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DEVELOPMENT OF A SPIROMETER FOR PULMONARY FUNCTION ANALYSIS WITH DISEASE CLASSIFICATION SYSTEM USING SMARTPHONE.

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Abstract

Respiratory diseases such as asthma, chronic obstructive pulmonary disease (COPD), and restrictive lung conditions continue to affect millions worldwide, necessitating accessible and efficient diagnostic tools. This project presents the development of a portable, smartphone-integrated spirometer designed for real-time pulmonary function analysis and respiratory disease classification. The system measures key lung function parameters including Forced Vital Capacity (FVC), Forced Expiratory Volume in 1 second (FEV_1), and the FEV_1/FVC ratio using a low-cost, sensor-based flow measurement module. The collected data is transmitted to a smartphone via Bluetooth, where a custom mobile application processes and displays the results. The app utilizes machine learning algorithms to classify respiratory conditions into categories such as normal, obstructive, or restrictive patterns based on standard clinical criteria. Additionally, the system includes personalized

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health feedback and motivational messages to encourage regular testing and better management of chronic conditions. Respiratory diseases such as asthma, chronic obstructive pulmonary disease (COPD), and restrictive lung conditions continue to affect millions worldwide, necessitating accessible and efficient diagnostic tools. This project presents the development of a portable, smartphone-integrated spirometer designed for real-time pulmonary function analysis and respiratory disease classification. The system measures key lung function parameters including Forced Vital Capacity (FVC), Forced Expiratory Volume in 1 second (FEV_1), and the FEV_1/FVC ratio using a low-cost, sensor-based flow measurement module.

1 Introduction

Respiratory diseases such as asthma, chronic obstructive pulmonary disease (COPD), and interstitial lung diseases affect millions globally, leading to increased healthcare burdens and diminished quality of life [1][2]. Accurate and early detection of these conditions is crucial to effective intervention and management. Spirometry is a primary diagnostic tool used to evaluate pulmonary function by measuring airflow and lung volumes, particularly Forced Expiratory Volume in one second (FEV_1) and Forced Vital Capacity (FVC) [3].

Despite its diagnostic value, traditional spirometry systems require bulky equipment, trained technicians, and clinical settings, which limit their accessibility in rural and underdeveloped regions [4]. In recent years, mobile health (mHealth) solutions have gained traction as they offer portability, affordability, and integration with artificial intelligence (AI) [5][6].

Advances in smartphone technology have enabled the development of mobile-based spirometers that use low-cost sensors and mobile applications to perform real-time pulmonary assessments [7]. These systems provide immediate feedback and can store or transmit data to healthcare providers remotely, improving monitoring and diagnosis in remote settings [8][9].

Integration of AI and machine learning (ML) in respiratory diagnostics has shown

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promising results in identifying disease patterns and classifying respiratory conditions such as obstructive vs. restrictive lung diseases with high accuracy [10][11]. These algorithms analyze spirometry curves and extracted features to support automated diagnostics, potentially reducing diagnostic errors [12].

Recent studies have developed convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to interpret complex lung function data from portable devices [13]. Some applications even incorporate voice recognition, cough analysis, and patient-reported symptoms to enhance diagnostic insights [14][15].

The COVID-19 pandemic further underscored the importance of remote diagnostic tools for lung health, leading to a surge in telemedicine and at-home spirometry research [16]. Smartphone-based systems offer an ideal platform due to their widespread adoption, connectivity, and sensor capabilities [17].

This project aims to develop a cost-effective, user-friendly spirometer that interfaces with smartphones via Bluetooth, allowing users to perform pulmonary tests and receive disease classification in real time. The proposed system employs flow sensors to capture breathing patterns, transmits data to a mobile app, and utilizes a machine learning model to classify respiratory conditions [18][19].

Such innovations can play a pivotal role in democratizing pulmonary healthcare, especially in under-resourced regions, by empowering users and reducing reliance on hospital-based diagnostics [20].

2 Experimental Procedure

The entire system consists of three major parts, a breathing circuit, a data processing unit on microcontroller and an android application for display and classification. **2.1 Breathing circuit**

2.1.1 Airflow Tube: Airflow tube is a component where the patient will inhale and exhale.

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The tube should be portable and easy-to-clean thus requiring a simple design with a large pressure difference in small tube length. Considering these factors, a custom airflow tube based on fleisch type pneumotachograph is designed. The orifice plate with multiple holes is shown in Fig. 2b. According to the spirometer standards ,the maximum airflow resistance of the airflow tube is 150 Pa/L/s. Therefore, the inner diameter of 28 mm (Fig. 1b) and total length of 120 mm (Fig. 1a). The parameters of the tube are decided by performing a flow study in ANSYS software (Fig. 1c and Fig. 1d) so that the standards are maintained. If the resistive disk with 29 holes of 2 mm diameter each is placed at the middle of the airflow tube of length 120 mm having inner diameter of 28mm (Fig. 1b), the pressure difference is 1598 Pa (shown in Fig. 1c), which is within the limit of 2100 Pa. Fig. 1d shows the laminar flow simulation in ANSYS for the airtube; where the mass flow rate is taken as 0.01715 kg/s for air with maximum volume flow rate of 14 L/s.

2.1

2.1.1 Pressure Sensor

A monolithic silicon differential pressure sensor (MPXV7007) with a range of -7 kPa to 7 kPa is chosen because the maximum expiratory manoeuvre is within the reliable voltage range and also temperature compensated over -40◦C to 125◦C. The MPXV7007 sensor converts the change of pressure into the voltage, with an offset specifically at 2.5 V instead of the conventional 0 V.

2.2 Data Processing in Microcontroller

A 32-bit 180 MHz ARM Cortex-M4 processor-based Teensy development board (cost INR 2,445.00) has been used as a data processing unit for its ability to handle complex algorithms. It has a 256-kb Random-access memory (RAM) and a 32-bit Digital to Analog output. All analog and digital pins are operated at 3.3 V. A microSD card slot is mounted on the board.

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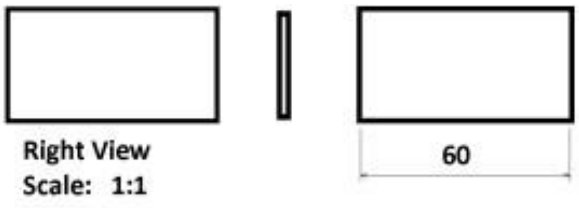
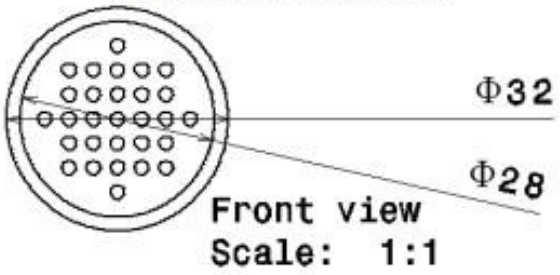
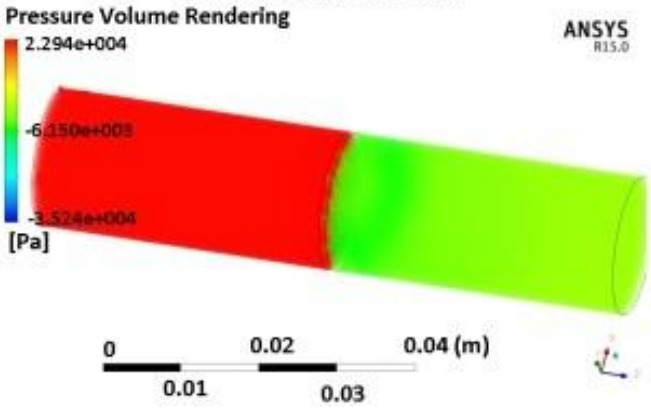


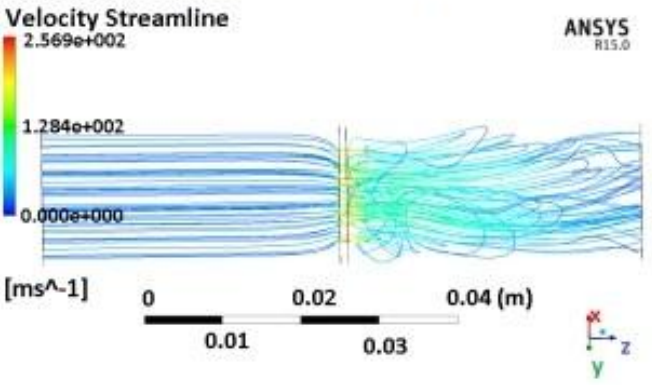
(a) Airflow tube dimensions.



(b) Flow resistance disk.



(c) Pressure distribution.



(d) Flow velocity profile.

Figure 1: Airflow tube (dimensions in mm).

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After converting the pressure signal into voltage by the differential pressure sensor, this is fed to the microcontroller through its analog input channel. As the analog input pins are operated at 3.3 V, the sensor signal have been scaled down by a potential divider circuit. The Allegro/Cadence software has been used for designing the PCB prototype. The entire prototype consists of three parts: powering circuit, the sensor circuit and the Teensy board. Bluetooth is connected with the serial communication ports of the controller. Fig. 3 shows the logical modules of the PCB prototype and their inter-dependency. For MPXV7007DP differential pressure sensor, the supply voltage range is 4.75 V DC to 5.25 V DC. A 9 V battery is used with the IC 7508 low drop out voltage regulator to get the 5 V DC. The Teensy board can also operate with 5 V DC but to use Universal Serial Bus (USB) port with an external power source, the power provided by the USB cable should be separated from the external power.

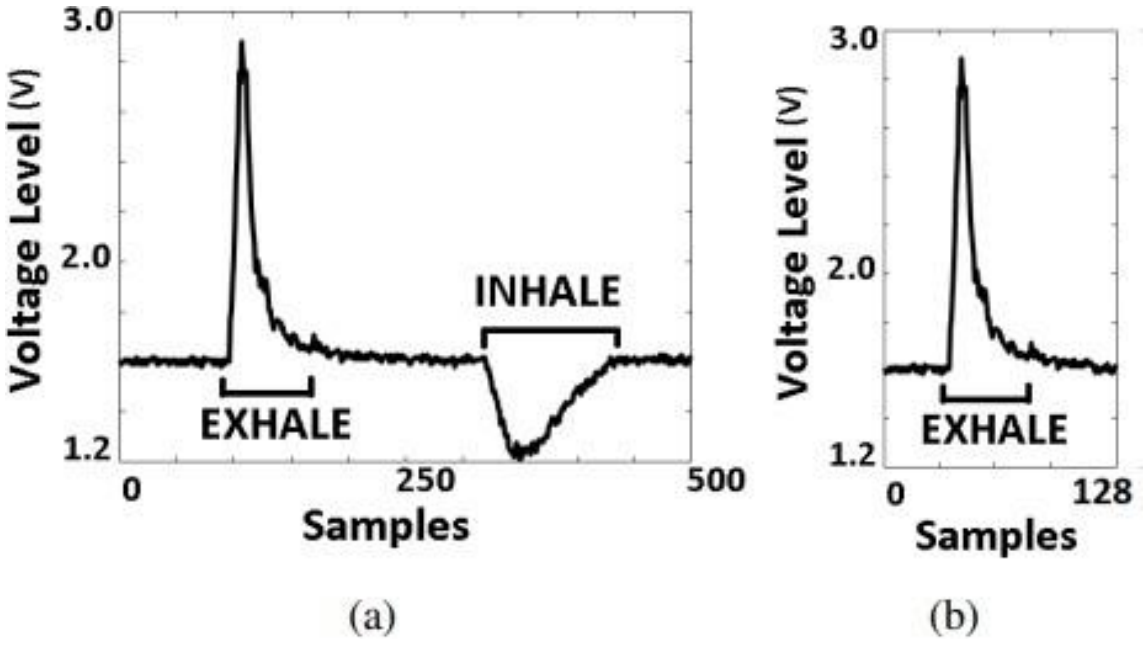

Figure 2: (a) Respiratory profile stored in microSD card and (b) Expiration half of the respiratory signal.

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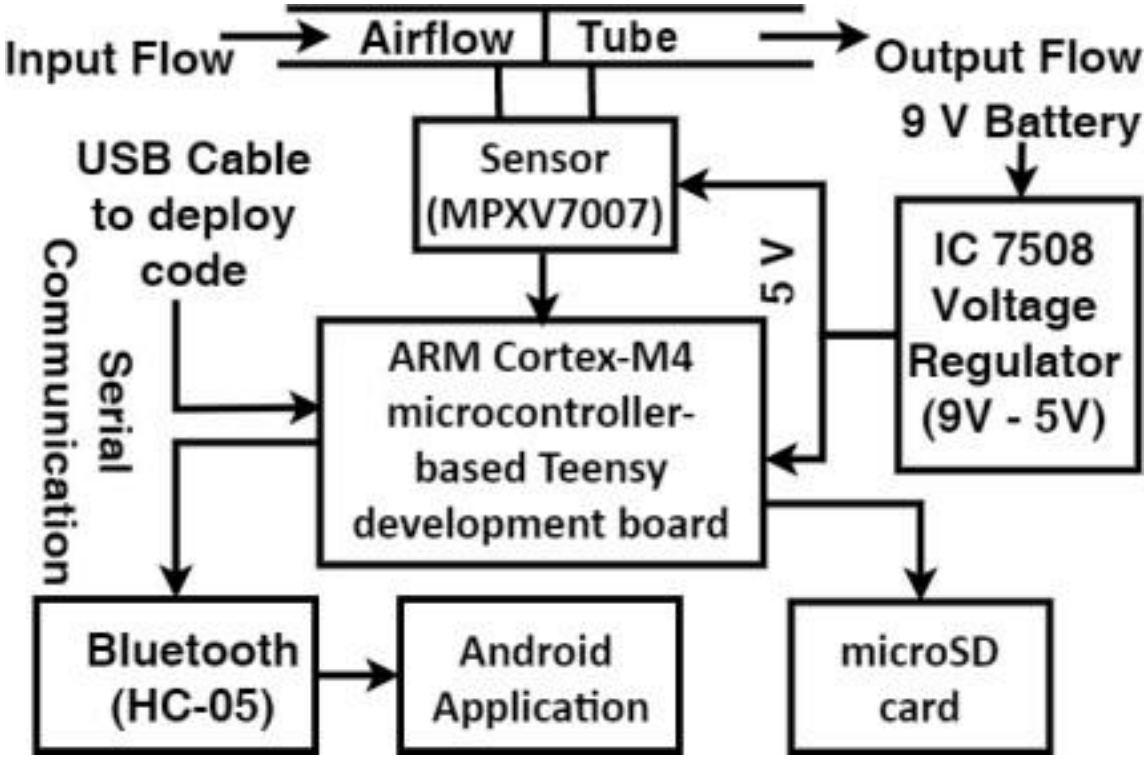

Figure 3: Logical modules of PCB prototype.

3 3Android application for display and classification

The Android application is the diagnostic and monitoring tool. This application is developed to acquire the respiratory data via Bluetooth and to calculate the FEV1, the FVC, and the PEF. The flow-volume graph and the time profile of the flow rate are computed here. The real-time classification of spirometry process will be the key feature of this application. The development of the android algorithm has been done in Android Studio and the application is tested on the android version 7.1 Nougat. The zoom in/zoom out feature in the display is an advantage to view the flow-volume and flowtime curves properly. The android application has following steps (Fig. 5):

- Select the Bluetooth device from the list.
- Fully inhale and click “Begin Recording” button and exhale.
- Press “Stop Recording” button.

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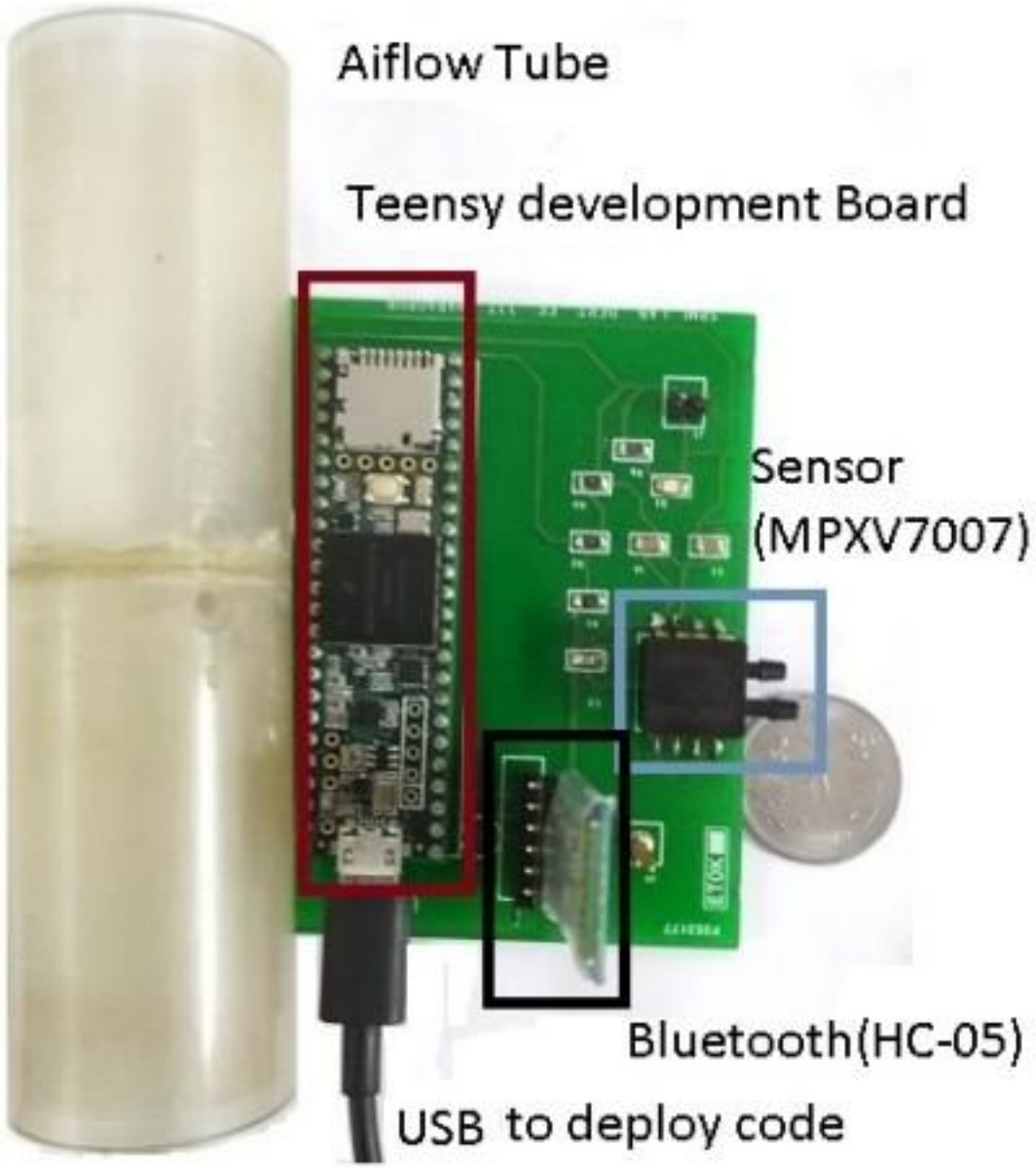

Figure 4: : Airflow tube with PCB prototype.

- After this, the parameters (the FEV1, the FVC, their ratio and the PEF) will be displayed .
- Click "View Plot" to show the graph (flow rate versus volume and flow rate versus time) .
- Click "Classify" button to check the lung condition (Normal or Abnormal) .

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• Click "Save" button to save spirometric measurements, the FEV1, the FVC, the FEV1/FVC (%) and the PEF.

In microcontroller coding, a threshold value has been set to prevent false triggering. If the subject clicks the "Begin Recording" button but does not exhale then the voltage values will not exceed the threshold value and the test will not start. Now if the subject starts the test properly but does not continue for 6 seconds, then a warning message "Perform the Test for at least 6 seconds or else Consult Doctor" (Fig. 5 (third one)) will appear. From the warning message, the subject will get to know that he should perform the test for 6 seconds and if he/she is unable to perform so then he/she should consult with a doctor. Based on the values of spirometric measurements (FEV1, FVC, and FEV1/FVC), a warning message, "Consult Doctor" (Fig. 5 (last one)), will be shown to the patient if any value is out of the normal range and the values are marked in red color. Irrespective of the classification results, the patient should consult the doctor based on this rule-based advisory regarding this warning.

4 Results and Discussions

In this work, the CNN clearly outperforms the LSTM. CNN has several advantages over LSTM for sequence modelling [21]. Convolutions in CNN can be carried out in parallel since the same filter is used in each layer whereas in LSTM, the predictions for later time steps must wait for their predecessors to complete. A long input sequence can be processed simultaneously in CNN but it can be processed sequentially in LSTM. Thus CNN converges much faster than LSTM (Fig. 6a and Fig. 6b). CNN has better control over the model's memory size by stacking convolutional layers or changing filter size. In case of a long input sequence, LSTM uses a lot of memory to store partial results for their multiple cell gates. However, in CNN, filters are shared across a layer, with the backpropagation path depending only on network depth. The plot of training and testing loss against the number of epochs

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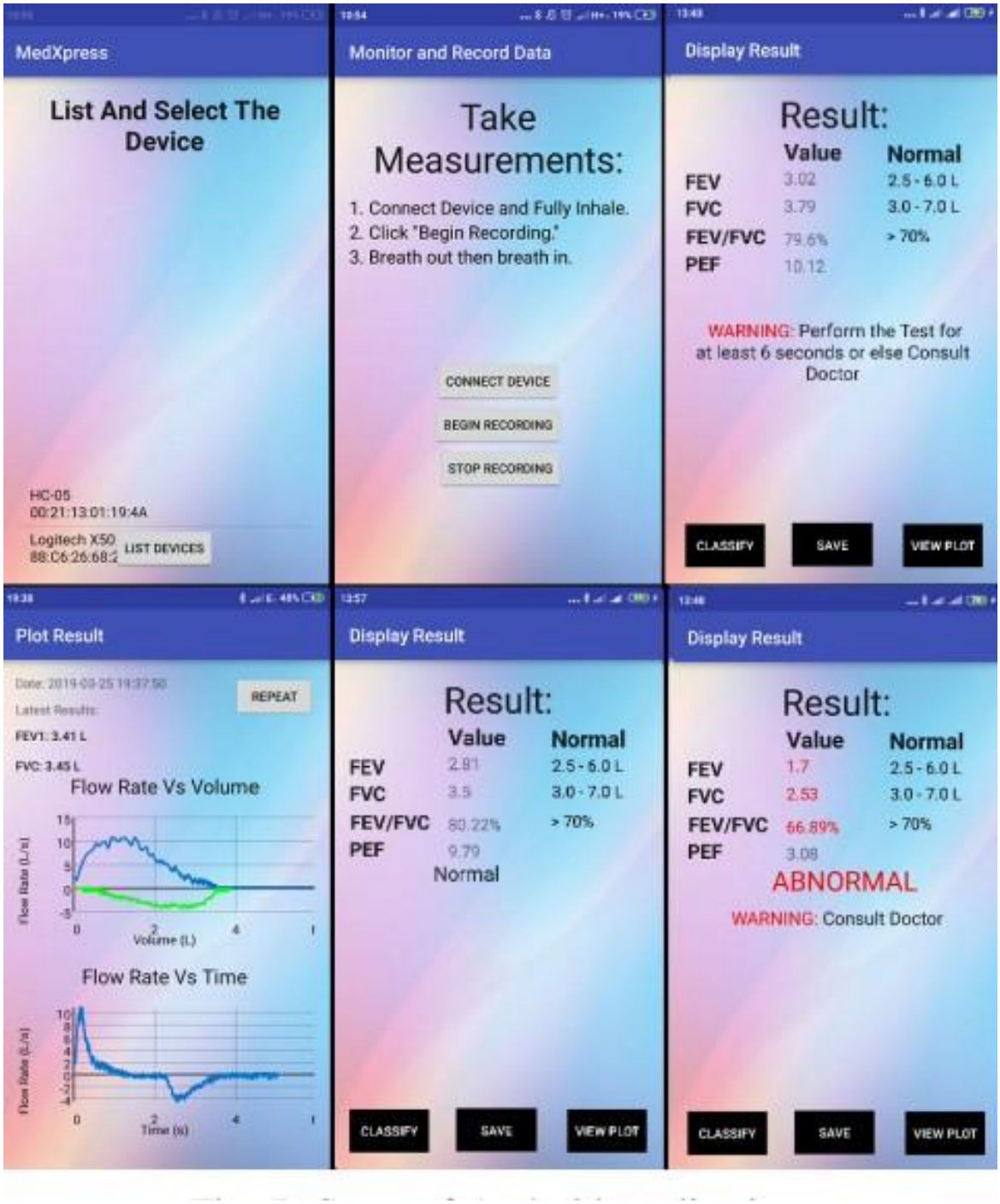

Figure 5: Steps of Android application.

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for both CNN and LSTM network clearly shows that CNN quickly converged to a virtually perfect solution, whereas the performance of LSTM is limited (Fig. 6a and 6b).

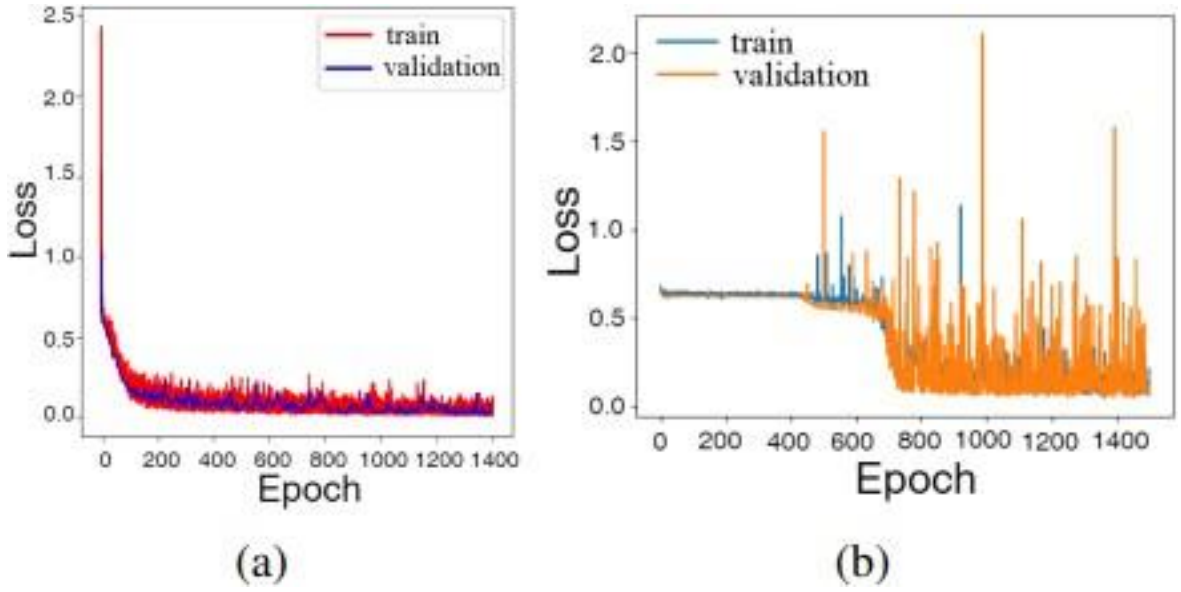

Figure 6: Loss versus Epoch for (a) CNN and (b) LSTM.

In this work, a detailed comparative study has been carried out by using both expiration and inspiration half(Fig.2(a)) and only the expiration half(Fig.2(b)) of the respiratory signal stored in the SD card. In Table 1, the accuracy, sensitivity and specificity of different classification methods have been shown for expiration half (only) and both expiration and inspiration half.

Methods	Accuracy (%)	Sensitivity (%)	Specificity (%)
DBN	88.07 (82.61)	97.81 (94.29)	66.71 (44.45)
SAE	92.95 (85.00)	93.48 (91.67)	90.91 (58.33)
LSTM	93.18 (81.95)	93.75 (88.89)	91.67 (66.67)
CNN + Inception	97.73 (86.65)	93.44 (95.45)	90.09 (62.50)
CNN	**98.98** (90.89)	**94.73** (99.27)	**91.01** (74.80)

Figure 7:

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: Performance of various classification methods

Considering the entire signal (both expiration and inspiration), the values have been shown within brackets. For example, in case of DBN, the accuracy, sensitivity and specificity are 88.07, 97.81 and 66.71 respectively for the expiration half only. In case of the entire signal, the respective parameters are 82.61, 94.29, and 44.45 which are given in the bracket. Table 1 suggests that the expiration signal performs better in disease classification than the entire (expiration and inspiration) signal. Important spirometric measurements like FEV1, FVC, FEV1/FVC and PEF are calculated from the expiration half of the flow-volume loop. In cases of obstructive lung diseases, such as asthma, bronchiectasis, COPD, and emphysema, the lungs are unable to expel air properly during exhalation. Thus the expiration half of the spirometry signal of the patients, suffering from these diseases, differs from that of the healthy subjects. By considering all these factors the expiration half is extracted from the raw signal and is fed to the classification model for training and validation.

4.1 Model Deployment to Android Application

After training, the pre-trained tensor flow model needs to be deployed on the Android application. Android has two basic repositories, Android Software Development Kit, written in Java and Android Native Development Kit, written in C++. The SDK is an interface for high-level coding. The Tensorflow model will run in NDK. To use Tensorflow functions on Android, the Tensorflow Android Archive is used. This is a wrapper file consists of all necessary dependencies required to implement Tensorflow on Android. After creating the environment, the model is deployed in the application to classify the lung condition (Normal/Abnormal) (Fig. 5). After importing the pre-trained model in the android application, the classification time of an instance on the Redmi 4 mobile phone with the Android Nougat operating system is 36 ms.

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4.2 Experimental results

The designed prototype has been validated in the Department of Pulmonary Medicine & Critical Care, AIIMS Bhubaneswar, India. It has been tested in the PFT room where patients have performed spirometry both in standard spirometer and the prototype spirometer. A total of 30 volunteers performed the test out of which 16 were diseased patients with an abnormal lung condition and 14 were healthy subjects. Table 2 shows the validation result of the designed spirometer with healthy and diseased cases. As a screening device for POC scenarios, 100% accuracy in classifying healthy cases and 80% accuracy in classifying diseased cases clearly suggests that the designed prototype will certainly benefit individuals by providing a home-based solution for spirometry.

Total Subjects	Healthy Subjects	Diseased Subjects	Classification Accuracy (for healthy)	Classification Accuracy (for diseased)
30	14	16	100%	80%

Figure 8:

Validation result of the designed prototype

4.3 Conclusion

Spirometry data vary with geographical location as the breathing pattern of human beings vary and the corresponding LLN equations change. As the classification condition of normal and abnormal lung condition will change, the classification model needs to be retrained with the data of that particular area. Here, in our study, data have been collected from the eastern part of India. The LLN values of FEV1, FVC and their ratio are predicted from standard reference equations from this part of the country. This is one of the limitations of this method. In the future, the proposed technique may be evaluated for the larger experimental database. Another limitation of the classification model is that the CNN model has been trained with the features extracted from the raw signal automatically. So the classification

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results may vary sometimes from manual judgement based on the values of spirometric measurements like FEV1, FVC and their ratio. In that case, as the developed application shows spirometric measurements as well so that patients can cross-check and verify. The prototype is a promising diagnostic tool in personal and point of care settings. The developed CNN-based pre-trained model can assist the patients by providing a preliminary diagnosis. As the spirometric results can be saved in the smartphone, it may be shared with the physician over the network. The user-friendly interface and the decision-making ability make the application distinctive. Patients in resourcelimited settings may not have access to sophisticated health monitoring systems. In this scenario, the proposed system is an important step towards the goal of Health for All.

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