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Article

Analyzing breath sounds by using deep learning in diagnosing bronchial blockages with artificial lung

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SUMMARY

Many common respiratory illnesses like bronchitis, asthma, and chronic obstructive pulmonary disease (COPD) lead to bronchial inflammation and, subsequently, a blockage. However, there are many difficulties in measuring the severity of the blockage. To detect the blockages associated with these illnesses, most medical staff have relied on patients' descriptions of their symptoms or the doctor's experience or monitoring through a medical device like the stethoscope. However, these diagnostic measures are error-prone and time-consuming, leading to frequent misdiagnosis and limitations in continuous perioperative monitoring. Therefore, a numeric metric to determine the degree of the blockage severity is necessary. To tackle this demand, we aimed to develop a novel human respiratory model and design a deep-learning program that can constantly monitor and report bronchial blockage by recording breath sounds in a non-intrusive way. A bronchial lung model would provide doctors or medical staff with a better understanding of patients' conditions and allow faster more targeted treatment. Performing these experiments demands a new design of the artificial respiratory system. Alternative to using human testing, there is more accuracy in characterizing human airways and obtaining various sizes of blockage samples. As a result, we developed a Google TensorFlow deep learning program that recognizes bronchial blockages through sound recordings at a >75% success rate. Through the experiments, the deep learning program had a 99.28% recognition rate when tested on eight representative blockages, demonstrating the potential of sound-based deep learning programs as a method of bronchial blockage analysis to diagnose respiratory illnesses.

INTRODUCTION

Air pollution, chemicals, dust, and recurrent respiratory illnesses in childhood all increase the risk of lung cancer (1). This calls for effective diagnosis of respiratory illnesses, especially for vulnerable populations like the youth. Even though chronic respiratory diseases (CRDs) cannot be cured, several therapy options like breathing techniques can assist people in managing their symptoms and improving their quality of life (2).

Also, meeting the needs of individuals living in low and middle-income countries who have CRDs has always been particularly challenging (3). Long-term, life-threatening CRDs such as asthma, chronic obstructive pulmonary disease (COPD), and bronchiectasis afflict people of all ages, genders, and races worldwide. As of 2017, approximately 545 million individuals or 7.4% of the world's population have chronic respiratory illnesses (4). Asthma, emphysema, and COPD are characterized by airway inflammation, blockage, and remodeling (5). Patients with chronic airway disorders are at increased risk of hospitalization. For example, between 3% and 20% of patients with COPD make at least one hospital visit per year (6). Asthma and COPD are the most prevalent CRDs, affecting 358 and 174 million people, respectively, with COPD itself being the third leading cause of death worldwide, causing 3.23 million deaths (7, 8). Treatment of both illnesses faces several obstacles, including under and overdiagnosis, unknown pathophysiology, and a lack of consistent categorization making effective diagnosis crucial (9). Therefore, this calls for effective determining of the bronchial blockages that lead to diagnosis of these CRDs (and other respiratory illnesses) to allow for effective treatment and therapy options to be employed.

Past research has used multiple methodologies and clinical to improve the diagnosis of respiratory illnesses, like CRDs, due to the lack of standardized biomarkers for every disease. There is ongoing research going on to improve the framework of these methodologies. For example, one study used machine learning (ML) and computer-based acoustical techniques to construct an artificial intelligence (AI) system that could identify the pathophysiology of airways (10). However, this study was not conducted in a clinical setting, simply proving the relationship between sound and airflow. Our study expands on this concept through modeling the respiratory condition. However, if proven applicable, ourstudy could help respiratory airway management greatly. In addition, another study used an exhaled breath condensate (EBC) metabolome to construct a random forest classifier, which could identify asthma patients with 80% sensitivity and 75% specificity with a sample size of 89 asthmatic patients and 20 healthy controls (11). This research helped in the identification of asthma endotypes, or specific phenotype clusters, through EBC data in machine learning, demonstrating the potential of AI as a new diagnostic measure of respiratory illnesses that can incorporate various underlying pathologies (11). This study also shows the ability to use the chemical composition of breath to analyze CRDs but is limited in its clinical utility due to the difficulties of consistent metabolite extraction and lack of precision therapies (11).

In respiratory analysis, the state of the bronchi and alveoli is an important factor for the identification and severity of respiratory illnesses, especially common diseases like

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asthma and COPD (12). Specifically in bronchial airways, previous research theorized determining sound-producing locations (via blockages) within the bronchi via mathematical analysis and equations to determine the state of the bronchi and alveoli (13).

Therefore, our research aimed to build upon these past research models to use sound in the analysis of bronchial airway blockages, to help detect these inflammations that are indicative of respiratory illnesses including many different CRDs. We proposed a new artificial model of the human respiratory system to test the breath sounds of the bronchial airways and utilized a Google TensorFlow deep learning algorithm to recognize the breath sounds and determine the blockage model automatically. Our study makes several key innovations by proposing a new artificial lung system and using deep learning to focus specifically on the bronchi as a more applicable solution due to the high-power AI system that diagnoses these blockages not just simply exploring the relationship (13). In this study, we hypothesized that different shapes of bronchial airways lead to different frequencies of breath sounds so the deep learning program could determine the different 3D printed bronchial blockages at a recognition rate of over 75% for a significant accuracy rate. Ultimately, the goal of this research is to demonstrate the potential of a sound-based deep learning program as a non-invasive, efficient indicator of bronchial blockage to increase accuracy in respiratory illness diagnosis and efficiency in airway management.

RESULTS

The goal of this research was to develop a sound-based deep-learning program that recognizes 3D-printed bronchial blockages at a recognition rate of over 75%. We referenced current data on the anatomy of the human respiratory system to propose a respiratory system model (**Figure 1A-B**). With

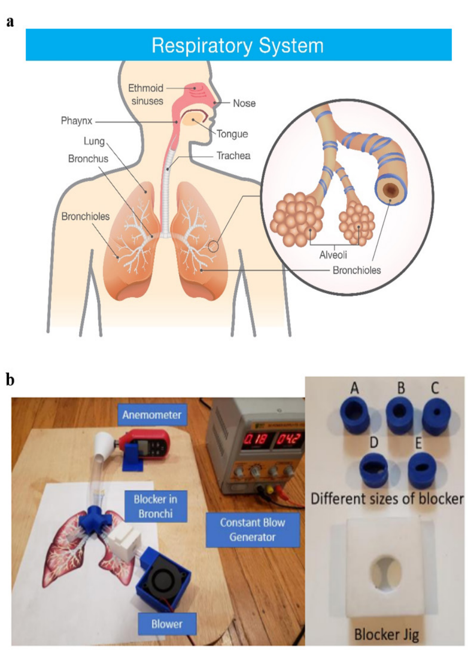

Figure 1: Modeling of human respiratory system. A) Human respiratory system (courtesy of ref. 16). **B)** Heuristic model of the human respiratory system

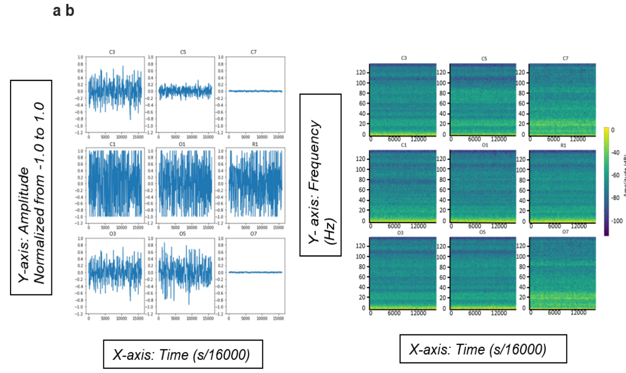

Figure 2: Waveform and Spectrogram graphical representation of differences in sound. A) Waveform graph with normalized amplitude of sound on a scale of -1.0 to 1.0. **B)** Spectrogram (converted from waveform) showing frequency changes over time. For both, the top row represents differences within different sizes of circle (C) shaped bronchial openings. The middle row represents the differences within different shapes (C1, O1, R1) with similar larger bronchial opening sizes (1 is the largest opening). The bottom row represents the differences within different sizes of oval shaped (O) bronchial openings.

this respiratory system model, we measured the breath sounds and the rate of the airflow with the various diameters of bronchi inflammation and subsequent blockage models to emulate the relationship between sound, airflow, and bronchial tube diameter.

We converted the audio data into spectrograms, which allows the Google TensorFlow deep learning program to perform image recognition via a simple convolutional neural network (CNN). As the program converted the data into waveform graphs, we concluded that as the diameter decreased, the amplitude of sound was more compact, closer towards the mean for all shapes (**Figure 2A**). The different shapes also resulted in different amplitudes, for example, the amplitude of circle-shaped blockages in general was less compact than the amplitudes of the rectangle-shaped blockages.

Colors represent the amplitude of frequency (in decibels), with darker/stronger colors indicating greater amplitudes at that frequency. The darker the colors, the higher the frequency. Smaller diameters yielded higher frequencies for all shapes. The magnitude of high sounds and frequencies ascended in order of ovals, circles, and rectangles (**Figure 2B**). This graphical representation of the sounds indicated a difference in the sound that allowed the deep learning program to identify and train its recognition system.

With the given sound data generated by the different-sized blockages, we trained the deep learning algorithm in the Google Tensor Flow framework, an open-source software library for deep learning. This method of AI learning uses a basic automatic speech recognition (ASR) model. The program used these spectrograms to train the model using a CNN to perform image recognition on these converted graphs. With continuous recognition training, the accuracy of the detection gradually approached close to 1, ultimately achieving a 99% success rate. Mean squared error (MSE) [a measure of how close a regression line is to the data points], and val_loss/test loss [errors when unknown/unfamiliar data is introduced] both approached 0 which indicated nearly no

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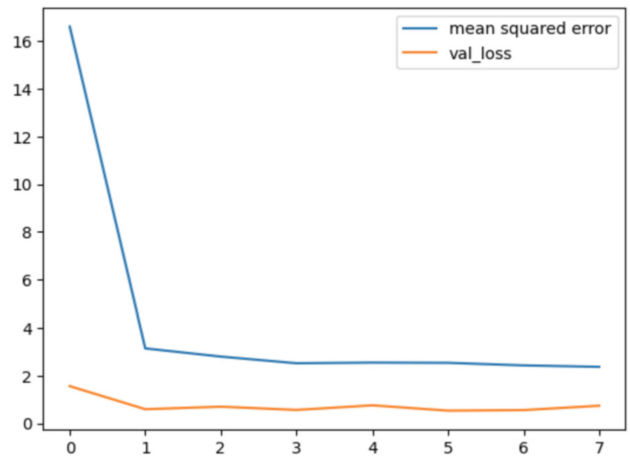

Figure 3: Inference process results of deep learning training. Mean squared error (a measure of how close a regression line is to the data points), and val_loss/test loss (errors when unknown/unfamiliar data is introduced) both approached 0.

loss/error in the detection (**Figure 3**). The training and testing samples were split by the deep learning program using the train_test_split function. While the MSE and val_loss approached 0, the accuracy reached values of 0.9928, a near 100% accuracy. The result of the inference yielded a 100% classification rate with no false positives or negatives for the circular blockages as representative samples for the other shapes as they were easy to measure and had clearer dimensions (**Figure 4**).

DISCUSSION

The goal of this research was to develop a deep learning model that could recognize bronchial blockages at a recognition rate of over 75% and our model reached a 99.28% accuracy rate. Along with the MSE and val_loss values approaching zero, this study affirmed its hypothesis and concluded the possibility of recognizing bronchial blockages based on sound through this artificial 3-D printed model. This research introduced and implemented an artificial intelligence algorithm, deep learning by Google TensorFlow, using CNN for an ASR model that accurately classified various types and severities of simulated bronchi blockages. This deep learning program showed over 99% accuracy, along with near-zero values for MSE and val_loss, indicating that the computer algorithm can accurately analyze differences in sound through spectrograms. We used FFT to model the sound data and discovered visual differences between these frequency-domain graphs. The complexity of the data prevented an accurate analysis through mathematical equations. However, the present study demonstrates that deep learning algorithms can accurately analyze the sound and changes in sound through spectrograms and waveform graphs.

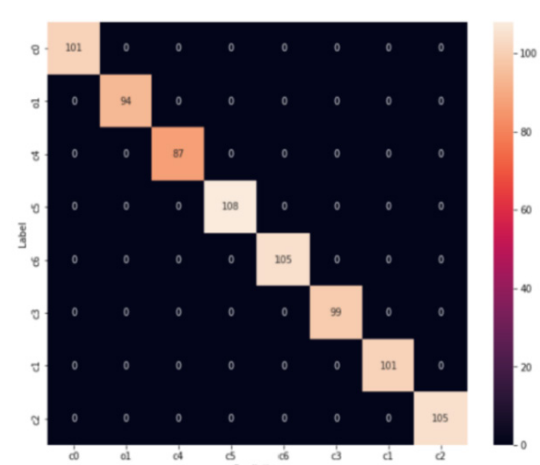

Figure 4: Confusion Matrix of Deep Learning Inference. The color legend shows the amount of samples tested for that specific bronchial blockage model, the black 0 boxes show that there were no false positives or negatives.

In the past, researchers have performed mathematical analyses of respiratory sounds to monitor the state of human airways. However, this was done to analyze the general health of the airways and the location of the sound source rather than identify bronchial blockages. Our research, however, uses computer analysis through Google TensorFlow to overcome the limitations of standard mathematical expressions. This program conducts a more precise analysis due to the high computing power of deep learning and the accuracy in the image recognition of spectrograms. Artificial intelligence has also been explored in the field of clinical pulmonology through the analysis of respiratory muscles (9). However, this prior analysis focused on respiratory muscle strength, as their goal was to support medical decision-making in diagnosis and required several different data points. We explored bronchial blockages with the goal of helping differential diagnosis of these respiratory illnesses as it provides more detailed information on the health of the airways. Also, this method of diagnosing these respiratory illnesses allows for affordable and nonintrusive monitoring. We used the singular variable of sound, allowing for a more convenient and less time-consuming analysis.

We used computer analysis of sound, allowing pattern recognition for a more holistic interpretation. No recognition systems exist to identify bronchial blockage shapes and sizes in clinical practice, especially through AI. Through our deep learning program, we hope to develop an app that will allow easy and accessible real-time analysis for bronchial blockages. However, while encouraging, our results should be interpreted in light of several limitations. First, since the bronchial blockages were created out of the 3D printing plastic (polylactic acid substrate), this research cannot exactly emulate bronchi blockages in humans as the plastic is typically stiffer and lighter than the human counterpart. Also, even if human subjects were used, blockages and inflammation vary along the bronchial tubes, requiring a more complex method of quantifying these blockages. This research also cannot connect bronchi blockages to specific respiratory illnesses, which would require a variety of human trials to determine whether the AI can identify the possible illnesses. Therefore, these questions are essential for future research that works on the implementation of this deep learning program.

In summary, this research proposed a new artificial respiratory system focused on the bronchial airways to test various shapes and sizes of 3D-printed bronchial blockages and record the sounds the stimulated breathing creates. This demonstrated the possibility of producing a controllable model and various bronchial blockage shapes for future applications of further precision in modeling nonlinear, variable bronchial

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inflammation that leads to blockages. Our Deep Learning program yielded a >99% recognition rate, and our study serves as a proof of concept that bronchial blockage shapes can be differentiated by sound. Overall, this research paves the way for constant and non-invasive methods to monitor bronchial health, an essential indicator for many respiratory illnesses such as bronchitis, asthma, and COPD.

MATERIALS AND METHODS

After the various sizes of bronchial blockage models were 3D-printed, we put these models into our artificial lung system, and sound data was recorded. We moved the recording throughout the 20 recordings of each blockage size, alternating between placing it left or right of the model. Blockages were labeled Cx, Ox, Rx, with x being a number with bronchi diameter decreasing as x increases. The C, O, and R labeled the shapes circle, oval, and rectangle respectively – different shapes used to represent the nonlinear, varying shapes of bronchial blockages (**Figure 5**). Data for all blockages was thus recorded and fed into the machine learning model. Defined shapes representative of airways (Cx = circle, Ox = oval, Rx =rectangular, Tx = test shapes, diameter decreases as x increases). We printed these shapes, the blocker jig, and all other structural components using 3D printing filament that has polylactic acid (PLA) as the substrate (HATCHBOX, Cat#B09WWJSCCS) using 3D printer (Creality 3D, Cat#B07K3SZBHJ). We used Ultimaker Cura 3D printing software to create various shapes and sizes in order to best emulate the high variety of bronchial blockages. This software also allowed for the precise fitting of the blockage components into the blocker jig). This respiratory model used a system of tubes and blowers to simulate the trachea and bronchi based on the average adult human proportions. This respiratory system consisted of airways with 8mm diameters approximated to the average adult human bronchi diameters (14). Exhalation wind speed was calibrated to approximate the average human exhalation rates of around 2-4 m/s (15). With the given sound data generated by the respiratory model for different-sized blockages, we trained the deep learning algorithm in a Google Tensor Flow framework using a basic automatic speech recognition (ASR) model. ASR allows for the recognition of sounds through short audio clips. The audio data is converted into spectrograms, which allows the deep learning program to perform image recognition via a simple CNN. The program converted the data into waveform graphs. The deep learning program then converted the waveform graphs into spectrograms by using a Short Time Fourier Transform (STFT). The spectrogram had time as the x-axis (s/16000) and frequency as the y-axis (Hz).

Experiment setup

We recorded sound from a linear Pulse-Code Modulation (PCM) recorder (Tascam, Cat #B07N1KLVNG) and wind speeds and temperature were captured using an anemometer (UNI-T, Cat #B07CKY5P2H). We continuously moved the recorder from being on the left or right or being far away or close to the model throughout the different recordings to ensure that recording device location was not a factor. We used the Audacity Sound Tool to standardize the various recordings by cutting them into one-second clips and changing sampling rates to 16 kHz. Then we duplicated these 20 recordings for each blockage size to create at least 960 copies of the recordings to run in the TensorFlow program. We used Google's open-source software library TensorFlow to import necessary data, standardize the data for testing, train the deep learning model, and display the results (see **Figure 6** for flow chart). Specifically, we used and modified a simple ASR model for the recognition of the different bronchial blockages due to the shortness of the breathing clips as the breathing sounds remain relatively consistent. The sound clips were originally in the waveform (WAV) format and

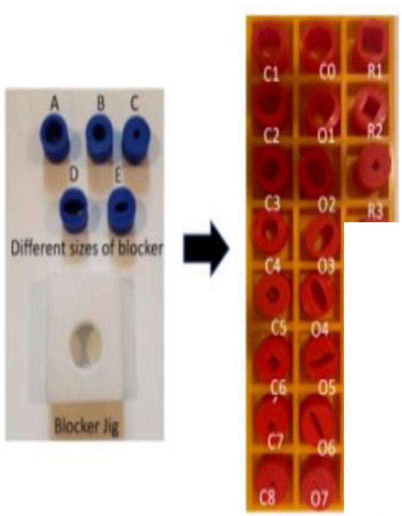

Figure 5: Bronchial blockage models tested. Blockages were labeled Cx, Ox, Rx, with x being a number with bronchi diameter decreasing as x increases. The C, O, and R labeled the shapes circle, oval, and rectangle respectively.

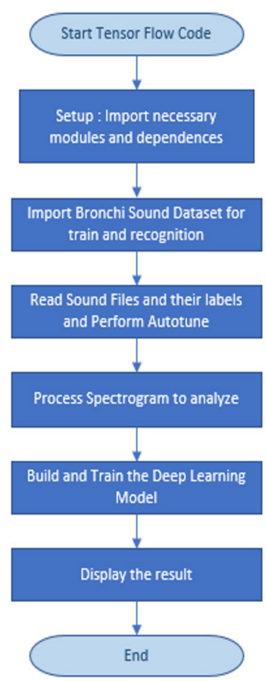

Figure 6: Flow chart representing the implementation of Deep Learning. Tracks the steps from start of TensorFlow code to the display of the result after analyzing the sound files.

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converted to spectrograms using STFT to display frequency changes over time in a 2D image for the training model. The model used a convolutional neural network (CNN) for image recognition on the transformed spectrogram images that track the sound over a time-domain for image recognition. For the use in this model, preprocessing is done: resizing downsizes the sample to help increase the training speed of the model and normalization is done to every pixel to standardize them based on mean and standard deviation.

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