StethoDoc: Democratising Screening for Lung Disorders with an Augmented Reality Guided Smart Stethoscope

Aria Vikram
ariavikram@gmail.com

1. INTRODUCTION AND OBJECTIVES

More than 1 billion people worldwide suffer from either acute (short-term medical issues) or chronic respiratory conditions (long-term medical problems) [1]. India alone accounts for 32% of the global burden of respiratory disease.[2]

This burden has been further escalated by the Acute Respiratory Distress Syndrome (ARDS) which is surfacing in a large number of people who have been affected by COVID-19 [5, 18]. The COVID-19 pandemic at the time of undertaking this research project has affected more than 56 million people worldwide, and 8 million people in India alone [21]. Recent studies show that COVID-19 survivors have an increased susceptibility to lung diseases such as pulmonary fibrosis, pneumonia, etc. due to the accelerated scarring of the lungs by the virus [3, 6, 7, 8]. As scarring results in a gradual decrease of lung function [4], continuous monitoring of recovered COVID-19 survivors through auscultation may play a vital role in detection and prompt intervention, thus, helping improve the long term prognosis of patients.

Pulmonary auscultation is the process of listening to lung sounds with the help of a stethoscope. A large number of pulmonary diseases like pulmonary fibrosis, pneumonia, asthma, COPD, etc., can be detected during auscultation by characteristic adventitious sounds such as wheezes and crackles [19]. However, auscultation is an art that requires substantial tacit knowledge. Therefore, the reliability of diagnosis largely depends on the expertise and hearing of the doctor [10]. Also, sound picked up by the stethoscope is often corrupted by background noise. Additionally, the diagnostician must be well-trained in positioning the stethoscope properly on the body as inaccurate placement may affect the quality of the sound heard [16]. Since the subjective nature of the auscultation method is widely recognized, this has led to new developments in computer-based techniques.

In the past few years, computer-based respiratory sound analysis has gained a vast amount of traction. Previous attempts at trying to computerize pulmonary auscultation have used artificial intelligence techniques such as Artificial Neural Networks, Support Vector Machines, Convolutional Neural Networks, Clustering approaches, etc. [9]. Machine learning techniques typically extract features, such as Mel Frequency Cepstral Coefficients (MFCC) statistics, in order to make predictions from breath sounds. These features are extracted from one breath cycle at a time. This is because adventitious (abnormal) breath sounds may be present in one breath cycle and not present in several prior and subsequent breath cycles. Therefore, annotating the breath cycles and marking the start and end times for each breath cycle from a

recording of several breath cycles is currently a necessity. However, manually annotating breath cycles is labour intensive and involves the time of trained personnel.
Thus, coming up with a way to avoid annotating lung sound recordings becomes a critical component of any effort to automate pulmonary auscultation.

An integral part of the auscultation process is the accurate positioning of the stethoscope on the patient's body which is crucial to obtain appropriate lung sounds. This is particularly hard for a layman to perform due to variation of auscultation points depending on the patient's body measurements, gender, etc. Therefore, medical professionals are required to conduct auscultation. However, rural India, comprising 71% of the nation's population, has access to only 36% of health care workers. This uneven distribution of health workers is seen in the private and public health sector too — more than 80% of doctors and 70% of nurses and midwives are employed in the private sector [13]. As a result, healthcare systems in many areas are overburdened. The inaccessible nature of primary healthcare in such locations leads to significant underdiagnosis of respiratory disorders and deprives many patients of timely treatment. This problem is amplified in pandemic situations when healthcare systems are further encumbered [11]. Existing solutions pertaining to computerized pulmonary auscultation of respiratory disorders also rely on trained medical professionals to accurately place the stethoscope on the person's body and thus, do not significantly alleviate the burden on the healthcare system.

Thus, the aim of this research project was to develop a reliable, accessible and easy-to-use solution for screening of pulmonary diseases in order to reduce the burden on the healthcare system and offer quality healthcare, thus democratizing auscultation.

2. INNOVATION

2.1 Auscultation site estimation using Augmented Reality

My system eliminates the need for a trained healthcare worker to carry out auscultation.Through the use of an algorithm based on a deep learning model, my system identifies auscultation sites on the patient's body with high accuracy. It then superimposes circles on the patient's body marking the auscultation sites. The volunteer attendant of the patient can then view the overlaid points through their smartphone screen and sequentially auscultate each site on the patient's body using a stethoscope. Furthermore, overlaid points are recalibrated in case the patient moves their body, thus enabling accurate auscultation. This system also works for any position and view (anterior, lateral or posterior views) of the patient (as long as the hips and shoulders of the patient are visible) such as standing, sitting, supine or prone positions. Additionally, the system works on patients wearing clothes (only light clothing is recommended) as well as those who are not wearing clothes.

2.2 Computer-based respiratory sound analysis

My approach uses a K Nearest Neighbours (KNN) classification model to detect adventitious pulmonary sounds. As mentioned in the introduction, analysis of breath sounds from live subjects requires annotation of the breath cycles in the recordings in order to calculate MFCC statistics on each breath cycle. If annotation is eliminated and MFCC statistics are calculated on the entire sound recording from a lung location, important information may get lost. In other words, if there are ‘n’ breath cycles, one may simply derive the MFCC statistics across all ‘n’ of those breath cycles. This would be done by first calculating the MFCC across time and then taking the mean and standard deviation for each of the coefficients. This approach may work if the adventitious breath sounds are repeated in each breath cycle. However, if an abnormal sound shows up only in a brief instant in time, it will go undetected as it may average out when the mean and SD are calculated over a longer time period.Thus important information will be lost if MFCC statistics are calculated for a long sound clip containing several breath cycles. I have come up with an alternative method to avoid annotating lung sound recordings while preserving prediction accuracy. In order to make accurate predictions,regardless of start and end times of breath cycles, I have created a novel ‘windowing’ method during preprocessing of sounds collected from live patients. This method improves prediction accuracy of the KNN on unannotated data samples and nullifies the need for annotation of sounds collected from live patients. In this method, I take several slices of the presented audio file with varying time durations. Thereafter, I derive MFCC statistics for each of these sliced sound clips. This increases the odds that the machine learning model will pick up abnormalities since the MFCC statistics are calculated on smaller sound durations.

Additionally, the KNN has been trained using Kaggle’s respiratory sounds database, a large recently-available public dataset which consists of samples with background noises(to simulate real-life situations), making my algorithm highly robust. Furthermore, the novel combination of extracting MFCC statistics(mean and standard deviation) as parameters for the KNN improves the accuracy of detection of adventitious sounds.

I propose an AI-enabled solution which uses an augmented reality app to guide any layperson (such as a family member, friend, etc) to efficiently place the stethoscope at the right auscultation sites on the patient’s body, collect pulmonary sounds from the patient and detect abnormalities, thus efficiently screening for pulmonary diseases and enabling continuous monitoring of patients who belong to vulnerable demographics (the elderly, recovering COVID-19 patients, etc). Thus, even an untrained volunteer will be able to operate the app to detect pulmonary abnormalities.

3. HIGH LEVEL SYSTEM DESCRIPTION

There are two key participants for the system. They are:

1. A patient care attendant - The attendant does not need to be a trained medical professional and can be an untrained layperson such as a family member, friend, etc.

2. The person being auscultated (patient) - The individual who is in need of screening for pulmonary disorders.

This is the high level description of the system in action:

1. The attendant of the patient opens the app and connects it to a stethoscope(via microphone).
2. The app brings up the camera on the phone and guides the attendant to point the camera towards the anterior view of the patient.
3. The app then shows up the key auscultation points where a stethoscope must be placed on the anterior part of the patient's body. The auscultation points are superimposed on the image of the patient's body thus making it easy for the attendant to place the stethoscope even without medical training.
4. The attendant then places the stethoscope on the points shown on the anterior part of the patient's body. The patient is instructed to breathe deeply with the mouth open by the app. Auscultation sound data is collected automatically when the stethoscope is placed on each point via the connection created in step 1 above. Respiratory data is collected for 10 seconds. This data can involve multiple respiratory cycles.
5. The app then instructs the attendant to point the camera to the back of the patient where the auscultation points are overlaid on the image of the patient's posterior and lateral sides.
6. The attendant places the stethoscope on each of the displayed points and sound data of 10 seconds duration each is collected.
7. After sound data has been collected from all 9 auscultation points (3 from the front and 6 from the back), the sound data is processed by the app and one of the following two predictions is provided:
    a. Normal - no adventitious lung sounds detected
    b. Abnormal - Adventitious lung sounds (crackles or wheezes) detected

The above system is depicted in Figure 1.

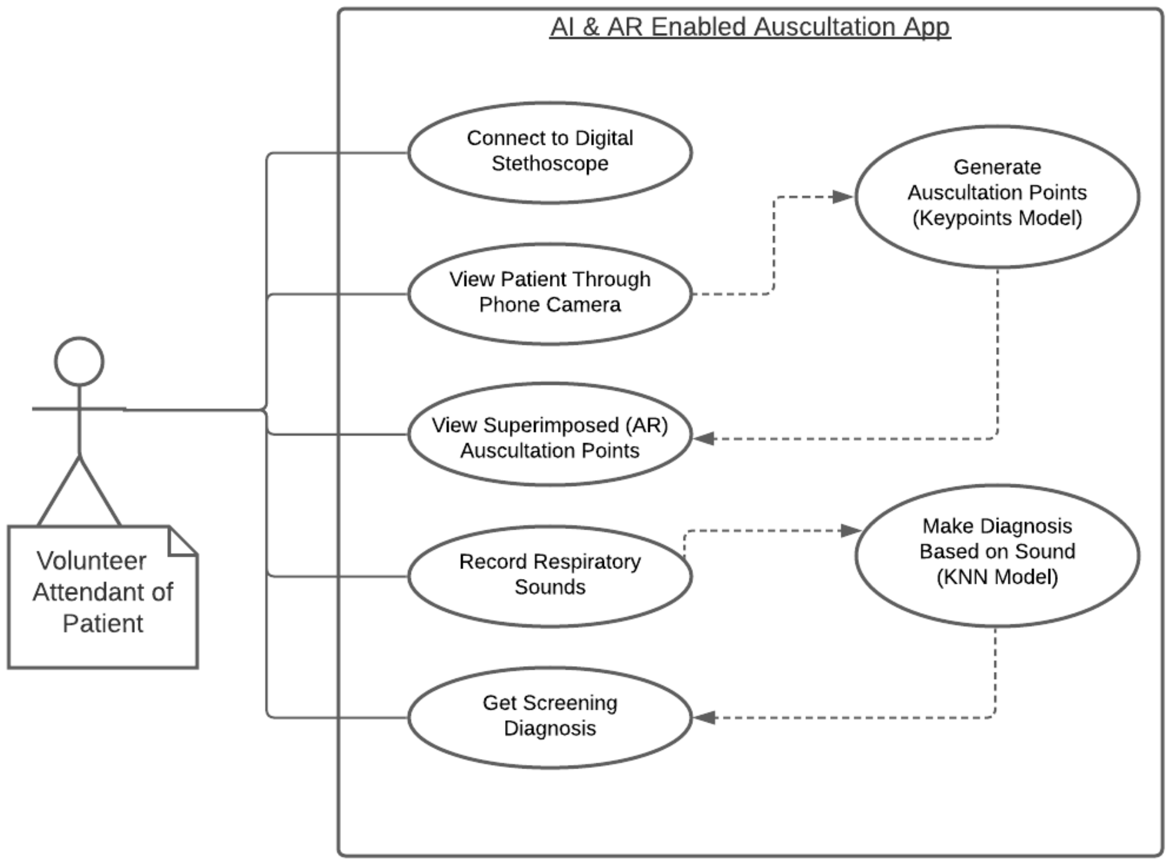
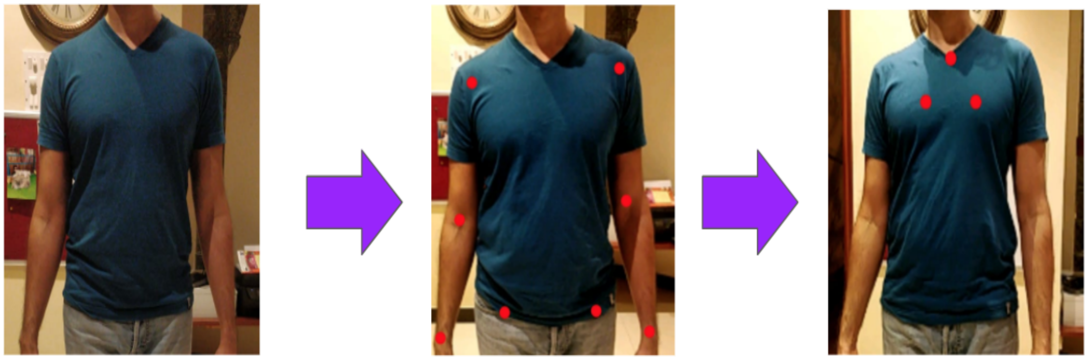


Figure 1 - Illustration of System in Action

This use case diagram shows how a user interacts with the system. The system resides as an app on a user's phone. When the user invokes the app, it brings up the phone's camera and shows auscultation points superimposed on a video feed of the patient. Once pulmonary sounds are collected using the connected stethoscope, a classification is made and the recording is labelled as "normal" or "abnormal".

The system is envisioned as an Android app that is connected to a stethoscope consists of 2 parts:

1. The augmented reality module - This module superimposes computer-generated points marking the auscultation sites on the camera feed of the patient's body thus providing an augmented view and making it easy for the attender to locate the auscultation points on the patient's body. (Algorithm depicted in Figure 2)
2. A sound classification module which takes in a sound file, extracts meaningful characteristics from the sound file and makes a prediction of normal or abnormal sound using a pre-trained machine learning model (KNN).



Raw frame After extracting key points After applying algorithm

Figure 2 - From the raw frame, we first obtain key points like shoulders and hips and then calculate auscultation points

4. DETAILED TECHNICAL DESCRIPTION OF THE SYSTEM

As described above, the system consists of two subsystems.

1. The subsystem which generates the augmented reality auscultation points
2. The subsystem which processes the sound data and makes a prediction

4.1 Technical Description of Augmented Reality Subsystem

To generate the auscultation points, my system relies on the COCO Keypoints model available in the Detectron2 platform from Facebook Research. The model identifies key points such as shoulder, hip, etc. on a supplied human image. Using these generated points, and in consultation with trained medical professionals, I have arrived at heuristics to calculate the 9 lung auscultation points being generated by my system.

4.2 Technical Description of Sound Data Prediction Subsystem

Once lung sounds are collected by the stethoscope and sent to the app, they need to be classified as being normal or abnormal. This constitutes the screening portion of my solution. To do this, I trained a machine learning model using an open sourced respiratory sounds database available on Kaggle. It includes 920 annotated recordings of varying length (10s to 90s.) Taken from 126 patients, this database has a total of 6898 respiratory cycles including normal breath sounds and adventitious sounds(crackles and wheezes). The data includes clear recordings as well as recordings with background noise in order to simulate real life conditions. The patients span all age groups - children, adults and the elderly.

My model is a K Nearest Neighbors Classifier which separates sounds based on their proximity to other sounds. This proximity is determined on the basis of statistics derived from Mel Frequency Cepstral Coefficients (MFCCs) which represent perceptually meaningful sound features. In order to analyze respiratory sounds, statistical features (mean and standard deviation) are taken from the extracted Mel Frequency Cepstral Coefficients(MFCC). These act as features for the KNN classifier.

My audio data preprocessing pipeline for training the model is as follows:

1. Each sound file has an associated label file . The label file contains the following information:
   - Start time of breath cycle
   - End time of breath cycle
   - Whether crackles is present (represented by 0 or 1)
   - Whether wheezes are present (represented by 0 or 1)

   The sound files were loaded into a numpy array format using a python audio library named Librosa. Even though the original audio files have higher sampling rates of 22,000 hz, the audio files were sampled at 8,000 Hz to accommodate for lower quality audio files during the human-testing phase.
2. The sound files were split based on breath cycles.
3. The sound clips and associated labels were split up into training and validation data (the training data consists of 70% of the total data and the validation data consists of 30% of total data). The validation and training data are split randomly.
4. 50 MFCCs are obtained for each sound clip. This was done using a built in Librosa function.
5. The statistical mean and standard deviation measures were derived from the MFCCs obtained above in order to reduce the time dependent frequencies into a single vector with 100 components.
6. The feature vector obtained above was standardized by removing the mean and scaling the vector to unit variance.

Once the model (with nearest neighbours parameter of 3) was trained on the training data and validated on the validation data, it was used to make predictions on respiratory sounds recorded by medical professionals from live human subjects.

Below is a brief description of the windowing method which was used for each recording during the real-world testing phase:

1. The audio sample was converted into a numpy array using the Librosa audio library.
2. The audio file was split into smaller time chunk windows disregarding length of breath cycles. The time chunk windows vary in time lengths to simulate real life breath cycle durations.
3. The audio clips were passed through the following preprocessing pipeline:
   a. MFCCs were generated,

    b. Means and standard deviations were obtained in a single vector for these MFCCs
    c. These MFCC statistics were transformed using the Standard Scaler created during training
4. The vectors representing the sound clips created through the model predictor were passed to the KNN.
5. If the KNN model predicted any of the clips as containing an adventitious breath sound, the whole recording was predicted as abnormal.

5. METHODS

Since my solution consists of two separate components, the following experiments were carried out:

- Experiment 1: Auscultation site estimation - Comparison of lung auscultation site estimation between a trained medical professional and my system.
- Experiment 2: Validation of KNN model on the public Kaggle dataset
- Experiment 3: Real World testing of system

The rest of the subsections below, describe the specifics of the materials and methods used for the above 3 experiments.

The following medical professionals acted as the baseline for my each of my experiments:

1. A trained medical doctor with over 6 years of experience
2. A nurse with over 6 years of experience in the emergency and ICU departments
3. A nurse with over 6 years of experience in providing geriatric care

5.1 Auscultation site estimation

A key component of my system and the value it provides to users is its ability to place lung auscultation points on a video feed of the patient's body. This makes placement of the stethoscope at the right location easier for non-medical professionals.

The purpose of this experiment was to make a comparison between how well my system estimates lung auscultation points in comparison to the estimation of these points by trained and experienced medical professionals.

The following auscultation points are normally used during clinical pulmonary examinations:

1. Trachea
2. Anterior Right Upper Lobe
3. Anterior Left Upper Lobe
4. Posterior Right Upper Lobe
5. Posterior Left Upper Lobe
6. Posterior Right Lower Lobe

7. Posterior Left Lower Lobe
8. Mid-Axillary Left Lobe
9. Mid-Axillary Right Lobe

Experiment 1 was carried out by first collecting digital photographs of human subjects representing a wide variety of ages, genders, body-shapes and lighting conditions. This validation set consisted of 40 images, capturing anterior, posterior and lateral views of people of varied genders, ages and races in different positions and different body compositions. This validation set also consisted of patients who were wearing light clothing and those who were not, to simulate real-life scenarios. Even though my system is intended to work with a live video feed and provide dynamic recalculation of auscultation points based on the pose of the human subject, I chose to work with photographs for this experiment due to the impracticality of a medical professional annotating every frame in the live video feed. The three medical professionals mentioned above independently annotated the auscultation sites on each of the photographs by using an online annotation tool called ‘Makesense.ai’, yielding a total of 540 measurements. Then I passed the photographs through my auscultation points estimation algorithm which generated the auscultation points on the same set of photographs.

My auscultation site estimation algorithm was run on the same image set and the Root Mean Squared Error (RMSE) between the algorithm’s predictions and the doctor’s ground truths were calculated. Statistical analysis of RMSE was done using the Pandas and NumPy Libraries in the Python Programming Language. RMSE was chosen as the evaluation metric used as it penalizes large errors. Also due to the variation in image sizes, RMSE values were normalized (scaled to a number between 0 and 1) so that it reflects the true error.

5.2 Validation of KNN model on the public dataset

As described earlier, my system is envisioned as a complete system that not only guides the patient’s attendant on auscultation points location but also provides a screening report in the event that an adventitious breath sound is present.

In order to assess the performance of the audio model on data that it has not encountered before, I created a test dataset. This was done using the commonly accepted machine learning practice of first splitting up the data into training and validation datasets. I split up my dataset randomly in a 70:30 ratio with 30% of the data clips being kept aside for testing the performance of my machine learning model. The training and testing splits were done using the Scikit-Learn Train-Test-Split module. Thus the validation dataset consisted of 2070 samples from the original dataset.

After the model was trained, the trained model was used to predict the presence of adventitious breath sounds (crackles and wheezes) on the validation dataset created earlier. Accuracy of the algorithm, precision, recall and F1 scores were calculated on the data using appropriate modules from Scikit-Learn. Using data generated by Scikit Learn, the confusion matrix was created using Seaborn, Pandas and Matplotlib.

5.3 Real world testing

The next experiment was to measure the performance of my system on live human subjects.

In order to validate the system, the three medical professionals mentioned earlier, collected lung sound recordings from 21 human subjects. The human subjects represented a wide variety of ages, genders and health conditions (such as pulmonary fibrosis, asthma, COPD, etc) including 5 subjects who have recovered from COVID-19. Subjects ranged from ages 18 - 83. The lung sounds were collected using a commercially available stethoscope Ayu stethoscope- with an audio sampling rate of 8000 Hz.Lung sounds were collected from each of the patients at 9 auscultation sites giving a total of 189 sound recordings, with 43 recordings containing adventitious sounds as annotated by the doctors. The human subjects were informed about the purpose of recording their lung sounds and signed informed consent forms were obtained prior to auscultation. Data privacy was maintained by anonymizing the names of the participants. During collection of the sounds, the medical professionals independently annotated each of the sounds collected by them as normal and abnormal. These labels were treated as the ground truth. Sound recordings from the same patients were also collected by a non-medical person (the researcher) with the help of the augmented reality module. Each of the sound recordings were 10 seconds in length and consisted of several breath cycles.

These recorded lung sounds were then passed through my audio preprocessing pipeline. In order to overcome the challenge of not being able to annotate breath cycles, the windowing approach described earlier was used. Sliced audio clips from the windowing function were then passed through the audio model to arrive at predictions.

My model classified the sounds as “Normal” or “Abnormal” based on the presence of wheezes and / or crackles in the audio clips. This was then compared with the ground truths described above and a confusion matrix as well as sensitivity, specificity and F1 scores were arrived at using Scikit-Learn modules. These measures of performance were chosen as they are commonly accepted measures in the machine learning community and provide numbers that are easy to compare with other models. In this case as well, data generated by Scikit Learn was used to create the confusion matrix using Seaborn, Pandas and Matplotlib.

6. RESULTS

6.1 Auscultation site estimation

The average RMSE value for all the 9 points across the 3 medical professionals was approximately 0.04. Thus the algorithm has an accuracy of approximately 96%.
The RMSE values (rounded to 3 decimal places) compared to each medical professional’s estimation for every point is shown in Figures 3, 4 and 5. The Average RMSE values for each point across all 3 medical professionals is shown in figure 6 .

Average RMSE across all images across all 9 points for all 3 medical professionals =0.0397 ≅ 0.04

Nurse 1 (Table 1)

Auscultation Point	RMSE
Trachea	0.017
Anterior Left Lobe	0.052
Anterior Right Lobe	0.054
Posterior Left Upper Lobe	0.022
Posterior Right Upper Lobe	0.022
Posterior Left Lower Lobe	0.056
Posterior Right Lower Lobe	0.058
Mid Axillary Left Lobe	0.057
Mid Axillary Right Lobe	0.059

Figure 3
Average RMSE across all images calculated between the first nurse's predictions and model's predictions across each auscultation site

Nurse 2 (Table 2)

Auscultation Point	RMSE
Trachea	0.016
Anterior Left Lobe	0.028
Anterior Right Lobe	0.024
Posterior Left Upper Lobe	0.025
Posterior Right Upper Lobe	0.028
Posterior Left Lower Lobe	0.055
Posterior Right Lower Lobe	0.057
Mid Axillary Left Lobe	0.057
Mid Axillary Right Lobe	0.059

Figure 4
Average RMSE across all images calculated between the second nurse's predictions and model's predictions across each auscultation site

Auscultation Point	RMSE
Trachea	0.012
Anterior Left Lobe	0.013
Anterior Right Lobe	0.019
Posterior Left Upper Lobe	0.030
Posterior Right Upper Lobe	0.031
Posterior Left Lower Lobe	0.054
Posterior Right Lower Lobe	0.054
Mid Axillary Left Lobe	0.057
Mid Axillary Right Lobe	0.057

Figure 5
Average RMSE across all images calculated between the doctor's predictions and model's predictions across each auscultation site

Auscultation Point	RMSE
Trachea	0.015
Anterior Left Lobe	0.031
Anterior Right Lobe	0.032
Posterior Left Upper Lobe	0.0256 ≅ 0.026
Posterior Right Upper Lobe	0.027
Posterior Left Lower Lobe	0.055
Posterior Right Lower Lobe	0.056
Mid Axillary Left Lobe	0.057
Mid Axillary Right Lobe	0.058

Figure 6
Average RMSE across all images across all medical professionals for each point

The RMSE shows that the algorithm is highly accurate in spite of the fact that both the doctor and the algorithm had to mark a set of points (exact coordinates). In practicality, any such minor discrepancies arising between the algorithm's and the doctor's site estimation will be compensated by the larger radius of the stethoscope's diaphragm.

6.2 Pulmonary Abnormality Detection using KNN

Evaluation metrics used were accuracy, precision, recall and F1 scores. The F1 score is considered a necessary metric when classes are imbalanced. As abnormal sounds are less frequent than normal sounds, F1 score was used as an evaluation metric .

6.2.1 Validation of KNN model on the public dataset: The algorithm had an F1-Score of 80% on the Kaggle dataset. The precision was 78% and the recall was 81%. The overall accuracy of the algorithm was 81%. The confusion matrix of the model on this dataset is shown in Figure 7.

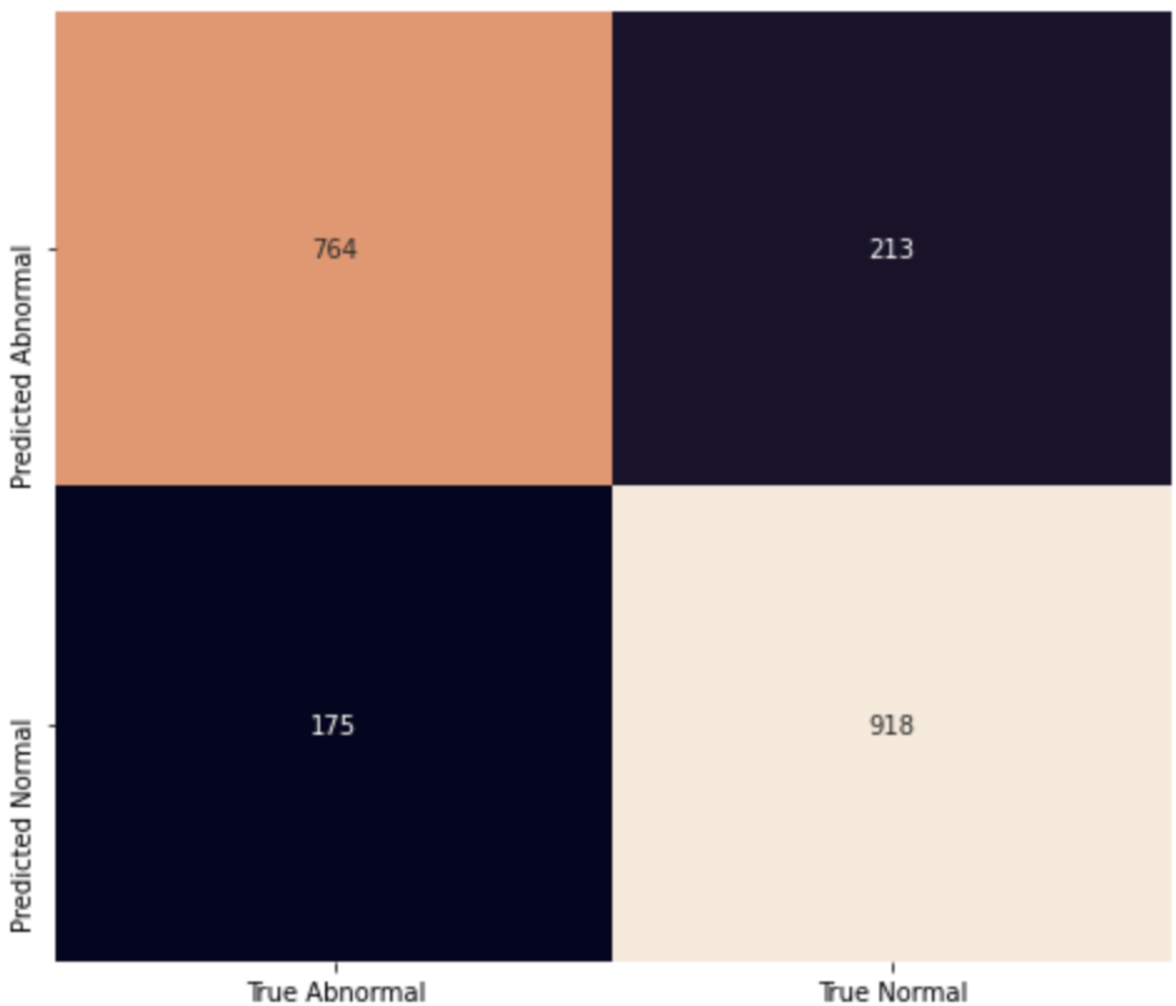


Figure 7
Confusion Matrix for Public Dataset (Kaggle Respiratory Sounds Dataset)

6.2.2 Real world testing of the system: The system had an F1-Score of 81% on data obtained from live subjects. The precision was 76% and the recall was 88%. The overall accuracy of the algorithm was 91%. The confusion matrix of the model on the live-subject data is shown in figure 8.

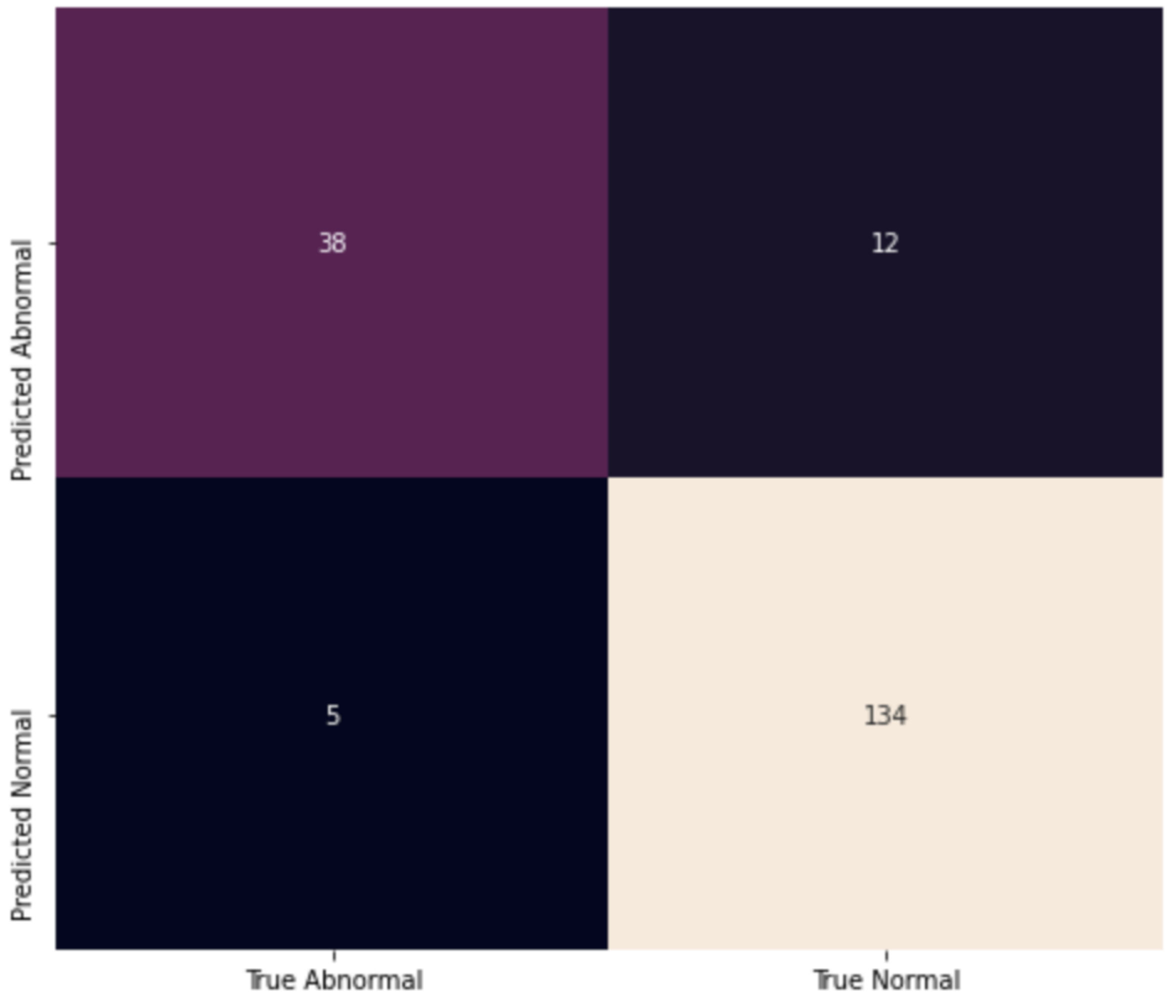


Figure 8
Confusion Matrix for Live Subject Recordings

7. CONCLUSION

From the above discussion, we see that the proposed system has many strengths:

- *Can be operated by an untrained volunteer* - This integrated system does not require a trained medical professional to operate it. Thus, It can be operated by a layperson (family member, friend,etc). Furthermore, it can be used for collective use in rural healthcare drives as it can be operated even by untrained volunteers. Thus it acts as a preliminary pulmonary screening tool and significantly reduces the burden on the healthcare system.

- *High accuracy ensures reliable screening of lung disorders* - The low RMSE on the auscultation site estimation model ensures that fewer errors will be made while placing the stethoscope on the subject's body - even if it is being operated by an untrained person.Further, the high accuracy of the pulmonary abnormality detection algorithm allows for quality healthcare and reduces chances of human error arising from background noise and lack of expertise.

- *Accessible nature of the system* - The accessible nature of this innovation allows for the early identification of pulmonary abnormalities, thus helping in early referral. This may help in early diagnosis of pulmonary disorders thus helping improve the long-term prognosis of many diseases.

- *System is safe, non-invasive and mobile* - Medical imaging (such as X-rays, CT scans etc.) requires a large number of personnel, has huge operating costs and requires a large investment of space and money for equipment. The mobile nature of my system allows for it to be used even in remote parts of the world as an alternative to medical imaging for preliminary screening. Additionally, pulmonary auscultation is non-invasive making it a safe form of screening.

- *System Allows for continuous monitoring and early detection (for recovering COVID patients)* - Continuous monitoring of patients helps in reducing burden on a patient's family and might increase chances of detecting an abnormality early on in its course. This serves a vital purpose for recovering COVID - 19 patients who are prone to lung damage.

8. FUTURE PLANS

Over the next 3 months, I also plan to use natural language processing to perform vocal resonance testing of the patient. This will allow for comprehensive screening of pulmonary disorders. Additionally, within this time, I also plan to conduct trials of the system with a larger group of people. Furthermore, I plan to validate the efficacy of my system in detecting pulmonary abnormalities in recovering COVID-19 patients.

To the best of my knowledge this is the first end-to-end pulmonary auscultation system which can be used by professionals and novices alike. It demonstrates high accuracy, making it a useful tool for pulmonary screening.

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