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An IOT, ML and Breath Based Non-Invasive Glucose Meter

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***Abstract** - The project introduces a non-invasive glucometer designed to revolutionize diabetes management through breath analysis. It focuses on identifying and analyzing volatile organic compounds (VOCs) in human breath that correlate with blood glucose levels. The process includes thorough chemical investigation to isolate and validate these VOCs as reliable biomarkers of glucose concentration. Advanced sensor design and calibration are crucial, utilizing cutting-edge materials and technology to create highly sensitive and accurate sensors for VOC detection. Beyond sensor development, the project leverages complex algorithms and machine learning techniques to establish precise correlations between VOC levels and blood glucose levels. A prototype will be created and tested with clinical samples to ensure that the device meets medical and regulatory standards. This multidisciplinary project combines chemistry, electronics, software engineering, and healthcare to deliver a seamless and user-friendly alternative to traditional blood glucose monitoring, eliminating the need for finger pricking. The aim is to improve patient comfort and compliance, leading to better diabetes management and enhanced quality of life for individuals with the condition.*
***Keywords:** Non-invasive glucometer, diabetes management, breath analysis, volatile organic compounds (VOCs), biomarkers, sensor design, machine learning, prototype development, clinical testing, glucose monitoring, multidisciplinary approach, patient comfort, quality of life.*

I. INTRODUCTION

Diabetes mellitus is a metabolic condition characterised by elevated blood glucose levels due to inadequate insulin production or cellular insulin resistance. This disruption in insulin function leads to various metabolic and health issues. In diabetic patients, insulin insufficiency causes lipolysis, in which the body breaks down fat for energy needs. Excess lipolysis can produce ketones such as acetoacetate, betahydroxybutyrate, and acetone. This accumulation can lead to ketosis and, in more severe cases, progress to diabetic ketoacidosis (DKA). The International Diabetes Federation (IDF) Diabetes Atlas presents alarming data, indicating that approximately 38.5% of diabetes cases are detected late, while a staggering 50.1% remain undiagnosed. Most current detection solutions, such as fingerprick test kits, require invasive procedures, which cause discomfort for patients. This pain often results in irregular blood glucose monitoring. The consequences of poorly managed or undiagnosed diabetes are dire. As highlighted by the World Health Organisation (WHO), diabetes has the potential to inflict considerable damage to crucial organs, including the eyes, nerves, heart, kidneys, feet, and blood vessels. Neglecting or failing to treat diabetes promptly can result in long-lasting disability or premature death. Given these severe outcomes, there is an immense need for innovative diabetes detection devices that are non-invasive, portable, affordable, and efficient, ensuring timely and accurate detection to mitigate potential health risks.

Electronic noses (E-noses) comprising specialised electrochemical sensors for odour detection have emerged as groundbreaking instruments in healthcare. Initially designed for food and environmental monitoring applications, E-noses can discern nuanced changes in scent profiles [7]. In healthcare, this innovation offers tremendous promise for elevating diagnostics and disease monitoring to new heights. Each electrochemical sensor within an E-nose is precisely calibrated to detect specific volatile organic compounds (VOCs) in an individual's breath [8]. Extensive research has substantiated the link between different VOCs and various diseases and the differences in the VOC concentration between individuals affected by certain health conditions and those who are healthy.

For example, VOCs such as acetone, isoprene, ammonia, methanol, propane, ethanol, isopropanol, and undecane are found in abnormal amounts in patients with lung cancer [9], [10] and acetone in those with diabetes [11] and heart failure [12].

In light of these findings, a compelling gap exists in the existing literature: development of a non-invasive multisensor blood glucose monitoring device harnessing these electrochemical sensors [5], [6], [13]. Such a device could revolutionise the monitoring of blood glucose levels (BGL), eliminating the discomfort associated with traditional piercing procedures. By non-invasively analysing VOCs in breath, this innovative approach offers a path to continuous, painfree BGL monitoring, aligning with the evolving landscape of patient-centric healthcare.

Coordinating AI (ML) calculations is pivotal to progress cell phone based wellbeing applications, including diabetes forecast and checking. ML calculations empower these applications to process and decipher the tremendous sum of sensor-created

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information, permitting more exact sickness recognition and customized medical services [14], [15]. For example, in EmoGlass [16], ML models can perceive profound states in light of physiological signs, voice tone, or facial articulations. In the forecast of diabetes, ML calculations process complex datasets that incorporate blood glucose levels, sensor voltages, diet data, active work, and ecological elements [13], [17].

GlucoBreath addresses a critical progression in diabetes discovery, offering a helpful and harmless answer for address the squeezing medical services difficulties related with diabetes. GlucoBreath principally comprises of three significant parts: a) the convenient, minimized, painless breath assortment and investigation gadget that examinations the VOCs present in the breath, named VOC-Analyser; b) the ML-based diabetes discovery framework; and c) the online UI (UI) for giving body fundamental subtleties as information and review the ML-anticipated diabetes report as result.

A portion of the critical commitments of our work are:

• GlucoBreath - a start to finish multi-sensor IoT and MLbased painless pre-indicative diabetes discovery framework joining a VOC-Analyser, a ML-based diabetes discovery framework, and an online UI to interface with input subtleties and view the diabetes report.

• VOC-Analyser - a multi-sensor IoT-based gadget to gather breath tests and examine their VOCs.

• BreathProfiles dataset - a dataset including sensor voltages acquired by handling 492 breath tests from different diabetic and non-diabetic patients from a presumed public clinic in India.

• Diabetes discovery ML models prepared on the BreathProfiles dataset.

• An Internet UI for entering the body vitals' subtleties into GlucoBreath and acquiring the ML-model-created diabetes forecast report.

• Observational approval of GlucoBreath by leading a clinical review and gathering information from 492 patients in a controlled climate. GlucoBreath accomplished the most noteworthy normal precision rates, with 96.9% for anticipating diabetes and 98.4% for evaluating the criticality of BGLs.

II. PRIOR RESEARCH

GlucoBreath is a crossing point of three related regions: E-nose also, harmless blood glucose observing, smartphonebased wellbeing applications, and ML calculations for medical care.

A. E-NOSE AND Painless BGL Observing

E-nose and harmless blood glucose observing methods have hanged diabetes determination, offering easy, helpful, and financially savvy options to customary techniques, for example, finger-prick testing. A portion of the new developments in this field depend on glucose checking in view of spit [18], breath [5], sweat [19], and the interstitial liquid (ISF) from the skin [20]. The E-nose includes different electrochemical sensors delicate to VOCs present in breath and hence help in breath examination in light of constituent VOCs [7]. The fundamental qualities of the E-nose that add to painless glucose checking incorporate harmlessness, moderateness, and usability. A new report showed the utilization of E-nose to classify breath tests from people with different medical issue with momentous exactness. The methodology included gathering breath tests, acquiring comparing synthetic sensor information, and utilizing ML calculations to characterize the information. Nonetheless, it is fundamental to perceive that these E-nose-based illness discovery frameworks are at present in the work-in-progress stage what's more, are impacted by different outside factors in the information assortment process.

Harmless blood glucose observing measures an individual's BGLs without drawing blood by penetrating the skin or on the other hand causing agony or injury. A new report [13] around here showed a painless BGL checking approach based on breath signal examination. This approach incorporates gathering breath tests from people determined to have diabetes what's more, exposing them to AI driven examination. This examination utilizes the Help Vector Ordinal Relapse strategy to classify each example into one of four classifications: {very much controlled, to some degree controlled, or inadequately controlled} sugar levels, accomplishing a precision pace of 68.66%. Be that as it may, the sort of breath test and the assortment time influence its execution. Future enhancements are expected, for example, the development of the dataset and the making of constant glucose checking gadgets, to understand its maximum capacity.

Likewise, a new painless breath-based diabetesidentification work by [5] grandstands DiabeticSense – a multi-sensor IoT gadget for distinguishing diabetes. Given a breath test and body vitals gave as information, DiabeticSense predicts in the event that the individual has diabetes or not. Nonetheless, their work has just been approved on an example size of 100 and has the best precision of 86.6%. Moreover, the work does not remark on the BGL of the individual.

III. MATERIALS AND METHODS

The general pipeline of GlucoBreath's working is shown in Fig. 1. The pipeline begins by getting a client's feedback: (a) segment and body indispensable information utilizing the Internet UI and (b) a breath test utilizing a birthday expand. The breath test is handled utilizing the VOC analyser, which produces a reaction as sensor voltages that go about as the delegate of the client's breath test or his breath profile. We explain that we don't expect to recognize the specific VOCs present in the breath test. All things considered, we utilized the consolidated sensor voltage values as the delegate breath test given as contribution to include designing and

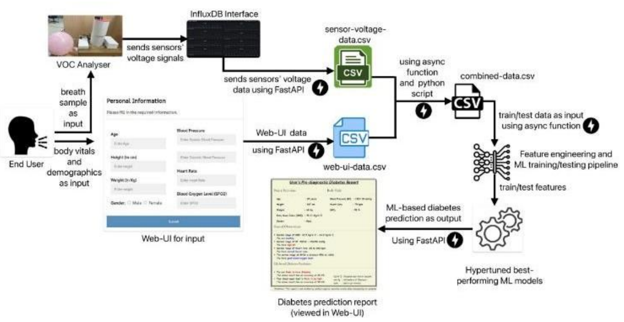

FIGURE 1. Overall Pipeline of our proposed method. The end user provides his (a) breath sample and (b) demographics and vital data of the body via the Web interface as input. The breath

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sample is processed by the VOC-Analyser, which generates sensor-based data, combined with the Web Ul data, and passed as input to the ML pipeline for feature engineering and training/ testing. Final ML-based Diabetes predictions are displayed as diabetes report on the Web UI.

preparing for the ML model. These sensor voltages and Web UI information are joined and taken care of into the ideally tuned best-performing ML models for include designing and testing for diabetes. The forecasts produced by the ML models are made accessible to the client as a pre-symptomatic diabetes report accessible Online UI. The diabetes report contains conventional wellbeing perceptions on body vitals gave as information and a few forecasts in view of diabetic-explicit ML, counting (a) in the event that the client has diabetes and (b) assuming the client has
diabetes, then the BGL of the client is moderate or high.

VOC-Analyser (Fig. 2) - a smaller multisensor IoT gadget intended for breath investigation, created to anticipate BGL. Minimal expense electrochemical metal oxide semiconductor (MOS) type sensors (Table 1) were used to identify the breath marks of the patients. MOStype sensors have cross-awareness for somewhere around 2 or 3 breath parts. The gadget utilized a group of sensors to dissect VOCs in breathed out breath and separate between sensor voltage reactions for individuals with diabetes and those without diabetes. The sensor voltage information acquired from a patient's breath test were named the patient's breath profile, addressing the VOC-Analyser sensors' reaction to the VOCs found in the breath test. Related to a singular's breath profile, different segment subtleties, counting age, orientation, weight, and level, as well as essential physiological information, for example, blood oxygen levels (estimated as SPO2), pulse, and pulse, were gathered through an online UI (nitty gritty in Segment III-B). Such breath profiles, socioeconomics, and body vitals information were gathered utilizing the VOC-Analyser from 492 patients from a presumed public medical clinic and put away in the BreathProfiles dataset. The elements extricated from the BreathProfiles information set were subsequently used to prepare and test different ML models that are some portion of our ML-based diabetes discovery framework.

A. VOC-ANALYSER—THE MULTI-SENSOR BREATH ANALYSIS DEVICE

The VOC-Analyser used a group of eight electrochemical resistive MOS-type sensors designed in an impermeable compartment (Fig. 2b). Every sensor utilized in this exploration works on a 5-volt DC power supply. A mugginess and temperature sensor was utilized inside the sensor chamber to identify immediate temperature and dampness inside the chamber. When the sensor yield had balanced out in a outside air climate, the sensor cluster was utilized to catch breath test marks, frequently called breath profiles. Sensor alignment included laying out stable baselines through approval under reference conditions with outside air to ensure the precision of sensor readings. The use of intensity to the gas sensor utilizing a microheater was an essential to accomplishing a predictable standard from the sensor yield. The gadget uses WiFi availability to store every member's sensor reaction to an outer Convergence cloud data set.

The VOC-Analyser's electronic power supply contains a switch-mode power supply to work the gadget. A MOSFET-based buck exchanging controller was utilized to give the 6.5 volt capacity to the gadget. A low dropout straight controller (LDO) gave the managed 5-volt power supply to the sensor exhibit, the sensor microheater and the microcontroller. A Wi-Fi empowered Esp32 microcontroller with a remotely associated high goal simple to-advanced (ADC) converter was utilized to distinguish the advanced reaction of the sensors and store it in the InfluxDB. The microcontroller furthermore, ADC of this gadget work on a 5-volt power supply.

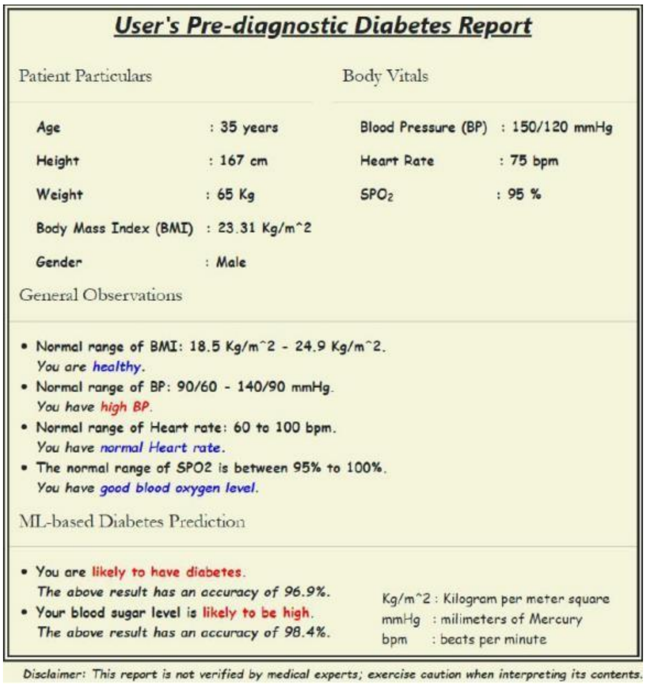

FIGURE 2. ML-generated Diabetes report

B. WEB-BASED INTERFACE DESIGN FOR USER INTERACTION

We utilize an electronic UI (UI) (displayed in Fig. 3) to bring the client's very own wellbeing related data, including the accompanying:
1) Socioeconomics: mature (in years) and orientation
2) Biometrics: level (in cms) and weight (in kgs)
3) Body vitals: circulatory strain (in mmHg) and blood oxygen level or SPO2 (in %age)

The ML-based pre-symptomatic diabetes report created for the info body vitals and breath test is shown to the client through Web UI, as displayed in Fig 4. The whole ML calculation utilizes the Google register engine6 to make the handling light for cell phones or edge gadgets that utilization the application. The client's wellbeing related information and sensor-based information from the VOC-Analyser are passed on to ML models (put in the cloud) utilizing FastAPI.7

C. ML-BASED DIABETES DETECTION SYSTEM

In the wake of dissecting the InfluxDB imagined sensor plots got from the BreathProfiles dataset and concentrating on the current writing, we chose to extricate highlights connected with different attributes of these plots, for example, spatial, recurrence, and shape. Table 3 presents the highlights chose and removed from

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the sensor voltage information in the BreathProfiles dataset. Since body vitals information were consistent for individual patients for a brief time frame, we accept these information with no guarantees and don't register any extra measurements. Since the dataset comprised of an inconsistent number of diabetic and non-diabetic patients, the include set was unequal. Thusly, we adjusted our include set utilizing SMOTE.8 We explored different avenues regarding different existing Destroyed forms (Destroyed, Fringe SMOTE,9 ADASYN-SMOTE10) to decide the one that helped us to acquire the most reliable outcomes. A few trial runs were performed to pinpoint the
most critical yet minimal elements that assume a urgent part in diabetes forecast. The ideal list of capabilities acquired was then, at that point, used to fabricate ML models. To decide the most dependable ML model to foresee diabetes, when prepared on our arrangement of highlights, we tried the exhibition of 13 state of the art ML
calculations, a significant number of them utilized in the writing to perform arrangement assignments. To additionally guarantee precise outcomes, these ML models were hypertuned utilizing their feedback boundaries and k-overlap cross-approval, and their exhibition results were assessed with a different arrangement of assessment measurements.

D. ETHICAL CONSIDERATION

We got moral endorsement for our exploration from the institutional survey board. Every one of the members were educated of their cooperation in the review, and their assent was taken before their association in the information and breath test assortment exercises.

IV. CONCLUSION, LIMITATIONS AND SCOPE FOR FUTURE WORKS

In this project, we have developed a non-invasive system, GlucoBreath, aimed at accurately monitoring blood glucose levels by analyzing volatile organic compounds (VOCs) present in human breath. The system is designed to detect specific VOCs correlated with glucose levels, eliminating the need for invasive finger-prick tests. This project focuses on creating a multi-sensor IoT device, the VOC-Analyser, which captures breath samples and uses advanced sensor technology to identify key biomarkers. By integrating machine learning models, GlucoBreath enables precise diabetes prediction, providing users and healthcare professionals with a convenient and reliable tool for monitoring. The project includes data collection, model development, training, and validation with clinical samples to ensure high accuracy and regulatory compliance. Future work can involve expanding the dataset for broader population coverage and enhancing the sensor technology to improve accuracy. Additionally, the system can be integrated with wearable devices and cloud-based analytics, positioning GlucoBreath as a comprehensive, user-friendly solution for continuous and pain-free diabetes management.

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