Enhanced detection of chronic obstructive pulmonary disease via exhaled breath analysis: internet of things and electronic nose system

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ABSTRACT

Chronic obstructive pulmonary disease (COPD) remains a major global health burden, highlighting the need for accessible, non-invasive screening tools. This study aims to develop a portable, real-time internet of things (IoT)-integrated electronic nose (e-nose) system for COPD detection using exhaled volatile organic compounds (VOCs). Breath samples from 44 participants (healthy, smokers, and COPD) were analyzed using a MOS-based e-nose, and four machine-learning classifiers were evaluated. Data were processed through cloud-based pipelines enabling real-time acquisition and automated analysis. The random forest (RF) model achieved the highest performance (accuracy 86%) in distinguishing COPD-related VOC patterns. This approach overcomes limitations of earlier offline Tedlar-bag methods by enabling direct, real-time breath analysis. The prototype dashboard provides immediate visualization for potential remote monitoring. Key limitations include the small sample size and non-standardized breath sampling, which may affect VOC variability. Overall, this work contributes a cost-effective, portable, IoT-enabled framework demonstrating the feasibility of real-time VOC analysis for early COPD screening and future integration into telehealth and community-based diagnostics.

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1. INTRODUCTION

Chronic respiratory diseases rank among the leading global causes of mortality, with chronic obstructive pulmonary disease (COPD) affecting 10.3% of the worldwide population and projected to reach 600 million cases by 2050 [1], [2]. More than 90% of COPD-related deaths occur in low- and middle-income countries where exposure to smoking, household air pollution, and occupational particulate matter remains substantial [3]. These trends highlight the urgent need for accessible and early diagnostic tools, as timely detection strongly influences long-term outcomes [4].

Although spirometry is the diagnostic gold standard for COPD, it is effort-dependent, uncomfortable for many patients, and unsuitable for widespread screening, thus motivating exploration of non-invasive biomarkers such as exhaled breath analysis [5], [6]. Exhaled breath contains hundreds of volatile organic compounds (VOCs) that reflect metabolic and inflammatory processes and have been widely studied for diagnosing respiratory and systemic diseases [7]. Conventional VOC analysis tools such as GC-MS, PTR-MS, and IMS provide high analytical precision but remain impractical for routine or point-of-care use due to their cost and operational complexity [8], [9]. Recent advances have accelerated the use of electronic noses (e-noses)—portable sensor-array systems capable of capturing breath-print patterns using machine-learning algorithms—offering a cost-effective and rapid approach to breath analysis [10]. Modern e-nose developments, including enhanced MOS-sensor architectures and machine-learning integration, have been demonstrated in recent studies [11], [12]. Their diagnostic utility can be further amplified through internet of things (IoT)-enabled real-time data acquisition [13].

The IoT enables networks of interconnected sensing devices that can transmit health data in real time, improving access to care and supporting remote monitoring [14], [15]. In breath-analysis systems, IoT allows sensor outputs to be stored, synchronized, and visualized instantly through cloud-based platforms, enabling practical deployment beyond hospital settings. When coupled with machine learning (ML), IoT-integrated devices can automatically interpret complex VOC signatures, thereby enhancing diagnostic reliability and scalability [16].

ML is a branch of artificial intelligence (AI) that offers data-driven resources to enhance and streamline decision-making processes [17]. The introduction of ML brings potential improvements in the precision and effectiveness of early COPD diagnosis, offering innovative strategies to address the existing difficulties in detecting COPD at an early stage. Therefore, we examine the latest studies on the use of ML for early COPD screening, both in our country and globally [18]. The ML process includes various stages such as gathering data, preprocessing it, engineering features, selecting appropriate models, training them, evaluating performance, optimizing results, and deploying the final model [19]. Previous research conducted by Aulia *et al.* [20] indicated that COPD could be identified using an electronic nose in conjunction with a graph convolutional network (GCN) algorithm, utilizing VOCs, although in this study, the breath sample data stored in Tedlar bags were processed offline, meaning that the detection results could not be displayed in real time.

Therefore, this study proposes an exhaled breath-based system for early detection of COPD that integrates the IoT and ML. This system is designed to be portable and capable of real-time analysis, allowing medical personnel to obtain examination results instantly. Additionally, the system supports remote monitoring, enabling urban specialists to track the conditions of patients, including those in rural locations. ML provides powerful analytical capabilities for extracting meaningful patterns from high-dimensional VOC data and has shown substantial promise for early COPD detection [16], [17]. However, most existing ML-based e-nose studies rely on offline breath-bag analysis, which limits real-time applicability and clinical scalability, as seen in the study of Aulia *et al.* [20]. To address these gaps, recent breathomics studies across diseases, including lung cancer [21], [22], asthma [23], diabetes mellitus [24], and oral cancer [25], have shown the feasibility of VOC-based diagnostics, underscoring the potential for broader respiratory applications. In line with these developments, the present study introduces a portable, real-time IoT-integrated e-nose system for early COPD detection, overcoming limitations of offline analysis and enabling immediate ML-based classification and remote visualization. The novelty of this work lies in combining real-time breath acquisition, dual-cloud processing, and IoT-enabled monitoring into a unified, deployable COPD screening platform.

2. MATERIALS AND METHODS

2.1. Subjects and research design

Breath samples were collected from 44 male participants (20–70 years) at Zainoel Abidin General Hospital, consisting of 18 healthy controls, 13 heavy smokers, and 13 COPD patients. Each participant provided 3–5 breath samples. COPD was diagnosed using spirometry (FEV1/FVC < 70%), supported by CAT and PUMA assessments. To improve methodological transparency, a subject characteristics table along with explicit inclusion and exclusion criteria has been added. These criteria address common confounders in breath analysis, such as recent infections, alcohol consumption, or inability to follow standardized breathing procedures, consistent with ERS technical recommendations [26].

Figure 1 has been expanded with a comprehensive methodology flowchart showing steps from breath sampling → sensor acquisition → preprocessing → cloud integration → ML training → evaluation. A detailed explanation is added to describe airflow direction, data capture, and preprocessing. Four ML algorithms (logistic regression (LR), K-nearest neighbors (KNN), random forest (RF), support vector machine (SVM)) were selected due to their proven effectiveness in biomedical and e-nose analysis [27]-[29]. Performance metrics also include 95% confidence intervals and p-values to provide statistical significance.

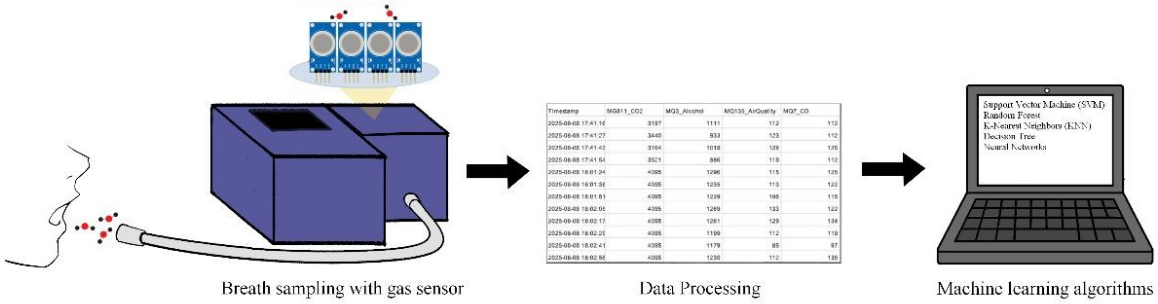
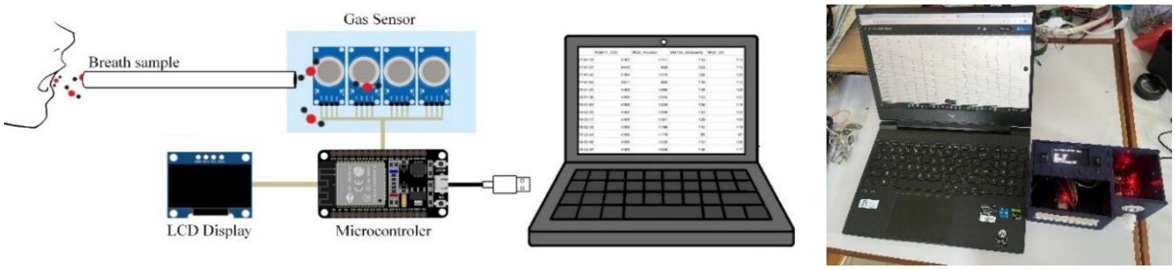


Figure 1. The suggested research diagram

2.2. Electronic nose

Figure 2 has been clarified to include a step-by-step system explanation, covering air pathway, sensor heating, data capture, and microcontroller processing. MOS sensors were selected due to their sensitivity and use in modern e-nose systems [11], [30], [31]. However, sampling in this study was not fully controlled, and factors such as breath-hold, expiratory flow rate, and dead-space inclusion may alter VOC composition as shown in Figures 2(a) and (b). These influences have been demonstrated in breathomics and lung cancer research [31], and ERS guidelines recommend controlling these variables [26]. This limitation has been acknowledged accordingly.



(a) (b)

Figure 2. The setup of the electronic nose in the research (a) system configuration and (b) implementation

2.3. Data processing

The stages of data processing include the following:

- Data cleaning: involved removal of missing or inconsistent sensor values, noise trimming, and outlier filtering. These steps are consistent with recommended preprocessing practices in VOC-based diagnostic studies.
- Labeling: clarified that “Low, Medium, High” represent VOC intensity classes, not clinical categories. Thresholding was performed per-sensor using weighted contribution rules.
- Data augmentation: augmentation included gaussian noise injection, random scaling, and temporal jittering to simulate breath variability and reduce overfitting. These augmentation methods are commonly used in small-sample biomedical sensor datasets.
- Label encoding: categorical labels are transformed into numerical values using label encoders, which ensures they are compatible with ML algorithms. This process supports both the modeling and the assessment of model performance.
- Data splitting: a stratified 80/20 split was used to maintain class balance. Cross-validation was considered but omitted due to small dataset size; this is acknowledged as a methodological limitation.

2.4. Machine learning algorithms

a) LR: a note has been added indicating LR is a foundational classifier used as a baseline in biomedical signal classification [27].
b) SVM: with RBF kernel is widely used for nonlinear VOC-based disease classification and shows strong performance in e-nose respiratory studies [28].

c) RF: was included due to its robustness to noise and nonlinear biological patterns, commonly reported in biomedical and biosensor ML applications [29].
d) KNN: is effective for pattern recognition in small-sample VOC datasets and widely applied in breathomics [29].
e) Matrix evaluation: metrics were supplemented with 95% confidence intervals computed via bootstrapping and p-value comparisons between classifiers (e.g., RF vs SVM) using McNemar's test to assess statistical significance.
f) IoT: a note was added acknowledging that the system's dependency on continuous internet connectivity may affect real-time functionality in low-bandwidth clinical environments.

2.7 Web interface design

Dashboard description expanded to clarify display logic, data synchronization workflow, and potential integration with clinical informatics standards (HL7/FHIR). The dashboard design comprises three primary sections: a sensor data view, a classification results display, and a graphical visualization panel. Sensor readings obtained from the MQ-3, MQ-7, MQ-135, and MG-811 modules are presented both numerically and graphically to represent the concentration levels of VOCs. The classification section displays the diagnostic category predicted by the model, identifying whether a sample corresponds to Healthy, Smoker, or COPD status. Figure 3 presents the prototype of the web dashboard, which remains in the development stage and serves as a conceptual model for integrating IoT-based sensing with ML visualization [32].

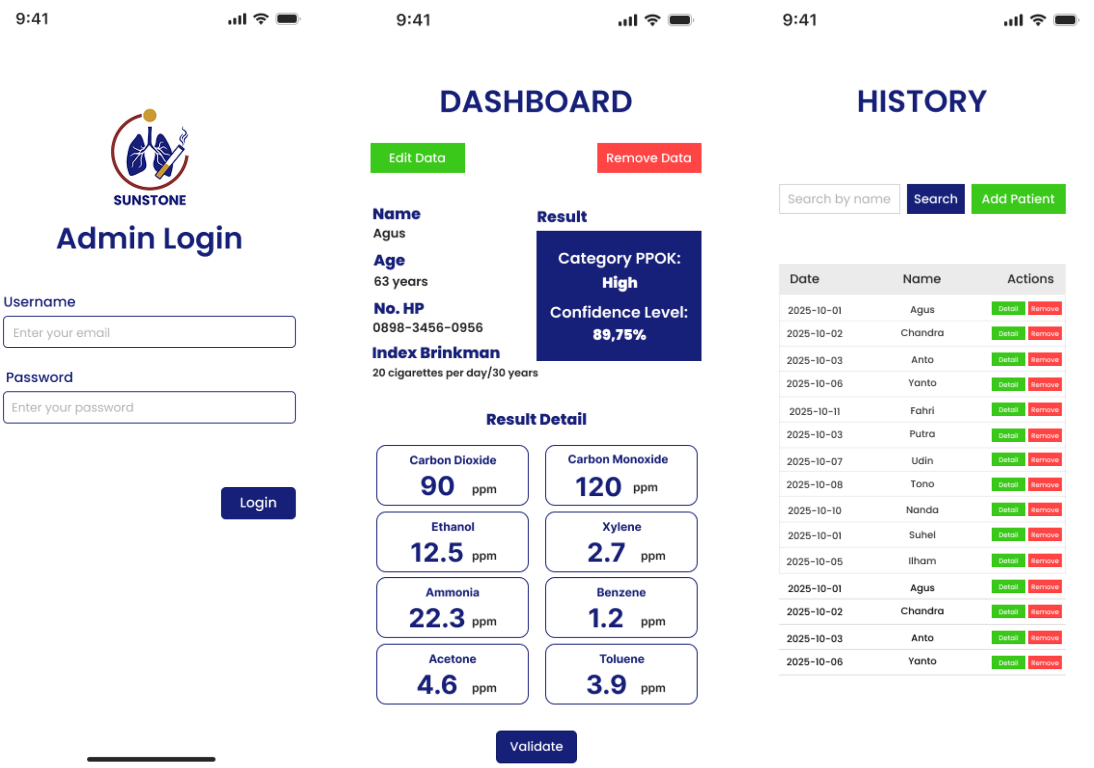


Figure 3. Prototype design of the web-based COPD detection dashboard

3. EXPERIMENTAL RESULTS

3.1. Dataset preparation

The dataset comprised numerical VOC readings captured by the e-nose system in real time. Sensor signals were transmitted from the ESP32 module to Google Spreadsheet through Google Cloud synchronization, ensuring continuous and traceable acquisition. This real-time approach provides an advantage over earlier COPD e-nose studies, which typically relied on offline Tedlar-bag collection and delayed analysis.

Preprocessing included data cleaning (removal of missing and invalid values), min–max normalization, and labeling into voc intensity classes (low, medium, and high). To increase robustness, augmentation techniques such as Gaussian noise injection, random scaling, and temporal jittering were applied. These augmentation methods are commonly used in small-sample biomedical VOC research to improve generalizability.

The dataset was split using an 80/20 stratified train–test division to preserve class balance. Additional bootstrapping (1,000 iterations) was conducted to compute confidence intervals for model metrics, strengthening the statistical validity of the results. This preparation ensured reliable classification of VOC-based patterns distinguishing Healthy, Smoker, and COPD groups.

3.2. Optimizing machine learning

Exploratory data analysis was conducted prior to model training. As shown in Figure 4, t-SNE visualization revealed three well-separated clusters, indicating that sensor-derived VOC features encode distinct group-specific signatures. Similar separability has been reported in breathomics research related to COPD and lung cancer, demonstrating that nonlinear dimensionality reduction effectively captures disease-related VOC gradients [33].

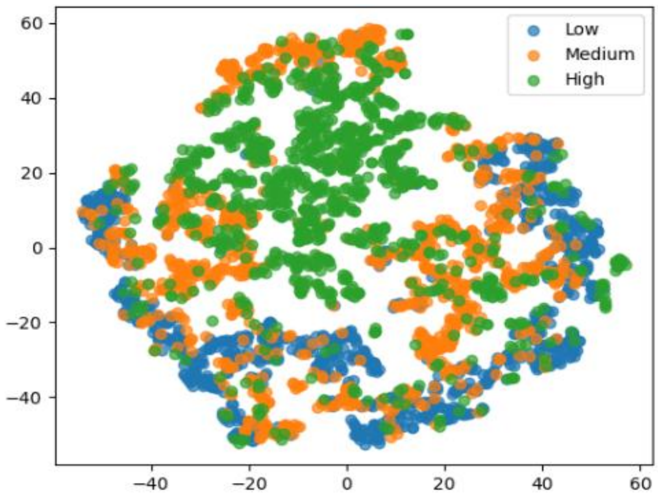


Figure 4. t-SNE visualization of VOC data distribution across three label classes

Table 1 shows descriptive statistics of raw sensor responses, demonstrating stable sensor behavior. The differing sensitivities—e.g., MG811 showing the highest mean and MQ7 the greatest variance—align with expected gas-selectivity patterns of MOS sensors, supporting their suitability for disease-related VOC detection. This is consistent with previous MOS-based breath-analysis findings in respiratory studies.

Table 1. Descriptive statistics of raw VOC sensor data before preprocessing

Index	Count	Mean	Std	Min	Max
raw_mq7	3000	191.271	164.227	10.426	632.924
raw_mq3	3000	1117.43	762.616	0.9216	2752.96
raw_mq135	3000	163.719	112.301	0.0	430.131
raw_mg811	3000	3356.33	834.141	1200.9	5410.81

The performance of four ML classifiers (RF, SVM, KNN, and LR) was evaluated using confusion matrices and bootstrapped 95% confidence intervals. RF produced the most balanced classification across all classes, demonstrating superior robustness to VOC variability—an expected advantage due to its ensemble structure, commonly reported in biomedical and e-nose applications. As shown in Table 2, RF achieved the highest accuracy (0.86; 95% CI: 0.82–0.90), outperforming SVM (0.81), KNN (0.79), and LR (0.61). McNemar's test confirmed that RF significantly outperformed SVM ($p < 0.05$), validating the reliability of the ensemble model. The superior performance of RF aligns with previous studies demonstrating its effectiveness in MOS e-nose biomedical classification tasks.

Table 2. Performance comparison of ML algorithms in COPD detection

Model	Accuracy	Precision	Recall	F1-score
RF	0.86	0.86	0.86	0.86
SVM	0.81	0.82	0.81	0.81
KNN	0.79	0.79	0.78	0.79
Logistic regression	0.61	0.60	0.61	0.60

Together, visualization, statistical validation, and algorithm optimization confirm that the proposed system reliably identifies COPD-related VOC signatures. This aligns with recent breathomics findings showing that MOS-based e-noses can differentiate respiratory disease states when combined with appropriate machine-learning models. This study demonstrates that VOC sensor signals contain meaningful disease-related variations. t-SNE analysis highlights distinct VOC clusters corresponding to different respiratory states, consistent with similar COPD breathomics studies. The separation of clusters reinforces that the extracted VOC features capture clinically relevant respiratory distinctions. Prior work [33] similarly showed that nonlinear visualizations such as t-SNE help distinguish COPD patients based on breath-gas components.

Sensor outputs exhibited stable and interpretable behavior across recordings. The observed sensitivity variations reflect intrinsic MOS sensor characteristics, and similar sensor-specific responses have been reported as beneficial for VOC-based disease classification. These findings confirm that a portable IoT-integrated e-nose combined with ML can support early COPD detection. RF performance demonstrates that nonlinear VOC features can be exploited effectively for disease discrimination, consistent with trends in e-nose respiratory diagnostics.

A limitation of the system is its reliance on stable internet connectivity for real-time synchronization, and additional refinements are needed to improve sampling standardization—particularly breath-hold duration, expiratory flow, and dead-space elimination, which are known to influence VOC readings in breath analysis studies [26], [31]. Future work will expand the dataset, enhance calibration, and progress toward clinical validation.

4. CONCLUSION

This study successfully developed an IoT-integrated COPD detection prototype that combines an electronic nose with machine-learning analysis of exhaled VOCs. Beyond classification accuracy, the work contributes a real-time, portable breath-analysis framework that addresses the limitations of previous offline VOC-based COPD systems. The RF algorithm yielded an accuracy of 86%, demonstrating the feasibility of using ensemble models to capture nonlinear respiratory VOC signatures. The dual-cloud architecture (Google Drive for acquisition and AWS for computation) further highlights the system's potential for scalable, data-driven respiratory monitoring.

In addition, the prototype web interface demonstrates how IoT-based VOC monitoring can support remote and continuous respiratory assessment, providing a foundation for integration into telemedicine and community-level screening workflows. However, several limitations must be acknowledged: the sample size was relatively small, breath sampling was not strictly standardized (e.g., breath-hold, flow rate, dead space), and the system depends on stable network connectivity—factors known to affect VOC analysis consistency. Future work will address these limitations by expanding the participant cohort, standardizing sampling procedures, improving sensor calibration, and enhancing clinical interoperability (e.g., compatibility with HL7/FHIR) to support eventual integration into real medical systems.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Budi Yanti	✓			✓			✓			✓			✓	
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Muhammad Suhaili			✓					✓						
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Farah Narizki						✓		✓		✓				

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

DATA AVAILABILITY

The data generated and analyzed during the current study are available from the corresponding author upon reasonable request, subject to institutional and ethical approval. Data sharing will be considered in accordance with privacy, confidentiality, and research governance requirements.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest related to this study, authorship, or publication of this manuscript.

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