GlucoSync: Machine Learning-Based Non-Invasive Glucose Prediction Using Beer Lambert Law

Tanmay Mayekar
Artificial Intelligence & Data Science
SIES Graduate School of Technology
Navi Mumbai, India

Om Walunj
Artificial Intelligence & Data Science
SIES Graduate School of Technology
Navi Mumbai, India

Viranch Rewaskar
Artificial Intelligence & Data Science
SIES Graduate School of Technology
Navi Mumbai, India

Dr. Neethu Sabu
Artificial Intelligence & Data Science
SIES Graduate School of Technology
Navi Mumbai, India

Prof. Pragati Akre
Artificial Intelligence & Data Science
SIES Graduate School of Technology
Navi Mumba, India

Abstract— *Non-invasive glucose monitoring is a transformative approach to diabetes management, offering a painless and convenient alternative to traditional invasive methods. The GlucoSync Project, a novel system for non-invasive glucose prediction using the MAX30102 sensor and the Beer-Lambert Law. The system captures photoplethysmogram (PPG) signals at red and infrared wavelengths to calculate light absorbance, which is then used as input to a machine learning model for glucose prediction. Additionally, the system provides real-time heart rate and SpO2 measurements. The GlucoSync application features a secure, user-friendly interface, including login/logout functionality and a dynamic dashboard displaying users' health data. Experimental results demonstrate the feasibility of the approach, with the machine learning model achieving high accuracy in glucose prediction. GlucoSync represents a significant step toward low-cost, portable, and non-invasive glucose monitoring solutions.*

Keywords - Non-invasive glucose monitoring, MAX30102 sensor, Beer-Lambert Law, Machine learning, Photoplethysmogram (PPG), Absorbance Rate, SpO2, Heart Rate.

I. INTRODUCTION

Diabetes mellitus is a global health crisis, affecting over 463 million adults worldwide and projected to rise to over 700 million by 2045[6]. Traditional glucose monitoring methods, such as finger-prick blood tests, are invasive, painful, and inconvenient, leading to poor patient compliance. Non-invasive glucose monitoring has emerged as a transformative alternative, with optical methods based on the Beer-Lambert Law gaining significant attention for their ability to measure glucose concentration through light absorption rate [7][9].

Recent advancements in sensor technology, Internet of Things (IoT), and machine learning (ML) have opened new possibilities for non-invasive health monitoring systems.[2] Photoplethysmography (PPG) sensors, such as the MAX30102 and MAX30100[7][9], have been widely used for pulse oximetry and heart rate monitoring. These sensors operate on the principle of light absorption by biological tissues, which can be leveraged to estimate glucose concentrations in the bloodstream using the Beer- Lambert law [9]. The ability to analyze light absorption at different wavelengths provides a promising foundation for developing a non- invasive glucose monitoring system.[10]

This paper introduces GlucoSync, an IoT-integrated real- time non-invasive glucose monitoring system that utilizes an optical sensor (MAX30102), an Arduino UNO microcontroller, and a machine learning model for glucose prediction. The system collects raw red and infrared (IR) light intensity data from a user's fingertip, processes it using cloud-based machine learning algorithms, and displays real-time glucose levels through a mobile application developed with Flutter.[5] By integrating IoT, ML, and cloud computing, GlucoSync aims to provide an accessible, cost-effective, and user-friendly solution for continuous glucose monitoring [3].

Unlike traditional methods that require periodic blood sam- pling, GlucoSync offers real-time monitoring, enabling users to track glucose fluctuations dynamically [9]. This is particularly beneficial for individuals with diabetes who require continuous monitoring to manage their condition effectively. The system's integration with a mobile application ensures seamless data visualization, historical trend analysis, and potential alerts for abnormal glucose levels, making it an ideal solution for personalized diabetes management. By leveraging technology and data generation techniques, the GlucoSync project aims to facilitate effective health management, ultimately improving quality of life and reducing the risks associated with chronic health conditions.

Motivations:

1. Tackling a Global Health Challenge with a Non-Invasive, Real-Time Monitoring Approach: GlucoSync is designed to address the growing global burden of diabetes and cardiovascular diseases, which collectively impact millions and pose significant health risks if left unmanaged. Unlike traditional methods that rely on invasive techniques such as finger-pricking, GlucoSync offers a non- invasive alternative, significantly improving user comfort and compliance.[6] By continuously monitoring vital parameters like glucose levels, SpO_2, and heart rate in real- time, users are empowered to make informed decisions about their health. This proactive approach not only supports early intervention but also encourages users to stay engaged in their personal health journey, ultimately promoting better long- term outcomes.[3]

2. Enhancing Accuracy and Accessibility through Advanced Technology and User-Centric Design: GlucoSync integrates cutting-edge technologies like the Beer-Lambert Law and machine learning algorithms to ensure accurate glucose level prediction based on physiological data such as absorbance from red and infrared light.[9] This scientific foundation enhances the reliability of predictions, making the system trustworthy for everyday use. Complementing its technical strengths is a thoughtfully designed mobile application that features a seamless login/signup process, interactive dashboards, glucose history visualization, and device connectivity.[8] These features make the platform accessible and easy to use for a broad audience, including those with minimal technical experience, thereby boosting user satisfaction and engagement.[5]

II. LITERATURE REVIEW

Numerous research studies have explored advancements in health monitoring systems, emphasizing the integration of wireless technology, non-invasive glucose measurement, and machine learning for disease prediction. The literature highlights the significance of wearable and smart health monitoring devices in enhancing real-time tracking of vital signs, such as heart rate, blood pressure, and blood oxygen levels. Additionally, researchers have demonstrated the feasibility of non-invasive glucose monitoring through photodiode-based sensing, enabling continuous monitoring with minimal discomfort. Moreover, machine learning techniques offer higher accuracy and efficiency in disease detection.

Kai Zhang et.al [5] focused on non-invasive blood glucose estimation using a PPG signal. It employs signal processing and machine learning techniques to extract features from PPG waveforms for glucose level prediction. It mainly emphasizes the accuracy and real-time capability of the system using wearable sensors.

Daniyan et.al [4] integrates IoT with machine learning for continuous glucose monitoring. It involves sensors transmitting data to a cloud-based system for remote monitoring. The paper highlights ease of access, real-time alerts, and AI-based prediction models for personalized health tracking.

G R Ashisha et.al [3] proposes a health monitoring system combining multiple parameters like heart rate, SpO_2, and temperature, along with glucose level detection. It uses a mobile app and Bluetooth- based communication for real-time display and remote healthcare access.

Chenwei Feng et.al [1] explores the use of neural networks for blood glucose level prediction based on photoplethysmography signals. It specifically compares different deep learning models and optimizes them for better accuracy. It focuses on model performance and signal analysis.

Emre Oner Tartan et.al [12] discusses a portable non-invasive glucose monitoring device that uses NIR (Near-Infrared) light and optical sensors. It emphasizes the use of hardware-based detection and signal processing to estimate glucose concentration without pricking. The study also includes calibration for different skin tones and focuses on user safety and comfort.

Alkeya et.al [11] integrates a health monitoring system using IoT and machine learning. It monitors multiple parameters like SpO_2, heart rate, and glucose levels, combining them with predictive analysis. The application is cloud-connected and supports real-time health tracking with alerts and reports.

1. Gaps in Existing Research:

While existing studies have advanced non-invasive glucose monitoring, several gaps remain. Most systems lack a user-centric mobile interface for seamless data visualization and interaction. Real- time integration of multiple health parameters (e.g., glucose, HR, SpO2) with secure cloud storage is often overlooked. Additionally, few studies combine the Beer-Lambert Law with machine learning for glucose prediction while ensuring scalability and accessibility. GlucoSync addresses these gaps by integrating optical sensing, machine learning, IoT, and a Flutter-based app with Supabase for secure, real-time monitoring and user engagement.

III. PROPOSED METHODOLOGY

The GlucoSync project introduces an innovative health monitoring solution that combines real- time data collection, predictive analytics, and user-friendly interfaces to address the limitations of existing glucose monitoring systems. The system employs a hardware model utilizing the MAX30102 sensor combined with an ESP32 Arduino. This setup enables the non-invasive collection of vital health metrics, specifically heart rate and SpO2 levels, ensuring continuous monitoring for a comprehensive view of the user's health status.

1. Hardware Development: Design and implementation of a hardware model utilizing the MAX30102 sensor and ESP32 Arduino to capture real-time heart rate, SpO2 and photoplethysmogram (PPG) signals at red (660 nm) and infrared (880 nm) wavelengths. Integration of the hardware components to ensure accurate and reliable data collection for further analysis.
2. Data Collection: The MAX30102 sensor emits red and infrared light into the user's finger and measures the reflected light to capture PPG signals. The raw intensity values for both wavelengths are recorded and transmitted to the ESP32 microcontroller for further processing. The data collection module also measures heart rate (HR) and blood oxygen saturation (SpO2) using established algorithms.
3. Preprocessing: The raw PPG signals are preprocessed to remove noise and artifacts. A low-pass filter is applied to smooth the data, and Beer-Lambert Law is used to calculate absorbance for both red and infrared wavelengths. The absorbance values are computed as:

$$A_{Red} = \log_{10}(I_{0Red} / I_{Red}) \text{ [For Red Light]}$$

$$A_{IR} = \log_{10}(I_{0IR} / I_{IR}) \text{ [For Infrared Light]}$$

where I_0Red and I_0IR are the baseline intensities, and I_{Red} and I_{IR} are the transmitted intensities.

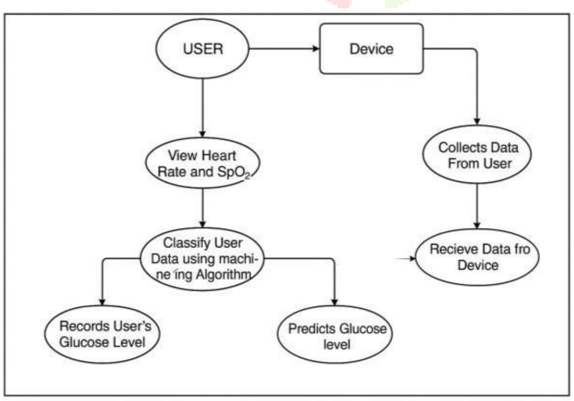

Fig 1. Block Diagram

4. Machine Learning Model: The preprocessed absorbance values are used as input as a machine learning model for glucose prediction. The model is trained on a dataset of labeled glucose concentrations, which includes absorbance values, HR, and SpO2 measurements. A lightweight regression algorithm is employed to ensure real-time performance on the Arduino UNO microcontroller. The model outputs the predicted glucose concentration, which is displayed on the screen and transmitted to the user application.

RSE, RAE, RMSE, and R^2 are regression evaluation metrics. RSE and RAE show how much the prediction errors deviate from actual values relative to a baseline. RMSE measures the average magnitude of errors, sensitive to large deviations. R^2 indicates how well the model explains the variance in the data, with values closer to 1 showing better performance.

Formula Used:

Mean Absolute Error:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}|$$

Mean Square Error:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2$$

Root Mean Square Error:

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2}$$

Coefficient of determination:

$$R^2 = 1 - \frac{\sum(y_i - \hat{y})^2}{\sum(y_j - \hat{y})^2}$$

Where,

$y\hat{} = Predicted\ Value\ of$ y

y = Mean Value of y

5. User Application: The GlucoSync application provides a secure, user-friendly interface for monitoring health data.

- Login/Logout Functionality: Ensures data privacy and security.
- Dynamic Dashboard: Displays real-time glucose levels, HR, SpO2, and historical trends.

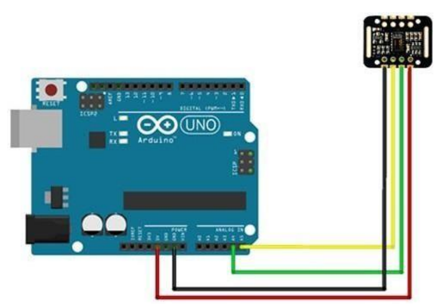

Fig 2. Schematic Diagram of Hardware Connection

MAX30102 pin	Arduino UNO pins	Descriptive
VCC	5V / 3.3V	Power Supply
GND	GND	Ground
SDA	A4(SDA)	Data line for I2C communication
SCL	A5(SCL)	Clock line for I2C communication

Table 1. Connection between MAX30102 and Arduino UNO

The GlucoSync project encompasses a comprehensive approach to health monitoring, focusing on glucose level prediction through the analysis of heart rate, SpO2 and absorbance rate data.

- User Input: This block represents the user's input into the system, where heart rate and SpO2 data is collected via the MAX30102 sensor connected to an Arduino.
- Arduino UNO & MAX30102 Sensor: The Hardware layer that collects the real-time data for Heart Rate and SpO2 and sends it to the system.
- Dataset: Since real-time glucose levels cannot be collected directly, a pre-existing dataset is used for glucose data. This block will represent the dataset being fed into the system for training and predictions.
- Machine Learning Algorithm: This block shows the use of a linear regression model implemented in TensorFlow. The model will estimate glucose levels based on the input feature of Absorbance Rate.
- Data Processing: The block where heart rate and SpO2 data is analyzed and combined with the generated glucose data.
- Prediction: This block illustrates the application predicting glucose levels from the processed data.
- User Interface: Dashboard: Shows the predicted glucose levels, heart rate, and SpO2 data to the user. Profile Management: Features for users to log in, view health history, and update their profile.

IV. RESULT

The GlucoSync system incorporates both hardware integration and software-based predictive analytics to provide an end-to-end health monitoring solution. The results section is divided into two parts: hardware implementation and software interface.

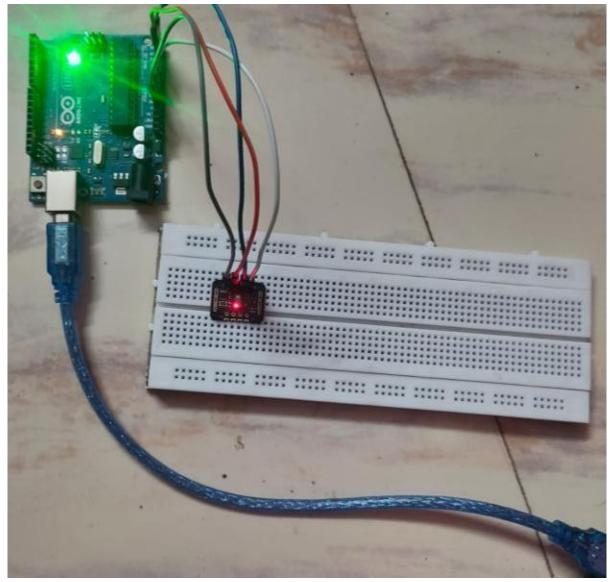

Fig 3. Hardware Component

Arduino UNO:
The Arduino UNO is a microcontroller board based on the ATmega328P, used in the GlucoSync project to collect real-time heart rate and SpO_2 data via the MAX30102 sensor. It transmits this data through serial communication to the application for further processing and glucose level prediction. The board provided reliable and accurate vital signs, supporting the system's goal of non-invasive health monitoring.

MAX30102:
The MAX30102 is a sensor used to measure heart rate and SpO_2 using red and infrared light. In the GlucoSync project, it connects to the Arduino UNO to collect real-time health data. This data is sent to the application for glucose level prediction. The sensor enables non-invasive and continuous monitoring.

The sensor readings are transmitted via USB to the PC or Android application, where they are analysed and visualized. The Arduino Uno collects heart rate and SpO_2 data in real-time from the MAX30102 sensor, providing a steady stream of data for prediction.

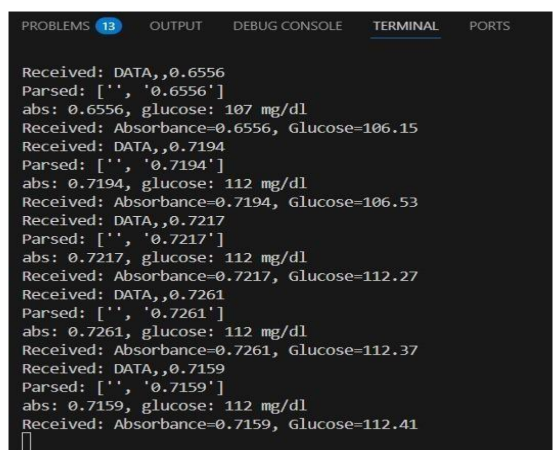

Fig 4. Glucose Results

Actual Value (mg/dl)	Predicted Value (mg/dl)
138.4	135
135.2	140.5
99.9	99.1
146.1	141.1
83.5	80.9
110.9	111.4
108.5	110.9
130.7	130
101	99.8
111.9	112.3

Table 2. Actual vs Predicted Glucose

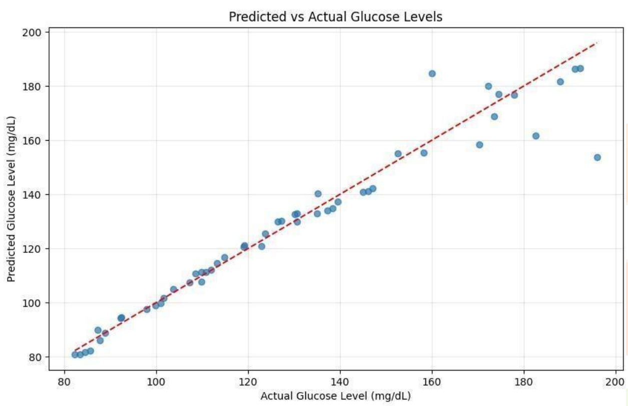

Fig 5. Actual vs Predicted Glucose Graph

System	Real-Time Monitoring	UI	Storage
Kai Zhang et al.[4]	Yes	Limited	No
Daniyan et al.[3]	Yes	Basic	Yes
G.R. Ashisha et al.[2]	Yes	Basic	No
GlucoSync	Yes	Advanced (Flutter)	Yes

Table 3. Comparison with Existing System

System	Accuracy (R^2 Score)
Kai Zhang et al. [4]	N/A
Chenwei Feng et al. [3]	0.85
Daniyan et al. [2]	N/A
GlucoSync	0.93

Table 4. Accuracy Comparison of GlucoSync with Existing Systems

V. CONCLUSION AND FUTURE WORK

This paper presents GlucoSync, a novel IoT-based approach for real time non-invasive glucose monitoring using optical sensors, machine learning, and a Flutter mobile application. By leveraging the principles of the Beer-Lambert law, the system effectively estimates glucose concentrations based on light absorption variations. The integration of IoT and ML enhances real-time processing capabilities, while the mobile application ensures user-friendly access to health data. Experimental results demonstrate the feasibility of the approach, but further validation is required to improve accuracy and reliability.

Future work includes refining the machine learning model with larger datasets, incorporating deep learning techniques, and optimizing real-time data processing for better accuracy. Additionally, clinical validation through extensive trials will be crucial for regulatory approval and real-world deployment.

Enhancements such as adaptive calibration, personalization glucose trend analysis, and secure data storage through blockchain technology can further solidify GlucoSync as a reliable alternative to traditional glucose monitoring methods. With continuous improvements, this system holds the potential to revolutionize diabetes management and improve the quality.

REFERENCES

[1] Chenwei Feng, Yu Sun, Xiaoxin Wu, Fuchun Jiang, Lin Tao, Jiahao Zheng Selection of Noninvasive Features in Wrist-Based Wearable Sensors Predict Blood Glucose Concentrations Using Machine Learning Algorithms. NCBI (2023).

[2] G R Ashisha, S Thomas George, X Anitha Mary, K. Martin Sagayam, Analysis of Diabetes Disease Using Machine Learning Techniques (2022).

[3] Ilesanmi Daniyana, Smart Ikuponiyib, Lanre Daniyanc, Ikenna Damian Uchegbub, Khumbulani Mpofua. Development of a Smart Glucose Monitoring Device. ScienceDirect (2022).

[4] KAI ZHANG AND WENJIELING Sports Institute Health Monitoring of Human Multiple Physiological Parameters Based on Wireless Remote Medical System. IEEE (2022).

[5] Santosh, R., & Gupta, A.” Leveraging GANs for Glucose Data Augmentation in Health Monitoring Apps”. IEEE Transactions on Neural Networks and Learning Systems. (2021).

[6] Brain Bogue-jismenez, Douglas Powell, Ana Doblas, Selection of Noninvasive Features in Wrist-Based Wearable Sensors to Predict Blood Glucose Concentrations Using Machine Learning Algorithms. PubMed (2022)

[7] Zhang, Y., & Li, J.” Deep Neural Networks for Predicting Blood Glucose Levels”. IEEE Access (2022)

[8] Tanvir Tazul Islam, Md Sajid Ahmed, Md Hassanuzzaman, Syed Athar Bin Amir and Tanzilur Rahman, ¡Blood Glucose Level Regression for Smartphone PPG Signals Using Machine Learning. (2021)

[9] Li, J., Liu, W., Tang, M., & Liu, C.” Deep Learning Algorithms for Glucose Prediction in Diabetes Management”. Journal of Biomedical Informatics. (2021).

[10] El-Sappagh, S., & Islam, S. R.” A Survey on Machine Learning Models in Health Monitoring Systems”. Journal of Healthcare Engineering. (2021).

[11] Alkeya, Neelima Devi, K Salomi Monica, IOT based Smart Healthcare Monitoring Systems (2021).

[12] Emre Oner Tartan, Cebrail Ciflikli, An Android Application for Geolocation Based Health Monitoring, Consultancy and Alarm System (2021)