A Case Study: Adopting Artificial Intelligence to Distinguish Chronic Cough in Taiwan

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***Abstract*— the aim of this study is to provide a home care solution for recognizing the chronic respiratory diseases via cough sound analysis AI model. The proposed model is based on a deep learning architecture, recurrent neural network (RNN), and has been trained and tested with real world chronic cough sounds collected and labelled by professional physicians, and three chronical respiratory diseases, Allergic Rhinitis (AR), Gastroesophageal reflux disease (GERD) and asthma are considered in this work. Furthermore, we also trained the model to classify whether a cough is a dry or a wet one, which is a valuable indicator as part of clinical queries before any medical diagnosis or treatments. The proposed method has shown that the trained model is capable of providing reliable predictions for the target diseases without any intervention from professional medical staff, and this is a potential rescue for the patients who have had a hard time accessing timely medical consultations or clinics do not have sufficient manpower. As long as the trained model is able to execute on mobile devices such as smart phones or mobile tablets, it can be beneficial to enhance the home-based care for patients of chronical respiratory diseases and reduce the consumptions of medical resources.**

Keywords-component: chronic disease care, home care, chronic cough assessment, artificial intelligence, machine learning

I. INTRODUCTION

Coughing do not always imply to be signs or symptoms of illness, it could be a defensive reflex mechanism of inner immune system [1]. Several different stimulations may be causes cough, such as changes in weather conditions or individual's behaviors like drug use or smoking. According to [2], coughs could be classified into three categories based on the duration of time. The acute cough is less than 3 weeks; subacute cough is between 3 to 8 weeks, and the chronic cough lasts more than 8 weeks. It's clear and straightforward to classify a cough base on the definition mentioned above, yet to provide precise medical assessment and appropriate treatment is still a difficult task to respiratory physicians. Since there are lots of causes for refractory cough, many guidelines of cough consultation and care instructions had been developed and established for healthcare quality promotion. In [3], the authors focused on etiology review process in clinics, aimed to discover an unmet need for treatments for respiratory diseases**.** Previous study [4] has shown that similar symptoms of chronic cough may be diagnosed as different diseases depending on region or country. According to the statistics released by Ministry of Health and Welfare (Taiwan), "bronchitis, emphysema and asthma" was ranked as the 7th leading cause of death [5].

As mentioned in WebMed, it is not easy to distinguish chronic cough from COVID-19 [6]. In Taiwan, a patient's follow-up treatment for chronic cough is likely to be interrupted due to the fear of COVID-19. Thus, to identify the relationship between a cough and the causes of it become more and more important, especially during the COVID-19 pandemic.

Recently, many AI-based solutions have been proposed to identify covid-19 quickly from acoustic information with minimal resources [7]. And some researches focused on developing apps on mobile devices for cough analysis, for example, Hyfe App had collected a library of up to a million cough sounds for training an AI algorithm and provided an estimated diagnosis for patients [8]. On the other hand, chronic diseases have a large impact on quality of life and medical expenses. According to [9], 60 percent of American adults have a chronic disease such as Type 2 diabetes, asthma and heart disease. Thus, an analytic model that can detect the hidden diabetes cases could be extremely beneficial for the society, as McCammon stated, "*Given the number of complication events per person per year, a health plan that uses this model to target the top 100 riskiest members can expect annual savings of approximately $500,000, and those members can potentially avoid unnecessary hospitalizations.*" .

The primary goal of this work is to build up a safe, effective AI-based model for chronic cough recognition. In the following, we present the data collection process and the distribution of the data we've collected in section II, the problem formulation and details of the proposed AI model architecture are introduced in section III. The experimental configuration and the prediction results are shown in section IV. Finally, conclusions and some potential future works are presented in section V.

II. DATA COLLECTION AND DATA PREVIEW

Collecting medical data such as cough sound records involves both technical and privacy considerations. Before recording any audio for this experiment, the physicians explained the research plan and acquired permissions or oral consents from patients who were willing to participate this experiment. Then, the nurses started recording with the handy recorder (Zoom H1n model, with the highest sampling resolution of 96kHz/24-bit WAV) aside of physicians' desks without interrupting the clinical consultation and diagnostic process. Inevitably, the original recorded audio clips will contain a large number of blanks, background sounds, conversations between doctors and patients, and environmental noises. We manually extract useful cough sounds from the raw audio clips, and this process will be detailed later in this section. For these recorded raw data, we define "a case" to be valid if it satisfies two conditions. First, the diagnosed results, that is, diseases, of a patient should be recorded completely. Second, the audio records of the patient should contain at least one cough sound with minimal length for the experiment and without severely corrupted. Two hospitals are involved in the data collection, and the process had spanned over months. There were 51 out of 63 cases had been recognized as valid, and the longest clinical visiting took about 15 minutes to complete. Within the 51 valid cases, the average age of the patients is 54 years old, and the gender composition is of 28 females and 23 males. Though there are 20 types of distinct diseases involved in the patients' records, we only focused on the most appearing three diseases amount them as the targets of our AI classification model. The three diseases are: AR, GERD, and asthma. Furthermore, the clinician had tagged the cough sounds to be dry or wet coughs based on their professional judgment. Normally, a wet cough comes along with a large amount of sputum, and this feature distinguished itself from a dry one. The number of dry and wet coughs and corresponding diseases are shown in Table 1.

Table 1: diseases and cough types of experimental data

Disease(s)	Dry Cough	Wet Cough	Not Annotated	Total
AR	24	22	0	46
GERD	20	20	1	41
Asthma	17	18	0	35
AR, GERD	40	2	0	42
AR, Asthma	0	30	0	30
Asthma, GERD	0	6	0	6
Others	24	17	1	42
Total	125	115	2	242

There are 242 recorded audio clips, each clip contains at least one cough sound segment, and all the segments are manually tagged with their corresponding disease(s) using the free and open source audio software "Audacity" [10] (Copyright © 2021 Audacity Team). Those segments with length shorter than 0.2 second are excluded from the experiment, and the duration of all the labelled cough segments are between 0.2 ~ 1.5 seconds. Thus, this results in total 279 qualified cough segments for our experiment. The appearance frequencies of target diseases are listed in Table 2, and the length distribution of cough segments is depicted in Figure 1. Please notice that the cough segments which were not being annotated as AR, GERD or asthma do not imply that the cough sounds come from healthy people, it just means that the sounds do not belong to any one of the three types of diseases. Moreover, a single cough sound could indicate more than one disease.

Table 2: The number of cough segments by diseases

Disease	Appearance frequencies of disease
AR	126
GERD	91
ASTHMA	88

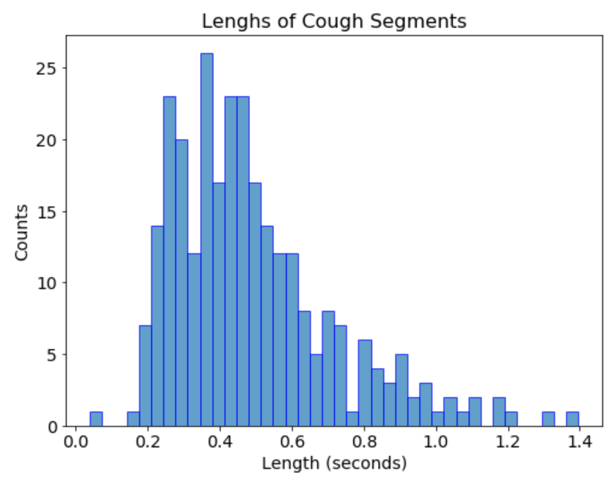

Figure 1: the distribution of the length of cough segments

III. Classification Model in Detail

In this section, the details of the proposed artificial intelligence model is presented. Since the raw audio clips were cropped into cough segments in advance, we first resample the audio with sample rate 22050 Hz and extract the Mel-Frequency Cepstral Coefficients (MFCC) from each segments, the number of coefficients was chosen to be 48. Since the lengths of segments differ from each other, the resulted MFCC sequences are of different lengths either. We define the input length of MFCC sequences to be 65, if a resulted MFCC sequence is shorter than 65, it will be padded with zeros to keep all the inputs having the same lengths. After the preprocessing stage, a recurrent neural network (RNN) based model follows, it takes the MFCC sequences as inputs and generates outputs corresponding to the target labels, AR, GERD, asthma, and an additional label for indicating a cough is dry or wet. The problem is formulated as a multi-label classification problem, that is, multiple labels could be assigned to an input instance at the same time. In our case, the model reflects the fact that a cough sound could reveal the information of more than one category of diseases. The RNN model is composed of two gated recurrent unit layers (GRU) [11] and followed by two dense layers. The two GRU layers contain 48 and 32 cells respectively, and the dropout rate of both layers are set to be 0.25 to avoid overfitting. The two dense layers uses tanh and sigmoid as activation functions, and the sigmoid at the final layer produces four outputs ranging from 0 to 1.0, which could be interpreted as probabilities and provide the users an intuitive indicator to understand the meaning of the predicted outcomes. Binary cross-entropy has been adopted as the loss function during training, which is one of the most commonly used one for multi-label classification problems. A flowchart of the proposed model is illustrated in Figure 2.

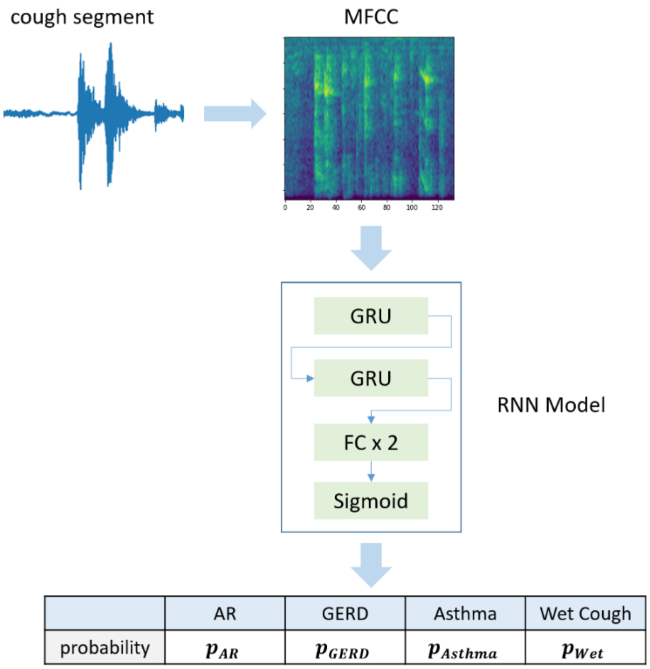

Figure 2: flowchart of the proposed method

IV. Experiment and Results

To evaluate the proposed approach, we first split the 279 qualified cough segments into train and test sets. We use 25% of the data for testing, so there are 209 segments for training and 70 segments for testing. However, 209 samples is far from capable of training a decent modern artificial intelligence model, so we utilized the data augmentation technique to increase the size of training set by transforming the cough segments under certain constraints. We assume that the characteristics and hidden information within a cough sound would not be altered under slight perturbation and distortion. Based on this assumption, a single training sample is augmented into 50 by slightly changing the speed, pitch, and adding normal distributed noises randomly. The augmented training set contains about 10000 transformed samples, and we expect it will reveal more information, and the model trained on the augmented dataset will benefit from it and produce better generalization for this task. During the data augmentation process, the length of a cough segment is randomly stretched to 80% ~ 120% of its original length, the pitch is randomly shifted up or down by 3 quarter-tones. Finally, a normal distributed random noise is added with intensity up to 25% of the maximal amplitude of the original cough data.

In the following, the experimental result is presented. We first examine the individual prediction accuracy for the three target diseases and the classification of a wet cough (the complement of a dry cough), and then a more detail view from ROC AUC curves will be showed. The prediction accuracy of the train and test set for all targets are listed in Table 3, the results show that the trained model provided accuracy higher than 0.65 for both GERD and asthma, and the accuracy is about 0.6 for wet cough prediction. On the other hand, the predicted accuracy for AR is rather unsatisfactory during both training and testing phase. This might imply that the cough sounds give less discriminative information for AR patients, but more detail examinations are necessary to confirm this conjecture. The confusion matrices of predicted results for AR, GERD and asthma are shown in Table 4 through Table 6 respectively. The ROC AUC curve of the target diseases and the micro ROC for training and testing sets are presented in Figure 3 and Figure 4.

Table 3: The accuracy of predicted results

	AR	GERD	ASTHMA	Wet
Train	0.565	0.699	0.689	0.622
Test	0.629	0.643	0.714	0.614

Table 4: Confusion Matrix of AR

	Train		Test	
	True	False	True	False
True	77	37	27	12
False	54	41	14	17

Table 5: Confusion Matrix of GERD

	Train		Test	
	True	False	True	False
True	131	10	40	7
False	53	15	18	5

Table 6: Confusion Matrix of Asthma

	Train		Test	
	True	False	True	False
True	97	40	37	15
False	25	47	5	11

V. Discussion & Concultsion

In this work, we've proposed an artificial intelligence model to recognize three types of chronic respiratory diseases from audio cough sounds. Although deep learning has shown its excellent performance in various applications, collecting sufficient data for a real word medical problem is still difficult and complicated task due to the privacy and ethical considerations.

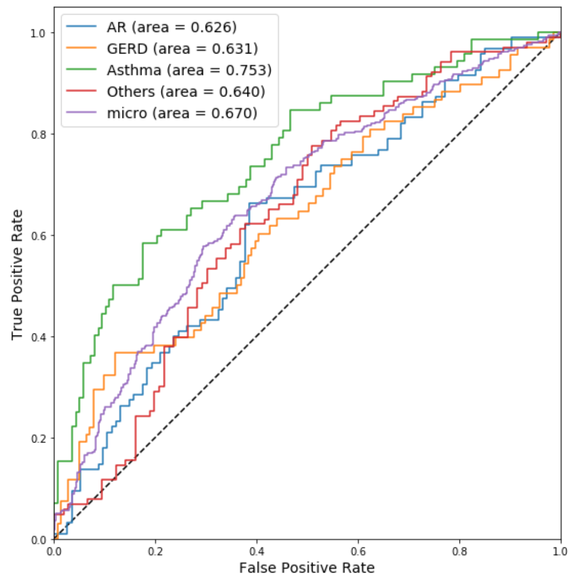

Figure 3: The ROC AUC curves for training set

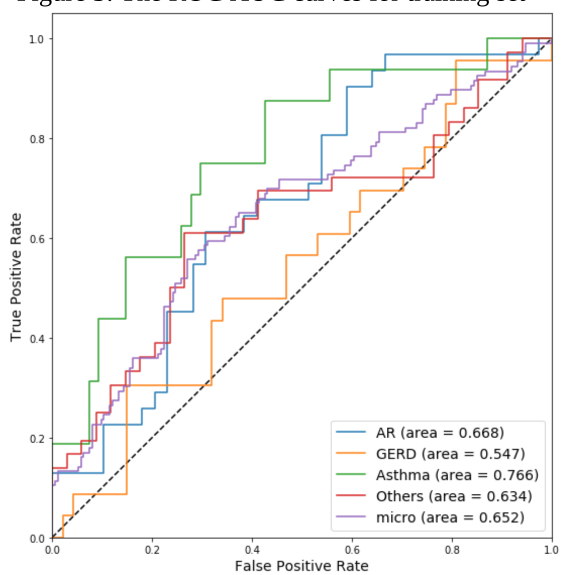

Figure 4: The ROC AUC curves for test set

In order to use the data in an effective way, the data augmentation technique has been adopted to improve the model generalization. The results show that there is no significant difference in accuracy for training and testing sets, this implies that the resulted model has not been suffered from severe over-fitting. However, the data is still fall short to achieve a satisfactory performance for the standard of a serious medical application. In order to improve the results, collecting more quality data is one of the most straightforward potential solutions. On the other hand, rather than preparing more data targeting on this specific problem, we might try to make use of other existing dataset contains common cough sounds such as ECS-50 data set [12] to learn more general patterns from cough audios and expect to increase the model predictive power.

Building a quality AI model for medical purpose is not an easy task, but the benefits could be fruitful once it could be a help for the medical staff. This project has been executed for more than 8 months for collecting the audio data, yet it had been suspend for s few weeks due to the COVID 19 outbreak. Even till today, we are still under the impacts of the pandemic, and this brings barriers to collect data from patients. In another perspective, an AI solution might be helpful for identifying cough diseases and reducing the cost of diagnosis, but we still need more pathological examination for further clinical checks. For example, a clinical examination is necessary to identify mycoplasma pneumoniae. In the future, we expect to improve the prediction accuracy and port the proposed algorithm onto mobile devices to evaluate its performance.

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