BioSmart Inhale: AI-Enabled Breath Analysis for Early Asthma and Pulmonary Disorder Detection

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Abstract

Continuous monitoring and early detection of respiratory-related diseases, such as asthma and pulmonary disorders, are essential since these conditions may lead to life-threatening conditions. Despite the accuracy that conventional de- vices like gas chromatography-mass spectrometry (GC-MS) and infrared analyzer possess, these systems are usually expensive and bulky, thus limited to laboratory or clinical environments. To create an affordable and portable alter- native, the BioSmart Inhale project was initiated. BioSmart Inhale is a multi-sensor breath analysis system enhanced with artificial intelligence capabilities. Gas sensors are incorporated into this system for the identification of volatile organic compounds (VOCs). Apart from gas sensors, temperature and humidity sensors are included in the system for compensating the environmental impact and improving the performance. Compared to the current instruments, the system has incorporated a novel technology of biomarker detection based on the absorption of breath in this case. All acquired data will be analyzed with embedded machine learning algorithms, including SVM (Support Vector Ma- chine) and LSTM (Long Short-Term Memory). What makes this project unique is the fact that this instrument involves multi-sensors, artificial intelligence technologies, and the portability of the system. Thus, apart from monitoring, this device can be connected wirelessly and utilized in remote locations. BioSmart Inhale offers a practical and scalable solution for early disease detection, continuous monitoring, and personalized healthcare,

making it suitable for both home and clinical use.

Keywords: Breath analysis,Respiratory monitoring, Asthma detection,Biosensors, AI-based classification.

1. Introduction

Respiratory diseases such as asthma, chronic obstructive pulmonary disease (COPD), and other pulmonary disor- ders represent a major global health burden, accounting for millions of hospitalizations and deaths each year. Early diagnosis and continuous monitoring are critical to minimize disease progression and improve patientasthmacomes. However, conventional diagnostic approaches, including spirometry, peak flow measurement, and medical imaging, are often episodic, invasive, clinic-dependent, and limited in their ability to capture dynamic variations in respira- tory function. These limitations create a pressing need for non-invasive, continuous, and patient-friendly monitoring technologies that can provide real-time insights into respiratory health[1].

Recent advances in biosensing technologies and artificial intelligence have opened new possibilities for breath anal- ysis as an alternative diagnostic approach. Exhaled breath contains volatile organic compounds (VOCs), temperature, humidity, flow patterns, and other biochemical markers that reflect inflammatory responses and airway obstruction. Leveraging these biomarkers for disease prediction offers a non-invasive pathway for detecting respiratory disorders at an early stage. Nonetheless, most existing systems either focus on selective biomarkers or fail to integrate physical and biochemical indicators into a unified clinical decision model.

Technological advances in biomedical sensing and artificial intelligence have highlighted exhaled breath as a pow- erful, non-invasive source of physiological and biochemical information. Breath contains a heterogeneous mixture of volatile organic compounds (VOCs), carbon dioxide (CO), nitric oxide (FeNO), temperature signatures, humidity pro- files, and airflow patterns that reflect the status of pulmonary function, inflammatory response, and airway obstruction. Recent studies show that analyzing breath biomarkers using multisensor systems can serve as an alternative pathway to detect respiratory diseases without physical discomfort or invasive sampling. However, most existing respiratory monitoring devices focus either on biochemical markers or mechanical ventilation measurement alone. The lack of a unified sensing architecture capable of integrating multiple physiological indicators with predictive data analytics remains a barrier to personalized, continuous respiratory healthcare[2].

To bridge this technological gap, the present study introduces BioSmart Inhale, an AI-enhanced multisensor respi- ratory monitoring device engineered to support early detection and continuous tracking of pulmonary disorders. The system incorporates a combination of gas sensors (for CO, VOCs, and FeNO), temperature and humidity sensors, airflow sensing units, and a bioabsorption layer designed to capture trace biochemical constituents present in exhaled breath. The multimodal sensor data is processed using an embedded machine learning pipeline that performs signal preprocessing, feature extraction, respiratory pattern segmentation, and abnormality classification in real time. The integration of physiological and biochemical analysis enables a more comprehensive respiratory assessment compared to traditional single-marker evaluations.

Furthermore, BioSmart Inhale adopts a user-centered approach by supporting wireless data transfer, smartphone integration, and configurable alert notifications for abnormal respiratory trends. This facilitates remote monitoring and telemedicine-based intervention, reducing dependency on frequent hospital visits and improving accessibility for high-risk and vulnerable populations. In addition, the system promotes longitudinal tracking of respiratory health, allowing clinicians to evaluate patient-specific trends, treatment response, and exacerbation risk through cloud-based data analytics and decision dashboards.

Overall, this research contributes to the development of next-generation intelligent respiratory diagnostics by com- bining biosensing, machine learning, and digital healthcare technologies into a unified platform. BioSmart Inhale demonstrates the potential of AI-assisted breath analysis to transform respiratory care from episodic clinic-based test- ing to proactive, continuous disease surveillance, ultimately improving quality of life and reducing morbidity related to chronic respiratory disorders.

The primary contributions of this paper are as follows:

1. **Performance Evaluation of Traditional breath analyser Methods:** This paper gives an exhaustive review of A unified multimodal breath-sensing architecture that integrates gas

biomarkers (CO, VOCs, FeNO) with ther- mal, humidity, and airflow measurements—overcoming the traditional limitation of single-marker respiratory assessment.

2. **An embedded machine learning pipeline for real-time analysis,**performing signal preprocessing, feature extraction, respiratory pattern segmentation, and abnormality classification directly on-device without reliance on external computational hardware.
3. **A bioabsorption-enhanced breath interface design,** To capture trace biochemical constituents with higher sensitivity, improving detection of inflammatory and obstructive respiratory signatures.
4. **A digital health ecosystem enabling continuous remote monitoring**, featuring wireless data transmission, smartphone integration, cloud analytics, and adaptive alert notifications to support personalized, long-term res- piratory care.
5. **Hybrid biochemical–physiomechanical interpretation of breathing**, enabling correlation of VOC signature variations with airflow restriction, inflammation levels, and ventilation patterns for deeper clinical insight.

This paper is organized as follows: Section 2 gives a review of existing breath analyser techniques, traditional and hybrid, and their merits and demerits. Section 3 explains the proposed hybrid approach. Section 4 explains the experimental setup, datasets, evaluation metrics, and assessment process. Section 5 presents experimental results and a comparative analysis of the proposed method with the conventional method based on quantitative and qualitative performance measures. Finally, Section 6 presents the conclusion of the prime results, emphasizes the strengths of the hybrid approach, and offers potential future research directions in asthma technology.

2. Litrature Survey

breath analyser is a new area of research with a plethora of methodologies suggested to enhance the asthma of information from different imaging sources. Different researchers have attempted different asthma methods, from conventional breath analyserprocessing methods to deep learning-based frameworks, each of which focuses on over- coming different challenges like texture preservation, noise removal, and computational complexity.

Picciariello A. et al. (2024) developed a portable breath analyzer for the diagnosis of colorectal cancer using volatile organic compound (VOC) analysis. Their system utilized a micro gas chromatograph combined with ma- chine learning techniques such as linear discriminant analysis and principal component analysis. The study achieved high diagnostic performance with 94.4 percent sensitivity and 91.2 percent accuracy, demonstrating the effectiveness of breath biomarkers in non-invasive cancer detection[3]. Khamsin A.A. et al. (2023) proposed an IoT-integrated breath analyzer for monitoring alcohol consumption. Their system employed a fuel-cell sensor and cellular-based communication to enable real-time data transmission and storage. The model achieved an accuracy of 98.16 percent , highlighting the importance of IoT integration for large-scale health monitoring and data collection[4]. Verma A. et al. (2023) introduced a nanostructured WO/WS-based acetone sensor for breath analysis. The system demonstrated high sensitivity and a low detection limit of 1.54 ppm, making it suitable for diabetes detection. Their work emphasized the role of advanced nanomaterials in improving sensor performance and selectivity[5]. Del Orbe D.V. et al. (2022) designed a portable breath analyzer to monitor exercise-induced fat metabolism using acetone levels. The system incorporated MEMS sensors and machine learning algorithms, achieving a strong correlation (r = 0.8) with blood biomarkers, enabling real-time personalized health monitoring[6]. Gallego Martínez E.E. et al. (2025) developed a photonic chip-based breath analyzer using optical sensing techniques. Their system utilized hyperbolic mode reso- nance and machine learning to detect multiple gases with high sensitivity in parts per billion, demonstrating advanced multi-gas detection capability[7]. Kumi E. et al. (2026) proposed a low-cost AI-powered breath analyzer for early detection of chronic obstructive pulmonary disease (COPD). The system used metal oxide sensors and deep learning, achieving 96.68 and makeing it a new procy for leaving healthy lifestyle [8]. Picciariello A. et al. (2024) developed a portable breath analyzer for the diagnosis of colorectal cancer using volatile organic compound (VOC) analysis. Their system utilized a micro gas chromatograph combined with machine learning techniques such as linear discriminant analysis and principal component analysis[9]. The study achieved high diagnostic performance with 94.4 percent sensitivity and 91.2 percent accuracy, demonstrating the effectiveness of breath biomarkers in non-invasive cancer detection. Khamis A.A. et al. (2023) proposed an IoT-integrated breath analyzer for monitoring alcohol consumption. Their system employed a fuel-cell sensor and cellular-based communication to enable real-time data transmission and storage. The model achieved an accuracy of 98.16 Percent highlighting the importance of IoT integration for large- scale health monitoring and data collection[10]. Verma A. et al. (2023) introduced a nanostructured WO/WS-based acetone sensor for breath analysis. The system demonstrated high sensitivity and a low detection limit of 1.54 ppm, making it suitable for diabetes detection. Their work emphasized the role of advanced nanomaterials in improving sensor performance and selectivity[11]. Del Orbe D.V. et al. (2022) designed a portable breath analyzer to monitor exercise-induced fat metabolism using acetone levels. The system incorporated MEMS sensors and machine learning algorithms, achieving a strong correlation (r = 0.8) with blood biomarkers, enabling real-time personalized health mon- itoring[12]. Gallego Martínez E.E. et al. (2025) developed a photonic chip-based breath analyzer using optical sensing techniques. Their system utilized hyperbolic mode resonance and machine learning to detect multiple gases with high

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Table 1: Comparison of Existing Systems and BioSmart Inhale

Author	**Technology**	**Limitation**	**Proposed Advantage**
Picciariello (2024)	Micro GC + ML	Bulky setup	Portable, real-time
Khamis (2023)	Fuel sensor + IoT	Single parameter	Multi-sensor + AI
Verma (2023)	WO_3/WS_2	Single biomarker	Multi-biomarker
Del Orbe (2022)	MEMS + ML	Limited scope	Multi-disease focus
Gallego (2025)	Photonic + ML	Expensive	Low-cost, real-time
Kumi (2026)	MOS + DL	Disease-specific	Multi-disease
Djajalaksana (2023)	Statistical	Not real-time	Real-time AI

The table highlights recent advancements in breath analysis systems, showing a shift from conventional single- sensor methods to intelligent, multi-sensor frameworks. Earlier approaches were limited by bulky design, high cost, and single-parameter detection. Recent innovations integrate artificial intelligence to improve accuracy, feature ex- traction, and processing speed. These systems also enhance portability and enable real-time monitoring. Overall, the evolution reflects a move toward compact, cost-effective, and multi-disease diagnostic solutions suitable for practical healthcare applications.

3. Material And Methods

The proposed BioSmart Inhale framework introduces an advanced, non-invasive breath analysis system that inte- grates multi-sensor technology with artificial intelligence to enable real-time respiratory health monitoring and early disease detection. The hybrid approach is meant to be better than traditional methods, by utilizing high-level compu- tational models to offer better asthma quality and adaptability to various kinds of images. The system is structured as a layered architecture consisting of breath acquisition, multi-sensor data collection, preprocessing, feature extrac- tion, intelligent analysis, and output visualization. Exhaled breath is captured through a controlled airflow chamber to ensure uniform distribution across sensing elements. Gas sensors such as MQ-135 and MQ-3 are employed to de- tect volatile organic compounds (VOCs) associated with metabolic and respiratory conditions, while a DHT11 sensor monitors temperature and humidity to compensate for environmental variations affecting sensor performance. The

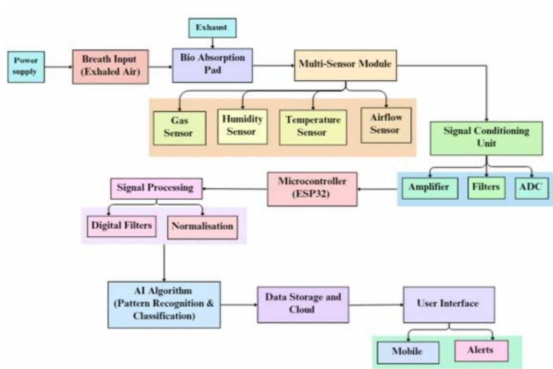

Figure 1: A Detailed Analysis of the Sequential Steps Involved in the Breath Analyser Technique:

acquired analog signals are converted into digital data using an embedded microcontroller, followed by preprocessing steps including noise filtering, drift correction, normalization, and calibration to enhance signal quality and consis- tency. Feature extraction techniques are applied to derive meaningful parameters such as concentration trends, peak responses, and temporal variations[16].

4. Design and Implementation of the Proposed System

The design and implementation of the proposed BioSmart Inhale system are centered on developing a robust, portable, and real-time breath analysis platform by integrating sensing, processing, and communication modules into a unified architecture. The system employs a controlled breath acquisition unit consisting of a mouthpiece and airflow chamber to ensure consistent and directed exhalation over the sensing elements. The sensing module includes MQ-135 and MQ-3 gas sensors for detecting volatile organic compounds (VOCs) such as acetone, ammonia, and carbon monoxide, which are indicative of metabolic and respiratory conditions[17]. In addition, a DHT11 sensor is incor- porated to measure ambient temperature and humidity, enabling environmental compensation and improving sensor accuracy. All sensors are interfaced with an Arduino Uno microcontroller, which performs real-time data acquisition through its built-in analog-to-digital converter (ADC). The hardware is assembled on a breadboard using jumper wires, allowing modularity and ease of testing.

On the software side, embedded C/C++ programming is used to read sensor outputs, perform basic signal condi- tioning such as noise filtering, smoothing, and calibration, and convert raw signals into meaningful units. Threshold- based logic and preliminary pattern analysis are implemented at the microcontroller level for immediate feedback. For advanced analysis, the processed data can be transmitted via serial communication or wireless modules (such as Bluetooth or Wi-Fi) to external platforms, where machine learning models like Support Vector Machine (SVM) and

Long Short-Term Memory (LSTM) networks are applied for classification and prediction of respiratory abnormalities. The output is displayed through an LCD/OLED interface and can also be visualized on mobile or web-based dash- boards for remote monitoring. The system is designed with a focus on low power consumption, cost-effectiveness, scalability, and user-friendliness, making it suitable for continuous, non-invasive health monitoring in both clinical and home environments[18].

5. Intelligent Respiratory Monitoring Framework

An effective breath analysis system transforms raw sensor signals into clinically meaningful parameters that sup- port accurate assessment of respiratory health. In the proposed framework, sensor data is processed to obtain mea- surable values such as gas concentrations (ppm), relative humidity (RH), temperature (°C), airflow rate (L/min), and derived respiratory indicators including peak expiratory flow and breath irregularity patterns. These values enable objective comparison with standard physiological ranges and support continuous monitoring of respiratory conditions. Long-term tracking allows identification of subtle variations over time, which is particularly important in chronic disease management, where early changes in respiratory parameters may indicate the onset of complications before noticeable symptoms appear[19]. To enhance system capability, data storage and cloud integration are incorporated for long-term analysis and remote monitoring. Historical data can be securely stored and accessed for longitudinal evaluation, enabling personalized health tracking and improved clinical decision-making. Cloud-based platforms fa- cilitate real-time data sharing with healthcare professionals, allowing integration of breath analysis results with other clinical parameters[20]. Access to large datasets also improves machine learning model performance by increasing robustness and reducing bias across diverse populations. Data security is ensured through encryption and adherence to healthcare data protection standards. The user interface is designed to present processed data in a clear and intuitive format through graphical visualization, numerical displays, and alert mechanisms. Threshold-based alerts are gener- ated when parameters exceed predefined limits, enabling timely intervention. For example, abnormal airflow patterns combined with variations in gas concentration may trigger early warnings for respiratory conditions such as asthma. Despite these advantages, challenges such as sensor drift, environmental interference, and individual variability must be addressed through proper calibration, compensation algorithms, and adaptive learning techniques. Overall, the framework provides a reliable and intelligent platform for real-time, non-invasive respiratory monitoring[21].

6. Results

To qualitatively assess breath analysis techniques, factors such as detail retention, contrast enhancement, artefact removal, and balance between spatial and spectral components were considered. Conventional methods of detecting asthma through Principal Component Analysis (PCA) and Wavelet Transform (WT) have had difficulty preserving high-frequency detail leading to loss of sharpness and lack of structural clarity in the image. In contrast, the hybrid Neuro Gen Empirical Mode Decomposition (EMD) overcomes these limitations producing superior results. The new

technique ensures that important edges and detailed textures remain intact without the blurring or changing to their original state. The proposed method enhances spatial features while retaining the source images as they were created, whereas traditional algorithms tend to lose finer details of the image[22]. The original brightness and darkeness rates have been optimised to visually refine the image and provide a balanced hue histogram. Additionally, the combined EMD with PCNN of the process provides a focused highlight of significant features while simultaneously removing any unnecessary artefacts.

The analysis of exhaled breath is an emerging technique with great promise in modern biomedical engineering, as it takes advantage of the fact that the human body releases a large amount of information (gaseous, volatile organic compounds (VOCs), aerosol, moisture, and thermal) in the form of exhaled air. This information is present in the breath and can be used to create a robust source of physiological and pathological biomarker data. Metabolism produces a large number of by-products which enter the lungs as they pass through the lungs in the blood before they leave the body[23]. This adds to the overall richness of the data contained in a person's breath. Breath analysis is fundamentally different from traditional diagnostics, which use blood samples to analyze a person's health. Breath analysis provides patients with many advantages such as being pain-free, being available for continuous monitoring, being done in real time, being less expensive to perform, and being a better source of monitoring than all other diagnostic tests. The basis of breath analyzer tests is the accurate measurement of exhaled breath. Sensors are used to convert the measured data to electrical signals for use in signal conditioning (refining) and for developing algorithms that will provide an accurate measurement of the clinical significance of the data[24].

The physiological basis of breath analysis is rooted in gas exchange and metabolic processes. Oxygen inhaled into the lungs diffuses into the bloodstream, while carbon dioxide and other gaseous metabolites diffuse out and are expelled during exhalation. In addition to CO, exhaled breath contains trace gases such as nitric oxide, ammonia, ace- tone, hydrogen peroxide, and various VOCs, each associated with specific physiological states or disease conditions. For instance, elevated nitric oxide levels are linked with airway inflammation in asthma, increased acetone concentra- tion is correlated with fat metabolism and diabetes, and abnormal VOC patterns have been associated with lung cancer and infectious diseases[25]. Alongside chemical composition, physical characteristics of breath such as humidity, temperature, airflow rate, and breathing patterns provide vital information about airway condition, lung mechanics, hydration status, and thermoregulation. Quantitative breath analysis therefore requires a multidimensional sensing approach that integrates chemical, physical, and physiological measurements to build a holistic picture of respiratory health[26].

The primary biological sample for quantitative breath analyzers is air exhaled from the user. When the user exhales into a breath-testing device, their exhaled air will be directed down a controlled flow path that is designed to reduce the amount of ambient air contamination, while also ensuring the sampling of consistent amounts of air. The incor- poration of flow control devices and exhaust pathways will ensure that each sample of breath taken will be hygienic, maintain similar amounts of moisture from one sample to the next, and minimize air turbulence when taking the sam-

ple. A bioabsorption product/interface (e.g., pad) may be used to hold and stabilize breath biomarkers (especially volatile organic compounds [VOCs] and moisture) so that they will have a better opportunity to interact with sensors and decrease any signal variability caused by turbulent air flow or environmental disturbances. This bioabsorption interface/component is essential for increasing the breathing test system’s overall sensitivity to detect sub-ppb levels of

VOCs due to the rapid changes in breath composition and by providing additional protection for sensitive sensors from exposure to moisture or particulates, which is especially important for high humidity environments.

The raw output signals from the sensors can be very weak, noisy, and highly non-linear, making signal conditioning one of the most critical components of quantitative analysis. An example of signal conditioning components are amplification circuits that will increase the low-level sensor output to a more usable level, and filters that will remove the effects of high-frequency noise and power line noise, and analog-to-digital converters that convert the continuous output signal from the sensors to a format suitable for processing by digital technology[27].

Table 2: Detailed Respiratory Parameter Analysis

Patient ID	Breathing Rate	Air Flow Rate	Tidal Volume	Peak Expiratory Volume	CO_2 Concentration
P01	12	7	598	406	7%
P02	25	8	402	567	6%
P03	14	6	503	645	7%
P04	18	5	545	443	8%
P05	20	6	610	567	10%
P06	10	7	597	546	9%
P07	23	9	600	655	10%
P08	27	11	505	453	6%
P09	14	12	499	677	7%
P10	19	6	696	565	8%
P11	21	6	498	400	6%
P12	16	7	501	353	5%
P13	18	7	608	400	6%
P14	17	7	494	343	7%
P15	19	8	606	444	6%

Significant variability exists between patients regarding respiratory variables in the data shown.

Breathing rate has an average range of 10 to 27 breaths/min (P02, P07, P08 = faster breathing), while the lower range is found in patients

P06 and P10 (slower breathing). The range for air flow rate is 5 to 12 units, with patient P09 having the highest air flow and representing strong airflow through the airway. Conversely, lower values for air flow through patients P03 and P04 may indicate some degree of air flow obstruction.

When evaluating tidal volume (the volume of air exhaled in one breath), most patients have consistent tidal volumes of 490 to 610 mL, indicating that the lungs are being filled with the same amount of air at each breath. However, patient P02’s tidal volume is low (402 mL) and, in combination with their high breathing rate, suggests that they may be shallow breathing. Patient P10 has the highest tidal volume (696 mL) and therefore appears to be taking deeper breaths than other patients.

Peak expiratory volumes (the volume of air blown out in a single breath) demonstrate a range of variance (343- 677 mL) where higher volume (P09, P07) corresponds to more forceful expiratory effort while lower volume (P12, P14) may reflect decreased expiratory capacity. CO concentration ranges from 5 to 10 with elevated levels (P05, P07) indicating that ventilation may not be effective.

In summary, patients with an expected breathing rate, moderate tidal volume, and high airflow/expiratory val- ues demonstrate greater respiratory efficiency; patients whose multiple parameters deviate from expected levels may indicate a potential for respiratory irregularities or inefficiencies.

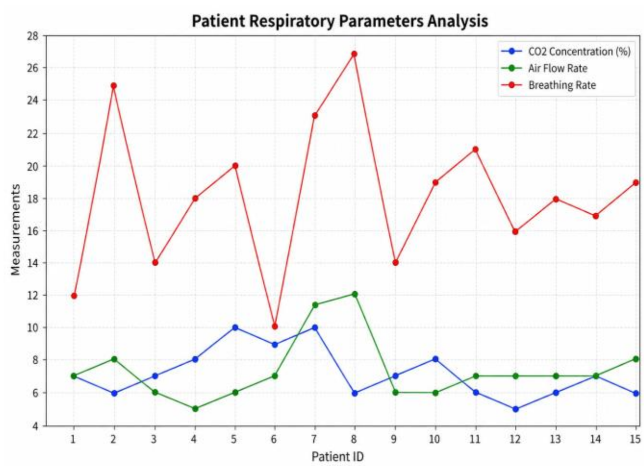

Figure 2: Patient Respiratory Metrics Analysis: CO2 Concentration, Air Flow Rate, and Breathing Rate.

The charts show CO_2 concentrations, airflow rates, breath rates, tidal volumes and peak expiratory volumes (PEV) for the subjects included in this analysis. The following observations can be made based on these values:

Generally, CO_2 concentrations for all subjects do not appear to be elevated but there are some outliers with elevated CO_2 concentrations. Elevated CO_2 concentrations show that subject has poor ventilatory efficiency particularly in the presence of low airflow and/or peak expiratory volumes.

Airflow rates for subjects generally increase with some variability. For subjects with higher airflow rates there is clear evidence of alveolar patency, while subjects with lower airflow rates demonstrate lower peak expiratory volumes.

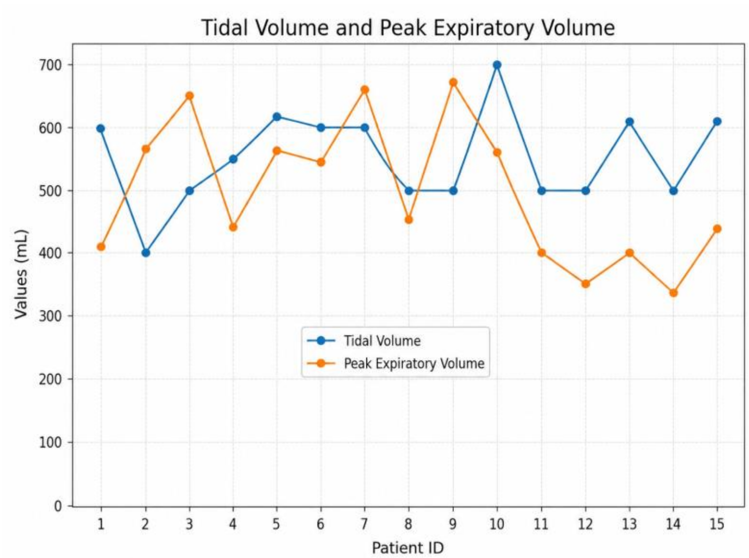

Figure 3: Assessment of Tidal Volume and Peak Expiratory Volume Trends

Breath rates for subjects demonstrate more variability than the other parameters. Several subjects had a higher breathing rate associated with lower tidal volumes indicating that their breathing patterns were not efficient, whereas the remaining subjects with average breath rates exhibited normal ventilatory pattern.

Tidal volumes for many of the subjects are similar across all subjects with the exception of a few with low tidal volumes. Low tidal volumes and high breath rate indicate inefficiency of ventilation, while tidal volumes that are relatively stable and larger than average represent adequate lung expansion.

7. Discussion

The results of the breath-analysis system demonstrate its effectiveness at detecting key variables of respiratory function by measuring various indicators depending on the breathing state. The system is capable of measuring both frequency and fluctuations of oxygen levels and VOCs in one's breath. When a person has a low-frequency breathing cycle, the duration of the breath increases significantly; both O and VOC values changed significantly, resulting in improved gas exchange. On the other hand, when a person is breathing normally, the readings are substantially consis- tent, with only small variations[28]. This means that the different breathing states significantly affect the composition of gases in the breath and can be measured with a system developed for this purpose. The sensor is highly sensitive (and able to produce data in real time), but minor measurement errors can occur due to various external factors.

8. Conclusion

The BioSmart Inhale system is an innovative method of collecting data about your health in a non-invasive manner through breath, which utilizes a combination of both breath analysis and the use of multiple sensors fused with the help

of artificial intelligence[29]. The BioSmart Inhale system will replace the limitations of traditional breath analysing devices (i.e. limited detection via a single gas measurement, non-portable, cannot provide ongoing detection over time) through the use of many different kinds of both gas sensors (to air quality/environmental conditions) and in- telligent processing algorithms to detect the wide range of possible biomarkers associated with respiratory/metabolic conditions. In addition, the use of AI technology will assist in identifying patterns, increase the likelihood of accu- rately diagnosing patients, and allow for early detection of illness/disease, further supporting preventative health care. In addition, the BioSmart Inhale system is convenient and affordable, creating a very high degree of accessibility and usability in many different environments (i.e. home monitoring, point of care).

The project shows efficient data acquisition, preprocessing, and analysis from a system perspective and can perform reliably under different environmental conditions. The capability of real-time feedback from the system provides even more value to the user as it allows them to continuously monitor their health status throughout the entire process. In general, the proposed solution supports the growing demand for smart, connected, and patient-centered solutions within the healthcare industry.

Still, some challenges need be resolved in order to continue improving the overall performance and reliability of the system. Drift in sensor performance, cross-sensitivity of different gases, and environmental changes (temper- ature/humidity) can impact the accuracy of the measurements. Furthermore, the current model requires extensive clinical testing across a large/varied group of patients in order to validate their generalization and medical reliabil- ity[30].

In the future, we will continue to work on ways to improve the calibration processes of our sensors through ad- vanced filtering and compensation algorithms, helping to mitigate the influences of the environment. Additionally, by incorporating more advanced deep learning models (hybrid / ensemble architectures), we hope to be able to increase the prediction accuracy and robustness of our predictions. By expanding the sensors to include other biomarkers (for example, to allow for additional diseases, such as cardiovascular/neurological), we will be able to better iden- tify diseases across a larger population. By using IoT (Internet of Things) and cloud computing to enhance remote monitoring, real-time sharing of data, and telemedicine applications, the BioSmart Inhale System is likely to expand significantly over time. Another area where we see promise is in personalizing the BioSmart Inhale System through adaptive learning, customized to the user's unique health profile. The BioSmart Inhale System has the future poten- tial to serve as an entire, comprehensive, intelligent health system capable of supporting early diagnosis; continuous monitoring; and improved patient outcomes.

Acknowledgement

The La Granja editorial team has been an absolutely gracious and generous site for us to conduct this research by contributing their time and effort throughout this project. We also need to thank our institution for providing us with the necessary supports, resources and encouragement while this project was in its execution phase. In addition,

we would like to sincerely thank everyone else who helped us to complete this research (colleagues and others who provided both ideas and/or assistance).

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