



SMART SPIROMETER USING IOT & AIML

¹Bhavna Purushottam Parate, ²Divya Hemant Choudhary, ³Sneha Bharat Ravte, ⁴Vilas Moon

¹Student, ²Student, ³Student, ⁴Assistant Professor

Department of Electronics and Telecommunication Engineering
Terna Engineering College, Nerul, Navi Mumbai, India

Abstract: This paper presents the design and implementation of a smart spirometer for real-time respiratory health monitoring using Internet of Things (IoT) and machine learning techniques. The system employs a differential pressure-based sensing mechanism to measure airflow and estimate key lung function parameters such as Forced Expiratory Volume in one second (FEV1) and Forced Vital Capacity (FVC). An ESP32 microcontroller is used for data acquisition, processing, and wireless transmission of results to a mobile application for remote monitoring. To ensure reliable measurements, both hardware-level filtering and software-based signal processing methods are incorporated to reduce noise and improve stability. The calculated spirometric parameters are further utilized in a supervised machine learning framework, where clinically referenced threshold-based labeling is applied to generate structured training data. The trained model classifies respiratory conditions into normal and abnormal categories based on learned patterns. The proposed system provides a portable, low-cost, and user-friendly solution for continuous respiratory assessment and preliminary screening of conditions such as COPD and asthma. While the classification is guided by clinically established thresholds, the system demonstrates the integration of IoT and machine learning for accessible healthcare monitoring.

Index Terms - Smart Spirometer, Internet of Things (IoT), ESP32 Microcontroller, Differential Pressure Sensor, Lung Function Monitoring, Machine Learning, Respiratory Disease Detection, Respiratory Health Monitoring, Embedded Systems, COPD.

I. INTRODUCTION

Respiratory diseases such as Chronic Obstructive Pulmonary Disease (COPD) and asthma are among the leading causes of morbidity worldwide, significantly affecting the quality of life of millions of individuals. These conditions often progress gradually and may remain undiagnosed until they reach a severe stage, making early detection and continuous monitoring extremely important. Regular assessment of lung function enables timely intervention, better disease management, and reduction in hospitalization rates. Spirometry is one of the most widely accepted and reliable techniques for evaluating pulmonary function, providing key parameters such as Forced Expiratory Volume in one second (FEV1) and Forced Vital Capacity (FVC), which are essential for identifying abnormalities in respiratory performance. Despite its clinical importance, traditional spirometry equipment is often expensive, bulky, and requires trained personnel for operation. As a result, its usage is largely confined to hospitals and diagnostic centers, limiting accessibility for routine or home-based monitoring. This creates a gap between the need for frequent respiratory assessment and the availability of convenient diagnostic tools. With the rapid advancement of embedded systems, sensor technologies, and wireless communication, there is an opportunity to bridge this gap by developing portable and cost-effective solutions that can operate outside clinical environments. The integration of Internet of Things (IoT) technology has enabled real-time data acquisition, remote monitoring, and seamless connectivity between devices and users. IoT-based healthcare systems allow physiological data to be transmitted and visualized through mobile or web applications, enhancing user engagement and accessibility. In parallel, machine learning techniques have gained significant attention for their ability to analyze biomedical data and identify patterns that may not be easily interpretable through conventional methods.

These techniques can assist in classifying health conditions and supporting decision-making processes. In this work, a smart spirometer system is proposed that combines sensor-based airflow measurement, embedded processing, IoT connectivity, and machine learning-based classification. The system utilizes a differential pressure-based sensing approach to capture airflow data, which is processed using an ESP32 microcontroller to compute essential spirometric parameters such as FEV1 and FVC. The processed data is displayed locally and transmitted wirelessly for remote monitoring. Furthermore, a supervised machine learning approach is incorporated, where clinically referenced threshold-based labeling is used to generate training data and classify respiratory conditions into normal and abnormal categories. The primary objective of this work is to develop a compact, affordable, and user-friendly device capable of performing preliminary respiratory assessment outside clinical settings. By integrating IoT and machine learning with spirometry, the proposed system aims to provide an accessible solution for continuous monitoring, early detection of respiratory abnormalities, and improved awareness of lung health among users.

II. LITERATURE SURVEY

Several research efforts have focused on developing portable and intelligent spirometry systems to improve accessibility and early detection of respiratory diseases. In recent studies, machine learning techniques have been integrated with spirometry devices to enable automated classification of respiratory conditions. For instance, one approach utilizes a flow sensor combined with a Raspberry Pi to capture respiratory signals and extract key features, which are then classified using algorithms such as Support Vector Machine (SVM), Naive Bayes, and ensemble voting methods. This demonstrates the potential of combining embedded systems with machine learning for automated detection of abnormalities such as wheezing [1].

In parallel, IoT-based spirometry systems have been developed to facilitate remote monitoring and patient self-care. One such system employs a pressure sensor and a NodeMCU microcontroller to acquire lung function data and transmit it to a mobile application via Wi-Fi. The application categorizes respiratory conditions based on calculated parameters and stores data in a cloud database, enabling continuous monitoring and accessibility [2]. These systems highlight the growing importance of connectivity in modern healthcare solutions.

Further advancements have addressed the integration of spirometry devices with comprehensive communication platforms. A system using an MPX5100DP pressure sensor and Arduino Nano has been proposed to measure key spirometric parameters such as FEV1 and FVC, while simultaneously enabling data sharing across mobile, desktop, and web interfaces. This approach bridges the gap between home-based monitoring and clinical supervision by allowing healthcare professionals to access patient data remotely [3].

Low-cost and portable spirometers based on differential pressure sensing and microcontroller platforms have also demonstrated promising results in terms of accuracy and usability. For example, a system utilizing a Venturi-based airflow measurement approach with an Arduino and Bluetooth module achieved high accuracy when compared to standard clinical spirometers, making it suitable for home monitoring applications [4].

Additionally, studies validating commercial portable spirometers have shown strong agreement with laboratory-grade equipment, indicating the feasibility of reliable home-based lung function testing [5].

Recent innovations have also explored alternative sensing mechanisms, such as biomimetic airflow sensors inspired by biological structures. These systems offer advantages such as reduced airflow resistance and improved sensitivity, along with user engagement features like gamified interfaces for respiratory training [6]. Such developments indicate a shift toward more user-friendly and continuous monitoring solutions.

Despite these advancements, many existing systems rely on either standalone measurement, IoT-based monitoring, or machine learning-based classification independently. Limited work has focused on integrating all these components into a unified, low-cost system while also utilizing clinically referenced thresholds for data-driven classification. The present work addresses this gap by combining pressure-based sensing, IoT connectivity, and supervised machine learning within a single platform, providing a practical solution for preliminary respiratory assessment.

III. METHODOLOGY

The proposed smart spirometer system is designed as an integrated framework combining sensing, signal processing, IoT communication, and machine learning-based classification. The methodology is structured into distinct stages to ensure accurate measurement, processing, and analysis of respiratory data.

1. Signal Detection (Sensing)

The system utilizes a differential pressure sensor to detect airflow generated during the exhalation process. When the user exhales through the mouthpiece, a pressure difference is created across the sensor, which is

proportional to the airflow rate. This pressure variation is converted into an analog electrical signal, representing the respiratory activity in real time. The sensing mechanism forms the foundation of the system, as accurate airflow detection is essential for reliable spirometric analysis.

2. Signal Conditioning and Amplification

The analog signal obtained from the pressure sensor is typically low in magnitude and susceptible to noise. To address this, an operational amplifier (LM358) is used along with a resistor network to amplify the signal to a suitable level for processing. Additionally, capacitors are incorporated in the circuit to filter out high-frequency noise and stabilize the signal. This stage ensures that the signal is clean, stable, and within the acceptable range of the microcontroller's analog input.

3. Data Processing and Computation

The conditioned signal is fed into the ESP32 microcontroller, which performs analog-to-digital conversion (ADC) to obtain digital data. The system then computes the airflow rate using fluid dynamics relationships based on pressure variations. Numerical integration techniques are applied to determine the volume of air exhaled over time. From these calculations, key spirometric parameters such as Forced Expiratory Volume in one second (FEV1) and Forced Vital Capacity (FVC) are derived. The ratio of FEV1 to FVC is also calculated, which serves as an important indicator of respiratory health.

4. Output and Communication

The computed parameters are displayed locally on an LCD module to provide immediate feedback to the user. In addition, the ESP32 enables wireless communication by transmitting the data to a mobile application using the Blynk platform. This allows users to monitor their respiratory parameters remotely and maintain a record of their lung function over time. The integration of IoT enhances accessibility and enables real-time health monitoring outside clinical settings.

5. Advanced Analysis and Classification

To enhance the functionality of the system, a classification mechanism is incorporated using machine learning techniques. A dataset is generated from collected spirometric parameters along with user profile information such as age group and smoking status. Since clinically labeled datasets are not readily available, rule-based labeling is performed using clinically referenced spirometry thresholds. The labeled data is then used to train a supervised machine learning model, which classifies respiratory conditions into normal and abnormal categories based on learned patterns. This approach enables data-driven analysis and improves the capability of the system to provide preliminary screening of respiratory conditions.

Overall, the methodology integrates hardware design, signal processing, IoT connectivity, and machine learning into a unified system, ensuring accurate, real-time, and accessible respiratory monitoring.

Mathematical Modeling and Calculations

Mathematical Modeling and Calculations

The proposed system computes spirometric parameters using mathematical relationships derived from pressure-flow dynamics and numerical integration techniques.

1. Analog Voltage Conversion

The analog signal obtained from the pressure sensor is converted into voltage using the ADC of the ESP32:

$$V_{adc} = (ADC_value \times V_{ref}) / ADC_resolution$$

where

$$V_{ref} = 3.3V \text{ and } ADC_resolution = 4095.$$

2. Pressure Calculation

The measured voltage is converted into pressure by subtracting the baseline offset obtained during calibration:

$$Pressure = V_{adc} - Pressure_offset$$

Negative values are eliminated to avoid noise influence.

3. Airflow Calculation

The airflow rate is calculated using the relation derived from Bernoulli's principle:

$$Flow = A \times \sqrt{(2 \times P / \rho)}$$

where

A = Cross-sectional area of the tube

P = Pressure (in Pascals)

ρ = Air density (1.225 kg/m³)

In the implemented system, calibration and correction factors are applied:

Flow = $A \times \sqrt{(2 \times (\text{Pressure} \times 1000) / \rho)} \times \text{Calibration_factor} \times \text{BTPS_correction}$

These factors compensate for real-world variations and improve measurement accuracy.

4. Volume Calculation

The volume of exhaled air is computed using numerical integration of airflow over time:

Volume = $\int \text{Flow} \times dt$

In discrete form:

Volume = Volume + (Flow \times Δt)

where Δt is the time interval between successive readings.

5. FEV1 Calculation

Forced Expiratory Volume in one second (FEV1) is calculated as the volume exhaled during the first second of the exhalation process:

FEV1 = Volume at t = 1 second

6. FVC Calculation

Forced Vital Capacity (FVC) is defined as the total volume of air exhaled during the complete exhalation process:

FVC = Total accumulated volume

7. Ratio Calculation

The ratio of FEV1 to FVC is calculated as:

FEV1/FVC Ratio (%) = $(\text{FEV1} / \text{FVC}) \times 100$

This ratio serves as a primary indicator for respiratory condition assessment.

8. Classification Logic

Based on clinically referenced thresholds, the respiratory condition is classified as:

For Children:

Ratio \geq 85% \rightarrow Healthy

Ratio < 85% \rightarrow Risk

For Adults:

Ratio \geq 75% \rightarrow Healthy

Ratio < 75% \rightarrow Risk

For Elderly:

Ratio \geq 70% \rightarrow Healthy

Ratio < 70% \rightarrow Risk

These thresholds enable preliminary screening of respiratory abnormalities such as COPD and asthma.

The above mathematical modeling forms the foundation for real-time computation and classification of respiratory parameters in the proposed smart spirometer system.

IV. IMPLEMENTATION DETAILS

A) System Architecture

The overall system architecture is designed to enable real-time acquisition, processing, and analysis of respiratory data in a structured and efficient manner. The architecture comprises multiple functional units, including a sensing unit, signal conditioning unit, processing unit, communication module, output interface, and classification module, which collectively ensure accurate and continuous monitoring of lung function. The process begins with the sensing unit, where the user exhales through a mouthpiece, generating airflow that is detected by a differential pressure sensor. The sensed analog signal is then passed to the signal conditioning unit, which amplifies and stabilizes the signal using an operational amplifier along with passive components. This ensures that the signal is suitable for further processing.

The conditioned signal is fed into the processing unit, where the ESP32 microcontroller performs analog-to-digital conversion and computes essential spirometric parameters such as airflow, volume, Forced Expiratory Volume in one second (FEV1), and Forced Vital Capacity (FVC). The processed data is then utilized for further analysis.

For communication, the system incorporates an IoT module through the built-in Wi-Fi capability of the ESP32, enabling transmission of data to a mobile application for remote monitoring. The output interface includes an LCD display for real-time visualization of results and an LED indicator for quick status indication.

Additionally, a classification module is integrated into the system to analyze the computed parameters. Based on clinically referenced thresholds and machine learning-based logic, the system classifies the respiratory condition into normal or risk categories. This structured architecture ensures seamless data flow from sensing to decision-making, enabling efficient and user-friendly respiratory health monitoring.

B) Hardware Implementation

The hardware design of the proposed system focuses on achieving a compact, low-cost, and portable spirometer by integrating efficient electronic components. The system consists of sensing, processing, power management, and output modules, each contributing to the overall functionality.

The sensing unit is based on the MPX5010 differential pressure sensor, which measures the pressure difference generated during the exhalation process. Due to its high sensitivity and accuracy, the sensor is suitable for capturing variations in airflow required for spirometric analysis. The output of the sensor is an analog voltage that varies with breathing intensity.

To process the sensed signal, an ESP32 microcontroller is used as the central processing unit. It performs analog-to-digital conversion (ADC) of the amplified signal and executes all computational tasks required for determining lung parameters. The ESP32 is selected due to its high processing capability, built-in Wi-Fi and Bluetooth features, and suitability for IoT-based applications.

The signal conditioning stage is implemented using an LM358 operational amplifier, which amplifies the weak analog signal from the sensor to a level suitable for accurate processing. The LM358 is chosen due to its low power consumption and ability to operate with a single supply voltage, making it ideal for portable systems.

For user interaction, a 16×2 LCD display is incorporated to present the calculated parameters such as FEV1, FVC, and classification results. Additionally, an LED indicator is used to provide a visual alert based on the detected respiratory condition.

The power supply system is designed to ensure stable and portable operation. A 3.7V rechargeable battery is used as the primary power source. A TP4056 charging module is integrated for safe and efficient battery charging. To regulate voltage levels required by different components, DC-DC buck and boost converters are utilized, ensuring proper voltage conversion and stable performance of the system.

Passive components, including resistors and capacitors, are used to support signal conditioning and circuit stability. Resistors (4.7k Ω , 100k Ω , and 220 Ω) are used for gain setting and current limiting, while capacitors (0.1 μ F, 0.1 μ F, and 10 μ F) are incorporated for noise filtering and signal stabilization.

The overall hardware design emphasizes portability, energy efficiency, and reliable performance, making the system suitable for continuous respiratory monitoring in non-clinical environments.

C) Circuit Integration

The circuit integration of the proposed system is designed to establish proper interfacing between the sensing unit, signal conditioning stage, and processing module to ensure accurate and stable data acquisition. The connections are implemented based on a structured design to maintain signal integrity and reliable operation.

The MPX5010 differential pressure sensor is used as the primary sensing element. Its power pins are connected to the supply rails, with VCC connected to the positive rail and GND to the common ground. The output of the sensor, which provides an analog voltage proportional to the pressure difference, is connected to the non-inverting input (Pin 3) of the LM358 operational amplifier.

The LM358 operational amplifier is configured to amplify the low-level sensor signal. Its VCC (Pin 8) is connected to the positive supply rail, while GND (Pin 4) is connected to the common ground. A feedback network is implemented using resistors, where the inverting input (Pin 2) is connected to ground through a resistor and also connected to the output (Pin 1) through another resistor. This configuration sets the required gain for signal amplification. The amplified output from Pin 1 of the LM358 is then directly connected to the analog input pin (GPIO 34) of the ESP32 microcontroller.

The ESP32 serves as the central processing unit and is powered through its 3.3V supply pin, with all ground connections tied to a common reference to ensure stable operation. The processed signal is used for computation of spirometric parameters.

For output indication, an LED is connected to GPIO 2 of the ESP32 through a current-limiting resistor, with the cathode connected to ground. This provides visual feedback based on the classification result.

The power management system is designed to ensure stable voltage supply to all components. A rechargeable battery is used as the primary power source, along with a TP4056 charging module for safe charging. DC-DC buck and boost converters are incorporated to regulate voltage levels as required by different modules, ensuring consistent and reliable system performance.

The complete circuit is designed and verified using EasyEDA, ensuring correct connectivity and layout. Proper grounding, signal routing, and component placement are maintained to minimize noise and ensure accurate signal processing. This integrated design enables efficient operation of the smart spirometer system in real-time conditions.

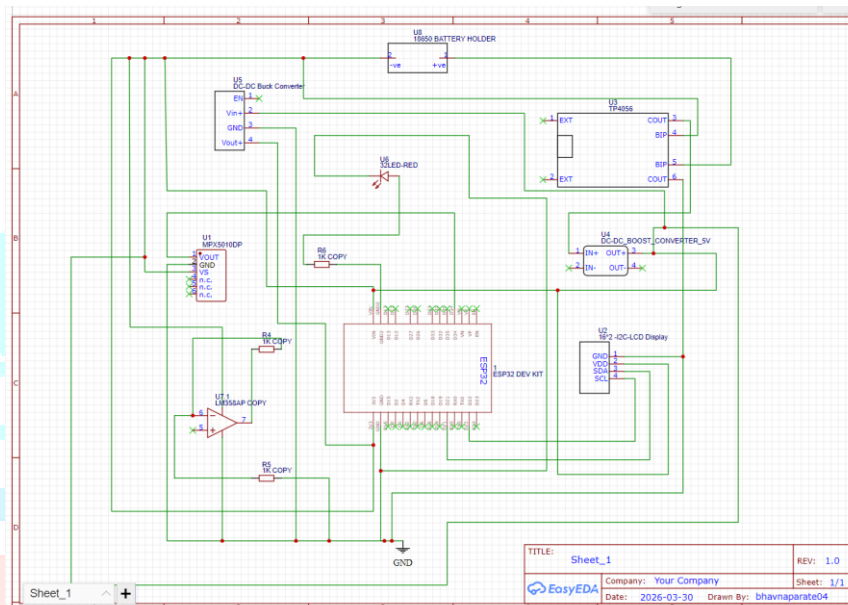


Fig. 1: Circuit Diagram

D) Software Framework

The software framework of the proposed smart spirometer system is designed to perform real-time data acquisition, signal processing, computation of spirometric parameters, classification, and communication. The implementation is carried out on the ESP32 microcontroller, ensuring efficient and continuous operation. The system begins with an initialization phase, where the ESP32 configures the input-output pins, establishes communication with the LCD display, and connects to the Wi-Fi network for IoT functionality. During this stage, sensor calibration is also performed to determine the baseline pressure value, which helps in minimizing offset errors during measurement. Once initialized, the system continuously acquires analog data from the pressure sensor using the built-in analog-to-digital converter (ADC) of the ESP32. The raw sensor signal is subject to noise and fluctuations; therefore, software-based filtering techniques such as moving average and smoothing are applied to stabilize the readings and improve accuracy. After filtering, the processed signal is converted into pressure values and further into airflow using appropriate mathematical relationships derived from fluid dynamics principles. The airflow data is then integrated over time to compute the volume of air exhaled. Based on this, key spirometric parameters such as Forced Expiratory Volume in one second (FEV1) and Forced Vital Capacity (FVC) are calculated. To ensure accurate measurement, the system incorporates exhalation detection logic. The start of exhalation is identified when the airflow exceeds a predefined threshold, and a timer is initiated. The system continues to track airflow and volume until the end of exhalation is detected, either when the airflow falls below a threshold or when a maximum time limit is reached. This ensures correct calculation of FEV1 at one second and FVC at the end of the breathing cycle. The computed parameters are then used for classification of respiratory condition. The ratio of FEV1 to FVC is calculated and compared with clinically referenced thresholds. Based on this, the system classifies the respiratory condition into healthy or risk categories. In addition, a supervised machine learning approach is incorporated, where the model is trained using labeled data derived from clinical thresholds to enable data-driven classification. Finally, the results

are displayed to the user through multiple interfaces. The calculated parameters and classification outcome are shown on a 16×2 LCD for immediate feedback. Simultaneously, the ESP32 transmits the data to a mobile application via IoT connectivity, enabling remote monitoring and visualization of respiratory health parameters. The software framework thus integrates real-time processing, intelligent analysis, and communication, forming a critical component of the smart spirometer system.

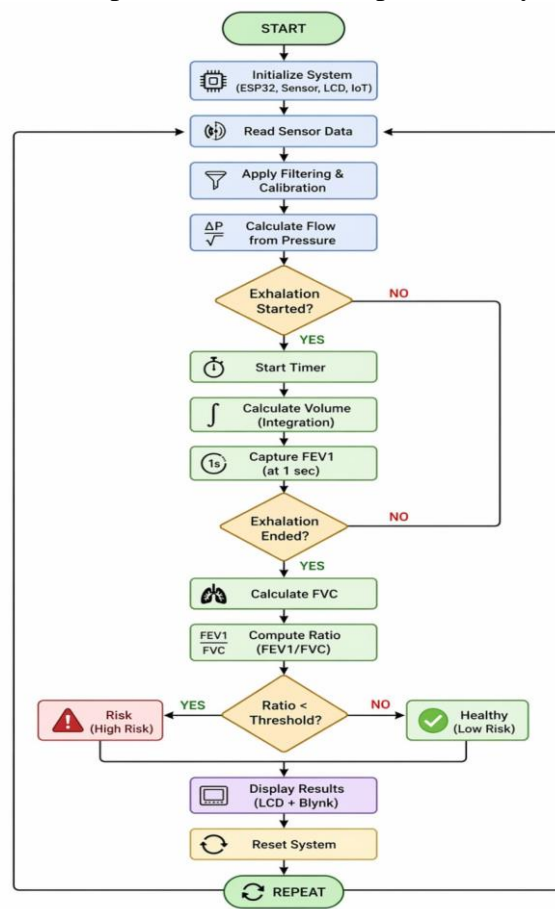


Fig. 2: Flowchart

V. RESULTS

The proposed smart spirometer system was successfully developed and tested for real-time measurement and analysis of respiratory parameters. The system was able to accurately capture airflow during exhalation using the pressure sensor and process the data through the ESP32 microcontroller. The implementation demonstrated stable and reliable performance under different testing conditions.

During operation, the system effectively measured key spirometric parameters such as Forced Expiratory Volume in one second (FEV1) and Forced Vital Capacity (FVC). These parameters were computed using real-time airflow data and numerical integration techniques. The calculated values were displayed on a 16×2 LCD module, providing immediate feedback to the user. Additionally, the data was transmitted to a mobile application through the Blynk platform, enabling remote monitoring and visualization.

The system also demonstrated efficient exhalation detection, where the start and end of the breathing cycle were accurately identified based on predefined thresholds. This ensured proper timing for FEV1 calculation and accurate determination of FVC. The inclusion of filtering techniques significantly reduced noise in sensor readings, resulting in stable and consistent output values.

For analysis, the ratio of FEV1 to FVC was computed and used as a primary indicator for respiratory condition assessment. Based on clinically referenced thresholds, the system classified the results into healthy and risk categories. The classification results were indicated through both the LCD display and an LED indicator, providing clear and immediate interpretation.

The integration of IoT functionality allowed continuous data monitoring through a mobile interface, enhancing accessibility and usability of the system. The overall system performance demonstrated that a low-cost, portable device can effectively perform preliminary respiratory assessment outside clinical environments.

The results confirm that the proposed system is capable of real-time respiratory monitoring, accurate parameter computation, and reliable classification. However, it is important to note that the system is intended for preliminary screening and not for clinical diagnosis. Further improvements, such as the use of clinically

validated datasets and advanced machine learning models, can enhance the accuracy and applicability of the system.

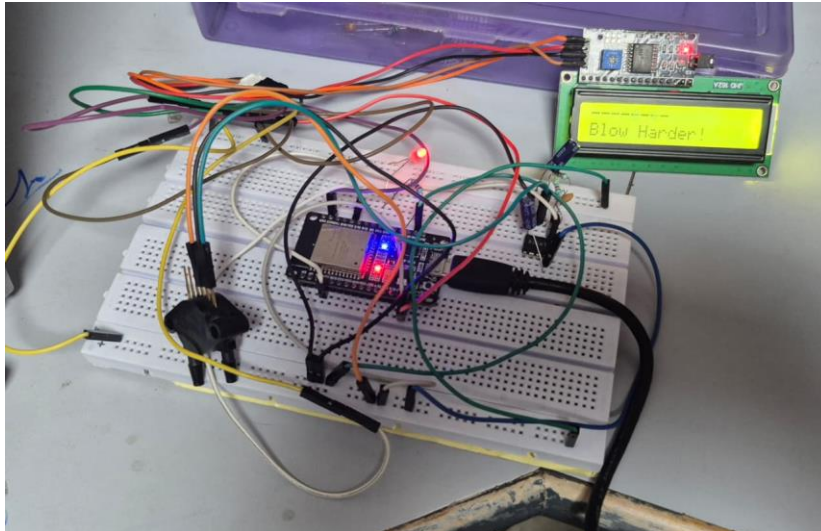


Fig.3: Experimental Setup and Output of Smart Spirometer System

V. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

This paper presents the design and implementation of a smart spirometer system for real-time respiratory monitoring using Internet of Things (IoT) and machine learning techniques. The developed system successfully measures key spirometric parameters such as Forced Expiratory Volume in one second (FEV1) and Forced Vital Capacity (FVC) using a pressure-based sensing approach integrated with signal conditioning and ESP32-based processing. The system provides real-time analysis and feedback through an LCD display and enables remote monitoring via an IoT platform, enhancing accessibility and usability. A classification mechanism based on clinically referenced thresholds, along with a supervised machine learning approach, is incorporated to perform preliminary screening of respiratory conditions such as COPD and asthma. The proposed solution is compact, cost-effective, and portable, making it suitable for non-clinical environments while supporting continuous monitoring and early detection of respiratory abnormalities. However, the system is intended for preliminary assessment and not as a replacement for clinical diagnosis. Future research can focus on improving accuracy through advanced machine learning models trained on clinically validated datasets, developing a doctor-side dashboard for live report monitoring, enabling telemedicine-ready integration for remote consultation, incorporating AI-based breathing pattern tracking for deeper analysis, and designing a multi-language user interface to improve accessibility for diverse users, thereby enhancing the overall effectiveness and real-world applicability of the system.

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