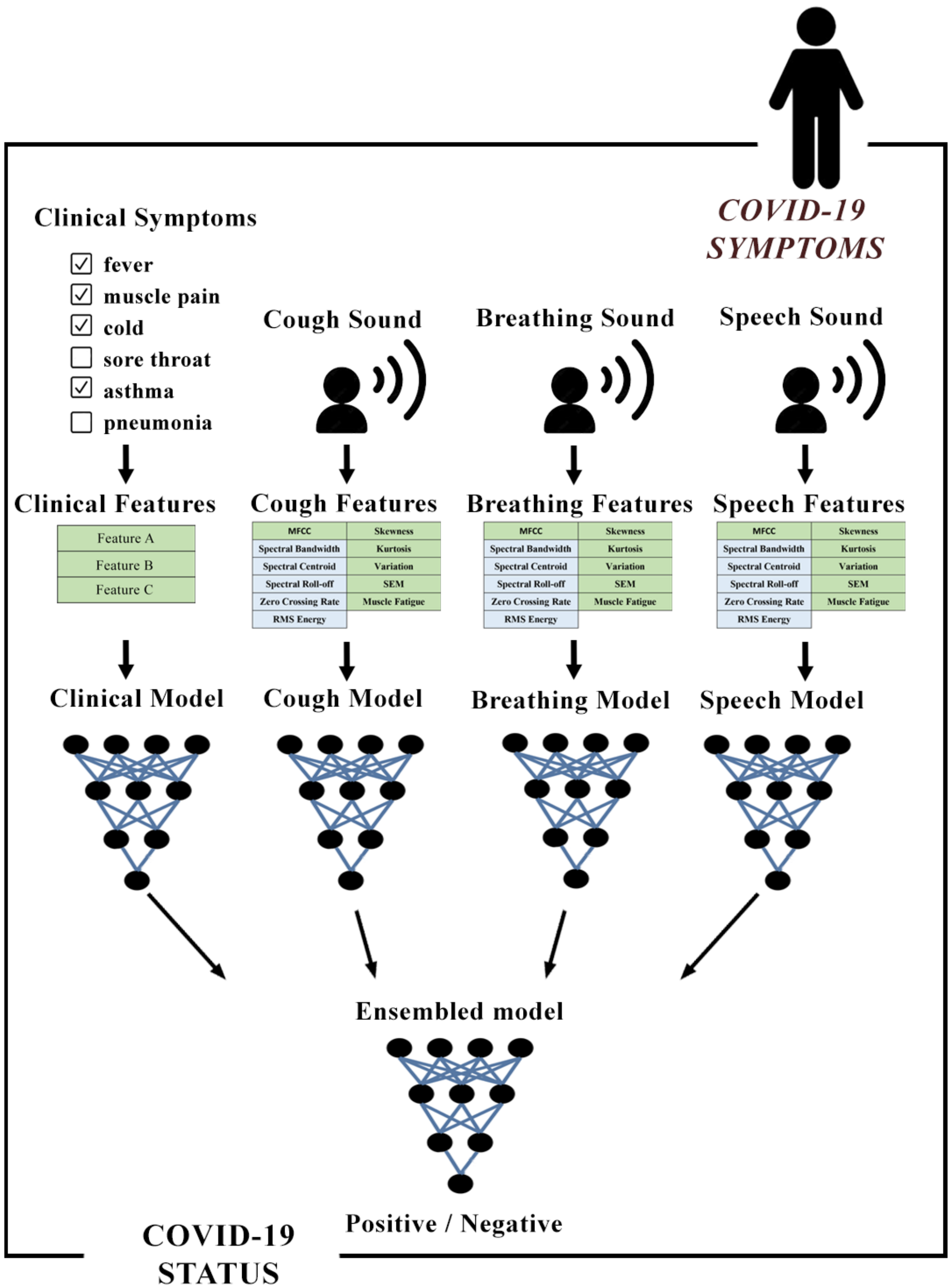


Fig. 11. The summary of all steps used by our detector to diagnose COVID-19 using the external symptoms only.

6 Conclusion

In this study, we continued our efforts in the diagnosis of COVID-19 using Machine Learning and its external symptoms such as cough, respiratory sounds, and here we have discussed the importance of using clinical symptoms features such as (fever, muscle pain, cold, sore throat, asthma, pneumonia, and chronic lung disease) for creating more reliable detectors and diagnostic tools of COVID-19. Using the Coswara dataset that contained 9 different types of sounds (cough, breaths, speech, etc..) for each volunteer as well as their clinical information labeled with their COVID-19 status, we could train 10 different classifiers with the samples released before May 2021. And to evaluate the performance of those classifiers in detecting COVID-19, we used more samples published in the next 5 months to create several testing groups. By testing those groups, we found that a hybrid combination of sound models and the clinical symptoms model could achieve the best performance with an average accuracy of 91%. While the sound models are still effective in the long term to detect the presence of COVID-19 in the samples collected after several months of training those models regardless of the changes that occurred to the virus.

List of Abbreviations

COVID-19	Coronavirus Disease of 2019
WHO	The World Health Organization
RT-PCR	The reverse transcription-polymerase chain reaction
AI	Artificial Intelligence
IOT	Internet Of Things
AUC	Area Under Curve
ACC	Accuracy
CNN	Convolutional Neural Network
ResNet	A residual neural network
LSTM	Long short-term memory
SVM	Support Vector Machine
MFCC	Mel Frequency Cepstral coefficients
SEM	Standard Error of the Mean
RMS	Root Mean Square

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أداة تخشيص طويلة المدي لمرض الكوفيد ١٩ عن طريق الذكاء الاصطناعي والأعراض الخارجية للمرض

في هذا البحث نقدم طرقنا المستخدمة في عمل أداة لتشخيص مرض الكوفيد-١٩ تعتمد على الذكاء الاصطناعي دون الحاجة إلي إجراء اختبارات سريرية أو كيميائية وذلك عن طريق مراقبة وتحليل البيانات التي تصف الأعراض الخارجية للمرض مثل الكحة، وأصوات الجهاز التنفسي وبعض الأعراض السريرية الأخري مثل ارتفاع درجة الحرارة و البرد و احتقان الزور وغيرهم. والهدف من أداة التشخيص هذه هو أن يتم استخدامها في التجمعات البشرية الكبيرة لتوقع الحالات المصابة في المراحل المبكرة للمرض والحد من انتشار الفايروس و توجيه الحالات المشتبه بها إلي الكشف السريري والمختبري.

ولبناء هذه الأداة قمنا باستخدام العديد من نماذج التعلم العميق التي تهدف إلي تحليل البيانات التي تم جمعها من حالات مؤكدة بمرض الكوفيد-١٩ وبيانات أخري لأشخاص أصحاء بغرض التعلم منها وانشاء مصنفات يمكنها فيما بعد توقع الحالات الإيجابية والسلبية من الأعراض الخارجية فقط. وبعد التجارب العملية وجدنا ان النماذج التي تم تدريبها على عينات صغيرة وتم جمعها مبكراً في العام الماضي، كانت قادرة علي الكشف عن وجود الفايروس في العينات التي تم جمعها بعد شهور من تدريب هذه النماذج. كما استطاعت نماذجنا تحقيق دقة تصل إلي ٩١% عند الكشف على ٣١٣ عينة تم جمعها بعد شهور عدة من تدريب هذه النماذج، وهذا بدوره يؤكد فعالية أداة التشخيص المقدمة في هذا البحث لتشخيص مرض الكوفيد بشكل فوري وسريع اعتماداً على الأعراض الخارجية فقط وبغض النظر عن التحورات التي تحدث للفايروس.