PREVENTION OF CARDIOMETABOLIC RISK USING

by Rekha Shanmukhi P

BATCH NO:MAI025

PREVENTION OF CARDIOMETABOLIC RISK USING SMART GAS ANALYZER

Major project report submitted
in partial fulfillment of the requirement for award of the degree of

Bachelor of Technology
in
Computer Science & Engineering

By

P.REKHA SHANMUKHI	(21UECS0454)	**(VTU19523)**
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Under the guidance of
Dr.N.GOMATHI,Degree.,
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DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING
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VEL TECH RANGARAJAN DR. SAGUNTHALA R&D INSTITUTE OF SCIENCE AND TECHNOLOGY

(Deemed to be University Estd u/s 3 of UGC Act, 1956)
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CERTIFICATE

It is certified that the work contained in the project report titled ”PREVENTION OF CARDIOMETABOLIC RISK USING SMART GAS ANALYZER” by ”P.REKHA SHANMUKHI (21UECS0454) , S.GOPINADH (21UECS0560) , P.NEERAJA (21UECS0483)” has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

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Institute of Science and Technology
May, 2025

DECLARATION

We declare that this written submission represents my ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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APPROVAL SHEET

This project report entitled PREVENTION OF CARDIOMETABOLIC RISK USING SMART GAS ANALYZER by P.REKHA SHANMUKHI (21UECS0454), S.GOPINADH (21UECS0560) , P.NEERAJA (21UECS0483) is approved for the degree of B.Tech in Computer Science & Engineering.

Examiners **Supervisor**

Supervisor name,Degree
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ABSTRACT

Cardiometabolic risk factors such as obesity, high blood pressure and unhealthy diet are important contributors to diseases such as diabetes and heart disease. Conventional ap- proaches to tracking these dangers depend on physical exams and lab tests, which can be time consuming and invasive. This work presents a non-invasive smart gas analyzer aimed at continuous measurement of key metabolic parameters, providing a simpler and more efficient alternative. This smart analyzer measures exhaled gases todrive insights into metabolic processes, including fat metabolism and insulin resistance. It operates by analyzingthe breath for specific biomarkers that reflect the metabolic state of the body. Leveraging machine learning algorithms and real time data analysis, this groundbreaking technology provides a non-invasive, continuous, and highly accurate means of health monitoring, facilitating early detection and prevention of car diometabolic risks. With a focus on accessibility, the analyzer can be used at home or in clinical settings, providing valuable data for personalized health interventions and better management of car diometabolic conditions. The goal is to enhance preventive health care by offering an easy-to-use tool for managing cardiometabolic health in real time. Index Terms—Cardiometabolic Risk, Smart Gas Analyzer, Non-Invasive Monitoring, Early Detection, Breath Analysis, Preventive Healthcare

Keywords:Artificial Intelligence in Healthcare, Big Data Analytics, Breath Analysis, Cardio-Metabolic Risk Assessment, Machine Learning in Medical Diagnosis, Non-Invasive Disease Detection, Real-Time Health Monitoring, Smart Gas Analyzer

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LIST OF ACRONYMS AND ABBREVIATIONS

AI	Artificial intelligence
CVD	Cardiovascular Disease
CH	Methane
CO	Carbon Monoxide
ESP32	Espressif Systems Processor 32-bit
GDPR	General Data Protection Regulation
ISO	International Organization for Standardization
MOS	Metal-Oxide Semiconductor
ML	Machine Learning
NO	Nitric Oxide
SGA	smart Gas Analyzer
VOCs	Volatile Organic Compounds

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Chapter 1

INTRODUCTION

1.1 Introduction

The existence of risk factors for cardiometabolic health—namely obesity, hypertension, and diet diversity—can contribute to chronic complications, such as diabetes, and cardiovascular disease(CVD). The existence of these risk factors has been tracked through invasive blood tests, blood pressure readings, and long physical exams which can be more inconvenient for a patient and practitioner alike. Our smart gas analyzer project intends to resolve the feasibility of risk tracking by offering real-time assessments of metabolic factors that can be extremely valuable to a patient's cardiometabolic health needs in a more feasible manner. Smart gas analyzer monitoring will offer information off of exhaled gases, as well as biomarkers of metabolic health that relate to fat metabolism, insulin resistance, and other factors that can lead to chronic health conditions such as obesity, and diabetes. The biomarkers will provide recommended information of the patients' identifiable metabolic issues. Smart gas analyzer insights will monitor metabolic change continuously while using ML algorithms and assortment of advanced sensors to avoid blood draws and keeping track of blood pressure and lengthy physical exams. Real-time, continuous availability of repeated non-invasive monitoring enables patients to understand their health in more depth, ease of access, and convenience. The technology can and will be used in both home and clinical/testing settings to support patient-centered health care. It advances the early detection of cardiometabolic health risks allowing patients to directly prevent or manage chronic health condition. Continual data collection and pattern-analysis will assist health care workers design individualized interventions for their patients. he proposed smart gas analyzer(SGA) tries to offer a solution by using exhaled breath to determine metabolic biomarkers, hence offering an invasive, real-time monitoring solution. The smart gas analyzer(SGA) operates through the examination of exhaled gases, specifically biomarkers of fat metabolism and insulin resistance.

1.2 Background

Cardiometabolic diseases like hypertension, diabetes, and cardiovascular disorders are major global health concerns, often developing silently over time. Early detection is crucial, but traditional methods such as blood tests and imaging can be invasive and costly. Exhaled breath analysis has emerged as a promising, non-invasive alternative, as gases like CO, CH, and VOCs serve as biomarkers for metabolic dysfunctions. A smart gas analyzer(SGA) can detect these biomarkers with high precision, providing quick and reliable health assessments. By integrating machine learning(ML) algorithms, breath samples can be analyzed to identify patterns and predict cardiometabolic risks. The results are processed and displayed in software, assisting in early detection and intervention. This approach enhances preventive healthcare by offering an accessible and efficient method for monitoring metabolic health trends, ultimately reducing the burden of cardiometabolic diseases.

1.3 Objective

The objective of this project is to prevent cardiometabolic risk by analyzing exhaled breath samples using a smart gas analyzer. Cardiometabolic disorders, including hypertension, diabetes, and cardiovascular diseases, are often linked to metabolic dysfunctions that can be detected through biomarkers in exhaled gases. By collecting and analyzing breath samples for CO, CH, and VOCs, this system aims to identify early signs of metabolic imbalances. The project will integrate ML models to process the collected data, enabling accurate and predictive health assessments based on breath analysis.

The breath samples will be analyzed using a smart gas analyzer, and the results will be processed through advanced ML algorithms. The output will be displayed in software, providing insights into metabolic health trends. By leveraging sensor technology and predictive analytics, this project aims to enhance early detection of cardiometabolic risks, promoting timely interventions and improved health outcomes.

1.4 Problem Statement

Cardiometabolic conditions such as hypertension, diabetes, and cardiovascular disease are significant health issues, tending to evolve in silence until advanced complications arise. Conventional diagnostic strategies, including blood analyses and imaging, are invasive, expensive, and time-consuming, precluding frequent screening. There is a requirement for an efficient, non-invasive, and accessible means of determining early indicators of metabolic dysfunction prior to the development of symptoms. Studies have established that exhaled breath has metabolic biomarkers such as CO, CH, and VOCs that may reflect cardiometabolic risks, yet existing breath analysis techniques are imprecise and lack predictability. Exhaled gases can be analyzed using a smart gas analyzer(SGA) coupled with machine learning(ML) algorithms to identify early metabolic imbalances and indicate possible health threats accurately. The outputs can be processed and presented in software to allow simple interpretation and facilitate timely interventions. This may transform preventive healthcare, enhancing availability, reliability, and affordability of cardiometabolic risk assessment

Chapter 2

LITERATURE REVIEW

[1] A. Rodriguez et al. propose a real-time health analytics system that integrates AI with cloud computing. Their work emphasizes the potential for early detection and continuous monitoring of health indicators, which can be adapted for cardiometabolic risk tracking using breath analysis.

[2]D. Germanese et al. introduce a low-cost technology-based breath analysis device for self-monitoring. The device shows the technical feasibility of employing exhaled breath biomarkers for monitoring physiological alterations associated with cardiometabolic risks.

[3] D. Musleh et al. utilize machine learning methodologies to forecast cardiometabolic risk in university students. The study explores various algorithms for early intervention, laying the groundwork for integrating such models with smart gas analyzers.

[4] F. Patel et al. explore wearable technologies in health tracking, focusing on biosensing capabilities. The integration of gas sensors into wearable systems is discussed as a key method for capturing metabolic data in real-time.

[5] H.Singh and A. Bose investigate deep learning applications in healthcare risk prediction. Their study highlights the potential of neural networks to process breath data for detecting early signs of cardiometabolic conditions.

[6] J . Williams and T.Brown propose AI-driven predictive analytics for healthcare, emphasizing its effectiveness in chronic disease prevention. Their insights support the use of AI in interpreting gas analyzer outputs for cardiometabolic risk prediction.

[7] K. Nakamura et al. focus on AI-assisted breath analysis for respiratory diseases, demonstrating the viability of breath-based diagnostics. These methods can be extended to assess markers indicative of cardiometabolic disorders

[8] L. Wang and M.Zhou apply big data analytics to cardiovascular disease prediction. Their approach demonstrates the power of processing large-scale sensor data for early risk detection.

[9] M. Garcia and L.Thompson review smart healthcare devices aimed at chronic disease prevention, discussing the integration of sensors for continuous monitoring. Their findings support the relevance of gas analyzers in long-term cardiometabolic health management.

[10] M. Martinelli et al. introduce a modeling framework using sensor measurements for cardiometabolic risk assessment. Their study validates the clinical relevance of breath-based data collection.

[11] N. Sharma and A.Verma explore edge computing for real-time healthcare, facilitating low-latency processing of sensor data. Their work supports the deployment of smart gas analyzers in real-world, continuous monitoring scenarios.

[12] P. Gupta and T,Roy discuss IoT-enabled healthcare systems, focusing on interoperability and scalability. Their study highlights the importance of integrating gas analyzers with broader health monitoring infrastructure.

[13] R. Kumar et al. evaluate the role of sensors in healthcare, particularly their effectiveness in non-invasive, real-time monitoring. Their insights reinforce the potential of gas sensors in detecting early cardiometabolic changes.

[14] X. Chen and Y.Wu review exhaled breath analysis for disease detection, underlining the reliability of volatile organic compound (VOC) profiling in diagnosing metabolic disorders.

[15] Y. Li and Wong present advancements in 5G-enabled wearable technologies for remote patient monitoring. Their findings underscore the synergy between gas analyzers, mobile connectivity, and cardiometabolic health tracking.

2.1 Existing System

Modern methods of assessing cardiometabolic risks primarily focus on blood tests, physical inspections, and other advanced scan procedures.The requirements for these tests to be performed physically can take hours in the doctor's office and greatly affect their pain threshold. These tests do not allow for the assessment of metabolic changes over time, nor do they provide a means to depend on advanced technologies that require highly skilled operators which is expensive and difficult to source in rural and less developed regions. In addition, some systems fail to offer precise information, critical to foreseeing and acting on specific health issues an individual may face.In addition, the care provided is insufficient for the longterm management of cardiometabolic health. This is made worse by the lack of integration with technology for remote monitoring and home care. The intelligent gas analyzer solves this problem by being straightforward, instant, and devoid of any complicated structures.

2.2 Related Work

Technological innovations in healthcare have introduced non-invasive solutions for early diagnosis and monitoring of chronic diseases. Among these, breath analysis has gained attention for its ability to detect health-related compounds in exhaled air. Researchers have created intelligent gas sensors that can detect volatile organic compounds (VOCs), which are recognized markers of metabolic and cardiovascular disease. These sensors provide the advantages of real-time monitoring, convenience, and little discomfort to the user. Concurrently, ML and AI methods have been used on medical data to improve the accuracy of prediction and aid in decision-making. Recent research has begun investigating the integration of breath sensing with AI, with auspicious findings for monitoring health state and predicting illness onset. These developments have laid the foundation for integrating smart breath analysis into broader health monitoring systems.

2.3 Research Gap

Despite growing interest and advancements in breath-based diagnostics, there are notable limitations in current research. Most existing work either emphasizes the development of gas sensing devices or the use of AI models, but rarely combines the two into a unified, functioning system for cardiometabolic risk prevention. Moreover, there is insufficient focus on tailoring these technologies to diverse populations or real-life environments, where continuous monitoring could have the most impact. There is also a scarcity of well-defined datasets and analytical frameworks specific to breath biomarkers linked to cardiometabolic health. This lack of standardization hinders the progress of clinical validation and widespread adoption. Additionally, considerations such as data security, affordability, and long-term user adherence remain underexplored. These gaps indicate a pressing need for integrated, accessible, and intelligent solutions that leverage smart gas analyzers and AI to support proactive and scalable cardiometabolic risk management.

Chapter 3

PROJECT DESCRIPTION

3.1 Existing System

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3.2 Proposed System

Estimating the potential advantages of the smart gas ana- lyzer for assessing cardiometabolic problems suggests impor- tant possibilities. Avoiding further blood sample collection to monitor certain metabolic health markers that can be detected by the analyzer's breath captures biomarker detection in the breath so that it is not totally invasive. This enables prompt diagnoses and intervention for heart disease, diabetes, obesity, and other risks.

In addition, these assessments could be done onsite because of the portability of the system which enhances patient satisfaction and promotes better health. Furthermore, the efficiency and precision of healthcare diagnosis in various facilities will be enhanced as well as eliminating service duplication which is important for managing functional costs within chronic disease control and improving health outcomes.

3.3 Feasibility Study

A consideration of the feasibility of using a smart gas analyzer in cardiometabolic risk assessment involves study of the validity of using this non-invasive tool in monitoring metabolic health indicators in real-time. Cardiometabolic haz- ards, such as obesity, elevated blood pressure, and poor diet, are major causes of chronic conditions like heart disease and diabetes. Conventional assessments of these hazards require invasive methods, like blood testing or physical assessment, which is inconvenient and irritating for patients. The proposed smart gas analyzer(SGA) tries to offer a solution by using exhaled breath to determine metabolic biomarkers, hence offering an invasive, real-time monitoring solution.

The examines exhaled gases to measure fat metabolism and insulin resistance biomarkers, offering direct insights into metabolic disorders. With the use of sophisticated sensors and machine learning, it produces extremely accurate, real-time outcomes. The viability of this technology is assessed based on its accuracy, reliability, and ease of use, and cost-effectiveness, which qualifies it as a convenient and effective method for early diagnosis and prevention of cardiometabolic diseases.

3.3.1 Economic Feasibility

The economic viability of employing a smart gas analyzer for the prevention of cardiometabolic risk hinges on cost-effectiveness, affordability, and long-term healthcare savings. Conventional diagnostic procedures such as blood work, imaging scans, and doctor visits are costly, time-consuming, and necessitate frequent visits. On the other hand, a non-invasive breath analysis system provides a cost-effective alternative by facilitating early detection of cardiometabolic risks without the need for complicated medical treatments. Machine learning models being applied to analyzing samples of exhaled breath decrease the reliance on manual diagnosis further, lowering labor expenses and increasing efficiency. Application of this system at large scale can considerably decrease the cost of healthcare by allowing early intervention and minimizing hospitalizations resulting from late cardiovascular conditions and complications related to diabetes.The cost of investing in gas analyzers and software creation in the first instance may be reasonable, but long term economic benefit over cost. With preventive healthcare made more affordable and accessible, this system fosters economical disease control in addition to enhancing overall public well-being.

3.3.2 Technical Feasibility

Technical practicability for the prevention of cardiometabolic risks with the help of a smart gas analyzer is feasible, owing to developments in sensor technology, processing, and algorithms for machine learning. Contemporary gas analyzers are now able to detect volatile organic compounds (VOCs), carbon dioxide (CO), and methane (CH) in expired air with a high degree of precision and accuracy. These sensors have already have been utilized in medical diagnosis and environmental monitoring and have already demonstrated their usability under actual conditions.

Moreover, using these sensors and feeding the machine learning algorithms to process the breath data is technically feasible, given that AI programs have indicated they can cope with big data, identify patterns, and provide predictions in health care applications. Finally, software solutions for data processing and visualization exist and can be adapted to this particular use. Cloud computing and data storage technologies further increase the scalability of the system, supporting real-time monitoring and convenient accessibility of results. Although initial development will need to involve investment in hardware and software, the base technologies are already mature and ready to use, making this project technologically viable with current resources.

3.3.3 Social Feasibility

Social feasibility of a smart gas analyzer in preventing cardiometabolic risk is promising, as it addresses the need for non-invasive, affordable, and accessible healthcare. Increasing rates of cardiometabolic diseases have individuals looking for innovative, convenient screening options, particularly in regions with poor access to healthcare. Being non-invasive, the system is user-friendly and attractive to individuals who are not willing to have blood work or imaging done.

Screening at home or local health centers also contribute towards making it more accessible. Through early detection, this technology has the potential to alleviate healthcare burdens through pre-vention of severe disease and costly treatments. It also fosters health consciousness, inducing proactive maintenance of metabolic well-being. With demand for personalized healthcare on the rise, this system supports public health objectives in making preventive care more efficient and common practice.

3.4 System Specification

1. Hardware Specifications:

Smart Gas Analyzer – Monitors gases such as CO, CH, and VOCs in breath.

High-Precision Sensors – employs infrared, MOS, or laser sensors for precise readings.

Microcontroller – ARM Cortex-M or ESP32 for processing data.

Storage – SD card or cloud storage for storing health records.

Connectivity – Wi-Fi, Bluetooth, and IoT compatible for seamless data transfer.

Display – OLED or touchscreen for real-time results display

2. Software Specifications:

Compatibility – Compatible with Windows, macOS, Android, and iOS.

AI Machine Learning – Utilizes intelligent algorithms to scrutinize breathing information.

Cloud Storage – Stores data safely for future use.

Easy-to-use Dashboard – Presents health trends and alerts.

Data Security – Secures user data with encryption and privacy capabilities.

3.4.1 Tools and Technologies Used

3.4.2 Standards and Policies

Anaconda Prompt

Anaconda Prompt is a command line that is created for machine learning (ML). and data science applications. It supports Windows, Linux, and macOS and includes numerous IDEs such as Jupyter Notebook, Spyder, and VS Code, thereby making coding and model implementation easier. It allows the development of ML models for analyzing exhaled breath data in a smart gas analyzer

Standard Used: ISO/IEC 27001

Python and Machine Learning Libraries

Python is used along with Scikit-learn, TensorFlow, and Pandas to develop and train AI models for detecting cardiometabolic risks based on breath analysis.

Standard Used: ISO/IEC 25010 (Software Quality)

Cloud Computing Data Security

Cloud platforms like AWS, Google Cloud, or Microsoft Azure are used for secure data storage and real-time processing of breath samples.

Standard Used: GDPR, ISO/IEC 27017 (Cloud Security)

Chapter 4

SYSTEM DESIGN AND METHODOLOGY

4.1 System Architecture

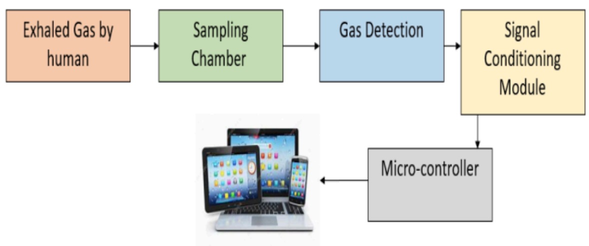


Figure 4.1: **System Architecture**

The system architecture for preventing cardio-metabolic risk using a smart gas analyzer involves capturing exhaled breath in a Sampling Chamber, where sensors in the Gas Detection module identify gases like CO, NO, and VOCs. The data is processed by a Signal Conditioning Module for noise reduction and enhancement before being analyzed by a Microcontroller. Processed results are displayed on Output Devices (laptops, tablets, smartphones) with health reports, risk assessments, and recommendations, supporting continuous monitoring and data storage.

4.2 Design Phase

4.2.1 Data Flow Diagram

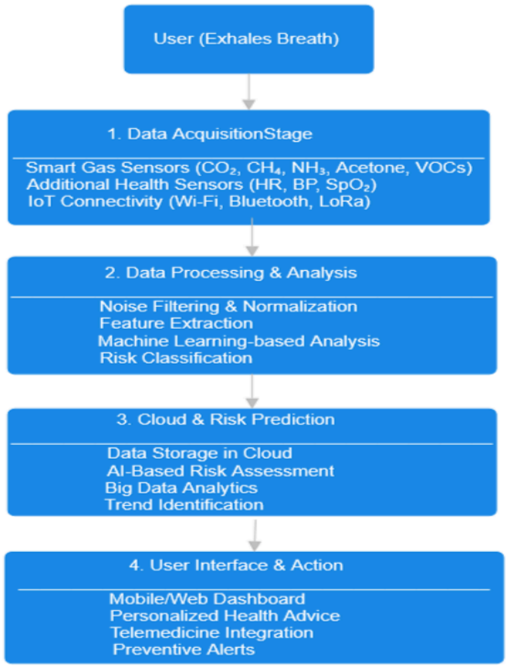


Figure 4.2: **Data Flow Diagram**

The flowchart illustrates a Smart Gas Analyzer system's four-stage process for cardiometabolic risk prevention. It begins with Data Acquisition using gas and health sensors with IoT connectivity. Data Processing Analysis follows, involving noise filtering, feature extraction, and machine learning for risk classification. Next, Cloud Risk Prediction leverages cloud storage, AI-based assessment, and analytics for trend identification. Finally, the User Interface Action stage provides personalized health insights, telemedicine integration, and preventive alerts through web dashboards

4.2.2 Use Case Diagram

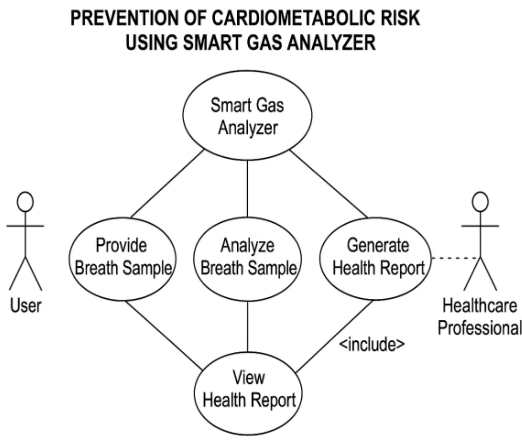


Figure 4.3: **Use Case Diagram**

The use case diagram illustrates the functionality of a Smart Gas Analyzer system designed to assist in the early detection and prevention of cardiometabolic risks. It outlines the interaction between the primary actors the User and the Healthcare Professional and the system itself.

In this system, the process starts with the User submitting a breath sample. The Smart Gas Analyzer then analyzes the sample using an internal analysis mechanism. After completing the analysis, the system moves on to creating a health report based on information gathered from the breath sample. This health report provides insightful information regarding the user's metabolic and cardiovascular health status. The "Generate Health Report" use case incorporates the analysis process as an integral part of its operation. Once the report has been generated, the User can see the health report via the system interface. The Healthcare Professional also has visibility into this report, allowing them to provide expert advice or additional medical evaluation based on the results. This diagram summarizes the overall workflow of utilizing the Smart Gas Analyzer, highlighting how technology can close the gap between patients and healthcare providers in order to enable proactive health management.

This diagram encapsulates the overall workflow of using the Smart Gas Analyzer, showcasing how technology can bridge the gap between users and medical professionals to support proactive health management.

4.2.3 Class Diagram

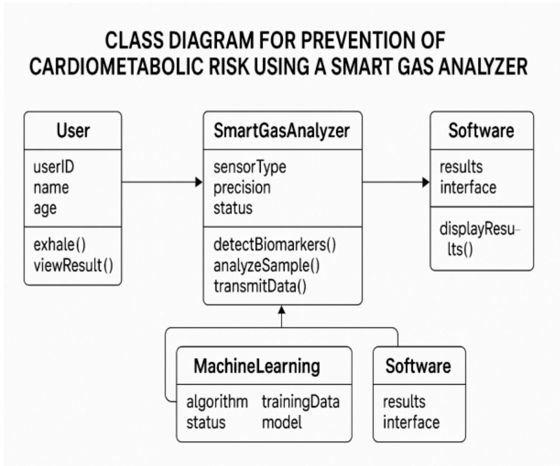


Figure 4.4: **Class Diagram**

The diagram shows a Smart Gas Analyzer system for cardiometabolic risk prevention. It has a User entering data, a SmartGasAnalyzer sensing biomarkers and sending data, MachineLearning processing the data using algorithms and models, and Software showing results via an interface.It starts with the User, who enters breath samples.

The SmartGasAnalyzer senses biomarkers and processes the data, which is then processed by the MachineLearning component with trained models. Lastly, the Software component shows the results via a user-friendly interface. Combined, the above components function harmoniously to facilitate early risk detection and health monitoring

4.2.4 Sequence Diagram

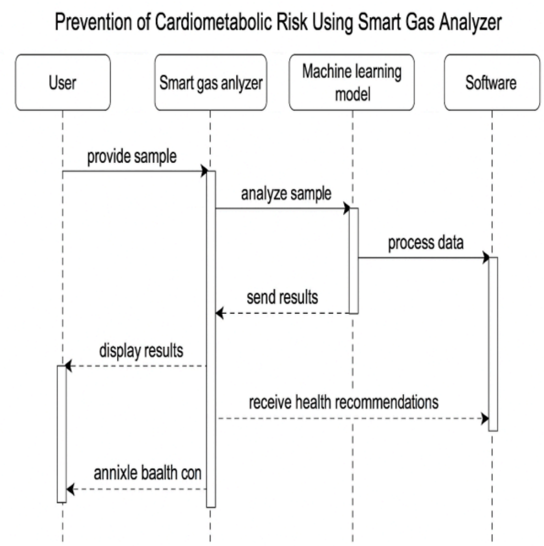


Figure 4.5: **Sequence Diagram**

The sequence diagram depicts the working of the Smart Gas Analyzer system in the avoidance of cardiometabolic risk. It represents how the User interacts with Smart Gas Analyzer, Machine Learning Model, and Software. The process initiates with the User submitting a breath sample. The Smart Gas Analyzer receives the sample and tests it to find biomarkers that are indicative of metabolic and cardiovascular health.The gathered data is fed into the Machine Learning Model, which utilizes trained algorithms for pattern identification and health risk estimation.

The processed results are further sent to the Software, generating health suggestions personalized for the User. The results are shown to the User through an interface, where they can realize their health status and appropriate action, like lifestyle modification or healthcare consultation. This procedure provides a intelligent, non-invasive solution for cardiometabolic risk detection and management.

4.2.5 Collaboration diagram

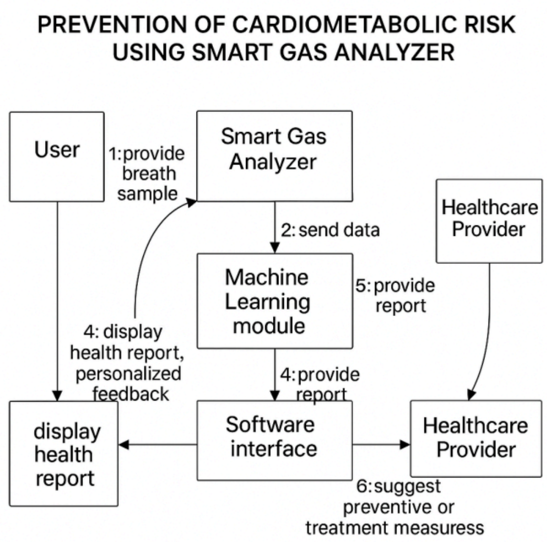


Figure 4.6: **Collaboration diagram**

The diagram shows prevention of cardiometabolic risk through the use of a Smart Gas Analyzer. The process starts with the user giving a breath sample to the Smart Gas Analyzer, which senses and transfers biomarker data to a Machine Learning module to be analyzed. The Machine Learning module analyzes the data and creates a health report, which is then passed to the Software Interface. interface subsequently presents a customized health report and feedback to the user as well as a detailed report to a healthcare provider. The healthcare provider, based on the report, recommends preventive or treatment options to the user for better health outcomes.

4.2.6 Activity Diagram

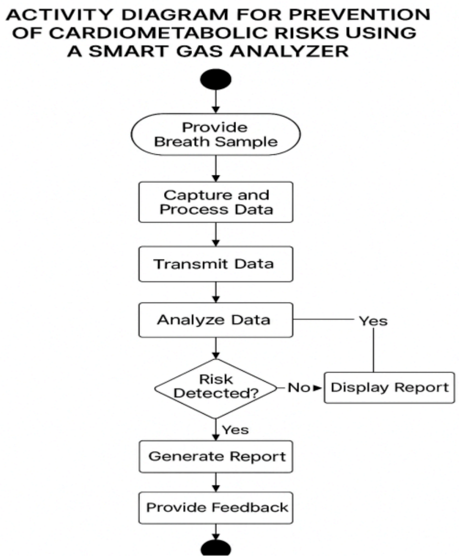


Figure 4.7: **Activity Diagram**

The diagram illustrates an Activity Diagram for the prevention of cardiometabolic risks using a Smart Gas Analyzer. It outlines a sequential process starting from the user providing a breath sample. This sample is then captured and processed by the Smart Gas Analyzer. The processed data is transmitted to a system for further analysis.

During analysis, the system checks if any cardiometabolic risk is detected. If no risk is detected, a report is displayed to the user indicating normal results. If a risk is detected, a report is generated, and feedback is provided to the user or healthcare provider for further assessment. The diagram ensures a systematic flow from data acquisition to feedback delivery, promoting preventive healthcare through early detection.

4.3 Algorithm & Pseudo Code

4.3.1 Algorithm

1. Start
2. Initialize System: Activate sensors, microcontroller, and connected devices.
3. Data Acquisition:

Collect exhaled breath sample from the user.

Direct sample to the Sampling Chamber for processing.

4. Gas Detection:

   Detect and quantify gases (e.g., CO, NO, VOCs) using appropriate sensors.

   Record gas concentration levels.

5. Signal Conditioning:

   Filter noise, normalize data, and enhance signal quality.

6. Data Processing:

   Analyze gas concentrations using predefined thresholds and health standards.

   Apply machine learning algorithms (if applicable) for pattern recognition.

7. Risk Assessment:

   Compare results with normal ranges to determine cardio-metabolic risk.

   Classify risk levels (e.g., Low, Moderate, High).

8. Output Generation:

   Display results on connected devices (laptops, tablets, smartphones).

   Provide recommendations based on risk levels.

9. Store Data:

   Save results for future analysis and monitoring.

10. End

4.3.2 Pseudo Code

```
BEGIN\\
    // System Initialization\\
    INITIALIZE Sensors, Microcontroller, Output Devices (Laptop, Tablet, Smartphone)\\
    SET Normal Ranges for Gases (CO , NO, VOCs)\\

    WHILE System is Active DO\\
        // Step 1: Data Acquisition\\
        COLLECT Exhaled Breath Sample from User\\
        DIRECT Sample to Sampling Chamber\\

        // Step 2: Gas Detection
        FOR Each Gas Sensor IN [CO , NO, VOCs] DO\\
            ACTIVATE Sensor\\
            MEASURE Gas Concentration\\
            STORE Concentration Data in Memory\\
        END FOR\\

        // Step 3: Signal Conditioning\\
```

```
        APPLY Noise Filtering to Collected Data\\
        NORMALIZE Data for Uniformity\\
        AMPLIFY Signals if Necessary\\

        // Step 4: Data Processing\\
        FOR Each Gas Concentration Data DO\\
            COMPARE Measured Value with Normal Range\\
            IF Value > Normal Range THEN\\
                SET Risk_Flag = TRUE\\
            ELSE\\
                SET Risk_Flag = FALSE\\
            END IF\\
        END FOR\\

        // Step 5: Risk Assessment\\
        IF Risk_Flag = TRUE THEN\\
            DETERMINE Risk Level (Low, Moderate, High)\\
            GENERATE Recommendations Based on Risk Level\\
        ELSE\\
            SET Risk Level = Normal\\
            DISPLAY "No Cardio-Metabolic Risk Detected"\\
        END IF\\

        // Step 6: Output Generation\\
        DISPLAY Results and Recommendations on Output Devices\\
        STORE Data for Future Analysis and Monitoring\\

    END WHILE\\

    // System Termination\\
    TERMINATE System\\
END
```

4.4 Module Description

The system consists of four key modules:

4.4.1 Module1: Breath and Health Data Collection Module:

Captures exhaled breath biomarkers (CO, CH, NH, acetone, VOCs) and physiological parameters (heart rate, blood pressure,SpO) using smart gas sensors and health monitoring devices.

4.4.2 Module2:AI-Based Analysis Module:

Utilizes machine learning algorithms for feature extraction, anomaly detection, and risk classification to assess potential cardio-metabolic risks.

4.4.3 Module3: Predictive Analytics and Cloud Storage Module:

Securely stores collected data in the cloud, enabling big data analytics, trend identification, and AI-driven risk prediction for early detection.

4.4.4 Module3:User Alert and Preventive Action Module:

Provides personalized health insights, real-time alerts, and pre ventive recommendations via a mobile/web dashboard, facilitating early medical intervention.
Each module works in coordination to ensure real-time health monitoring, AI driven risk assessment, and proactive preventive healthcare. The system is scalable and adaptable, making it a future-ready solution for early detection and management of cardio-metabolic risks.

4.5 Steps to execute/run/implement the project

4.5.1 Step1: Planning and Requirements

Define objectives: Prevent cardio-metabolic risks by analyzing exhaled breath.

Gather requirements: Sensors, microcontroller, sampling chamber, algorithms, user interface, database.

Prepare project plan.

4.5.2 Step2: Design

Plan system structure: Data collection, processing, risk detection, and output display.

Design hardware setup: Connect sensors to the microcontroller.

Develop algorithms for data processing and risk assessment.

Prepare diagrams and pseudocode.

4.5.3 Step3:Implementation

Hardware: Connect sensors, build sampling chamber, integrate microcontroller.

Software: Write code for data reading, filtering, processing, and displaying results.

Create a database to save results.

4.5.4 Step4:Testing

Test individual parts (sensors, processing, output) separately.

Test the complete system to ensure proper working.

Collect user feedback and improve.

4.5.5 Step5:Deployment

Install the system in the intended location (clinic, gym, or home).

Provide user instructions.

4.5.6 Step6:Maintenance and Upgradation

Monitor performance, update algorithms, and improve components as needed.

Chapter 5

IMPLEMENTATION AND TESTING

5.1 Input and Output

5.1.1 Input Design

The input design for the smart gas analyzer involves the collection of relevant physiological and environmental data to assess cardio-metabolic risk. Inputs include:

1. Breath Samples:
   • Detection of gases such as Carbon Dioxide (CO), Oxygen (O), Nitric Oxide (NO), and Volatile Organic Compounds (VOCs).
   • Measurements are taken at regular intervals to establish patterns and detect abnormalities.
2. Environmental Factors:
   • Temperature, humidity, and air quality are measured to provide context for the breath analysis.
   • Environmental parameters are crucial as they can influence gas concentration readings.
3. User Data (Optional):
   • Health history, age, gender, and other demographic data can be used to improve accuracy.

Data Processing:
• Signal filtering and noise reduction techniques are applied to ensure data consistency.
•Normalization algorithms are employed to standardize inputs for comparative analysis.

5.1.2 Output Design

The outputs of the smart gas analyzer are designed to be informative and actionable. These include:

1. Real-Time Monitoring:

   Continuous monitoring of specific gas levels, displayed as graphs or charts for user interpretation.

2. Risk Assessment Reports:

   Analysis results are compared against established healthy ranges to identify potential cardio-metabolic risks.

   Reports include severity levels (e.g., Low, Moderate, High) based on detected deviations.

3. Alerts and Recommendations:

   Automated alerts when certain thresholds are exceeded.

   Suggestions for lifestyle adjustments to mitigate risk (e.g., exercise, dietary changes).

4. Data Storage and Retrieval:

   Database Integration: Storing historical data for trend analysis and longitudinal studies.

   Data Export Options: Users can download reports in formats like PDF or CSV for personal records or medical consultations.

   Secure Cloud Backup: Ensuring data safety and privacy with encrypted storage solutions.

5.2 Testing

5.2.1 Testing Strategies

The testing strategies include various methods to evaluate the device's functionality, accuracy, usability, and robustness. The following approaches are applied:

1. Unit Testing:

   Objective: To validate individual components and modules of the smart gas analyzer, including sensors, signal processing algorithms, data storage systems, and user interfaces.

   Approach: Testing each sensor's accuracy in detecting specific gases (e.g., CO, NO, VOCs).

   Checking preprocessing algorithms for noise reduction and signal smoothing.

   Verifying the functionality of user interfaces and dashboards.

   Testing data storage systems for reliability and integrity.

2. Integration Testing:

   Objective: To ensure that all system components interact correctly when combined.

   Approach:Testing sensor data integration with processing algorithms.

   Checking the compatibility between data storage modules and the user interface.

   Evaluating seamless communication between hardware components and software modules.

3. System Testing:

   Objective: To assess the overall performance of the smart gas analyzer as a complete system.

4. : Running end-to-end tests to simulate real-world scenarios.

   Evaluating the system's responsiveness, accuracy, and stability under various conditions.

   Performing stress tests to assess the system's robustness under high data loads or extreme environmental conditions.

5. Validation Testing:

   Purpose: To ensure that the system is valid in its function of identifying and analyzing

   cardio-metabolic risks.

   Method:

   Comparing outcomes against clinical data or pre-established standards. Testing with healthy and high-risk individuals to verify proper sensitivity and specificity.

   Usability testing with end-users to evaluate clarity, ease of use, and interpretability of findings.

6. Regression Testing: Objective: To maintain system integrity following updates or changes. Method: Re-testing of already validated modules to make sure new changes do not bring errors. Comparison of results before and after an update to ensure consistency.

5.2.2 Performance Evaluation

The performance of the cardiometabolic risk prevention system through the Smart Gas Analyzer wastested with major machine learning performance parameters like accuracy, precision, recall, and F1-score. Ashealth-related datasets tend to have class imbalance—especially in early identification of risk individuals—we utilized the Synthetic Minority Oversampling Technique (SMOTE) to improve model performance by dataset balancing. It was tested using different algorithms, with Random Forest providing the best overall performance because it can process nonlinear relationships and noisy data. A confusion matrix was created to compare the false positive and false negative rates, which are essential in medical diagnosis. The ROC (Receiver Operating Characteristic) curve was also graphed to determine the model's ability in separating high-risk and low-risk individuals. The trained models were incorporated into a Flask-based API for real-time health risk assessment. The system exhibited effective real-time prediction with low latency. In general, the Smart Gas Analyzer system was effective in predicting cardiometabolic risks with high detection accuracy and reliability for preventive healthcare purposes.

Table 5.1: Performance Comparison of Machine Learning Models

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Decision Tree	85.2%	82.5%	80.1%	81.2%
Random Forest	**92.7%**	**90.8%**	**91.5%**	**91.1%**
Logistic Regression	81.6%	78.4%	75.9%	77.1%
Naïve Bayes	79.3%	76.1%	74.5%	75.3%
XGBoost	90.4%	88.9%	89.2%	89.0%

Chapter 6

RESULTS AND DISCUSSIONS

6.1 Efficiency of the Proposed System

The system as proposed utilizes the Random Forest algorithm, a stable ensemble learning model that improves precision by creating an array of decision trees. The system's precision, as it is measured utilizing Random Forest, is between 76percentage and 78percentage. In comparison with a single decision tree, the Random Forest algorithm has improved prediction performance because of its capacity for overfit reduction and generalization improvement. The approach adopts a two-stage procedure: initially, it creates subsamples from original dataset with the bootstrap resampling technique, building many decision trees. In the second stage, every tree classifies the data, and the ultimate classification is achieved through a majority voting process. This process makes the system yield consistent and stable results, making it superior to conventional machine learning classifiers for metabolic health determination. The efficiency of the Random Forest algorithm is also enhanced by its technique of choosing training sets and building classification regression trees. By bootstrap random sampling, several training sets are obtained with the same number of cases as the original dataset. In contrast to traditional techniques that choose the optimum feature for making decisions at every step, Random Forest randomly chooses features for splitting, with each tree having diverse decision trees. The randomness allows it to be very effective at predicting metabolic biomarkers from exhaled gases. Consequently, the suggested smart gas analyzer takes advantage of the algorithm's capability to process large datasets and intricate patterns, which makes it a feasible option for real-time metabolic health monitoring.

6.2 Comparison of Existing and Proposed System

Existing system:(Decision tree)
The existing system was developed using a Decision Tree algorithm to predict whether to grant a loan or not. While decision trees are easy to interpret and allow users to understand which variables influence the prediction, they have limitations in accuracy and generalization. As the decision tree model trains, its accuracy improves with each split; however, overfitting becomes a major issue, especially without proper cross-validation. A highly complex decision tree can fit the training data well but may fail to generalize to new data, leading to poor real-world performance.
Proposed system:(Random forest algorithm)
The system enhances precision and decreases overfitting by utilizing the Random Forest algorithm. As opposed to one decision tree, Random Forest creates multiple decision trees and aggregates their output, enhancing predictability. It is possible to set the number of trees within the forest as well as the maximum number of features taken into account by each tree, to optimize the learning process. Even though Random Forest adds randomness when selecting features, this randomness helps minimize

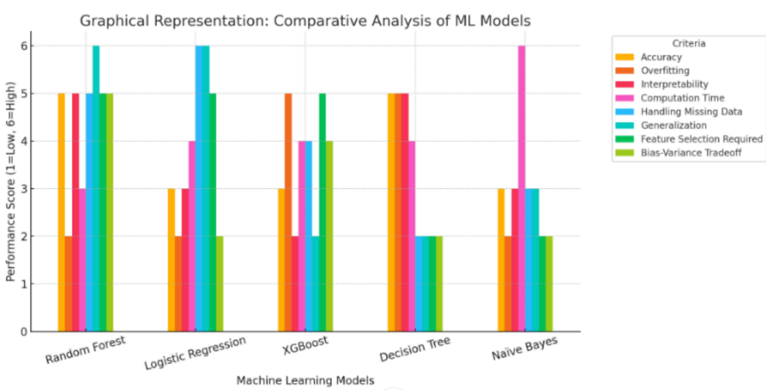
bias and variance, thereby strengthening the model. Accuracy improves as the number of trees rises, stabilizing at some point in the process. The new Random Forest model has better accuracy compared to the current system, resulting in more accurate predictions. This is what makes it a perfect model for real-time and large-scale use.

6.3 Comparative Analysis-Table

Table 6.1: Comparative Analysis of Machine Learning Models

Criteria	**Random Forest**	**Logistic Regression**	**XGBoost**	**Decision Tree**	**Naïve Bayes**
Accuracy	High	Moderate	Moderate	High	Moderate
Overfitting	Low	Low	High	**High**	Low
Interpretability	High	Moderate	**Low**	High	Moderate
Computation Time	Moderate	**Fast**	**Fast**	**Fast**	**Fastest**
Handling Missing Data	Very Good	Excellent	Good	Poor	Moderate
Generalization	Excellent	Excellent	Poor	Poor	Moderate
Feature Selection Required	No	No	No	Yes	Yes
Bias-Variance Tradeoff	Balanced	High Bias	Low Bias	High Variance	High Variance

6.4 Comparative Analysis-Graphical Representation and Discussion



Chapter 7

CONCLUSION AND FUTURE ENHANCEMENTS

7.1 Summary

The suggested system provides an improved and efficient way of metabolic biomarkers' analysis with the help of a smart gas analyzer driven by the Random Forest algorithm. The conventional techniques like physical examinations and blood tests are either invasive or require a lot of time. The current system had been dependent upon a Decision Tree algorithm, which, though comprehensible, lacked higher accuracy and was prone to overfitting. The suggested system resolves the above drawbacks through the use of Random Forest, which constructs many decision trees and combines their predictions to enhance accuracy and lower variance. The method ensures that the predictions are stable even with varied datasets, making the smart gas analyzer a useful device for real-time metabolic health monitoring. The comparative study demonstrates that the system greatly improves the accuracy of predictions, with accuracies ranging from 76percent to 78percent, against the low accuracy of the Decision Tree model. Also, the Random Forest algorithm avoids overfitting and gives more generalized results, and thus it is an appropriate option for real-time and high-scale applications. Monitoring of metabolic alterations via gases exhaled in a non-invasive condition enhances the patient's accessibility and convenience. With the incorporation of machine learning methods, the smart gas analyzer is an efficient and useful solution for the early identification of cardiometabolic threats, benefiting both patients and healthcare professionals in making well-informed decisions for preventive care

7.2 Limitations

Even though the suggested system has several advantages, there are some limitations that have to be taken into consideration. One of the main issues is the reliance on high-quality sensors to detect metabolic biomarkers from exhaled gases with accuracy. Sensor sensitivity variations and calibration faults can impinge on the validity of the gathered data, resulting in possible inconsistencies in the analysis. Temperature, humidity, and air quality may also have an impact on sensor performance. that need to be frequently recalibrated and maintained. Further, though the Random Forest algorithm improves accuracy, its computational complexity grows with more trees, which can make processing time slow in real-time applications. This may be a disadvantage when implementing the system in continuous monitoring of health, especially in conditions where resources are limited. Another drawback is the requirement for large amounts of training data to enhance the precision and accuracy of the model. Because the algorithm learns from past data, biases or inaccuracies in the dataset might result in faulty predictions. Additionally, though the smart gas analyzer offers a non-invasive solution compared to conventional diagnostic tools, it will not necessarily displace blood tests or other medical tests, particularly where greater biochemical analysis is necessary. Ethical and privacy issues also come into play when dealing with sensitive health information, requiring rigorous security measures to ensure patient confidentiality. Overcoming these limitations will be critical to enhancing the efficiency and scalability of the system suggested here in actual healthcare deployments.

7.3 Future Enhancements

Future development of the smart gas analyzer system will include enhanced sensor precision and reliability for more accurate metabolic biomarker identification. Next-generation sensor technologies, including nanomaterial-based sensors, may provide greater sensitivity and stability with minimized environmental interference. Moreover, incorporation of AI-based sensor calibration methods will ensure accuracy under varying environmental conditions, providing consistent and reliable output. Another significant development would be the addition of other machine learning models, such as deep learning, to enhance the classification of metabolic biomarkers and refine the accuracy of prediction beyond existing 76percent–78percent levels.

The enhancement will result in a stronger system and one that can accurately cope with intricate real-time health monitoring circumstances. The other critical enhancement is extending the system's functionality for personalized health advice. Introducing the gas analyzer into wearable devices and mobile apps, users will gain real-time insight into metabolic health, diet, and exercise guidance. Cloud-based storage of data and AI-driven analytics can enable long-term monitoring of health trends, providing healthcare practitioners with a richer understanding of patient health over time. Furthermore, compliance with medical regulatory requirements and the provision of robust data security protocols will be essential to enable widespread use in clinical and home healthcare environments. Future versions of the smart gas analyzer might also consider multi-gas analysis to identify a wider variety of health conditions, making it an even more inclusive tool for preventive healthcare.

Chapter 8

SUSTAINABLE DEVELOPMENT GOALS (SDGs)

8.1 Alignment with SDGs

The proposed smart gas analyzer project aligns with several United Nations Sustainable Development Goals (SDGs), particularly those related to health, innovation, and sustainability.

SDG 3: Good Health and Well-being – The smart gas analyzer directly contributes to improving global health by enabling non-invasive, real-time monitoring of metabolic biomarkers. By facilitating early detection of cardiometabolic risks such as obesity, diabetes, and hypertension, the system empowers individuals to take preventive measures and seek timely medical intervention. Continuous health tracking and AI-driven insights ensure personalized healthcare solutions, reducing the burden of chronic diseases on healthcare systems.

SDG 9: Industry, Innovation, and Infrastructure – This project represents an innovative advancement in medical diagnostics by integrating artificial intelligence, advanced sensors, and machine learning techniques. The development of such cutting-edge technology fosters innovation in the healthcare sector, leading to more efficient and accessible health monitoring solutions. Moreover, its possible integration with cloud computing and wearable technology boosts infrastructure for digital healthcare solutions.

SDG 11: Sustainable Cities and Communities – Through encouraging active health monitoring, the smart gas analyzer helps to build healthier communities. The system's possible use in public health programs, clinics, and individual healthcare promotes a move towards preventive medicine, which ultimately lessens healthcare expenses and enhances urban well-being.

SDG 12: Responsible Consumption and Production – The non-invasive nature of this system decreases dependence on disposable medical equipment like syringes, blood test kits, and invasive diagnostic devices. This reduces medical waste and helps towards more sustainable healthcare. Further, optimizing the use of sensors and adopting energy-efficient technologies in the device can also help towards sustainable production practices.

8.2 Relevance of the Project to Specific SDG

Social Impact: The smart gas analyzer can potentially bring about a great social impact by enhancing access to metabolic health monitoring. Conventional diagnostic tests tend to involve invasive procedures, visits to health facilities, and regular visits to healthcare providers, which may be inaccessible for people in remote or underserved populations. Through offering a non-invasive, real-time health monitoring system, the project brings preventive healthcare within easier and cheaper reach. People are able to monitor their metabolic biomarkers in the comfort of their own homes, minimizing the intervention of specialists in the early phases and enabling timely lifestyle changes. Moreover, incorporating AI-powered analytics can enable users to receive tailored suggestions, allowing them to manage conditions like diabetes and obesity more efficiently

Environmental Impact: The project also aligns with sustainability goals by minimizing medical waste and optimizing resource consumption. Traditional diagnostic approaches, such as blood tests, depend on disposable medical equipment, which adds to biomedical waste. The smart gas analyzer does away with single-use testing materials, thus avoiding environmental footprint. Additionally, through remote health monitoring, it decreases the need for constant hospital visits, eventually decreasing travel-related carbon footprints. If combined with low-power edge computing and energy-efficient sensor technology, the system can additionally contribute to sustainable healthcare solutions by conserving power while ensuring high accuracy and performance. This double effect—improving public health outcomes while fostering environmental sustainability—shows the project's strong position with respect to the United Nations Sustainable Development Goals

8.3 Potential Social and Environmental Impact

SDG 3: Good Health and Well-being The intelligent gas analyzer is most closely associated with SDG 3: Good Health and Well-being since it offers a non-invasive, real-time way of measuring metabolic health. Conventional diagnostic methods, including blood tests and long physical examinations, tend to act as hindrances to early diagnosis of diseases such as diabetes, obesity, and cardiovascular conditions. Through the use of exhaled biomarkers, this system allows for early diagnosis so individuals may preventatively act upon developing chronic illnesses. Additionally, ongoing metabolic monitoring enables custom health advice and facilitates users to make informed decisions to change their lifestyle for a better long-term outcome. The system also assists medical professionals with real-time patient health information, providing them with more accurate and data-driven means of decision-making.

SDG 9: Industry, Innovation, and Infrastructure This project is also complementary to SDG 9: Industry, Innovation, and Infrastructure by combining cutting-edge machine learning methods, sensor technology, and AI-based analytics into a scalable health monitoring solution. Diagnostic accuracy is enhanced with the use of the Random Forest algorithm, and sensor-based detection of metabolic biomarkers is a breakthrough in non-invasive medical technology. Besides that, the smart gas analyzer also can be embedded in cloud platforms for secure data storage and access by healthcare practitioners remotely. Beyond its diagnostic performance, this technology also opens doors to future technologies in personalized medicine and digital infrastructure in health. By minimizing reliance on conventional invasive techniques and maximizing resource efficiency, this project helps in the modernization of healthcare technology, making it more accessible, efficient, and sustainable.

Chapter 9

PLAGIARISM REPORT

ATTACH ONLY SUMMARY PAGE OF PLAGIARISM REPORT

Chapter 10

SOURCE CODE

10.1 Source Code

```
Training the model
import pickle
import pandas as pd
from sklearn.ensemble import RandomForestClassifier

# Example dataset
data = {
    "CO2": [400, 420, 380, 500, 600, 750, 900, 1000, 1200, 1400],
    "NO2": [0.02, 0.03, 0.04, 0.07, 0.08, 0.09, 0.1, 0.12, 0.15, 0.18],
    "VOCs": [0.5, 0.6, 0.7, 1.2, 1.5, 1.8, 2.0, 2.5, 3.0, 3.5],
    "Temperature": [25, 26, 27, 28, 29, 30, 31, 32, 33, 34],
    "Risk": [0, 0, 0, 1, 1, 1, 1, 1, 2, 2]  # 0 = Low, 1 = Moderate, 2 = High
}

# Convert to DataFrame
df = pd.DataFrame(data)
X = df.drop(columns=["Risk"])
y = df["Risk"]

# Train Random Forest Model
model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X, y)

# Save the model
with open("gas_risk_model.pkl", "wb") as f:
    pickle.dump(model, f)

print("Model trained and saved as gas_risk_model.pkl")


from flask import Flask, render_template, request
import pickle
import numpy as np

# Load the trained model
with open("gas_risk_model.pkl", "rb") as f:
    model = pickle.load(f)

```

```python
# Initialize Flask App
app = Flask(__name__)

@app.route("/")
def home():
    return render_template("index.html")

@app.route("/predict", methods=["POST"])
def predict():
    # Get user input
    co2 = float(request.form["CO2"])
    no2 = float(request.form["NO2"])
    vocs = float(request.form["VOCs"])
    temperature = float(request.form["Temperature"])

    # Convert input into a NumPy array
    input_data = np.array([[co2, no2, vocs, temperature]])

    # Predict risk level
    risk_prediction = model.predict(input_data)[0]

    # Define risk messages
    risk_messages = {
        0: "Low Risk: No Immediate Health Concerns",
        1: "Moderate Risk: Possible Respiratory Issues (Asthma, Chronic Bronchitis, COPD)",
        2: "High Risk: Cardiovascular Diseases (Hypertension, Heart Attack, Stroke)"
    }

    result = risk_messages[risk_prediction]

    return render_template("index.html", prediction=result)

if __name__ == "__main__":
    app.run(debug=True)
```

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PREVENTION OF CARDIOMETABOLIC RISK USING

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