University of Moratuwa

Department of Electronic and Telecommunication Engineering

Non-Invasive Glucometer Using NIR and Photoplethysmography

(GlucoPal)

Project Report

Team NeuroBytes

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Chapter 1

Introduction

1.1 Project Overview

Diabetes is a major global health issue and is rapidly becoming one of the leading causes of death. It occurs when the body fails to regulate blood glucose levels, leading to long-term complications that damage vital organs. As of 2021, over 540 million people worldwide were living with diabetes, with numbers projected to reach 783 million by 2045. Alarmingly, most of those affected live in low- and middle-income countries, where diagnosis and treatment are often delayed or inaccessible due to cost. In Sri Lanka, 20% of adults already have diabetes or pre-diabetes, with a third of cases going undiagnosed—largely due to limited screening options and growing lifestyle-related risk factors.

Traditional glucose monitoring methods are invasive and costly, making them impractical for widespread use in resource-limited settings like Sri Lanka. Continuous blood tests can be uncomfortable and unaffordable for many, especially for early detection or frequent monitoring. Our project addresses this gap by developing a non-invasive, low-cost, and user-friendly solution for diabetes detection and monitoring, aiming to improve accessibility, early diagnosis, and long-term health outcomes in communities most at risk.

Chapter 2

Literature Review

2.1 Optical Methods for Non-Invasive Glucose Monitoring

Among the various non-invasive techniques being explored, optical methods have shown promise [1]–[3]. These methods generally rely on the quantification of glucose molecules, which exhibit distinct characteristics when interacting with light at different frequencies, such as visible light, near-infrared (NIR), and ultrasonic waves [1]. While optical methods enable real-time quantitative monitoring, they have faced challenges in matching the accuracy of traditional electrochemical blood glucose meters in clinical settings [1].

2.1.1 Near-Infrared (NIR) Spectroscopy

Near-infrared spectroscopy is a promising non-invasive blood glucose monitoring technology [1], [2]. The principle involves analyzing a beam of infrared light that passes through or is reflected by human tissue to determine glucose content [1]. Glucose molecules interact with NIR light, causing absorption and scattering [1]. NIR light is particularly effective as it can penetrate body fluids and soft tissues [1]. The concentration of blood sugar can be estimated by detecting and calibrating the NIR spectrum absorption value after the light has partially absorbed while passing through human tissue [1].

Glucose molecules exhibit distinct absorption patterns in the 700–1100 nm wavelength region, which is also where most biological cells and tissues are relatively transparent [2]. Wavelengths around 780 nm and 940 nm are noted for their reaction in response to glucose concentration [2]. Specifically, 940 nm is considered a reliable wavelength for glucose detection because it has a relatively high absorption value for glucose in blood compared to other blood components and exhibits less interference from water absorption than wavelengths above 1000 nm [2]. The relationship between substance concentration and light absorption/transmittance is described by Beer-Lambert's law, where the decrease in light intensity is proportional to the concentration and path length [2]. By detecting the amount of transmitted light, the concentration can be calculated [2].

2.2 Photoplethysmography (PPG)

Photoplethysmography (PPG) is a non-invasive optical technique used to detect blood volume changes in the peripheral circulatory system [3], [4]. PPG signals can be obtained

from various body sites, such as the wrist, fingertip, or earlobe [3], [4]. The signal is generated by shining light (e.g., from LEDs at different wavelengths) into the tissue and measuring the light that is transmitted or reflected using a photodetector [4]. The amount of light absorbed or scattered varies with the pulsatile blood flow and the composition of the tissue and blood, including glucose levels [1], [2]. Glucose affects light scattering; a rise in glucose levels leads to decreased scattering and reduced total absorbed light [1].

Recent advancements in PPG technology, coupled with machine learning, have shown promise for non-invasive and economical blood glucose monitoring [4]. Studies have focused on using PPG signals from various sites, including the wrist, to estimate blood glucose levels [4].

2.3 Studies Combining NIR and PPG

Several research efforts have explored combining NIR principles with PPG for non-invasive glucose estimation. One study proposed a non-invasive blood glucose measurement system using Near Infra-Red Spectroscopy at a 940 nm wavelength [2]. This system utilizes a 940 nm IR emitter and a photodiode receiver, typically placed on a fingertip, to measure the amount of NIR radiation passing through the blood vessels [2]. The voltage output of the photodiode, which depends on the transmitted light, is correlated with blood glucose concentration [2].

A key challenge in such optical measurements is the influence of tissue thickness or width, as absorbance is directly proportional to the path length of light [2]. To compensate for variations in finger depth, one proposed method involves using an additional IR sensor to optically measure the distance between the emitter and receiver and normalize the IR absorbance readings to eliminate the effect of finger width [2].

Another approach combines dual-wavelength PPG (using 660 nm red light and 900 nm infrared light) with bioelectrical impedance measurements to estimate blood glucose [3]. The study noted that glucose has different absorption rates for different wavelengths [3].

2.4 Feature Extraction and Data Analysis

Extracting meaningful features from the acquired optical signals is crucial for accurate glucose estimation. For PPG signals, this can involve analyzing the waveform's characteristics. Statistical features such as the mean, variance, skewness, kurtosis, standard deviation, and information entropy derived from PPG signal peaks have been used [3].

Once features are extracted, machine learning algorithms are applied to build predictive models for blood glucose levels [3], [4]. Techniques explored include polynomial regression [2], Back-Propagation Neural Networks (BPNN) [3], and various gradient boosting algorithms such as CatBoost, XGBoost, LightGBM, and random forest [4]. Studies have shown that these machine learning algorithms can achieve high levels of accuracy in predicting blood glucose from PPG and other physiological signals, with performance evaluated using metrics like Pearson's r, Mean Squared Error (MSE), Mean Absolute Error (MAE), R2 score, and Clarke Error Grid Analysis (EGA) [3], [4]. Combining different types of features, such

as PPG waveform-based features and EMD-based features, can improve overall prediction accuracy [4]. The combination of dual-wavelength PPG and bioelectrical impedance features using a BPNN achieved an R2 of 0.997 and 100% of results in the clinically accurate region A of the Clarke EGA in one study [3].

2.5 Challenges

Despite significant progress, several technical bottlenecks hinder the widespread application and accuracy of non-invasive blood glucose monitoring technologies, including those based on optical methods like NIR spectroscopy and PPG [1], [3], [4]. Key challenges include:

- Weak signal detection: The signal related to glucose can be weak and requires effective amplification methods [1].
- Individual variations: Measurement accuracy is impacted by individual differences in human physiology and dynamic changes in body components [1].
- Measurement site: Identifying effective and consistent measurement sites (such as fingers or tongue tips) and developing supporting facilities for dynamic monitoring is necessary [1].
- Spectral overlap: Overlapping spectra from various tissue components make it challenging to accurately extract glucose-specific information, requiring effective extraction methods [1].
- Signal Noise and Artifacts: Motion artifacts and other noise can affect signal quality and accuracy, requiring signal processing techniques like filtering [3].
- Accuracy vs. Invasive Methods: The accuracy of current non-invasive technologies is still often not comparable to mainstream invasive methods in clinical practice [1].

Chapter 3

Feasibility

3.1 Hardware Components

Component	**Available At (Store + Link)**	**Price (LKR)**
940nm IR Emitter	Tronic LK	10
940nm IR Receiver	Tronic LK	20
ESP32 Microcontroller	Tronic LK	1340
Raspberry Pi	Tronic LK	23600**
TL084CN Operational Amplifier	Tronic LK	50
3D Printed Finger Clip	Rysera	4000*
Li-Po Battery (1200mAh, 3.7V)	Tronic LK	900
Boost Converter (XL6009)	Tronic LK	300
Charging Module (TP4056)	Tronic LK	60
OLED Display (SSD1306 128x64)	Tronic LK	540
Custom PCB (if needed)	JLCPCB (International Shipping)	6000*
	Total Cost	**36,820**

Table 3.1: Component List with Source and Estimated Price

*Prices for the PCB and 3D printing are approximate, and can be brought down when producing in bulk. Further, the PCB cost is for 5 PCBs (minimum order from JLCPCB.)

**Since the raspberry pi serves as a central server, it isn't included in the price of GlucoPal.

3.2 Software and AI Technologies

- The deep learning model is developed using Pytorch.
- It will run on Raspberry Pi, a capable edge-computing device.
- The ESP32 captures PPG signals and transmits them to the Raspberry Pi via Wi-Fi.

- The Raspberry Pi runs inference using the trained model and sends the glucose value back to the ESP32.
- The OLED Display (SSD1306) shows the result to the user.

All hardware components are either available locally in Sri Lanka or can be fabricated using local services. Additionally, if needed, the custom PCB for the sensor circuit can be ordered from international PCB manufacturing services such as JLCPCB, which offers affordable pricing and fast shipping to Sri Lanka.

The selected technologies are feasible and practical for implementing a non-invasive glucometer using current embedded hardware and machine learning platforms.

Chapter 4

Functionality

The following outlines the end-to-end functionality of the non-invasive glucometer system:

1. **Finger Placement:** The user places their finger between a custom 3D-printed clip that houses the IR emitter and receiver.
2. **PPG Signal Acquisition:** A 940nm infrared emitter and receiver detect variations in light absorption caused by blood flow, producing a photoplethysmography (PPG) waveform.
3. **Signal Conditioning:** The weak analog PPG signal is amplified and filtered using a TL084CN operational amplifier configured as an instrumentation amplifier. This enhances signal clarity by reducing noise.
4. **Microcontroller Sampling:** The conditioned analog signal is read by the ESP32 microcontroller through its analog-to-digital converter (ADC). The ESP32 then sends this data wirelessly to a Raspberry Pi over Wi-Fi.
5. **Signal Processing and Inference:** The Raspberry Pi preprocesses the received signal by filtering and segmenting it. Each segment is passed through a trained machine learning model developed using TensorFlow. The model estimates the blood glucose level for each segment, removes outliers, and computes an average value.
6. **Display Output:** The final glucose level is sent back to the ESP32, which displays it on an OLED screen (SSD1306, 128x64 resolution).

Chapter 5

Circuitry

Power Supply and Distribution

- A rechargeable 1200mAh Li-Po battery (2.7V nominal) serves as the primary power source.
- The battery is connected to both:
  - A TP4056 charging module, which enables safe USB-based charging.
  - An XL6009 boost converter, which steps up the voltage to 5V to power the main circuit.
- The 5V output from the boost converter is supplied to the PCB, which powers both the ESP32 microcontroller and the instrumentation amplifier circuit.

Main PCB Layout

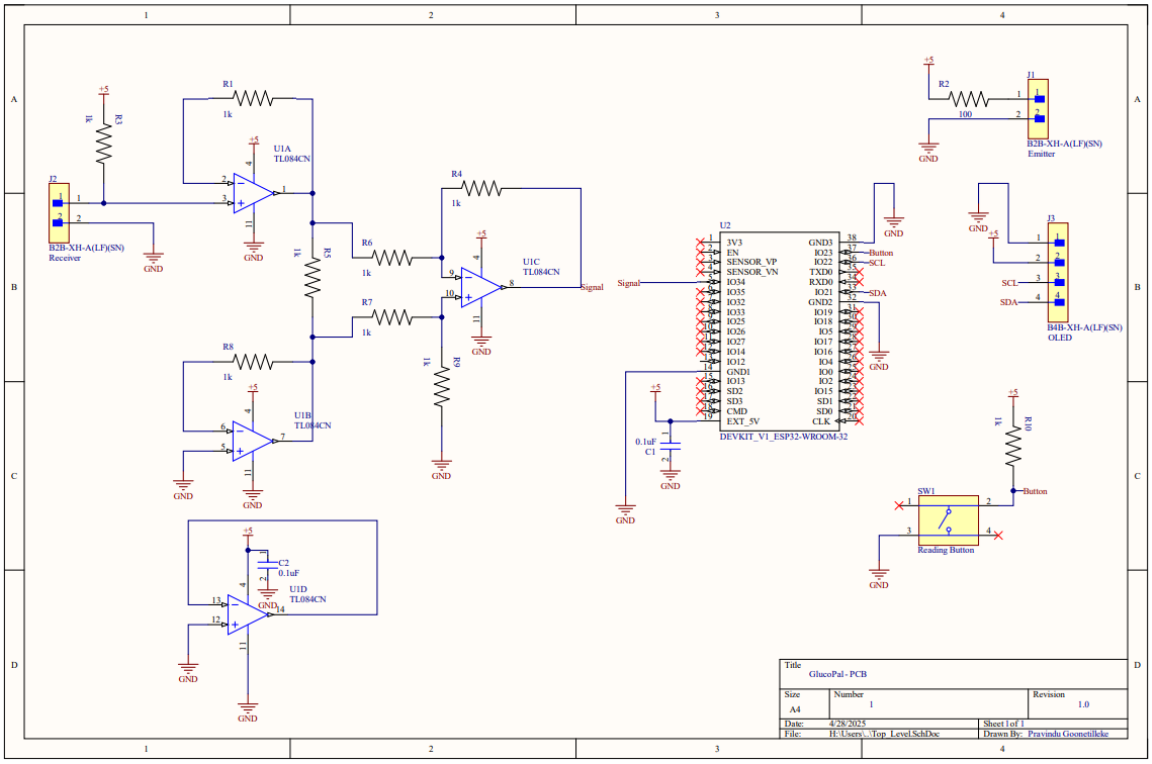


Figure 5.1: PCB schematic

- **Sensor Inputs:** JST connectors interface with the IR emitter and photodiode mounted in the finger clip.
- **Instrumentation Amplifier:** The PPG signal from the IR receiver is fed into a TL084CN-based instrumentation amplifier for amplification and noise suppression. The amplified signal is routed to the ADC pin of the ESP32.

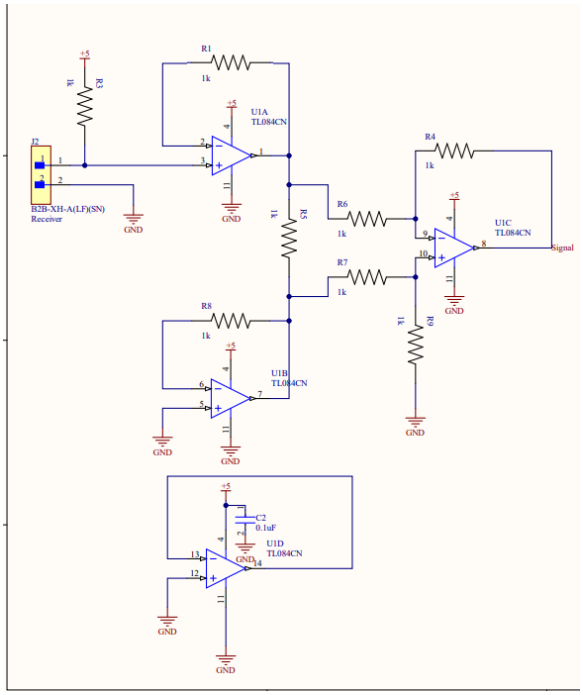


Figure 5.2: Instrumentation Amplifier

- **Microcontroller:** An ESP32 microcontroller handles signal acquisition, Wi-Fi communication, and OLED interfacing.

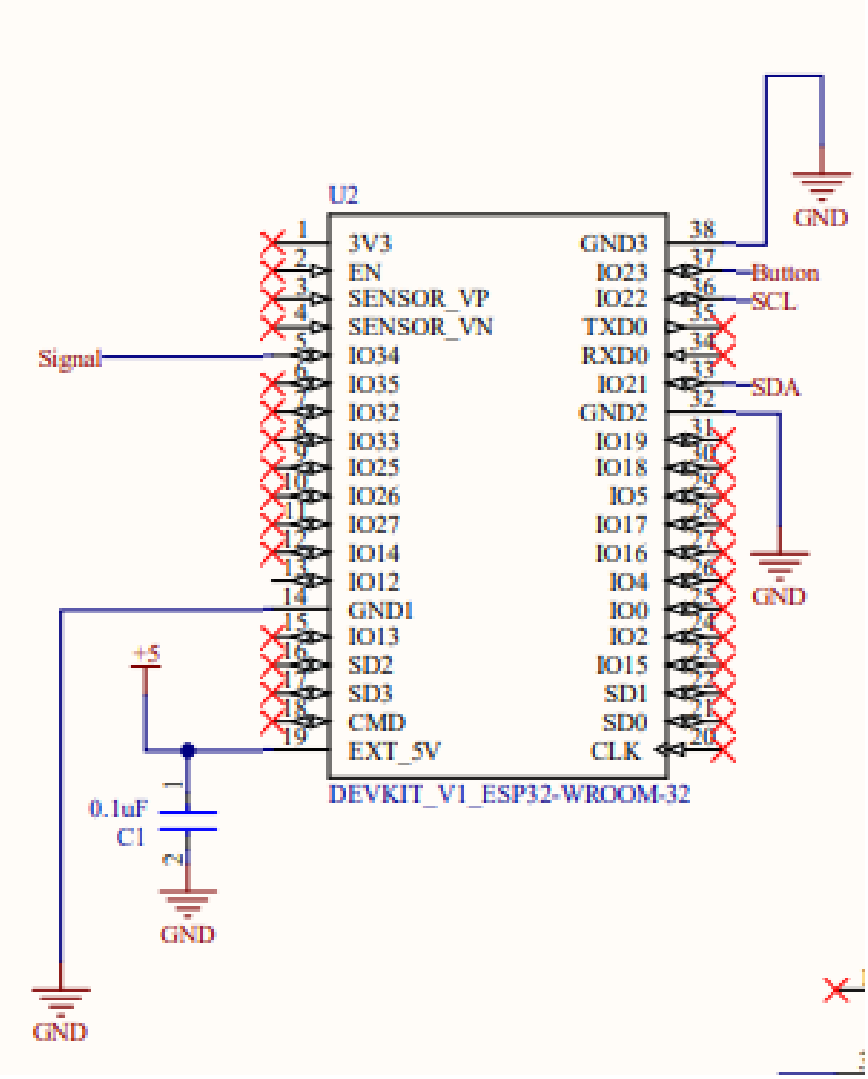


Figure 5.3: MCU : ESP32 Devkit V1

- **User Interface:** A tactile pushbutton is connected to the ESP32. When pressed, it initiates a new measurement cycle.
- **Display Interface:** A JST connector links the ESP32 to the OLED display (SSD1306, 128x64), which shows the final glucose reading.

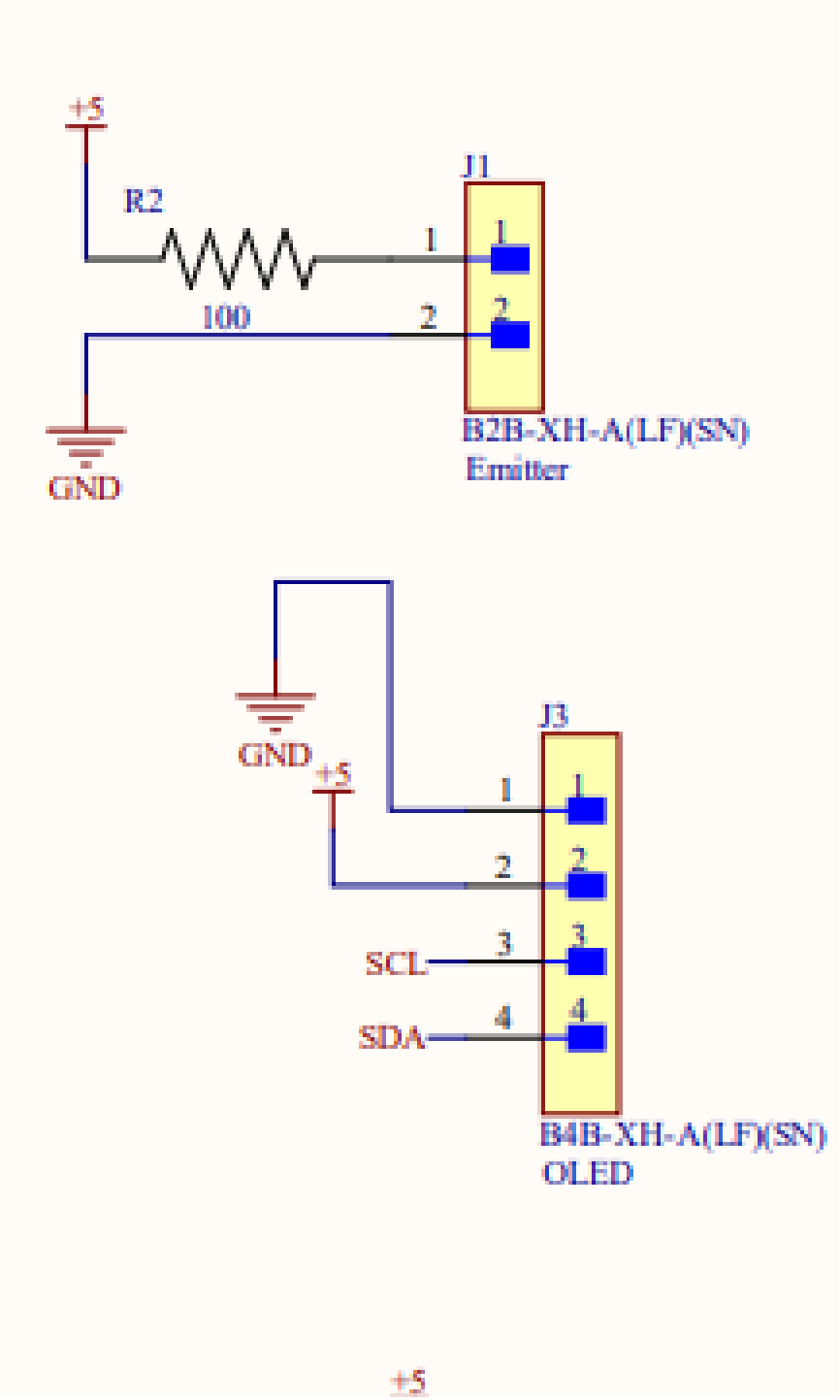


Figure 5.4: Peripherals

PCB Fabrication

The entire circuit is designed for single-board integration. The PCB can be fabricated through services like JLCPCB or similar vendors, allowing for high-quality production and

easy assembly.

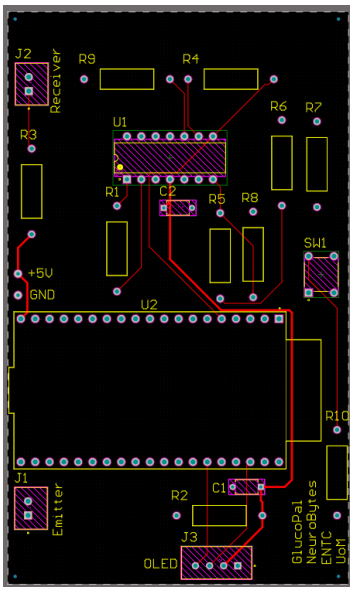


Figure 5.5: PCB Top Layer

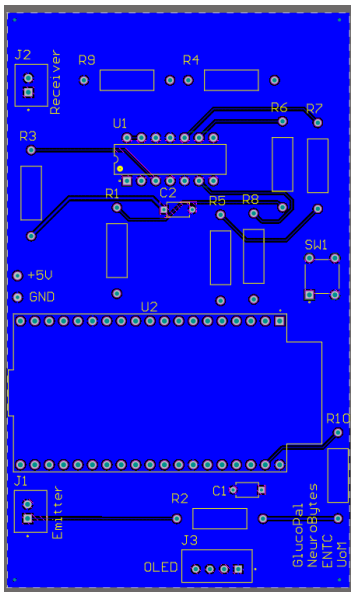


Figure 5.6: PCB Bottom Layer

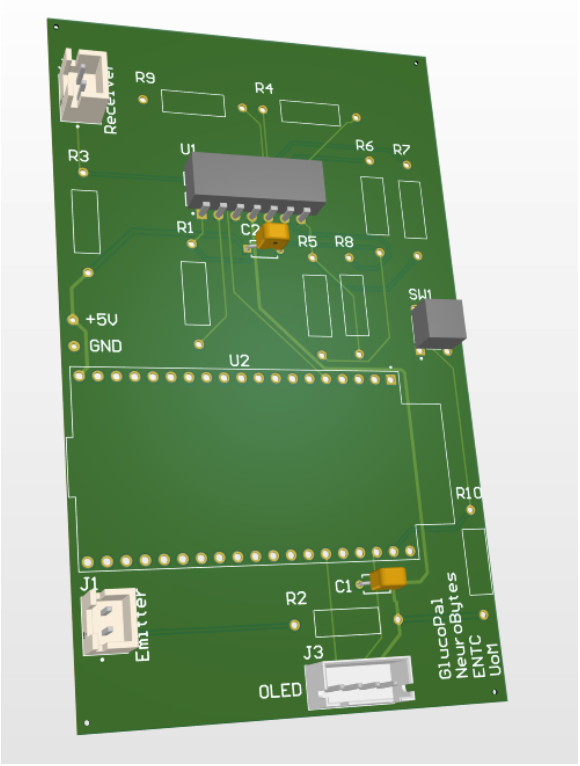


Figure 5.7: PCB 3D View

Chapter 6

Enclosure Design

The device enclosure has been custom-designed to house and support all essential components while ensuring user comfort and measurement accuracy. It consists of two interlocking parts:

- **Bottom Housing:** This section includes a groove where the user places their finger during measurement. It is also designed to securely mount the main PCB, power circuitry, OLED display, and buttons.
- **Top Cover:** This part fits snugly over the bottom housing and contains a second groove aligned with the transmitter-receiver sensor pair. It ensures proper alignment and shielding of the PPG receiver for optimal signal acquisition.

The enclosure also includes:

- A dedicated power button and a separate reading trigger button on the top surface for user interaction.
- An accessible charging port to charge the internal battery.

The design prioritizes usability, compactness, and integration, making the device portable and user-friendly for non-invasive blood glucose monitoring.

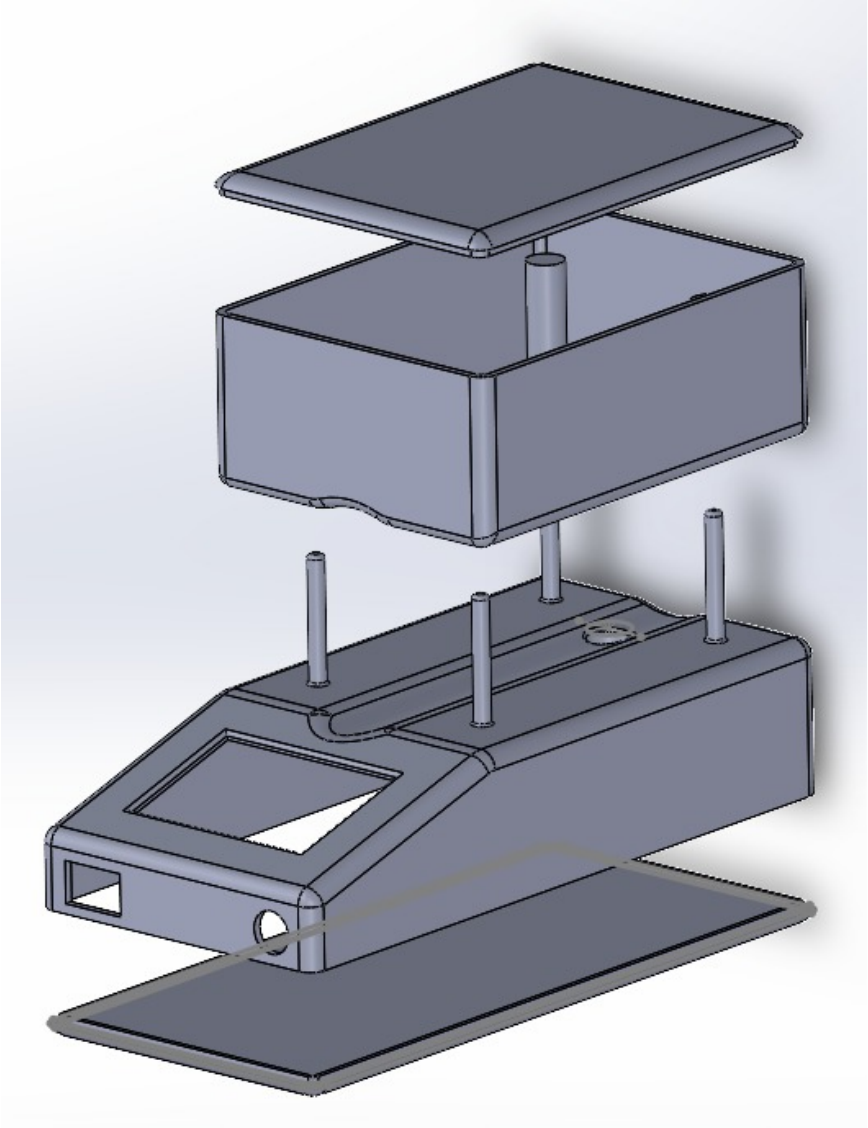


Figure 6.1: Enclosure

Chapter 7

Model Training and Results

We went through several research papers involving using PPG signals to predict the blood glucose levels.[5]. For the model building process we refereed the [5].

7.1 Dataset Description

The dataset used to train the deep learning model was collected by the Digital Systems Research Team at the University of Science and Technology of Mazandaran (MUST), Iran. [6] It contains 67 raw photoplethysmography (PPG) signals, sampled at a high frequency of 2175 Hz, from 23 individuals. Each sample is labeled with the participant's age, gender, and invasively measured blood glucose level, making it suitable for the purpose of our project.

The PPG signals were obtained using a green LED pulse sensor (550 nm) and a photodiode receiver, processed through amplification and filtering circuits, and digitized using an Atmega328 microcontroller. Blood glucose levels were measured using a standard Accu-Chek Active device. The dataset includes raw signals, corresponding labels, and signal plots. It is an open-source dataset, publicly available for research and development purposes.

7.2 Data Preprocessing

7.2.1 Downsampling

To reduce computational load and processing time, the original PPG signal, sampled at 2175 Hz, was downsampled to 100 Hz. This was done to balance between retaining essential information and reducing the dimensionality of the data. The process involved resampling the signal by interpolating between the original samples to generate a lower frequency signal, using linear interpolation. This step helps improve efficiency without significantly losing relevant signal features.

7.2.2 Signal Filtering and Normalization

- **Butterworth Filter Design:** Using the `scipy.signal` library, a third-order bandpass Butterworth filter was designed with cutoff frequencies of 0.5 Hz and 8 Hz. This configuration helps retain the physiological frequency components of the PPG signal while effectively removing low-frequency drift and high-frequency noise.

- **Zero-phase Filtering:** The filtered signal was processed using zero-phase filtering, also implemented via `scipy.signal`, to eliminate phase distortion. This approach applies the filter forward and backward, preserving the temporal structure of the signal and ensuring signal integrity.
- **Normalization:** The filtered signal was then normalized by subtracting the mean and dividing by the standard deviation. This standardization process ensures the signal has zero mean and unit variance, facilitating more efficient and stable model training.

7.3 Segmentation

To standardize the input length and improve computational efficiency, the PPG signal was divided into smaller, fixed-length segments. This was achieved by splitting the signal into consecutive windows of 1 second each, based on the sampling frequency (100 Hz). As a result, each segment contained 100 samples, enabling consistent input size for model training and better feature extraction from shorter, informative intervals.

7.4 Model Architecture: Customized ResNet34 Model

In the research paper we studied[5], three advanced deep learning models **ResNet34**, **VGG16**, and a **CNN-LSTM with Attention**—were explored for PPG signal analysis. Among these, ResNet34 demonstrated the best performance in terms of prediction accuracy and generalization ability. Therefore, we chose to implement a customized 1D ResNet architecture for training the model.

7.4.1 Framework and Libraries

The model was developed using **PyTorch**, a widely-used deep learning framework, along with modules from:

- `torch.nn` – for defining neural network layers
- `torch.nn.functional` – for activation functions and element-wise operations

7.4.2 Input and Data Flow

- **Input Shape**: The model accepts **1D PPG signal data** with a shape of $(\text{batch\_size}, 1, 100)$ where 100 corresponds to the number of time steps (or samples per PPG segment) at a 100 Hz sampling rate.
- Each segment is passed through the architecture for blood glucose level (BGL) prediction.

7.4.3 Model Structure

The architecture consists of the following layers:

- **Initial Conv1D Layer**:
  - `64 filters`, `kernel size 7`, `padding 3`

  - Followed by `BatchNorm1d` and `ReLU` activation
  - `MaxPooling1d` layer with `kernel size 3` for downsampling

- **Residual Blocks**:
  - **Layer1**: Three `ResidualBlocks` with `64 filters`.
  - **Transition Layer 1**: A `Conv1D` layer with `128 filters`, `BatchNorm1d`, and `ReLU` activation.
  - **Layer2**: Three `ResidualBlocks` with `128 filters`.
  - **Transition Layer 2**: A `Conv1D` layer with `256 filters`, `BatchNorm1d`, and `ReLU` activation.
  - **Layer3**: Three `ResidualBlocks` with `256 filters`.
- **Each ResidualBlock** consists of:
  - Two `Conv1D layers` (kernel size 3, padding 1), followed by `BatchNorm1d` and `ReLU`
  - A `skip connection` for residual learning
- **Pooling and Dense Layers**:
  - `MaxPooling1d` layer (kernel size 2) after each residual layer group for progressive downsampling.
  - `Global Average Pooling`: A global average pooling layer that reduces the dimensionality of the output to a 1D vector.
  - `Fully Connected Layer`: A dense layer with `256 units` and `ReLU` activation.
  - `Dropout Layer`: A `Dropout` layer with a dropout rate of `0.5` for regularization.
  - `Output Layer`: The final dense layer has `1 unit` with `linear activation` for regression output (predicting the blood glucose level).

7.4.4 Output

- A single continuous value representing the predicted **blood glucose level (BGL)** for the input PPG segment.

7.5 Model Evaluation and Accuracy

To assess the performance of our blood glucose prediction model, we conducted a comprehensive evaluation using both quantitative and clinical metrics. These evaluations aim to determine not only how well the model performs statistically but also how clinically acceptable its predictions are.

7.5.1 Quantitative Metrics for Predictive Accuracy

We employed two widely accepted metrics for evaluating predictive models:

- **Root Mean Squared Error (RMSE)**: RMSE provides a measure of the average magnitude of error between predicted and actual blood glucose values, expressed in mg/dL. It penalizes larger errors more heavily due to squaring of residuals:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}$$

  For our model:

$$\text{Test RMSE} = 16.42 \text{ mg/dL}$$

- **Mean Absolute Error (MAE)**: MAE quantifies the average absolute differences between predicted and actual values, treating all errors equally:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|Y_i - \hat{Y}_i|$$

  For our model:

$$\text{Test MAE} = 13.41 \text{ mg/dL}$$

These values indicate that the model achieves a relatively low prediction error, demonstrating good accuracy for practical applications.

7.5.2 Clinical Accuracy using Clarke Error Grid (CEG) Analysis

Beyond statistical evaluation, we conducted a **Clarke Error Grid (CEG)** analysis to assess the clinical significance of the model's predictions. The CEG classifies predictions into five zones:

- **Zone A**: Clinically accurate predictions.
- **Zone B**: Benign errors with no impact on clinical outcome.
- **Zone C**: Overcorrected errors leading to unnecessary treatment.
- **Zone D**: Potentially dangerous errors from missed hypo/hyperglycemia.
- **Zone E**: Critical errors with opposite treatment suggestions.

The Clarke Error Grid plot (see Figure 7.1) illustrates the distribution of predicted vs. reference glucose values across these zones. Most of the predictions fall within **Zone A** and **Zone B**, indicating high clinical acceptability. Only a few points lie in Zones C–E, suggesting minimal risk of clinically significant errors.

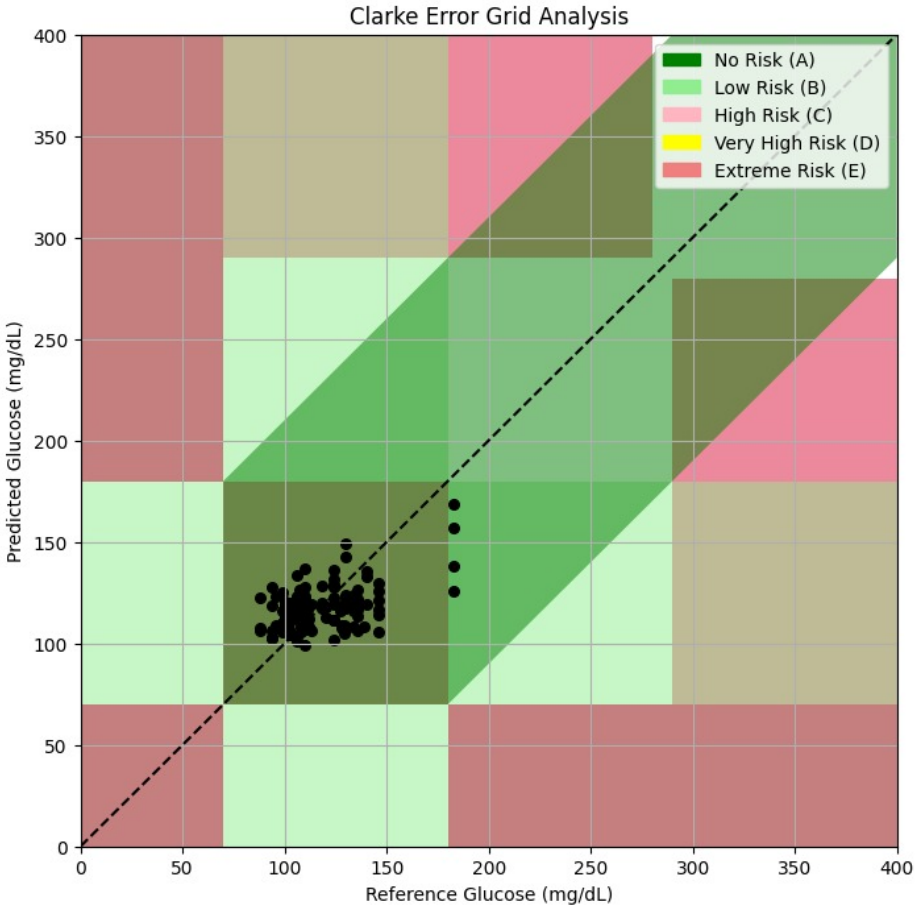


Figure 7.1: Clarke Error Grid showing the clinical accuracy of the model's glucose predictions

Chapter 8

Simulation Results

8.1 Simulation and Preliminary Inference

To simulate real-world operation and test the initial performance of our system, we collected sample PPG signals using an early prototype of our non-invasive device.

By observing the following signals, we can see how the pre-processing succeeds in removing most of the noise as well as variations due to finger motion.

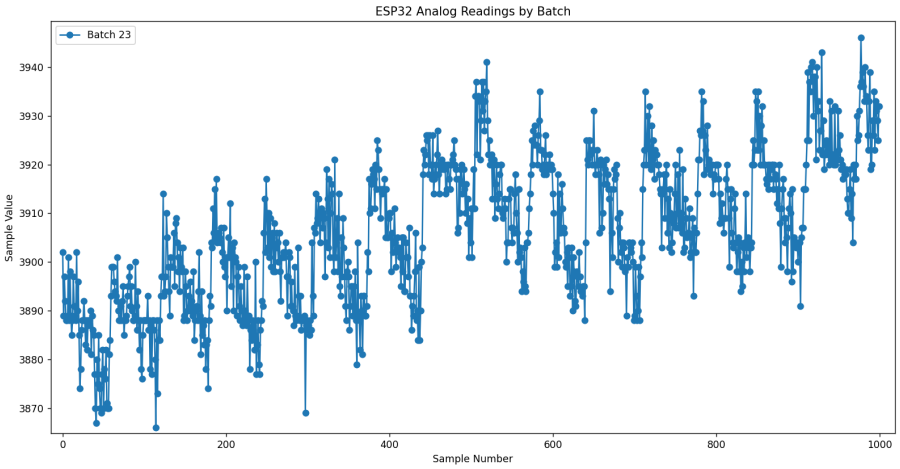


Figure 8.1: Raw PPG Output from ESP32

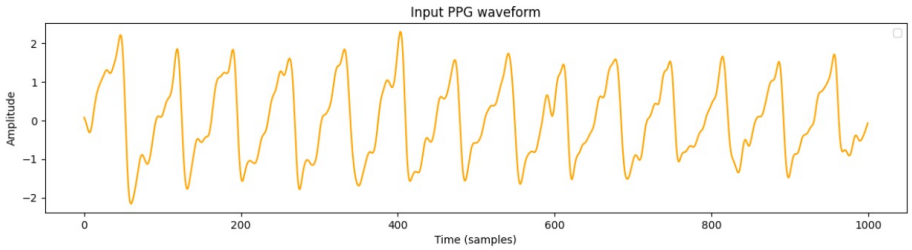


Figure 8.2: PPG After Pre-Processing

These signals were then input into the current deep learning model to perform inference and estimate the blood glucose level.

```
predictions = test_model_with_new_data(model, 'Data_9.csv')

# Print predictions
print(predictions)
```

```
tensor([136.5317, 128.7275, 108.5878, 149.0885, 121.7645, 121.2583, 106.6909,
        122.6709, 107.8643])
```

Figure 8.3: Model Inference Result on Prototype Data

As shown in Figure 8.3, the model predicted a glucose value that significantly deviated from the actual ground truth measurement of **90 mg/dL**, obtained using a standard invasive glucometer.

This error is attributed to the fact that the current model has not yet been fine-tuned using our own device's PPG data. The model was trained on publicly available datasets, which may not fully reflect the characteristics of our hardware and signal acquisition setup.

To address this, we are currently in the process of obtaining ethical approval from the **Faculty of Medicine, University of Moratuwa** to collect paired PPG and glucometer readings from volunteers. This dataset will be used to fine-tune and validate the model for improved accuracy in real-world use.

Chapter 9

Regulatory Aspects

9.1 Data Collection and Ethical Approval

To fine-tune our deep learning model for better accuracy, we are in the process of collecting a custom dataset. This dataset will include:

- **Ground Truth**: Blood glucose level readings measured using an FDA-approved invasive glucometer.
- **Input Signal**: Corresponding PPG waveforms captured using our non-invasive prototype device.

No personal or identifiable data will be collected, stored, or shared. Only the PPG waveform and matched glucose readings will be used strictly for the purpose of model training and evaluation.

To ensure that our data collection process adheres to ethical standards, we are currently seeking approval from the **Faculty of Medicine, University of Moratuwa**. This ethical review will ensure that all necessary medical and human subject research protocols are followed appropriately.

Ethics Review Committee
Faculty of Medicine
University of Moratuwa

Tel: 0112640051 Ext: 5501, 5502 email: fom-erc@uom.lk

For Office Use Only

Application No: ……/…… **Date received:** ___/___/_____

Version: ……..

Name of Applicant: (Prof/Dr/Mr/Ms) ……

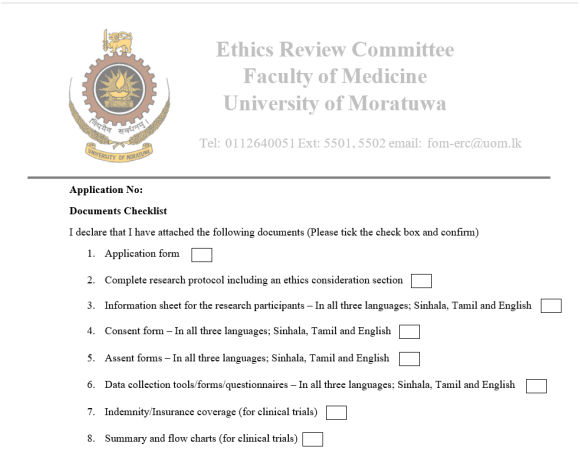
APPLICATION FORM – HUMAN RESEARCH

This form should be filled **online** and **signed** by the principal investigator who requests ethical approval for a research project involving **human subjects**. All entries should be typed and handwritten forms will not be accepted. No cages should be left blank.

The spaces in this form are expandable as you type.

Please read the **instructions to applicants carefully when completing the application** and ensure all relevant documents as per the document checklist are submitted.

Figure 9.1: Ethics Review Committee Application



Ethics Review Committee
Faculty of Medicine
University of Moratuwa

Tel: 0112640051 Ext: 5501, 5502 email: fom-erc@uom.lk

Application No:

Documents Checklist

I declare that I have attached the following documents (Please tick the check box and confirm)

1. Application form ☐
2. Complete research protocol including an ethics consideration section ☐
3. Information sheet for the research participants – In all three languages; Sinhala, Tamil and English ☐
4. Consent form – In all three languages; Sinhala, Tamil and English ☐
5. Assent forms – In all three languages; Sinhala, Tamil and English ☐
6. Data collection tools/forms/questionnaires – In all three languages; Sinhala, Tamil and English ☐
7. Indemnity/Insurance coverage (for clinical trials) ☐
8. Summary and flow charts (for clinical trials) ☐

Figure 9.2: ERC Checklist

All procedures will be conducted with full ethical considerations, and participation will be voluntary. Data will be anonymized and handled in compliance with institutional and research ethics guidelines.

The data to be collected includes:

- Blood glucose readings using a standard invasive glucometer (for ground truth).
- Corresponding PPG waveforms captured using our non-invasive device.

9.2 Intellectual Property (IP) Considerations

- The machine learning architecture used in our project is based on ResNet, a publicly available deep learning model. We do not claim ownership of the architecture itself.
- Our implementation leverages open-source libraries such as TensorFlow and PyTorch, which are used under their respective permissive licenses.
- Public datasets were used during the development phase to train and validate our model. These datasets are cited appropriately, and we do not claim IP over them.
- The trained model weights generated through our pipeline may be considered part of our IP, as they reflect specific optimizations and fine-tuning performed by our team.
- The signal processing pipeline and integration with our custom-built non-invasive PPG acquisition device represent potential IP contributions, particularly in hardware design and system integration.

We acknowledge the foundational work in the field and have cited all external sources used. Any novel contributions, particularly in device design and model integration, will be documented for potential IP protection or publication.

Chapter 10

Data Security and Privacy

Our project utilizes machine learning models trained on publicly available datasets as well as limited, anonymized data collected with the approval of the Faculty of Medicine, University of Moratuwa. The data used for fine-tuning includes photoplethysmogram (PPG) signals from our non-invasive device and corresponding blood glucose readings from a standard invasive glucometer. No personally identifiable information (PII) is collected, stored, or processed at any stage.

To ensure data security and compliance with ethical standards:

- All collected data is anonymized at the source, containing only signal values and reference glucose levels.
- No storage of user profiles, medical history, or biometric identifiers is performed.
- Data is stored temporarily in local, access-controlled systems only for the purpose of model evaluation and fine-tuning.

Chapter 11

Impact and Sustainability

11.1 Impact on the Healthcare Sector

The introduction of a non-invasive glucometer based on Near-Infrared (NIR) sensing and Photoplethysmography (PPG) has the potential to revolutionize diabetes management in Sri Lanka and beyond. The healthcare sector, particularly in developing countries, faces multiple challenges in glucose monitoring, including high costs, limited accessibility, and patient discomfort with invasive methods. GlucoPal directly addresses these issues and provides significant benefits to multiple stakeholders, including patients, healthcare providers, and the government.

11.2 Sustainability of GlucoPal

GlucoPal enhances sustainability by eliminating the dependence on disposable test strips, which contribute significantly to medical waste. Traditional glucose monitoring requires frequent pricking, leading to biohazardous waste and ongoing expenses. Our device, by utilizing Near-Infrared (NIR) technology and Photoplethysmography (PPG), removes the need for invasive procedures, reducing both environmental impact and healthcare costs. Additionally, the device is designed for long-term use with rechargeable batteries and durable components, ensuring minimal replacement needs. This approach not only minimizes medical waste but also provides a reliable, low-maintenance alternative for continuous glucose monitoring, making it a more sustainable choice for diabetes management.

Chapter 12

Limitations and Future Improvements

12.1 Limitations:

At present, the system relies on a Raspberry Pi as the main processing unit. The ESP32 microcontroller is only used for data acquisition, while model training and inference are performed on the Raspberry Pi. This design imposes several constraints:

- Increased hardware cost and overall system complexity.
- Reduced portability due to requirement of Wi-Fi connection.
- Data must be transmitted between the ESP32 and Raspberry Pi, introducing latency and raising potential data security concerns.

Further, the current machine learning model has been developed and tested on publicly available datasets, but it does not yet perform reliably when applied to data collected using our own hardware.

12.2 Future Improvements:

To address these limitations, the following enhancements are planned:

- **Model Optimization:** We aim to optimize and compress the deep learning model so that it can be deployed directly on the ESP32. This would allow the device to function as a standalone system, removing the need for a Raspberry Pi or cloud-based processing.
- **Data-Specific Fine-Tuning:** We plan to fine-tune the model using PPG and blood glucose data collected through our own hardware setup. This will improve the model's accuracy and reliability when applied to real-world use.
- **Improved Portability and Security:** Running the model on-device will result in lower power consumption, reduced production cost, and better protection of sensitive health data since no transmission to external servers will be necessary.

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