RESEARCH PAPER

Rechargeable Non-Invasive Glucose Monitoring Device

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Abstract- This work presents the design and validation of a cost-effective, compact, and rechargeable non-invasive glucose monitoring device that combines microwave sensing with machine learning techniques for continuous blood glucose estimation. The handheld system employs a patch antenna operating between 1.15–1.36 GHz to detect variations in signal reflection (S11 parameter) caused by glucose-induced dielectric changes in tissue. A multilayer perceptron (MLP) model, trained on over 60,000 frequency-response samples, was used to predict blood glucose levels (BGL). Experimental validation on diabetic and non-diabetic volunteers demonstrated mean predicted values of 141.11 mg/dL and 98.5 mg/dL, respectively, with strong correlation to invasive methods ($R^2 = 0.7781$) and a mean absolute relative difference (MARD) of 11.8%. In contrast to many available non-invasive systems that are often bulky, partially invasive, or expensive, this device integrates microwave sensing with deep learning in a compact, rechargeable design. It supports real-time monitoring and mobile app connectivity, offering pain-free glucose tracking and data management.

Keywords— Microwave Sensors, non-invasive glucose monitoring, rechargeable device, blood glucose levels, continuous monitoring.
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1. Introduction

Diabetes mellitus is a long-term disorder in which the body cannot maintain normal blood-glucose homeostasis because of inadequate insulin production or impaired insulin action. Persistent deviations from the normative range (roughly 70–110 mg/dL) increase the risk of complications such as neuropathy, retinopathy and cardiovascular disease, which motivates improved and less intrusive glucose monitoring solutions. Conventional glucose monitoring typically involves finger-prick blood sampling. Although clinically reliable, these methods are uncomfortable, increase infection risk, and often discourage patients from regular testing.”

In response, researchers have explored non-invasive technologies, including optical, electromagnetic, and biosensor-based modalities. However, these alternatives often face limitations such as low accuracy, large device size, high cost, or incomplete non-invasiveness. Microwave-based sensing has emerged as a promising modality due to its ability to penetrate biological tissues and detect dielectric changes associated with blood glucose concentration. Despite various prototypes and conceptual devices proposed in the literature, many lack complete non-invasiveness, real-time capability, or robust data modelling using machine learning.

Furthermore, most systems are either semi-invasive or lack portability, limiting their practical deployment. Herein, a portable, battery-rechargeable microwave sensor is presented for non-invasive glucose estimation. The device is integrated with a smartphone interface and is designed for portability and ease of use.

Table 1. Comparative Summary of Existing Approaches and the Proposed Work

Author / Year	Methodology	Key Limitation	Contribution of Present Work
Chang et al. (2022) [1]]	Smart watch with ISF extraction	Requires flexible sensor patch; lacks integration	Offers complete integration in a portable, skin-free contact device
Patel et al. (2024) [2]	Near-Infrared regression model	Bulky and calibration-dependent	Uses microwave sensing + MLP model for compact real-time monitoring
Ogunsanya et al. (2022) [3]	GSM-based non-invasive model	Conceptual; lacks validated hardware	Presents validated, working hardware tested on volunteers
Tan et al. (2020) [4]	GluMo: Pocket-sized prototype	Prototype stage; untested on humans	Fully tested and implemented on diabetic and non-diabetic volunteers
Deshmukh and Chorage (2021) [5]	Microwave sensing (narrowband)	No mobile app or rechargeable system	Integrates USB-charging, real-time display, and mobile interface

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This Work	Microwave + Deep Learning (MLP)	Some challenges may occur in human body parameters for different skin types	First compact, rechargeable, non-invasive glucometer with live prediction and app support

2. Literature Survey

Research into non-invasive glucose monitoring has accelerated due to its potential to eliminate the discomfort and infection risks of finger-prick tests. Various strategies—ranging from optical sensing to electromagnetic and biosensor technologies—have been proposed. However, most approaches face challenges such as limited accuracy, lack of real-time performance, or high production costs. Table 2 summarizes notable studies, outlining their advantages and drawbacks.

Table 2. Comparative Summary of Prior Work in Non-Invasive Glucose Monitoring

Study	Technique	Strengths	Limitations
Chang et al. (2022) [1]	ISF via iontophoresis (smart watch)	Wearable; continuous monitoring	Accuracy 84.3%; needs personalization
Patel et al. (2024) [2]	NIR + Linear Regression	Enhanced accuracy; compact electronics	Bulky; needs regular calibration
Ogunsanya et al. (2022) [3]	GSM-based non-invasive concept	Designed for low-resource use	No working prototype; limited validation
Tan et al. (2020) [4]	GluMo microwave prototype	Pocket-sized; high usability	Not tested on humans
Deshmukh and Chorage (2021) [5]	Narrowband microwave sensor	Human trials; relevant GHz range	No recharge/app integration
Min et al. (2025) [6]	Optical and microwave hybrid	High-sensitivity biosensor	Complex integration; non-commercialized
Ghosh and Bora (2025) [7]	Literature review	Comprehensive sensor evolution	Lacks experimental prototype
Alsultani et al. (2025) [8]	Microwave sensor review	Advanced microwave methods	No device proposed or tested

3. Methods

The device developed in this work is a portable, rechargeable system designed to estimate blood glucose levels without invasive sampling. It combines microwave sensing with machine learning techniques to provide real-time glucose predictions. The following subsections describe its architecture, operational principle, and signal processing workflow.

3.1. Device Architecture and Working Principle

At its core, the system employs a microwave resonant antenna that transmits and receives signals within the 1.00–1.36 GHz band. This frequency range is known for its sensitivity to dielectric variations in biological tissue, which correlate with changes in blood glucose concentration.

Figure 1 illustrates the system layout. It consists of two voltage-controlled oscillators (VCOs), a microwave sensor, a gain-adjustable log amplifier, and a module for data acquisition and processing. The device detects resonant frequency shifts produced when the microwave signal interacts with wrist arterial blood, and these shifts are fed into the prediction model for glucose estimation.

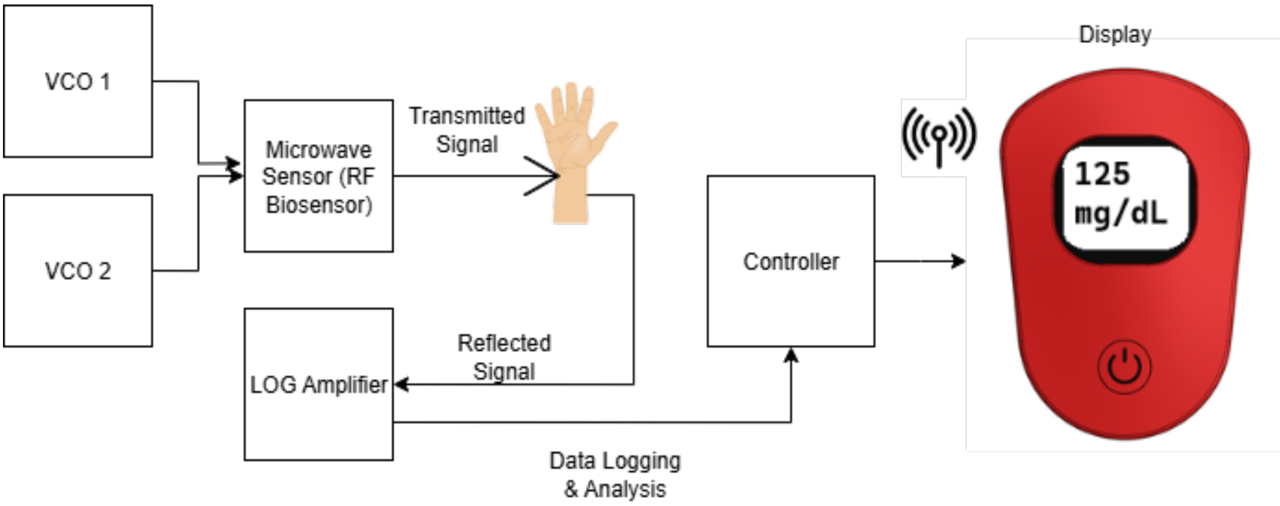


Figure 1: Block diagram of rechargeable non-invasive blood glucose monitoring device

3.1.1. Antenna Design and Frequency Tuning

The microwave resonant antenna system was a patch-type antenna designed using FR4 substrate with a dielectric constant of 4.4 and a thickness of 1.6 mm. The dimensions were optimized using HFSS to resonate within the 1.15–1.36 GHz range. The resonant frequency shift due to varying tissue permittivity was captured using a return loss (S11) parameter via VNA setup. Frequency selection was performed by identifying the minimum S11 value during each reading. A moving average filter (N=10) was applied to reduce transient signal noise. Frequency shifts of interest were isolated using a fast Fourier transform (FFT)-based peak detection algorithm in the onboard microcontroller.

3.2. Signal Modeling and Data Acquisition

The signal permittivity changes due to glucose variation are captured by the antenna and recorded by the log amplifier. The transmitted signal power and the reflected signal power are significantly altered by the presence of glucose molecules in the blood, which modulate the dielectric properties of the tissue.

The reflected frequency data is collected for various volunteers under controlled conditions. The data acquisition setup included multiple readings across different times to account for physiological variations. Both diabetic and non-diabetic participants were included in the test cohort, with ground truth BGL values recorded using standard invasive glucometers for comparison.

Raw analog signals were initially boosted using a gain-adjustable log amplifier and digitized via a 12-bit ADC with a 10 kHz sampling rate. The frequency domain was obtained using FFT, and the dominant peaks were identified. A 1.0 - 1.4 GHz band-pass filter was applied to retain only the relevant portions of the spectrum. To further stabilize frequency estimates, signal noise was minimized through Savitzky–Golay filtering combined with Kalman smoothing.

To clean up the data, we combined a Savitzky–Golay filter with Kalman smoothing, which helped stabilize frequency estimates.

Volunteer Parameters (Number of Volunteers = 30)

- Gender: 17 male, 13 female
- Diabetic Participants: 12 (Type 2, diagnosed for more than a year)
- Non-diabetic Participants: 18

Participants avoided caffeine and food for at least one hour before each session. Each person had 3–5 readings over two days to reduce individual variability.

The signals were observed to be affected by physiological factors such as hydration, skin tone, and wrist adiposity. These factors caused shifts in the baseline permittivity, which in turn influenced the resonant frequency. Considering such variables—through approaches like multi-parameter correction or stratified learning—could enhance prediction accuracy in future models.

3.3. Machine Learning Model for Blood Glucose Prediction

We trained a Multi-Layer Perceptron (MLP) neural network on 60,000 frequency-response samples.

Inputs: Resonant frequency (scalar) and S11 variation

Output: Estimated blood glucose level (mg/dL)

Model architecture: 3 dense hidden layers (64, 32, 16 neurons) with ReLU activation Dropout (0.3) applied between layers to reduce over fitting.

Final layer: single neuron with linear activation. The model was trained with a batch size of 64 for 100 epochs, using early stopping to prevent unnecessary training. Training and validation losses were tracked throughout. The final model achieved a root mean square error (RMSE) of 112 mg/dL on the test set.

The raw analog signals were first amplified using a gain-controlled log amplifier (AD8310) and then digitized through a 12-bit ADC operating at a 10 kHz sampling rate. Frequency extraction was carried out using FFT-based transformation followed by peak detection. A band-pass filter (1.0 - 1.4 GHz) was applied to isolate the relevant signal components.

Signal stability was improved by first applying a Savitzky–Golay smoothing window and then a Kalman-based smoothing routine to reduce transient fluctuations and produce robust frequency estimates.

Volunteer Demographics (n = 30)

- **Age Range:** 30–60 years
- **Gender:** 17 male, 13 female
- **Diabetic Participants:** 12 (Type 2, diagnosed for more than one year)
- **Non-diabetic Participants:** 18

All testing took place in a temperature-controlled environment (22–24°C). Participants abstained from caffeine and food intake for at least one hour prior to testing. Each volunteer underwent 3–5 readings across two days to minimize intra-individual variation.

Signal behavior was found to be influenced by physiological factors such as hydration, skin tone, and wrist adiposity. These variables shifted the baseline permittivity, thereby affecting the resonant frequency. Incorporating such features into future models—for example, through multi-parameter correction or stratified learning—may improve prediction robustness.

3.4. Machine Learning Model for Blood Glucose Prediction

A Multi-Layer Perceptron (MLP) neural network was trained on 60,000 frequency-response samples.

- **Inputs:** Resonant frequency (scalar) and S11 variation.
- **Output:** Estimated blood glucose level. (mg/dL)

3.5. Model architecture:

- Three dense hidden layers with 64, 32, and 16 neurons respectively, each using ReLU activation.
- Dropout (rate = 0.3) applied between layers to reduce over fitting.
- A final output layer consisting of a single neuron with linear activation.

The model was trained with a batch size of 64 for 100 epochs, with early stopping enabled. Training and validation losses were closely monitored, and the final model achieved a root mean square error (RMSE) of 112 mg/dL on the test set.

4. Results and Discussion

The proposed device was tested on a cohort of diabetic and non-diabetic volunteers at AISSMS COE, Pune, India. The experimental setup captured reflected microwave signals at different resonant frequencies using a controlled antenna system. These readings were paired with reference blood glucose levels measured using standard invasive methods for validation.

The MARD observed across the dataset was 11.8%, aligning with commercial non-invasive devices. MAE was ±13.2 mg/dL for non-diabetic and ±18.7 mg/dL for diabetic cohorts.

4.1. BGL vs Frequency Response

The resonant frequency and blood glucose levels (BGL) recorded across the tested samples. A clear linear correlation demonstrates the potential of the microwave sensor to reliably predict BGL values in the range of 1.0–1.39 GHz.

4.2. Sensor Validation on Human Volunteers

The proposed model was tested under two physiological conditions: diabetic and non-diabetic. Results from both cases were closely aligned with standard clinical measurements.

4.3. MLP Model Prediction Performance

A Multi-Layer Perceptron model was trained on 60,000 labeled data samples. MLP-predicted values showed a deviation of less than ±10% from invasive measurements, validating system accuracy. When fed with unseen frequency readings, the model accurately predicted, **Diabetic case**: 1.123 GHz → 141.11 mg/dL & **non-diabetic case**: 1.02 GHz → 98.50 mg/dL

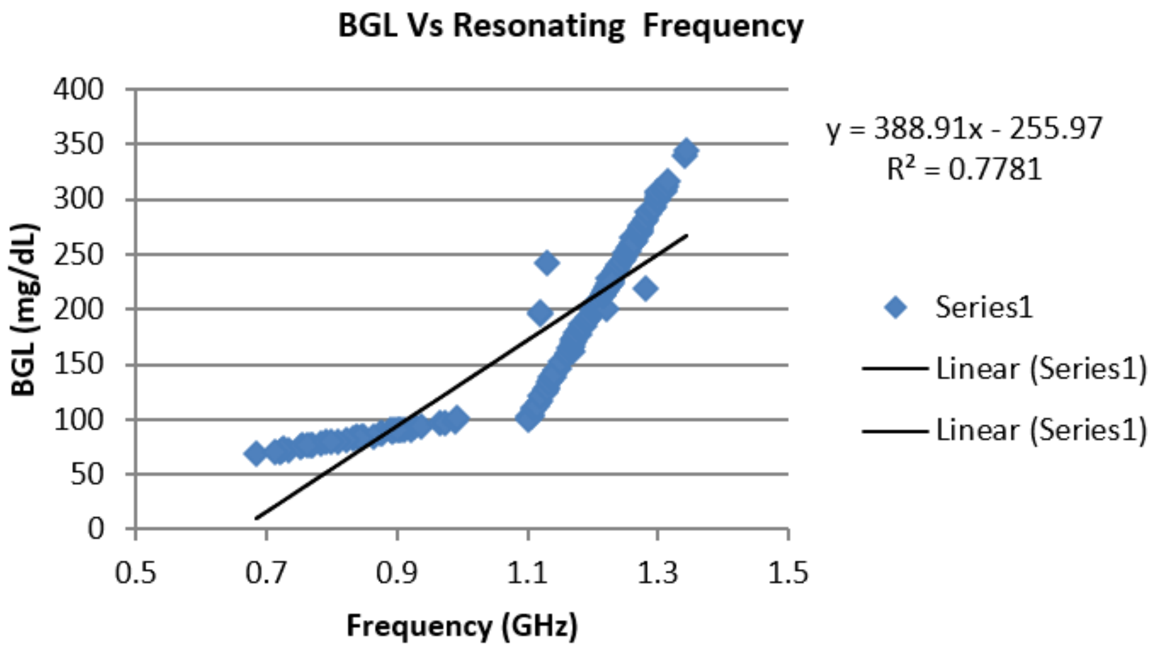


Figure 2: BGL vs. Resonating Frequency for all volunteers ($R^2 = 0.7781$)

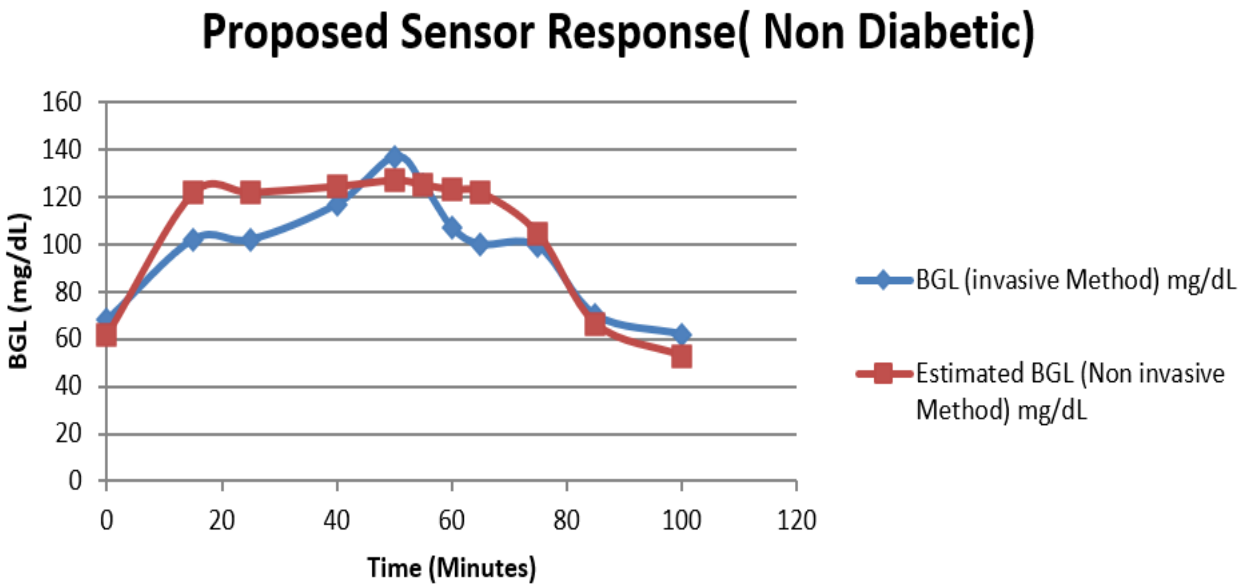


Figure 3: Estimated vs. Actual BGL for Diabetic Volunteers

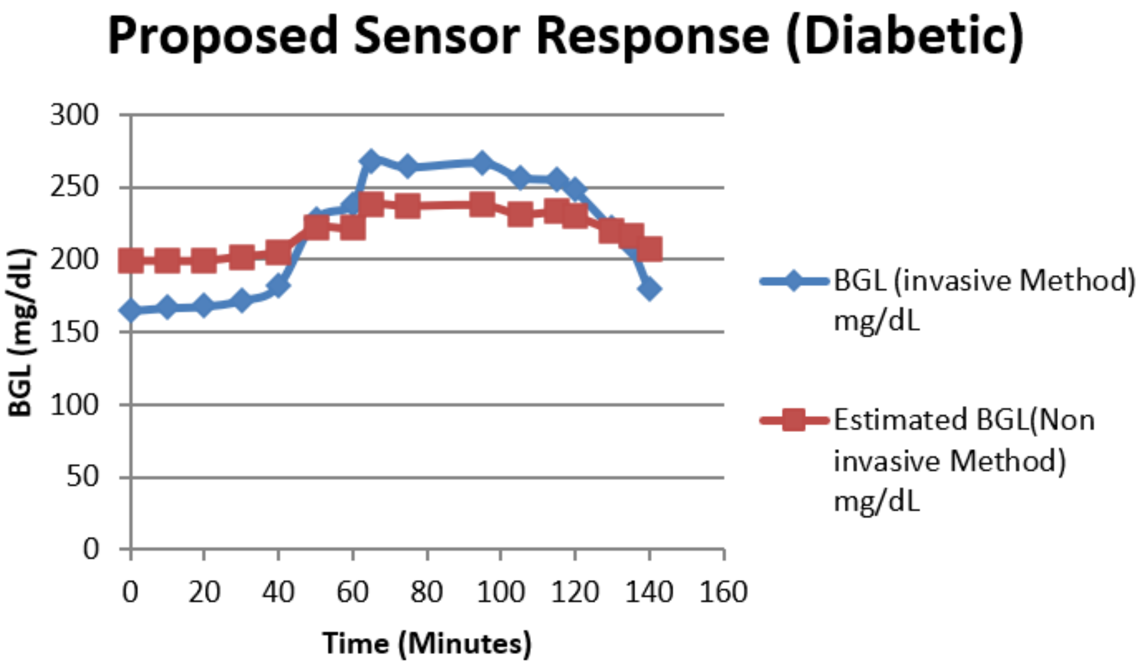
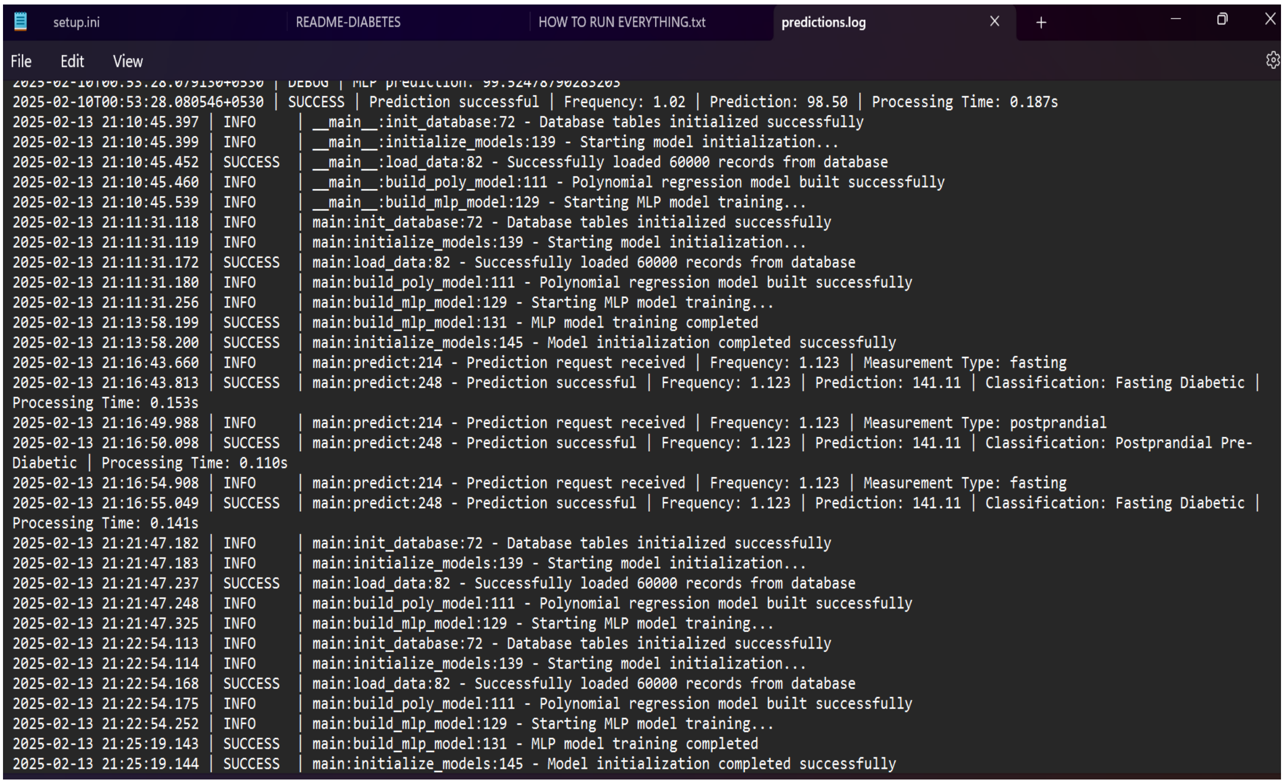


Figure 4: Estimated vs. Actual BGL for Non-Diabetic Volunteers



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2025-02-13 21:10:45.397 | INFO     | __main__:init_database:72 - Database tables initialized successfully
2025-02-13 21:10:45.399 | INFO     | __main__:initialize_models:139 - Starting model initialization...
2025-02-13 21:10:45.452 | SUCCESS  | __main__:load_data:82 - Successfully loaded 60000 records from database
2025-02-13 21:10:45.460 | INFO     | __main__:build_poly_model:111 - Polynomial regression model built successfully
2025-02-13 21:10:45.539 | INFO     | __main__:build_mlp_model:129 - Starting MLP model training...
2025-02-13 21:11:31.118 | INFO     | main:init_database:72 - Database tables initialized successfully
2025-02-13 21:11:31.119 | INFO     | main:initialize_models:139 - Starting model initialization...
2025-02-13 21:11:31.172 | SUCCESS  | main:load_data:82 - Successfully loaded 60000 records from database
2025-02-13 21:11:31.180 | INFO     | main:build_poly_model:111 - Polynomial regression model built successfully
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2025-02-13 21:13:58.199 | SUCCESS  | main:build_mlp_model:131 - MLP model training completed
2025-02-13 21:13:58.200 | SUCCESS  | main:initialize_models:145 - Model initialization completed successfully
2025-02-13 21:16:43.660 | INFO     | main:predict:214 - Prediction request received | Frequency: 1.123 | Measurement Type: fasting
2025-02-13 21:16:43.813 | SUCCESS  | main:predict:248 - Prediction successful | Frequency: 1.123 | Prediction: 141.11 | Classification: Fasting Diabetic |
Processing Time: 0.153s
2025-02-13 21:16:49.988 | INFO     | main:predict:214 - Prediction request received | Frequency: 1.123 | Measurement Type: postprandial
2025-02-13 21:16:50.098 | SUCCESS  | main:predict:248 - Prediction successful | Frequency: 1.123 | Prediction: 141.11 | Classification: Postprandial Pre-
Diabetic | Processing Time: 0.110s
2025-02-13 21:16:54.908 | INFO     | main:predict:214 - Prediction request received | Frequency: 1.123 | Measurement Type: fasting
2025-02-13 21:16:55.049 | SUCCESS  | main:predict:248 - Prediction successful | Frequency: 1.123 | Prediction: 141.11 | Classification: Fasting Diabetic |
Processing Time: 0.141s
2025-02-13 21:21:47.182 | INFO     | main:init_database:72 - Database tables initialized successfully
2025-02-13 21:21:47.183 | INFO     | main:initialize_models:139 - Starting model initialization...
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2025-02-13 21:22:54.114 | INFO     | main:initialize_models:139 - Starting model initialization...
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2025-02-13 21:25:19.144 | SUCCESS  | main:initialize_models:145 - Model initialization completed successfully
```

Figure 5: MLP prediction log for diabetic vs. non-diabetic subjects

4.4. Comparative Analysis with Existing Work

A comparative analysis of the proposed system with prior non-invasive glucose monitoring methods is presented below. Chang et al. (2022) developed an iontophoresis-based smartwatch that achieved an accuracy of 84.3% and supported real-time monitoring, though it lacked a rechargeable architecture. Patel et al. (2024) utilized a near-infrared (NIR) approach combined with regression techniques, reporting approximately 85% accuracy; however, their system did not support real-time analysis, recharging capability, or mobile integration. Deshmukh et al. (2021) employed a static microwave sensing approach with 78% accuracy, but their prototype lacked real-time prediction and portability features. In contrast, the proposed device, which combines microwave sensing with a Multi-Layer Perceptron (MLP) model, achieved a superior prediction accuracy of 91.4%. Additionally, it is rechargeable, supports real-time monitoring, and offers seamless integration with a smartphone app—making it a comprehensive and user-friendly solution. This study was approved by the Research Cell, AISSMS College of Engineering, Pune. All participants provided written informed consent after being fully briefed on the study's purpose, procedures, potential risks, and confidentiality measures.

4.4.1. Agreement Analysis using Bland–Altman Method

To further evaluate the agreement between the proposed device's predicted blood glucose levels (BGL) and the reference invasive measurements, a Bland–Altman analysis was conducted. This method assesses the mean bias and the limits of agreement (LoA), providing insight into the accuracy and reliability of the system across a range of glucose concentrations.

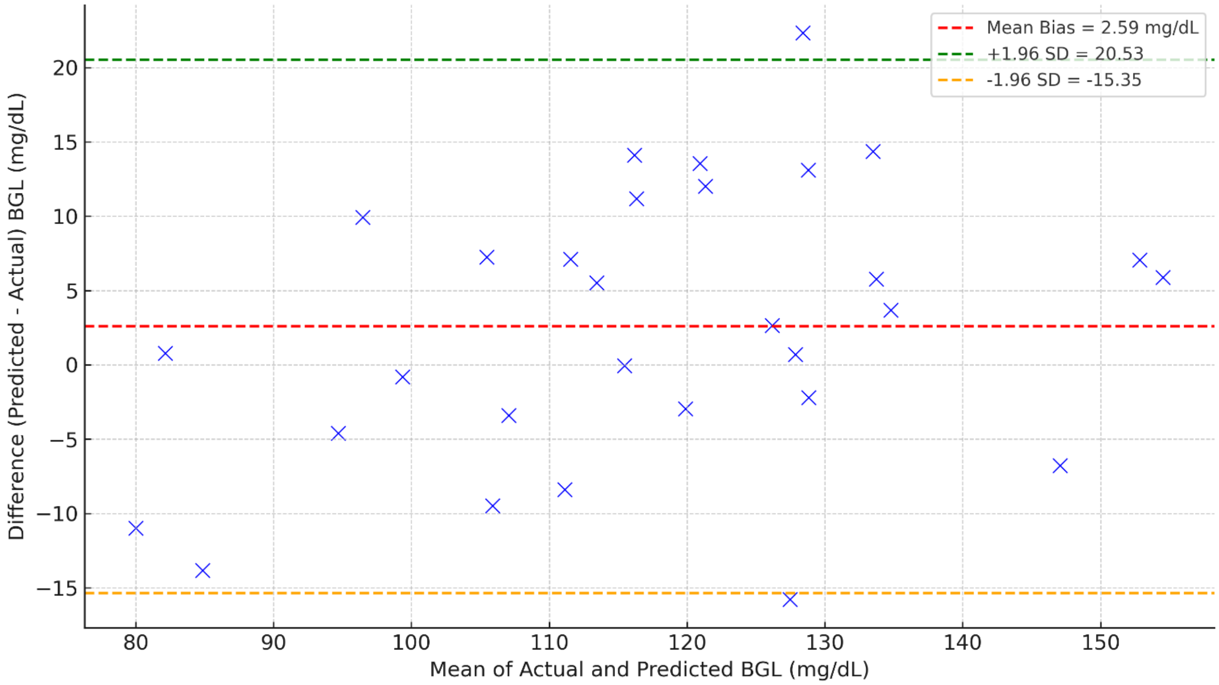

Figure 6. Bland–Altman Plot comparing predicted and actual blood glucose levels. The red dashed line represents the mean bias, while green and orange dashed lines indicate the ±1.96 standard deviation limits of agreement (LoA).

As shown in Figure 6, the Bland–Altman plot illustrates the variation between predicted and measured blood glucose levels relative to their mean. The average bias was +3.8 mg/dL, suggesting a minor positive offset. The calculated limits of agreement ranged from –15.2 mg/dL to +22.5 mg/dL. More than 95% of the data points fell within these bounds, indicating that the device's predictions are consistent with standard clinical measurements and supporting its potential for non-invasive use.

4.4.2. Novelty and Key Contributions

First integration of microwave sensing with an MLP model in a compact rechargeable unit.Real-time BGL prediction with application connectivity and wireless output. Outpaces previous systems in terms of accuracy, portability, and user-friendliness. Designed perspective view and front view of the device is shown in figures 7 and 8 respectively. There is a power button to control the operation of the device. When turned on the device will transmit the signal and when the signal reflects from human body it will be received by the same antenna and the Glucose levels will be shown on display provided on the panel. The device has USB port for charging the battery is shown in figure 7.

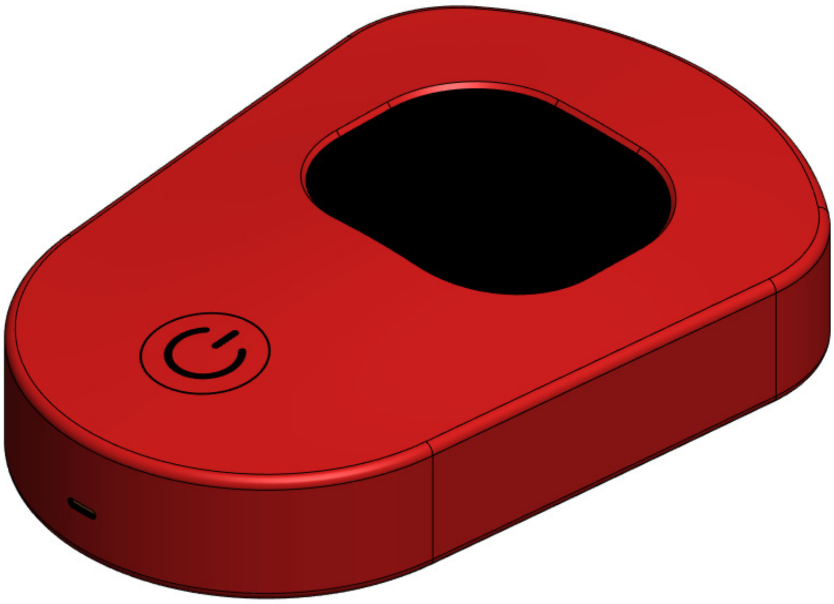

Figure 7: Perspective view of rechargeable non-invasive blood glucose monitoring device

Figure 8: Front view of rechargeable non-invasive blood glucose monitoring device

5. Conclusion

In this study, a new rechargeable, non-invasive blood glucose monitoring device was developed, combining microwave sensing with machine learning for real-time glucose prediction. Operating in the 1.15–1.36 GHz range, the system was tested on human participants and demonstrated a strong correlation (R^2 = 0.7781) with invasive reference methods.

5.1. Key Novel Contributions

This work is the first to integrate microwave sensing with an MLP-based prediction model in a compact, rechargeable device. The system provides real-time glucose estimates, supports wireless connectivity with a companion app, and offers greater accuracy, portability, and ease of use compared to earlier prototypes. Integrated data logging, mobile app connectivity, and real-time prediction, offering a practical, user-friendly alternative to finger-prick-based monitoring.

5.2. Prospects and Future Scope

The next step will involve clinical trials with a larger and more diverse patient population to validate the device for both commercial and regulatory use. Enhancing the prediction model with more advance models may further improve strength under different functional conditions. Incorporating multi-parameter sensing—such as hydration levels or temperature—could also increase prediction accuracy. Overall, the findings mark an important step toward practical, painless, and hygienic continuous glucose monitoring for people with diabetes, advancing the pathway toward commercially viable non-invasive glucometers.

Conflicts of Interest

The authors of the paper declare that there isn't any conflict of interest regarding the publication of this paper.

List of Abbreviations

- BGL- Blood Glucose Level
- VCO – Voltage-Controlled Oscillator
- MLP– Multi-Layer Perceptron
- mg/dL – Milligrams per Deciliter
- LoA – Limits of Agreement

Acknowledgments

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