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GLUCO-AID: Blood Glucose Monitoring System using IOT-based Wearable HRV Device utilizing Fuzzy Deep Neural Networks for Smart Healthcare

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APPROVAL SHEET

This project study entitled **"GLUCO-AID: BLOOD GLUCOSE MONITORING SYSTEM USING IOT-BASED WEARABLE HRV DEVICE UTILIZING FUZZY DEEP NEURAL NETWORKS FOR SMART HEALTHCARE",** has been prepared and submitted by the following proponents:

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ABSTRACT

Continuous glucose monitoring (CGM) systems are vital for effective diabetes management. However, existing systems face limitations in accuracy and user-friendliness. To overcome these challenges, this study proposes a CGM system that integrates a Bluetooth Low Energy (BLE)-based wearable device for heart rate variability (HRV) and a fuzzy deep learning algorithm. The primary objective is to assess the feasibility and effectiveness of this novel system. A wearable device was developed, enabling continuous monitoring of glucose levels and HRV data. Patients wore the device for a minimum of 5 minutes, after which the collected data was wirelessly transmitted to a mobile application. Subsequently, a fuzzy deep learning algorithm was employed to analyze the data and generate personalized glucose predictions and recommendations. To evaluate the proposed system, a pilot study was conducted, revealing superior accuracy and reliability compared to existing CGM systems. The fuzzy deep learning algorithm achieved a Mean Square Error of 10.73 milligram per deciliter (mg/dL). The system provided personalized glucose predictions and recommendations, thereby facilitating improved diabetes management. By employing a BLE-based wearable HRV device and a fuzzy deep learning algorithm, the proposed CGM system has the potential to revolutionize diabetes management. It offers more precise and reliable glucose measurements, as well as personalized recommendations for enhanced diabetes care. The system's user-friendly interface and wireless connectivity further contribute to its convenience and practicality for continuous glucose monitoring in smart healthcare.

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"Greatness comes from small beginnings." – Sir Francis Drake

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CHAPTER 1

THE PROBLEM AND ITS BACKGROUND

In this chapter, the problem statement and its contextual background are thoroughly examined, shedding light on the current limitations and challenges in existing continuous glucose monitoring systems for diabetes management.

1.1 Introduction

A chronic medical illness called diabetes is characterized by high blood glucose levels. Reduced insulin synthesis or diminished insulin efficacy are two possible causes of the onset of disease (Makroum et al., 2022). As the main hormone in charge of regulating the uptake of glucose from the bloodstream by diverse cells, including muscle and fat cells, insulin has a critical role to play. A lack of sufficient insulin prevents the body's cells from absorbing glucose, which interferes with glucose's proper use by the cells. (Makroum et al., 2022).

Over the past two decades, there has been a considerable increase in diabetes prevalence, making it one of the health crises with the fastest rate of escalation in the twenty-first century. An astounding 463 million people worldwide, or about one in every eleven people between the ages of 20 and 79, were affected by diabetes in 2019, according to the International Diabetes Federation (IDF). The umbrella organization has issued alarming predictions indicating that by 2030, there would be 578 million people worldwide who have diabetes, and by 2045, there will be an astounding 700 million.

Additionally, diabetes refers to a class of long-term metabolic illnesses defined by high blood glucose levels. A spectrum of long-term metabolic illnesses with increased blood glucose levels where either the pancreas fails to produce enough insulin or the body fails to use it properly, resulting in this disease.

An autoimmune condition known as type 1 diabetes occurs when the immune system attacks and kills the pancreatic cells that make insulin. Contrarily, the main risk factor for type 2 diabetes is insulin resistance, which is frequently brought on by leading a sedentary lifestyle (Cvetković et al., 2016).

Blood sugar levels fluctuate and might go up or down, which is a hallmark of diabetes. It is more likely that diabetic people will experience further health problems if these levels are persistently erratic. These problems are more likely to affect people with type 1 or type 2 diabetes (Makroum et al., 2022). Additionally, there are two general groups into which chronic consequences of diabetes can be divided: microvascular problems and macrovascular complications. Nephropathy, neuropathy, and retinopathy are examples of microvascular disorders, while stroke, peripheral arterial disease (PAD), coronary heart disease (CHD), and myocardial infarction are examples of macrovascular condition (Makroum et al., 2022).

Over the past ten years, wearable sensors have become increasingly prevalent for a variety of applications. They can accurately interpret accelerometer, gyroscope, and other readily available biosensor data to monitor basic bodily functions like breathing rate, ECG, and body temperature, as well as intricate ones like types of activities and energy consumption (Cvetković et al., 2016).

Wearable sensors have significantly gained traction and grown in popularity across a wide range of applications. They make it possible to measure vital physiological processes including heart rate, ECG, and body temperature. Furthermore, these sensors can efficiently analyze data from accessible biosensors like the accelerometer and gyroscope to reveal information about more complicated features like various types of activities and energy use (Makroum et al., 2022).

Due to its capacity to create algorithms that learn from previous instances without requiring particular programming for each situation, machine learning is acknowledged as a vital component of artificial intelligence. These systems have the capability of imitating or replicating human cognitive processes and intelligence-related abilities including reasoning, problem-solving, and learning. With significant implications for healthcare, machine learning has become one of the rapidly developing areas of expertise in the realm of computers and computation (Makroum et al., 2022).

In this study, we aimed to develop a wearable watch prototype system that could monitor and predict blood glucose levels in a non-invasive way that is based on the HRV and PPG signals that would be recorded continuously. A smart wearable that comprises a wireless transmitter and a MAX30102 PPG Module would be utilized for recording the PPG. The suggested method's flow encompasses the data collecting, feature extraction, machine learning, and statistical method aspects. The suggested technique makes the proposed method understandable by assisting doctors in seeing the distinctive HRV and PPG changes that are most relevant for automated identification of low or high glucose levels in everyone.

1.2 Background of the Study

Our study aimed to develop a prototype system using a wearable watch to continuously monitor and predict blood glucose levels in a non-invasive manner. This system relies on the continuous recording of HRV and PPG signals. The PPG signals would be captured using a MAX30102 PPG Module integrated into a smart wearable device equipped with a wireless transmitter. The suggested approach involves the sequential steps of feature extraction, data collecting, machine learning, and statistical analysis. By taking this tack, the recommended approach helps medical practitioners spot specific variations in HRV and PPG that are very important for the automated identification of low or high glucose levels in people.

The ongoing global COVID-19 pandemic makes it difficult for people with diabetes to get the required care they need to adequately manage their illness. People with diabetes may experience fewer complications and have a higher chance of sustaining a normal glucose level with real-time continuous glucose monitoring, which contributes to maintaining an ideal glucose level without clinical hypoglycemia. According to Ling et al. (2016), the only practical method for achieving painless blood glucose level control and enhancing the quality of life for diabetes patients by effectively managing hypoglycemia episodes is the development of non-invasive continuous glucose monitoring systems.

The creation of a non-invasive hypoglycemia monitoring system is one area where computational intelligence technologies have been the subject of recent research. Nguyen et al. (2006) conducted an evaluation and developed a non-invasive monitor for detecting hypoglycemia based on the strong correlation between physiological indicators and hypoglycemia. Utilizing the Bayesian neural network technique, this system makes use of physiological variables like heart rate (HR), corrected QT interval (QTc), and skin impedance. This device's sensitivity was found to be appropriate, but further development must be done to enhance its particularity. More extensive neural network algorithms must still be used in testing to gain better accuracy and precision.

Consumer interaction with technology and artificial intelligence has grown significantly during the last ten years. One essential facet of the ongoing technological revolution is how customers are embracing wearable technology. According to Makroum et al. (2022), wearable devices are described as intelligent computers integrated into various accessories such as clothing, fashion accessories, smartwatches, and everyday products used by consumers. These technologies are increasingly being employed in healthcare. This is primarily attributable to the variety of sensors built into these electronic devices, including those that are capable of identifying sound, images, movements of the body, and ambient light levels.

1.3 Research Gap

According to Lekha et al. (2021), the finger prick test is considered the gold standard for accurate measurement of blood glucose levels. Although this invasive technique has a number of drawbacks despite having a high degree of accuracy for detecting diabetes. These include the discomfort of the operation, the difficulty of having to take many readings throughout the day, the repeated puncturing of the skin, the chance of transmitting infectious diseases like hepatitis and HIV, and the gradual healing of diabetic wounds. In addition, this method prevents continuous monitoring, is intrusive, uncomfortable, and expensive, and has been proven to have a detrimental impact on patients' compliance with glucose tests (Porumb et al., 2020). The development of a non-invasive device for diagnosing diabetes has been going on due to the limits of invasive approaches being acknowledged (Lekha & Suchetha, 2021). Building upon this notion, our research aims to develop a non-invasive approach for accurately measuring blood glucose levels. In our study, we intend to employ a Neural Network algorithm to analyze HRV data and predict the blood glucose level of the individual being assessed.

1.4 Research Objectives

This study aims to develop a wearable device capable of extracting HRV using sensors embedded in the device which can predict blood glucose levels. Specifically, this study aims to:

1. To develop an IoT-based wearable device capable of extracting HRV Signals utilizing Heart Rate and PPG Sensors
2. To create an HRV-based Glucose Monitoring System Algorithm utilizing predictive and classification models via Machine Learning
3. To develop a mobile application incorporating the HRV-based Glucose Monitoring System Model
4. To establish connectivity between the IoT-based wearable device to the mobile application via BLE (Bluetooth Low Energy)
5. To test and evaluate the system functionality through deploying the overall device to healthcare professionals.

1.5 Significance of the Study

The creation of non-invasive methods for diagnosing and assessing disorders is one of medicine's most promising goals. This puts forward challenges for effective technological application, sensor positioning as well as equipment advancements. (Ponciano et al., 2020).

By integrating artificial intelligence methods with contemporary technology, such as medical equipment, wearable devices, and sensor technologies, more proficient chronic illness management services may be developed and implemented. A preliminary diagnosis can now be made by robots without the presence of a human doctor because of technological breakthroughs. Mobile devices can be linked to a wide range of other technologies to build comprehensive handheld health monitoring systems. They are practical because they are lightweight, convenient and could be embedded correctly to accommodate various measurements (Ponciano et al., 2020). The DOST Harmonized National Research and Development Agenda (2017–2022)'s Section 2 on health, which focuses on establishing diagnostics for early disease detection and prediction deploying current or emerging technologies, is in line with this study's objectives. Other than that, it is consistent with Goal 3D of the Sustainable Development Goals of the United Nations, which aspires to improve the capacity of all countries, particularly poor countries, in early warning and detection of potential risks to national and international health.

The result of this study will benefit the following:

Healthcare Providers. The GLUCO-AID system gives medical professionals a useful tool for remotely and instantly determining patients' blood glucose levels. Better patient outcomes, individualized treatment plans, and prompt interventions are made possible as a result. Healthcare professionals can learn about patients' glucose trends and patterns thanks to the system's data analytics capabilities, which enables more focused interventions and modifications to treatment plans.

Healthcare System. By enabling remote monitoring and lowering the need for in-person visits, the GLUCO-AID system has the potential to lessen the load on healthcare systems. This may result in reduced costs, better resource management, and more effective healthcare delivery. Furthermore, the system's capacity to provide personalized glucose forecasts and suggestions for better disease management, thereby lowering the risk of diabetes-related complications and corresponding healthcare costs.

Patients with Diabetes. Diabetes patients now have a precise and reliable way to check their blood glucose levels thanks to the GLUCO-AID device. The system allows patients the ability to make knowledgeable decisions about their diet, medications, and lifestyle through the provision of individualized glucose predictions and suggestions. This aids in better diabetes management and overall enhancement of health outcomes.

Research Community. The study of the GLUCO-AID system contributes to the growing body of information in the fields of digital health and diabetes management. Researchers acquire substantial details about the system's potential benefits, constraints, and possibilities for enhancement by assessing its viability and efficacy. Further advances in wearable technology, predictive algorithms, and continuous glucose monitoring systems that are utilized in the management of diabetes can be guided by this understanding of the condition.

Future Researchers. Subsequent studies will create upon the findings from this research to improve and expand the functionality of the prototype and its mobile application. For the system's continued development and enhancement, it will be a beneficial source of data that will allow for further developments in its effectiveness.

1.6 Scope and Limitations

The objective of this study is to create a prototype that can predict blood glucose levels using heart rate recordings of the individual being assessed. The focus is on the prediction aspect rather than addressing underlying conditions and complications that may affect electrocardiogram results. A multi-layer perceptron model will be used in the study for predicting blood sugar levels. It is vital to remain cognizant that the results from the built system might not be entirely correct because regression has inherent limits. The study intends to provide the user accurate blood glucose metrics, nevertheless.

1.7 Definition of Terms

This comprises the terminology that were developed by the researchers and used during the entire project study to ensure accurate concept interpretation.

Bluetooth Low Energy (BLE) - In comparison to conventional Bluetooth technology, low-energy Bluetooth technology uses a lot less power and has a smaller data capacity.

Continuous Glucose Monitor (CGM) - A system that monitors and measures the user's blood glucose levels continuously, day and night, and can warn them if they fall too low or rise too high.

Electrocardiogram - This alludes to a rapid test that can be utilized for assessing your heart's rhythm and electrical activity.

Heart Rate Variability (HRV) - The change in the intervals between subsequent heartbeats is referred to as heart rate variability.

Machine Learning (ML) - Artificial intelligence is the primary subject matter of the computer science branch of machine learning. In order to examine data in a way that mimics human learning, the system employs algorithms. The goal is for the machine to improve the accuracy of its learning and produce data for the user based on that learning.

Photoplethysmogram (PPG) - This is a reference to a simple technique used to identify variations in blood volume in peripheral circulation. It is a non-invasive, economical method that involves taking surface assessments of the skin.

Smartwatch - This describes a wearable item that closely resembles a wristwatch or other type of timepiece.

CHAPTER 2

REVIEW OF RELATED LITERATURES AND STUDIES

This chapter extensively explores the issue statement and its contextual background, providing a comprehensive analysis of the current drawbacks and obstacles found in the present continuous glucose monitoring systems utilized for managing diabetes.

2.1 Diabetes

2.1.1 Diabetes and its Definition

Diabetes is a chronic health condition characterized by elevated levels of glucose in the blood. The development of diabetes can be attributed to a reduction in insulin production or a decrease in the effectiveness of insulin (Makroum et al., 2022). Insulin plays a vital role as the main hormone responsible for controlling the uptake of glucose from the blood by different cells, such as muscle and fat cells. Insufficient levels of insulin impede the absorption of glucose by the body's insulin-dependent cells, disrupting the normal utilization of glucose (Makroum et al., 2022).

The pancreas produces insulin, a vital hormone that plays a crucial role in facilitating the uptake of glucose from the bloodstream into cells. This process allows glucose to be converted into energy or stored for future use. Furthermore, insulin is essential for the metabolism of proteins and fats. However, in cases of diabetes, there is a disruption in the regulation of blood glucose levels. This results in elevated blood glucose levels, known as hyperglycemia, which can occur due to either insufficient production of insulin or the ineffective response of cells to insulin (International Diabetes Federation, 2021).

2.1.2 Type I and Type II Diabetes

Diabetes is categorized into two main types: Type 1 and Type 2 diabetes. According to the International Diabetes Federation (2021), Type 1 diabetes is caused by an autoimmune process in which the body's immune system mistakenly attacks the pancreatic beta-cells responsible for insulin production. As a result, the body produces little to no insulin. The exact mechanisms underlying this destructive process are not fully understood, but it is believed to involve a combination of genetic predisposition, involving multiple genes, and an environmental trigger, such as a viral infection. While Type 1 diabetes can develop at any age, it is more commonly diagnosed in children and young individuals. Type 1 diabetes is recognized as one of the most prevalent chronic conditions affecting pediatric patients (International Diabetes Federation, 2021).

In contrast, Type 2 diabetes is the most prevalent form of diabetes, accounting for more than 90 percent of all diabetes cases worldwide. In Type 2 diabetes, the primary cause of elevated blood glucose levels is insulin resistance, a condition in which cells do not respond adequately to insulin. As insulin resistance worsens, the effectiveness of the hormone diminishes, leading to an increased production of insulin by the body in an attempt to compensate. However, over time, the pancreatic beta cells may struggle to meet the heightened demand, resulting in insufficient insulin production (International Diabetes Federation, 2021).

2.1.3 Complications due to Diabetes

Diabetes is associated with various complications, with vascular damage being a significant long-term effect. As mentioned by D. J. D., M.D. (2020), diabetes increases the risk of cardiovascular disease by a factor of two, and approximately 75% of deaths among individuals with diabetes are attributed to coronary artery disease. Other examples of "macrovascular" conditions include stroke and peripheral vascular disease, which are also linked to diabetes.

The most common microvascular complications of diabetes involve damage to the eyes, kidneys, and nerves. In terms of eye complications, damage to the blood vessels in the retina gives rise to a condition called diabetic retinopathy, which can cause gradual vision loss and potential blindness. The kidneys can also be affected, resulting in diabetic nephropathy characterized by tissue scarring, protein loss in the urine, and the development of chronic kidney disease that may necessitate dialysis or a kidney transplant. Diabetic neuropathy, a condition of nerve damage, is another prevalent consequence of diabetes. It is associated with symptoms such as numbness, tingling, pain, and altered pain perception, which can contribute to skin injuries. Foot problems related to diabetes, such as diabetic foot ulcers, pose significant challenges in treatment and may even require amputation. Additionally, proximal diabetic neuropathy can cause painful muscle wasting and weakness (D. J. D., 2020).

2.1.4 Causes and Risk Factors of Hypo and Hyperglycemia

The development of Type 1 diabetes is influenced by multiple genes, with specific HLA genotypes playing a notable role. However, the occurrence of diabetes in individuals with a genetic predisposition can be triggered by environmental factors such as viral infections or nutritional factors. Unlike Type 2 diabetes, the onset of Type 1 diabetes is not influenced by lifestyle factors (D. J. D., 2020).

The development of Type 2 diabetes is primarily influenced by a combination of lifestyle factors and genetics. Various lifestyle factors play a crucial role in the onset of Type 2 diabetes, including obesity (typically defined by a body mass index exceeding 30), lack of physical activity, poor dietary habits, stress, and urbanization. Excessive body fat is particularly associated with the disease, accounting for 30% of cases in individuals of Chinese and Japanese descent, 60-80% of cases in those of European and African descent, and 100% of cases in Pima Indians and Pacific Islanders. It's important to note that even individuals who are not classified as obese may still exhibit a high waist-to-hip ratio, which is also associated with an increased risk of developing Type 2 diabetes (D. J. D., 2020).

Dietary factors play a significant role in influencing the risk of developing Type 2 diabetes. Excessive consumption of sugar-sweetened beverages is associated with an increased risk of disease. The types of fats consumed also play a role, as saturated fats and trans fatty acids are linked to a higher risk, while polyunsaturated and monounsaturated fats are associated with a lower risk.

Additionally, a high intake of white rice has been identified as a potential factor in increasing the risk of Type 2 diabetes. Lack of physical exercise is estimated to contribute to approximately 7% of Type 2 diabetes cases (D. J. D., 2020).

2.1.5 Treatment and Management of Hypo and Hyperglycemia

Diabetes mellitus is a chronic condition that currently has no known cure, except in specific circumstances. The primary objective of managing diabetes is to keep blood sugar levels as close to normal (euglycemia) as possible without causing hypoglycemia. This is typically achieved through a combination of dietary adjustments, regular exercise, and the use of suitable medications. For individuals with Type 1 diabetes, insulin is the mainstay of treatment. In Type 2 diabetes, oral medications are commonly used, and insulin may be required in certain cases (D. J. D., 2020).

Effective management of diabetes has a significant impact on reducing the prevalence and severity of diabetes-related complications. Therefore, it is crucial for individuals with diabetes to acquire knowledge about the condition and actively engage in their treatment. The treatment goal is to achieve a target HbA1C level of 6.5%; however, this target should not be set lower and may be adjusted higher based on individual circumstances. Additionally, attention should be given to other health issues that can exacerbate the negative effects of diabetes, such as smoking, high cholesterol, obesity, hypertension, and lack of regular exercise. The use of specialized footwear is widely recommended to prevent the risk of foot ulcers or recurrence in individuals with diabetic feet at risk. However, the effectiveness of specialized footwear remains uncertain, as the evidence is inconclusive (D. J. D., 2020).

Metformin is frequently recommended as the initial treatment choice for Type 2 diabetes due to research indicating its potential to reduce mortality. However, regular use of aspirin has not shown improved outcomes in individuals with diabetes who do not have complications. In terms of diabetes management, the use of angiotensin-converting enzyme inhibitors (ACEIs) has been proven to enhance outcomes, whereas angiotensin receptor blockers (ARBs) have minimal impact (D. J. D., 2020).

In the treatment of Type 1 diabetes, insulin analogs or a combination of conventional and NPH insulin are commonly prescribed. For Type 2 diabetes, initial insulin therapy often involves the use of a long-acting formulation, followed by the addition of oral medications. The dosage of insulin is then adjusted and increased as necessary to achieve the desired therapeutic effect (D. J. D., 2020).

2.2 Biosignals

2.2.1 Heart-Rate Variability

Heart rate variability (HRV) is a physiological occurrence that pertains to the fluctuation in the duration between successive heartbeats, a process governed by the autonomic nervous system (Gusev et al., 2020). Gusev et al. (2020) emphasized that several investigations have established a correlation between

HRV and glucose levels, suggesting that diabetes results in a progressive deterioration of autonomic activity and reduced heart rate variability.

2.3 Common Methods of Detection of Hypo- and Hyperglycemic Events

2.3.1 Finger-Prick Test

The traditional approach to glucose monitoring in hospitals worldwide typically involves transferring a blood sample onto a slide, followed by the insertion of a commercially available strip into a glucometer. Subsequently, the glucometer is utilized to examine the blood sample on the slide, and within approximately 15 seconds, the measurement for finger-prick blood is obtained. To obtain a finger-prick blood sample, a small sterile lancet is used to puncture the pulp of the fingertip. The resulting drop of blood is then placed on a commercially available glucose oxidase test strip within a self-monitoring device. After a few minutes, the measurement is obtained and documented (Chopra & Kumar, 2011).

2.3.2 Oral Glucose Tolerance Test

Andrea et al. (2001) state that the aforementioned conventional method is appropriate for large-scale studies as it offers valuable insights into insulin secretion and its effects. Nonetheless, it does not directly assess insulin sensitivity.

The utilization of the Oral Glucose Tolerance Test (OGTT) is widespread and primarily developed for the evaluation of carbohydrate tolerance. However, its measurement of plasma glucose levels and the subsequent insulin response also offers valuable information regarding pancreatic cell function, including insulin secretion and the sensitivity of body tissues to insulin. Moreover, the

OGTT is employed for the assessment of insulin resistance ("Use of the oral glucose tolerance test," n.d.).

2.3.3 Hemoglobin A1C Test

The measurement of glycated hemoglobin (HbA1c) in blood serves as an indication of an individual's average blood glucose levels over an extended period. This measurement has now emerged as the recommended standard for diabetes testing and monitoring. The formation of glycated hemoglobin is a natural process within the physiological cycle. However, when there is an elevation in average plasma glucose levels, there is a corresponding increase in the amount of glycated hemoglobin present in the plasma. Hence, the measurement of HbA1c levels offers valuable insights into long-term glucose regulation in individuals with diabetes.

Glycated hemoglobin (HbA1c) can serve as a substitute for fasting blood glucose in the diagnosis of diabetes. It plays a vital role as an indicator of long-term glycemic control, as it reflects the accumulated history of blood glucose levels over the past two to three months. HbA1c not only offers a dependable measurement of chronic hyperglycemia but also exhibits a strong correlation with the risk of long-term complications associated with diabetes. Therefore, HbA1c holds significant importance as a tool for monitoring and managing diabetes (Cleveland Clinic, n.d.).

2.4 Non-Invasive way of Detecting Hypo- and Hyperglycemic Events

2.4.1 Hypo- and Hyperglycemic Events and Associated Cardiac Changes

Individuals who exhibit different early symptoms of diabetes mellitus or meet the diagnostic criteria for diabetes are at a heightened risk of mortality caused by cardiovascular disease (CVD). Moreover, both patients with diabetes alone and those who have diabetes alongside pre-existing CVD often receive insufficient treatment for cardiovascular risk factors. Diabetes-related changes in metabolic and autonomic function, coupled with escalated inflammatory and thrombotic signaling, hinder the ability of myocardial and vascular tissues to undergo remodeling and restore themselves after injury, thereby compromising their functionality and long-term viability.

Moreover, the heightened sympathetic tone associated with diabetes has been associated with changes in cardiac and vascular function, thereby contributing to conditions like hypertension, left ventricular dysfunction, and cardiac autonomic neuropathy. These alterations create a conducive environment for the onset of arrhythmias, silent myocardial infarction, and sudden death (Nesto, 2004).

2.4.2 HRV Changes due to Diabetes

In addition to the conventional electrocardiogram (ECG), researchers have started investigating other electrocardiographic techniques to identify specific markers of myocardial damage associated with diabetes. Studies consistently report certain findings in patients without cardiovascular complications, including tachycardia (elevated heart rate), shortened QRS and QT intervals, increased QT interval dispersion, reduced amplitudes of depolarization waves, shortened activation time of the ventricular myocardium, and flattening of T waves. These changes are more pronounced in patients with cardiac autonomic neuropathy. It is important to note that these electrocardiographic alterations in diabetic patients are not exclusive to diabetes and can occur in other conditions as well. The primary cause of these changes is believed to be an increase in sympathetic nervous system activity, indirectly supported by findings related to heart rate variability in these patients (Kittnar, 2015).

2.4.3 Heart Rate Variability (HRV) Based Glucose Measurement

In individuals with diabetes, there is an early decrease in autonomic function, which progressively worsens over time. Research has demonstrated that diabetic individuals experience a faster decline in heart rate variability (HRV) measures such as SDNN (standard deviation of normal-to-normal intervals) or rMSSD (root mean square of successive differences) and a slower increase in R-R interval compared to their baseline HRV levels over a follow-up period of 9 years. However, there were no significant differences in HRV between individuals with normal fasting glucose (NFG) and impaired fasting glucose (IFG). Among nondiabetic individuals, there was a weak and approximately linear correlation between fasting glucose levels and HRV, suggesting a relatively weak relationship without a discernible threshold at 5.6 mmol/l.

2.5. Non-Invasive Glucose Monitoring and Measurement Using ECG, HRV, and Machine Learning

Gusev et al. (2020) have highlighted through numerous studies that there exists a correlation between heart rate variability (HRV) and glucose levels, indicating that diabetes results in progressive autonomic dysfunction and reduced heart rate variability. In the domain of non-invasive blood glucose (BG) monitoring and screening for prediabetes/diabetes using electrocardiogram (ECG), J. Li et al. (2021) have proposed a DBSCAN-CNN approach that combines DBSCAN (Density-Based Spatial Clustering of Applications with Noise) and CNN (Convolutional Neural Network). Their approach has demonstrated high classification accuracy rates for different glucose levels, surpassing other CNN-based methods. Cvetković et al. (2016) focused on ECG and respiration data collected from a chest harness sensor. They employed machine learning algorithms and achieved high accuracy in predicting glycaemia for both type I and type II diabetes patients. Shaqiri et al. (2020) implemented machine learning and deep learning techniques to forecast glucose levels using HRV parameters. Their model attained a high accuracy score in classifying subjects as diabetic or non-diabetic. Lipponen et al. (2011) utilized Principal Component Analysis (PCA) and ECG parameters to detect hypoglycemic events. Ling et al. (2016) utilized an extreme learning machine (ELM) for hypoglycemia monitoring in Type 1 diabetes patients, achieving satisfactory performance during testing. These studies highlight the potential of ECG-based approaches in monitoring glucose levels and detecting diabetes-related conditions.

2.6 Comparative Matrix of Related Studies that utilized ECG, HRV and Machine Learning

Table 1 Comparative Matrix of Related Studies that Utilized ECG, HRV, and ML

Title	Machine Learning Model	Methodology	Results
Non-invasive monitoring of three glucose ranges based on ECG by using DBSCAN-CNN	DBSCAN-CNN An approach of fusing density-based spatial clustering of applications with noise and convolution neural networks.	The proposed DBSCAN includes two stages: a clustering stage and a processing stage. The study made a preliminary screening for ECG waveforms, a simple and effective algorithm was presented to achieve the detection of QRS width.	Classification: 87.94% in low glucose level 69.36% in moderate glucose level 86.39% in high glucose level Sensitivity: 98.48%, (Prediabetes/Diabetes screening based on ECG) Specificity: 76.75%.
Monitoring patients with diabetes using wearable sensors: Predicting glycemia using ECG and respiration rate	Logistic Regression Result is evaluated using a 10-fold-cross validation approach. Each set of attributes was tested using ten machine-learning algorithms.	The ECG signal was processed with an ECG feature extraction algorithm that extracts 13 parameters which describe the shape of the signal.	Prediction: 84 % accuracy in predicting glycaemia for patients with type I diabetes 88 % for patients with type II Recognition: 78 % accuracy for type I 76 % for type II.
Deep Learning Method to Estimate Glucose Level from Heart Rate Variability	AutoKeras An AutoKeras architecture of three hidden layers (32, 256, and 64 neurons, respectively) with an Adam optimizer alongside a learning rate of 0.001 coupled by a Binary Cross entropy loss function.	For this particular study two main HRV parameters are selected for the preceding experiments: Standard Deviation of Normal-to-Normal intervals (SDNN) and the Root Mean Square of Successive Differences between normal heartbeats (RMSSD).	92% is the score of the study's machine learning model based on its accuracy to predict whether a subject is diabetic or non-diabetic. However, the model's F1 score is 75%.
Hypoglycemia detection based on cardiac repolarization features	Principal Component Analysis (PCA) Classification Algorithm	For a classification of hypoglycemic and normoglycemic states ECG parameters such as QTc and RT-amplitude ratio were used, and estimation of these ECG parameters was done by using advanced principal component regression method.	Results show that detection of hypoglycemic events could be made passably from 15/22 (68%) measurements.
Non-invasive hypoglycemia monitoring system using extreme learning machine for Type 1 diabetes	An ELM-based neural network. This study used an extreme learning machine (ELM) for the training of single hidden layer feedforward neural network (FFNN)	The four physiological parameters of ECG are heart rate (HR), corrected QT interval of ECG (QTc), change of heart rate (ΔHR), and change of corrected QT interval of ECG (ΔQTc).	The testing performances of the proposed algorithm for detection of hypoglycemic episodes (sensitivity is 78.00% and specificity is 60.00%) for T1DM are satisfactory

CHAPTER 3

METHODOLOGY

In this chapter, outlines the research design, data collection procedures, and analysis techniques employed in the study. This involves processes, theories, or principles behind the project to develop an approach that matches objectives.

3.1 Research Design

To implement the glucose monitoring system, the researchers will develop a neural network algorithm and employ fuzzy logic techniques. These methodologies will enable the prediction of blood glucose levels based on the output of the PPG sensor, specifically the heart rate variability (HRV) signals captured by the MAX30102 sensor.

The neural network algorithm will be designed to learn and recognize patterns within the HRV data, allowing it to make accurate predictions of blood glucose levels. Neural networks have proven to be effective in modeling complex relationships and extracting meaningful features from input data. By training the neural network with a labeled dataset containing HRV signals and corresponding blood glucose levels, the algorithm will learn the underlying patterns and correlations, enabling it to make predictions on new, unseen data.

In addition to the neural network algorithm, fuzzy logic will be employed to handle uncertainty and imprecision in the blood glucose prediction process. Fuzzy logic provides a framework for dealing with vague and uncertain information, which is common in medical data. By defining fuzzy rules and membership functions, the researchers can capture the inherent ambiguity and variability in the relationship between HRV and blood glucose levels, enhancing the accuracy and robustness of the prediction system.

The combined use of neural network algorithms and fuzzy logic techniques offers a powerful approach for developing a reliable and accurate glucose monitoring system. These methodologies enable the system to effectively analyze HRV data and provide real-time predictions of blood glucose levels, ultimately aiding in the management and control of diabetes.

To implement the proposed glucose monitoring system using the Neural Network Algorithm and Fuzzy Logic, an experimental design will be followed.

Participants will be selected for the study, consisting of individuals with varying blood glucose levels. The MAX30102 PPG sensor will be utilized to collect HRV data from the participants, which will serve as the input for the system. The collected HRV data will then undergo processing through the developed Neural Network Algorithm and Fuzzy Logic.

3.1.1. Theoretical Framework

A theoretical framework is a conceptual framework that provides a comprehensive structure for understanding and analyzing a research problem. It serves as the foundation upon which a study is built, guiding the formulation of research questions, the selection of appropriate research methods, and the interpretation of results.

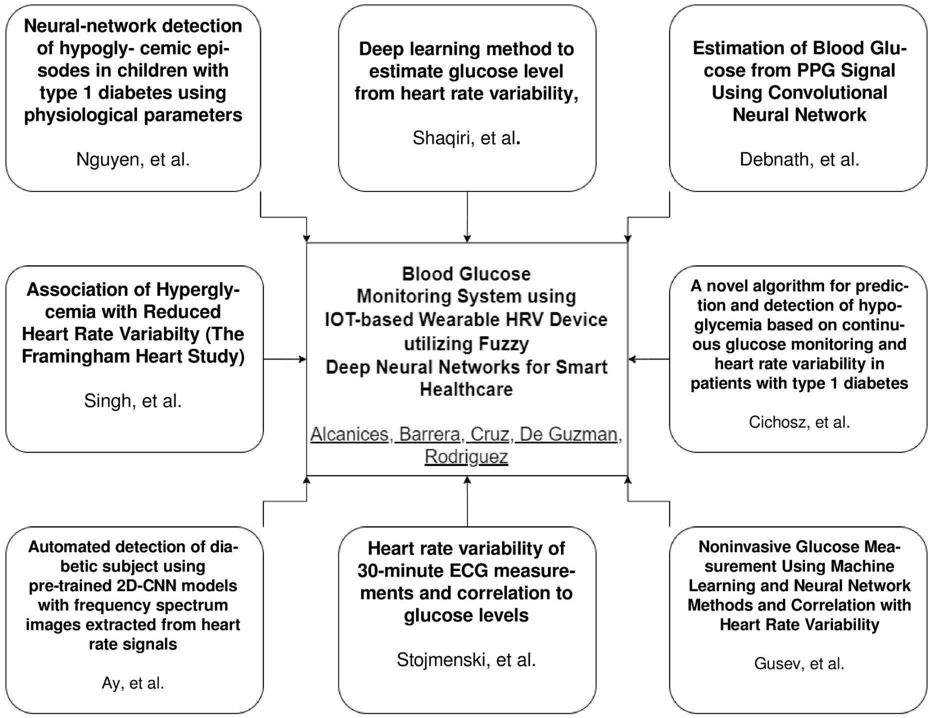

Figure 1. Theoretical Framework of the Study

The figure presented illustrates the interconnectedness of various studies that have contributed to the development of the current research study. Each study depicted in the figure has provided valuable insights, ideas, and concepts that have influenced the researchers' approach to using heart rate variability (HRV) for predicting blood glucose levels in patients.

These previous studies have explored different aspects related to HRV, blood glucose monitoring, and predictive modeling. They have examined the relationship between HRV and physiological indicators, investigated the use of HRV as a predictor for various health conditions, and explored the potential of HRV analysis in predicting blood glucose levels.

By drawing upon the findings and methodologies of these studies, the current research study has gained a solid foundation and built upon the existing body of knowledge. The insights and concepts derived from the previous studies have shaped the researchers' understanding of the potential of HRV as a predictive tool for blood glucose monitoring. They have provided a framework for formulating research questions, designing experiments, and analyzing the collected data.

Overall, the figure serves to highlight the collaborative nature of scientific research and the iterative process of building upon previous studies to advance knowledge in a particular field. The incorporation of ideas and concepts from these correlated studies has played a crucial role in shaping the current research study and has contributed to its scientific rigor and relevance.

3.1.2. Conceptual Framework

A conceptual framework is a structure that outlines the key concepts, variables, and relationships underpinning a research study. It serves as a roadmap for researchers, providing a clear understanding of the theoretical foundation and guiding the formulation of research questions and hypotheses.

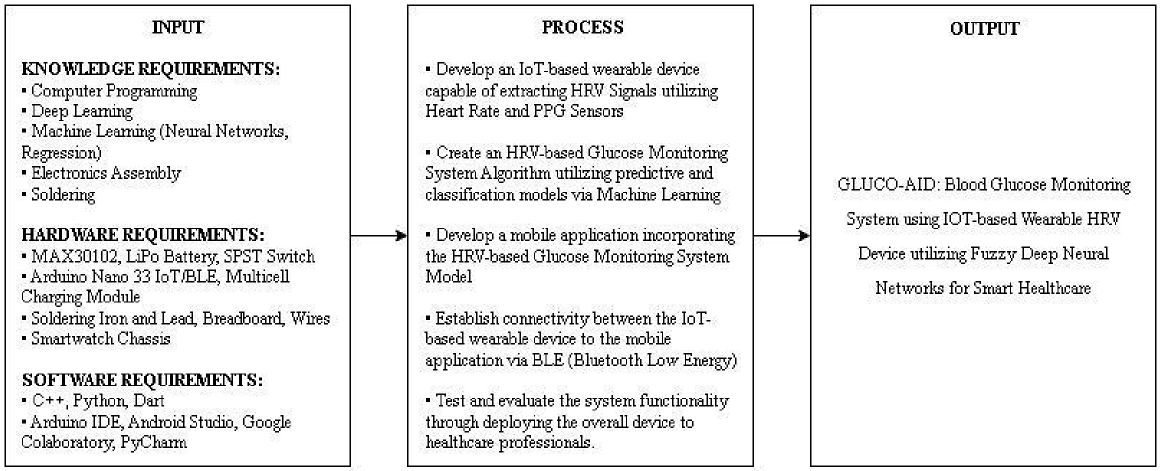

Figure 2. IPO Model of the Proposed System

In this experimental design, the glucose monitoring system will utilize HRV data captured by the PPG sensor (MAX30102) as the input. This data will encompass variations in heart rate over a specific time. The input data will then be processed through a developed Neural Network Algorithm and Fuzzy Logic. The Neural Network Algorithm will analyze patterns and correlations within the HRV data to predict the participant's blood glucose level. Meanwhile, the Fuzzy Logic component will handle uncertainties and variations in the HRV data using linguistic variables and membership functions. The output of the system will be the predicted blood glucose level, representing an estimated value based on the analysis of HRV data using the Neural Network Algorithm and Fuzzy Logic. Additionally, the system will generate statistical metrics such as accuracy, sensitivity, specificity, and error rates to evaluate its performance. A comparison will be made between the predicted blood glucose level and the actual measurements obtained from a standard blood glucose monitoring device, allowing an assessment of the system's accuracy and reliability in predicting blood glucose levels.

3.1.2.1. Block Diagram

A simplified block diagram is a visual representation that illustrates the main components and their interconnections within a system. It provides a clear and concise overview of the system's architecture and helps in understanding the flow of information or signals between different elements.

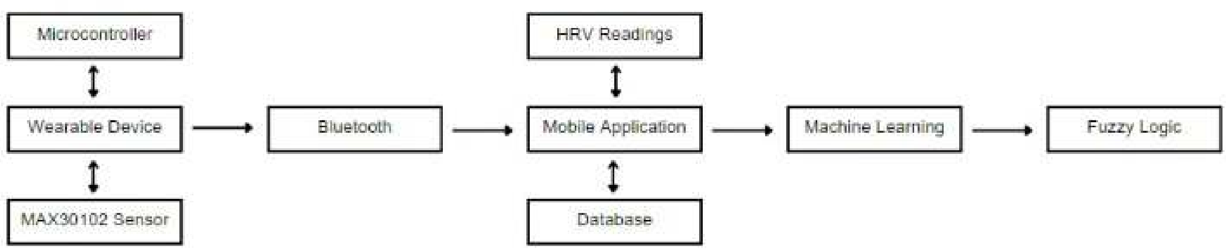

Figure 3. Simplified Block Diagram of the Proposed System

The study utilizes a simplified block diagram to illustrate the key components and their interactions in the GLUCO-AID project. The diagram showcases the flow of data and processes involved in non-invasive blood glucose monitoring.

At the center of the diagram is the smartwatch, which collects heart rate variability (HRV) signals from the user. These signals are transmitted via a Bluetooth Low Energy (BLE) network to a data processing unit, such as a smartphone or a computer.

The data processing unit applies preprocessing techniques, including bandpass filtering, to remove noise and extract relevant frequency components from the HRV signals. Feature extraction methods are then used to derive essential HRV features that capture important aspects of heart rate variability.

The pre-processed and feature extracted HRV data is fed into a neural network algorithm, specifically a multilayer perceptron (MLP), for predicting blood glucose levels. The MLP model consists of interconnected layers that perform computations and introduce non-linearity through activation functions.

To evaluate the accuracy of the predicted blood glucose levels, reference measurements are obtained from a finger-prick test using a medical-grade glucometer. Statistical analyses, such as mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE), are employed to assess the performance and reliability of the GLUCO-AID system.

The simplified block diagram provides a clear overview of the data flow and processes involved in the GLUCO-AID project, showcasing the integration of the smartwatch, BLE network, data processing, neural network algorithm, and performance evaluation. It serves as a visual representation of the system architecture, facilitating a better understanding of the non-invasive blood glucose monitoring approach employed in the study.

3.1.2.2. Network Architecture

A network architecture refers to the design and structure of a system's communication framework, outlining how different components and devices are connected and interact with each other. It provides a blueprint for organizing and managing data flow, ensuring efficient and reliable communication within the system.

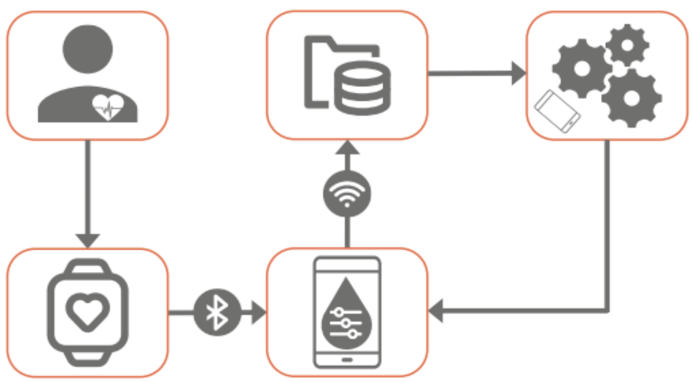

Figure 4. Network Diagram

The figure above shows the network architecture used in this project. A Bluetooth Low Energy (BLE) network architecture was utilized to establish seamless communication between the GLUCO-AID system components. BLE technology offers energy-efficient wireless connectivity, making it well-suited for wearable devices such as smartwatches.

The BLE network architecture enables the transmission of heart rate variability (HRV) signals from the smartwatch, which serves as the data source, to the data processing unit, such as a smartphone or a computer. The smartwatch, equipped with appropriate sensors, collects the necessary HRV data and securely transfers it via the BLE protocol.

The BLE network architecture provides several advantages for the GLUCO-AID system. It ensures a reliable and low-power data transmission between the smartwatch and the data processing unit, allowing for continuous and real-time monitoring of HRV signals. The energy-efficient nature of BLE technology contributes to prolonged battery life for the wearable device, enhancing user experience and reducing the need for frequent charging.

Moreover, the BLE network architecture offers a standardized and widely supported communication protocol, facilitating compatibility and interoperability between different devices and platforms. This enables seamless integration of the GLUCO-AID system with existing healthcare technologies and data processing frameworks.

It is important to note that the specific implementation details of the BLE network architecture, including the selection of BLE modules, protocols, and encryption mechanisms, were carefully chosen to ensure data security, privacy, and efficient communication. The utilization of the BLE network architecture in this study underscores its suitability for reliable and energy-efficient wireless communication, enhancing the overall functionality and usability of the GLUCO-AID system.

3.2 Materials and Equipment

The GLUCOAID System requires several essential components for its operation. First, the Arduino Nano 33 IoT serves as the core microcontroller platform for the system. It provides the necessary processing power and connectivity features for data acquisition and communication. The MAX30102 sensor is employed to capture vital physiological data, specifically heart rate variability (HRV), which is crucial for predicting blood glucose levels. The TP4056 module is utilized to charge the 3.7V Li-Polymer battery, ensuring a reliable power source for the system. To protect and house the components, a plastic enclosure is used, providing durability, and shielding from external elements. Finally, a rubber strap is included for comfortable and secure attachment of the GLUCOAID System to the user's wrist or body. Together, these components form a comprehensive and functional system that enables non-invasive glucose monitoring with convenience and accuracy.

3.3 Research Locale

The research study will be deployed in the vibrant and welcoming community of Barangay Medicion II-B, located in Imus City, Cavite. This locale was chosen due to its accessibility and the cooperation of the Barangay Officials, who have graciously allowed the researchers to conduct their study within their jurisdiction. Barangay Medicion II-B offers a diverse population, providing an opportunity to gather a representative sample of participants for the study. The community's support and willingness to participate in this research endeavor are highly appreciated and crucial for the successful implementation of the study. By conducting the study in Barangay Medicion II-B, the findings and outcomes will directly contribute to the understanding and improvement of glucose monitoring systems, benefiting both the local community and the broader scientific community.

3.4 Hardware Design

3.4.1 Schematic Diagram

A schematic diagram is a visual representation that uses standardized symbols and notations to depict the components, connections, and relationships within a system. It provides an intuitive and concise overview of the system's structure and functionality, aiding in understanding and analyzing its operation.

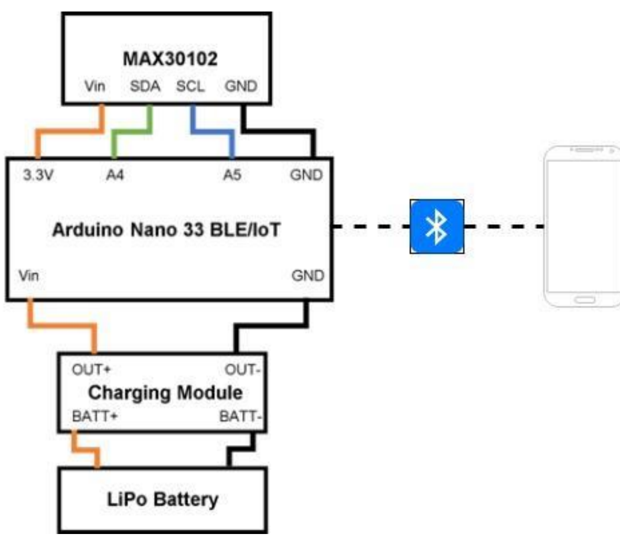

Figure 5. Schematic Diagram of the Proposed System

The schematic diagram visually represents the interconnections of various components in the smartwatch system. It shows the relationships between the sensors, microcontrollers, module, and additional equipment.

The schematic diagram highlights the wiring connections between the LiPo battery and the multi-cell charging module, ensuring safe and efficient charging. It further illustrates the power supply connection from the charging module to the Arduino Nano 33 BLE/IoT board, emphasizing the proper alignment of positive and negative terminals to prevent short circuits.

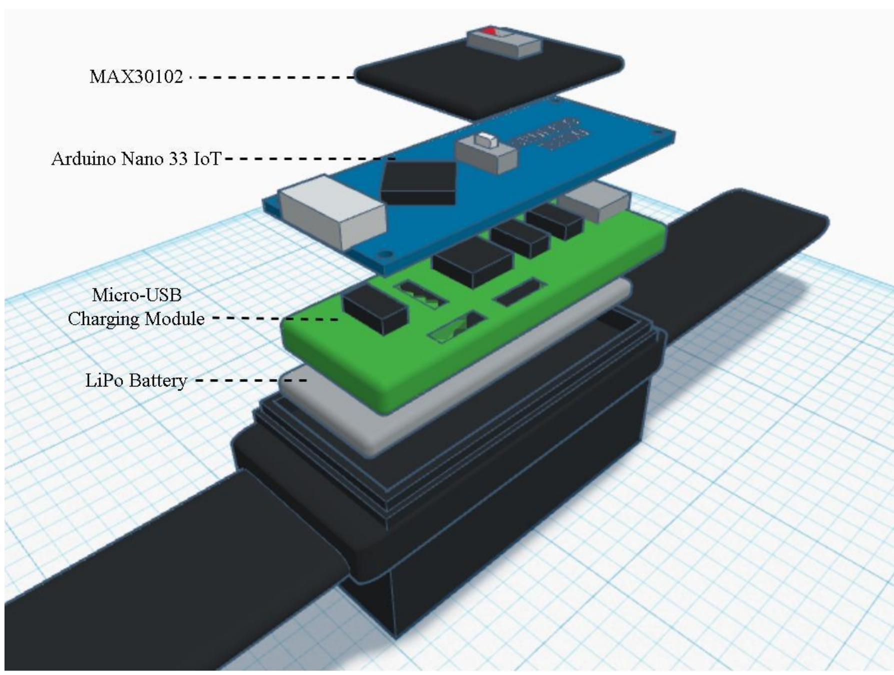

Figure 6. 3D Diagram of the Proposed System

The 3D and schematic diagram also depict the integration of the PPG sensor, such as the MAX30102, with the Arduino Nano 33 BLE/IoT. It showcases the connections between the sensor's VCC, GND, and SDA/SCL pins and the corresponding pins on the Arduino board.

Furthermore, the 3D diagram illustrates the arrangement of all assembled components within the smartwatch chassis, emphasizing secure positioning and organized wiring for a neat and compact assembly.

3.5 Software Design

3.5.1 Algorithm Selection

For the study, a neural network algorithm was chosen as the primary approach due to its ability to effectively capture complex patterns and relationships within the data. Neural networks have demonstrated strong performance in various machine learning tasks and have been extensively utilized in healthcare research, including blood glucose prediction.

The selected neural network algorithm, specifically a multilayer perceptron (MLP) model, offers flexibility in modeling nonlinear relationships between the input features and the target variable. MLPs are well-suited for regression tasks and can effectively learn from large datasets, enabling accurate prediction of blood glucose levels based on the input variables.

By employing a neural network algorithm, the study aims to leverage the model's capacity to capture intricate dependencies in the data, leading to improved prediction accuracy. The neural network's ability to adapt and learn from the training data will enable it to extract meaningful features and make reliable predictions of blood glucose levels.

The utilization of a neural network algorithm aligns with the objective of developing an accurate and robust prediction model for blood glucose monitoring. By carefully training and fine-tuning the neural network architecture, the researchers aim to optimize its performance and create a valuable tool for non-invasive blood glucose level estimation.

It is important to note that the specific architecture, hyperparameters, and training methodology of the neural network algorithm will be carefully determined and optimized through rigorous experimentation and validation. This ensures that the algorithm is tailored to the unique requirements and characteristics of the dataset used in the study, providing reliable and accurate predictions of blood glucose levels.

3.5.2 Neural Network Algorithm

This model was built to predict blood glucose levels (BGL) based on photoplethysmography (PPG) data. The model goes through several stages, including preprocessing, feature extraction, model architecture definition, and evaluation using mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE) as metrics of accuracy.

3.5.2.1 Pre-processing

Data preprocessing plays a vital role in preparing the input data for the model. For this study, a crucial preprocessing step involves applying a bandpass filter to the photoplethysmography (PPG) signals. The purpose of the bandpass filter is to eliminate undesired noise and extract the relevant frequency range necessary for heart rate variability (HRV) analysis. To achieve this, a commonly utilized low-pass cutoff frequency of 0.4 Hz and a high-pass cutoff frequency of 4 Hz are selected, aligning with established practices in HRV research. By incorporating this preprocessing function, the data is effectively prepared to enhance the accuracy and reliability of subsequent analyses, facilitating meaningful HRV interpretation.

3.5.2.2 Bandpass Filter

To implement the bandpass filter, the butter function from the scipy.signal module is utilized. A fourth-order Butterworth filter is selected for its favorable balance between frequency response characteristics and computational efficiency. This choice ensures effective filtering while optimizing computational resources.

The specific cutoff frequencies of the bandpass filter are determined by the desired frequency range for heart rate variability (HRV) analysis. By defining these cutoff frequencies, the filter effectively isolates the relevant frequencies associated with HRV, enabling accurate and meaningful analysis.

By employing the butter function from the scipy.signal module and selecting the appropriate filter order and cutoff frequencies, the bandpass filter successfully enhances the data preprocessing stage, facilitating robust HRV analysis in the research study.

3.5.2.3 Feature Extraction

Following the application of the bandpass filter, the subsequent step involves feature extraction from the preprocessed PPG signals. For this study, a set of five heart rate variability (HRV) features is selected. These features have demonstrated significant relevance in cardiovascular health assessment and offer valuable insights for predicting blood glucose levels (BGL). The chosen HRV features are as follows:

1. **SDNN (Standard Deviation of NN Intervals):** This feature quantifies the overall variability of the heart rate, providing a measure of general HRV.

2. **RMSSD (Root Mean Square of Successive Differences):** RMSSD reflects short-term variability and parasympathetic (vagal) activity, capturing variations between successive RR intervals.
3. **Mean RR Interval:** This feature represents the average heart rate over a specific time period, offering a comprehensive measure of HRV.

4. **PNN50 (Percentage of RR Intervals with Differences > 50 ms):** PNN50 indicates the proportion of adjacent RR intervals that differ by more than 50 ms, reflecting parasympathetic (vagal) modulation.
5. **TINN (Triangular Interpolation of NN Intervals):** TINN provides an estimate of the total variability of the heart rate, offering insights into the overall HRV pattern.

By incorporating these selected HRV features into the analysis, a comprehensive representation of the PPG signals is obtained, enabling effective assessment of cardiovascular health, and facilitating accurate prediction of BGL in the research study.

3.5.3 Blood Glucose Estimation

After preparing the input and output for the model, the data for each patient has been split to 80% for training and 20% for testing. The model architecture is defined below.

3.5.3.1 Model Architecture

The model architecture is based on a feedforward neural network, specifically a multilayer perceptron (MLP). It comprises five dense (fully connected) layers, each with a different number of units and activation functions. The first layer has 64 units, followed by a layer with 96 units, then 128 units, and finally a layer with 64 units. These layers introduce increasing complexity and abstraction to the model's representation. The input layer consists of 5 units, corresponding to the 5-heart rate variability (HRV) features used as inputs to the model. ReLU (Rectified Linear Unit) activation function is applied to the output of each layer, except for the final layer. ReLU introduces non-linearity, allowing the model to learn complex relationships and patterns. The final layer has a single unit without an activation function, as the task is regression-based. The objective is to predict a continuous blood glucose level (BGL) value. The mean square error (MSE) is employed as the loss function, measuring the average squared difference between the predicted and actual BGL values. For gradient optimization, the RMSprop optimizer is used, with a learning rate set to 0.001. This optimizer adjusts the model's parameters to minimize the loss function and improve performance. Considering the limited amount of data, a batch size of 1 is utilized, meaning that each training iteration processes one sample at a time. The model is trained for a total of 100 epochs, representing the number of times the entire dataset is passed through the model during training.

3.5.3.2 Choice of Metrics

The model's performance evaluation entails the utilization of three accuracy metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). These metrics are commonly employed in regression tasks to assess the model's predictive capability.

MSE serves as a measure of the average squared difference between the predicted and actual blood glucose level (BGL) values. It is computed by averaging the squared differences between predictions and actual values. A lower MSE value indicates a higher level of alignment between the model and the data. The mean squared error is given by the equation:

$$MSE = \frac{1}{N} \sum_{k=1}^{N} \left| y_{\text{target}} - y_{\text{predicted}} \right|^2$$

where y_{target} and $y_{predicted}$ are the ground truth and estimated blood glucose level for the kth element of the time sequence, respectively.

RMSE is derived from MSE and provides a measure of the root mean squared difference between the predicted and actual BGL values. It is used to quantify the standard deviation of the residuals, presenting a more comprehensible metric as it shares the same unit as the BGL values.

MAE, on the other hand, evaluates the average absolute difference between the predicted and actual BGL values. It offers insights into the overall magnitude of errors, irrespective of their direction.

By employing these metrics collectively, a holistic evaluation of the model's accuracy is obtained, capturing different facets of the prediction errors. This approach facilitates a comprehensive assessment of the model's performance.

3.5.3.3 Actual vs. Predicted Test

To graphically contrast the predicted values with the corresponding actual values, the Actual vs Predicted Test (Line Graph) was created. The model's predicted and actual values are simultaneously plotted on the same graph.

By directly comparing the predicted and actual numbers, this visual representation enables analysts to spot patterns, trends, and anomalies. The line graph gives an immediate and simple insight of how well the model's predictions match the actual data, indicating any possible strengths or areas of accuracy.

3.5.3.4 Multiple Trial Testing

Multiple trial testing is crucial for assessing and ensuring the reliability of the system. A total of 3 prediction trials were generated to ensure reliability of the proposed system. These trials were then averaged to be compared with the actual values.

This allowed the proponents to make necessary adjustments, improve reliability, and address usability issues to ensure that the system performs efficiently.

3.5.4 Blood Glucose Level and PPG Data Collection During Deployment

To validate the functionality and accuracy of the regression model, we collected PPG signals from 50 participants during real-world deployment. Simultaneously, we obtained invasive data in the form of blood glucose levels using a medical-grade glucometer known as GlucoLeader Value – Blood Glucose Meter. This glucometer, along with a lancet and disposable strip, accurately measures blood glucose levels in milligrams per deciliter (mg/dL). The PPG signals and blood glucose measurements were taken concurrently to ensure temporal alignment.

To ensure the reliability and clinical relevance of the blood glucose data, we followed a clinically recommended approach in obtaining the invasive measurements. This approach adheres to established protocols and guidelines, guaranteeing the accuracy and validity of the invasive blood glucose readings.

By collecting both PPG signals and invasive blood glucose data from the participants, we aim to comprehensively evaluate the model's performance and verify its accuracy in predicting blood glucose levels in our research study.

3.5.5 Mobile Application ("GLUCO-AID App")

The research study will employ Android Studio and Flutter to develop the user experience (UX) and user interface (UI) of the mobile application. The utilization of these software tools will enable the creation of a visually appealing and interactive application for the intended users.

In addition, Python 3 will serve as the primary programming language for the project. Python's versatility and extensive libraries make it an ideal choice for implementing the necessary algorithms and data processing tasks required for the research study.

By leveraging Android Studio, Flutter, and Python 3, the proponents aim to build a robust and efficient mobile application that meets the research objectives and provides an intuitive user experience for the target audience.

The mobile application has the following features:

1) *Blood Glucose Level in mg/dL (milligram per deciliter):* The GLUCO-AID system includes a real-time feature that enables users to view their exact blood glucose levels in milligrams per deciliter (mg/dL). This functionality provides users with immediate access to their current blood glucose readings, allowing them to monitor their glucose levels in real time. By displaying the precise blood glucose level, users can have a clear understanding of their current metabolic status. This information empowers users to make timely decisions regarding their diabetes management, such as adjusting their dietary choices, administering insulin, or seeking

medical assistance if necessary. The real-time blood glucose level feature enhances the usability and effectiveness of the GLUCO-AID system by providing users with valuable and actionable information at their fingertips. This real-time monitoring capability contributes to better self-awareness and enables proactive management of blood glucose levels, ultimately improving the overall health outcomes for individuals with diabetes.

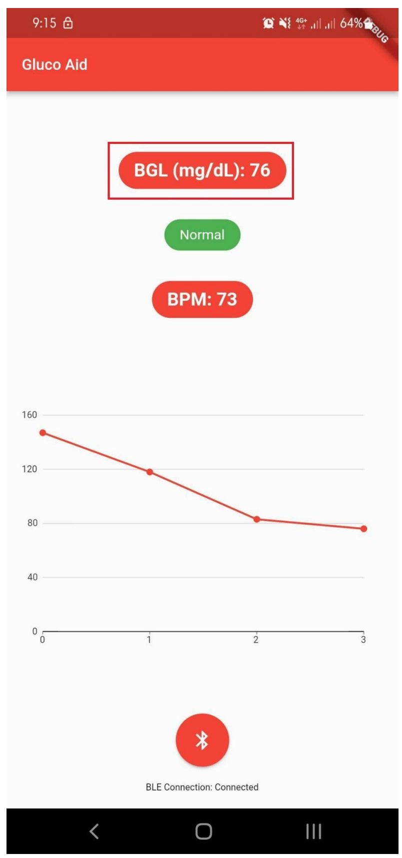

Figure 7. Display Indicator for BGL Measurement

2) *Range of the Blood Glucose Level of the User:* The system incorporates a feature that allows users to interpret their blood glucose levels as normal, low, or high. This functionality provides a user-friendly interface for individuals to easily understand and interpret their blood glucose readings. Based on the predicted blood glucose level, the system applies predefined thresholds to classify the level as normal, low, or high. These thresholds are set based on established medical guidelines and provide a context for users to assess their current blood glucose status.By presenting the blood glucose level in a clear and intuitive manner, users can quickly identify whether their levels fall within the expected range or if further action is required. This feature aims to empower users to make informed decisions regarding their dietary choices, medication management, and overall diabetes self-care. The ability to categorize blood glucose levels as normal, low, or high adds an additional layer of usability and practicality to the GLUCO-AID system, enhancing its value as a comprehensive tool for blood glucose monitoring and management.

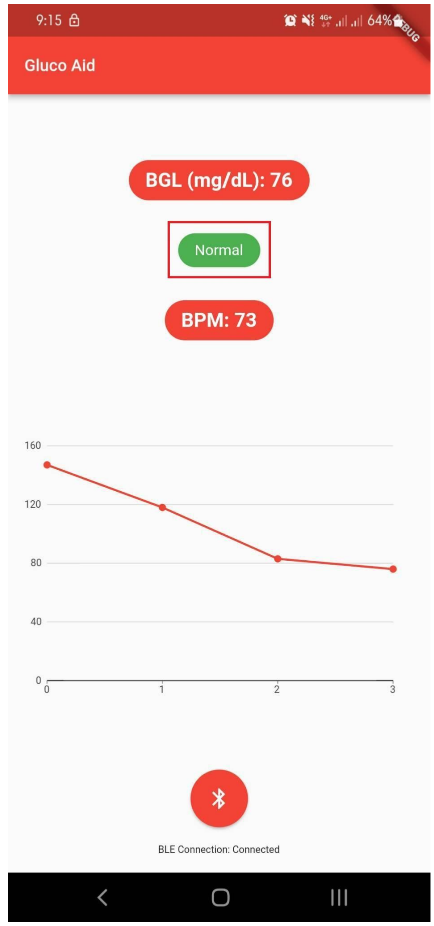

Figure 8. Display Indicator for Range of the BGL

3) *Heart Rate in beats per minute (bpm):* The GLUCO-AID system incorporates a feature that displays the user's heart rate in beats per minute (BPM). This feature provides users with real-time information about their heart rate, allowing them to monitor their cardiovascular activity. By presenting the heart rate in BPM, users can track their heart rate patterns and identify any irregularities or fluctuations. This information is particularly valuable for individuals with diabetes, as they may be at a higher risk of

cardiovascular complications. Monitoring the heart rate in real time enables users to assess their physical exertion levels, stress levels, and overall cardiovascular health. It can also serve as an indicator of the body's response to different activities, such as exercise or stress. The inclusion of the heart rate feature in the GLUCO-AID system enhances its functionality and provides users with a comprehensive tool for monitoring both their blood glucose levels and heart rate. By having access to this vital information, individuals can make informed decisions about their lifestyle choices and take appropriate steps to maintain their overall well-being.

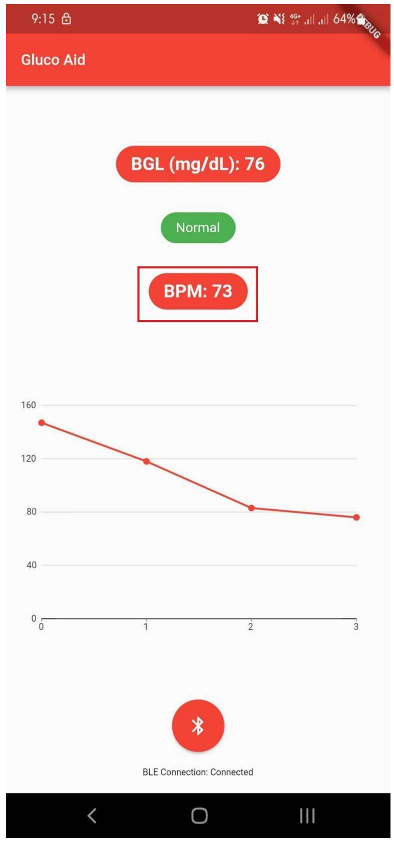

Figure 9. Display Icon for Heart Rate in Beats per Minute

4) *Graphical Representation of Previous BGL Readings in mg/dL:* The GLUCO-AID system includes a graphical representation feature that displays the user's previous blood glucose readings in milligrams per deciliter (mg/dL). This feature provides users with a visual representation of their blood glucose trends over time, allowing them to observe patterns and changes in their glucose levels. By plotting the previous BGL readings on a graph, users can easily track their blood glucose fluctuations and identify any recurring patterns or trends. This graphical representation offers a

convenient way to monitor and analyze the effectiveness of their diabetes management strategies, such as medication adjustments or lifestyle modifications. The visual display of previous BGL readings in mg/dL facilitates a deeper understanding of the user's glucose control and helps them make informed decisions about their diabetes self-care. It serves as a valuable tool for healthcare professionals as well, as they can assess the effectiveness of treatment plans and provide personalized recommendations based on the trends observed in the graphical representation. The graphical representation of previous BGL readings enhances the usability of the GLUCO-AID system by providing users with a comprehensive and intuitive visualization of their glucose levels. This feature empowers individuals with diabetes to proactively manage their condition and make informed decisions to maintain stable blood glucose control.

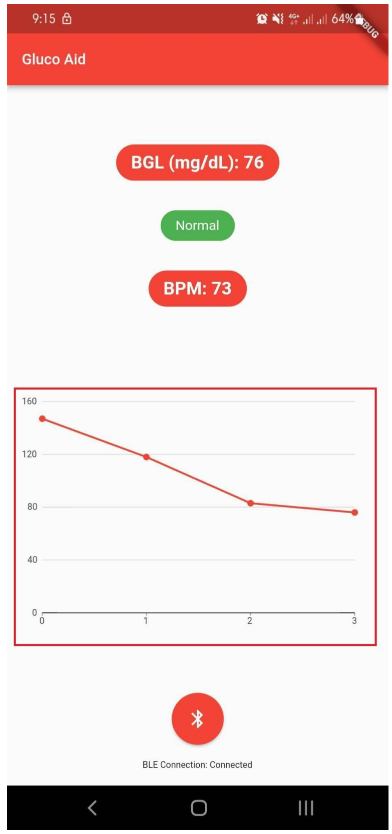

Figure 10. Display Icon for Graphical Representation of Previous BGL Readings in mg/dL

5) *BLE Connectivity Button:* The GLUCO-AID system is equipped with a BLE (Bluetooth Low Energy) connectivity button feature. This button enables users to establish a wireless connection between the GLUCO-AID device and other compatible devices, such as smartphones or tablets. By activating the BLE connectivity button, users can easily pair their GLUCO-AID device with the mobile application. This seamless wireless connection allows for convenient data transfer and synchronization between the device and external devices, facilitating real-time monitoring and analysis

of blood glucose levels. The BLE connectivity button enhances the user experience by eliminating the need for cumbersome cables or physical connections.

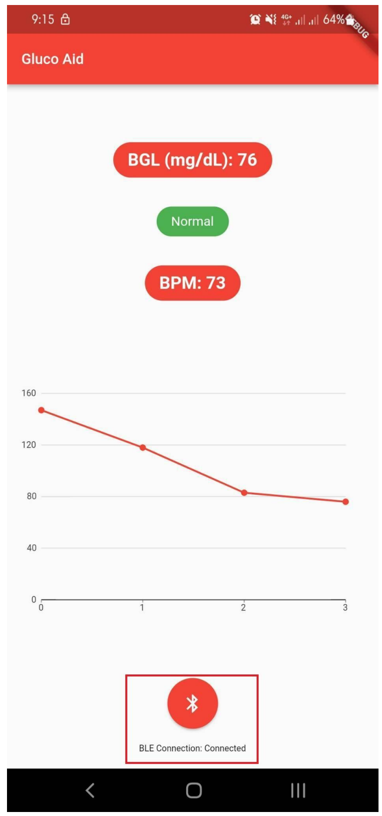

Figure 11. Display Icon for BLE Connectivity Button

3.5.6 Program Flowchart

A flowchart is a graphical representation that depicts the sequence of steps or activities within a system or process. It utilizes standardized symbols and arrows to illustrate the flow of information, decision points, and actions involved in achieving a specific objective. Flowcharts serve as a visual tool for understanding and analyzing system logic and process workflows.

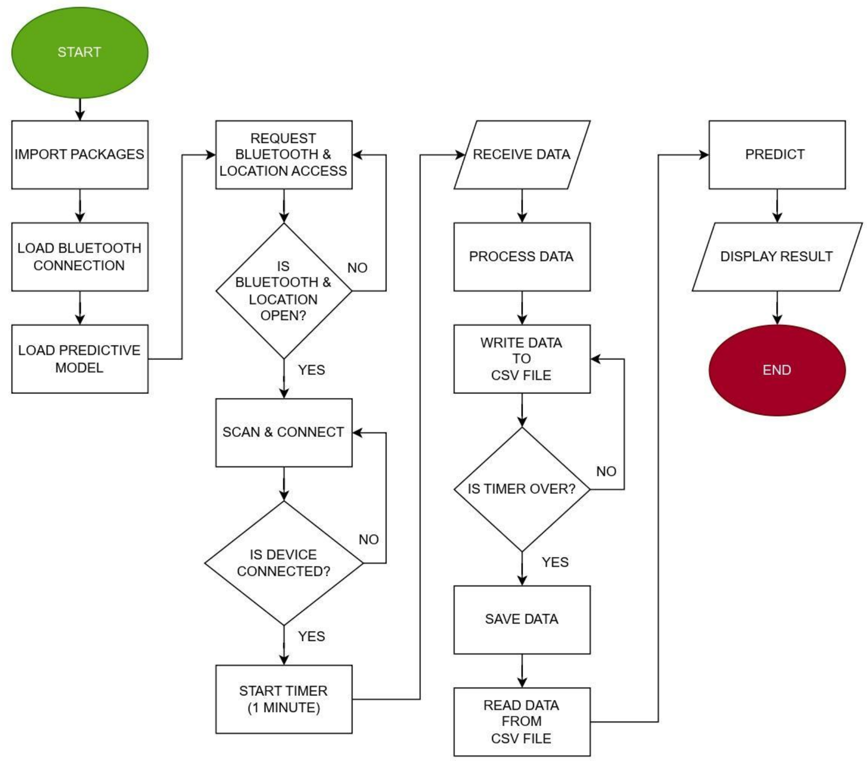

Figure 12. Gluco-Aid Application Flowchart

The figure presents the flowchart that outlines the steps and interactions within the GLUCO-AID mobile application. It illustrates the sequence of operations, starting from the user launching the application on their mobile device. The flowchart showcases the various functionalities of the application, including data input, real-time monitoring, prediction display, and user feedback.

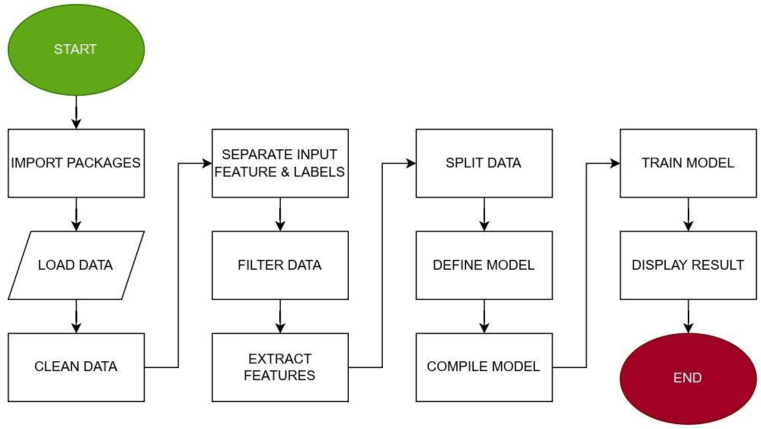

Figure 13. Machine Learning Flowchart

This figure represents the flowchart that outlines the step-by-step process of the machine learning model used in the GLUCO-AID system. The flowchart demonstrates the sequence of operations, starting from data preprocessing, feature extraction, model training, and prediction generation. It provides a clear visualization of the algorithmic steps involved in the model's functioning and highlights the decision-making process leading to accurate blood glucose level predictions.

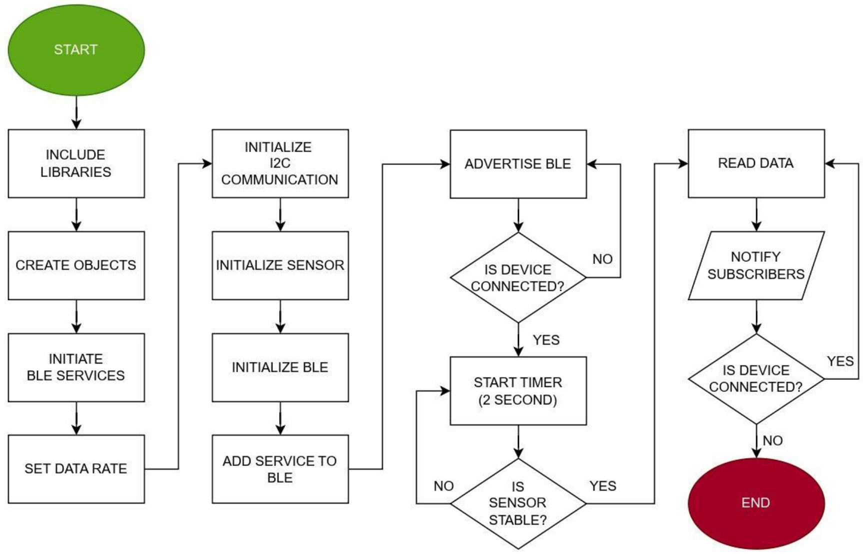

Figure 14. Gluco-Aid Smartwatch Flowchart

The figure displays the flowchart that illustrates the functionalities and interactions within the GLUCO-AID smartwatch. It depicts the sequential steps involved in data collection, sensor integration, signal processing, and transmission to the mobile application. The flowchart provides a visual representation of the smartwatch's operation and its integral role in facilitating real-time monitoring of heart rate variability and subsequent blood glucose level prediction.

3.6 Testing Procedure

Once the GLUCOAID system prototype is developed, it will undergo meticulous calibration, testing, and verification procedures to ensure its suitability for long-term usage. The functionality of the prototype will be thoroughly assessed, and all necessary documentation for deployment will be obtained. During the testing phase, participants will be requested to wear the GLUCOAID device for a minimum of 5 minutes. Following this, a healthcare professional will perform a finger-prick test to obtain actual blood glucose measurements. By comparing the predictions generated by the GLUCOAID device with the finger-prick test results, a comprehensive evaluation of its accuracy and reliability will be conducted. To examine any significant differences between the two methods, a multivariate statistical analysis will be employed. This analysis aims to assess the statistical significance across multiple variables, comparing the predictions generated by the GLUCOAID system with the corresponding finger-prick test results. The multivariate statistical analysis will provide valuable insights into the consistency and validity of the GLUCOAID system's measurements when compared to the established finger-prick method. This comprehensive approach allows for a thorough evaluation of the performance and accuracy of the GLUCOAID system across multiple dimensions, enabling a more robust assessment of its effectiveness in predicting blood glucose levels. Through this rigorous calibration, testing, and verification process, along with the t-test statistical analysis, the study aims to demonstrate the effectiveness and reliability of the GLUCOAID system in accurately predicting blood glucose levels. These findings will contribute to the advancement of a non-invasive and efficient glucose monitoring technique, potentially benefiting individuals with diabetes and healthcare professionals in managing the condition. The system has been deployed with 50 test subjects.

3.7 Statistical Analysis

Statistical analysis is the process of collecting and analyzing data to identify patterns and trends. It is a scientific method for extracting useful information from data.

For this study, a Likert scale was used. The Likert scale is a psychometric scale commonly used in questionnaires and surveys to measure a person's attitude, belief, or opinion towards a particular concept. It is a type of ordinal scale, meaning that the ratings can be ranked from least to most favorable.

Descriptive statistics are used to summarize and describe data. They can be used to calculate measures of central tendency (mean, median, mode). For this study, we will be using the mean value for each criterion and their total mean value. Mean ($\bar{x}$) is the average of a set of data. It is calculated by adding all the values in a set and then dividing them by the number of values.

$$\overline{x} = \frac{\sum_{i=1}^{N} x_i}{N}$$

3.8 Technical Evaluation

The technical evaluation of the GLUCO-AID system was conducted on 50 participants after testing. The technical evaluation form is focused on four criteria: effectiveness, efficiency, freedom from risk, and context coverage. This evaluation followed participant testing, gathering valuable feedback.

Five Criteria:

Effectiveness: This criterion evaluates how well the GLUCO-AID system performs its intended function of monitoring and managing blood glucose levels. It assesses the accuracy, reliability, and precision of the system in providing glucose measurements and predictions.

Efficiency: The efficiency criterion examines the system's ability to deliver accurate and timely results with optimal resource utilization. It assesses factors such as computational speed, energy consumption, and data transmission efficiency to ensure the system operates efficiently without unnecessary delays or resource waste.

Satisfaction: This criterion focuses on the satisfaction of the users on the results of the prediction and monitoring system and the experience of using the system.

Freedom from Risk: This criterion focuses on identifying and mitigating potential risks associated with the GLUCO-AID system. It considers aspects such as data security, privacy protection, and system robustness to ensure user safety and the integrity of sensitive health information.

Context Coverage: Context coverage assesses the system's ability to adapt and function effectively in various user contexts and scenarios. It examines factors such as user interface design, usability, and compatibility with different devices and platforms to ensure seamless integration into the user's daily routine.

Review of Participant Testing: The task-assignment phase of participant testing, which involved having users interact with the system, was extensively examined. During this time, user opinions and observations were gathered.

Analysis of Evaluation Findings: By analyzing each criterion's strengths and flaws, the evaluation results were analyzed. The evaluation mostly relied on the observations and participant responses.

Actionable Recommendations: Based on the evaluation, detailed and useful recommendations were created to solve found flaws and enhance the technical performance of the system.

Documentation of Evaluation Report: A thorough evaluation report was written, summarizing the conclusions, suggestions, and supporting data. The evaluation process, major findings, and the reasoning behind the recommendations were all clearly described in the report's narrative.

Sharing of Findings and Recommendations: The evaluation report was distributed to the appropriate parties, highlighting the need to address the noted technical issues to improve the functionality and applicability of the system.

3.9 Project Work Plan

The proponents would follow the project timeline based on the Gantt chart below:

Table 2: Project Timeline Indicating Milestones

★ - INDICATES PROJECT MILESTONE

	JUN 2022	JUL 2022	AUG 2022	SEPT 2022	OCT 2022	NOV 2022	DEC 2022	JAN 2023	FEB 2023	MAR 2023	APR 2023	MAY 2023	JUN 2023
Objective 0: Research and Design of the Project Plan								★					
Objective 1: Hardware Development									★				
Objective 2: Software Development													★
Objective 3: Training and Validation													★
Objective 4: Implementation and Deployment													★

CHAPTER 4

RESULTS AND DISCUSSION

This chapter presents the information of gathered data and analysis of the results based on the tests conducted.

4.1 Project Technical Description

The project titled "GLUCO-AID: Blood Glucose Monitoring System using IoT-wearable Device and Deep Learning Algorithms for Smart Healthcare" aims to develop a non-invasive continuous blood glucose monitoring system. This system utilizes Internet of Things (IoT) technology and Deep Learning Algorithms to predict blood glucose levels based on Heart Rate Variability (HRV) signals obtained from a heart rate sensor.

The prediction system consists of two main components: regression and feature extraction. The regression component leverages deep learning algorithms to perform accurate and reliable blood glucose level predictions. By analyzing the HRV signals, the system can infer the corresponding blood glucose levels, providing valuable insights for individuals managing their diabetes.

Additionally, the feature extraction component focuses on extracting relevant features from the HRV signals. These features serve as inputs to deep learning algorithms, aiding in the prediction process. By carefully selecting and extracting meaningful features, the system enhances the accuracy and robustness of the blood glucose predictions.

The integration of IoT technology allows for seamless data transmission and remote monitoring. Wearable devices equipped with the necessary sensors collect the HRV signals, which are then processed and analyzed by deep learning algorithms. This IoT-based approach ensures real-time and continuous blood glucose monitoring, empowering individuals with diabetes to proactively manage their condition.

Overall, the GLUCO-AID project combines IoT, wearable devices, and deep learning algorithms to create a reliable and non-invasive blood glucose monitoring system. By utilizing HRV signals and advanced prediction techniques, this system holds great potential to improve the quality of life for individuals with diabetes, enabling them to make informed decisions about their health and well-being.

4.2 Project Organizational Structure

4.2.1 Raw PPG Dataset with Corresponding Blood Glucose Level in .csv

The raw PPG dataset, along with the corresponding blood glucose level data, was obtained from Ms. Bidya Debnath. The dataset is stored in a .csv file format, allowing for easy access and analysis. This dataset serves as the foundation for training and evaluating the GLUCO-AID blood glucose monitoring system. The dataset contains a collection of PPG signals captured from individuals, synchronized with their respective blood glucose level measurements. These data points provide valuable information for developing and testing the prediction algorithms within the GLUCO-AID system. By leveraging this dataset, researchers and developers can explore the relationship between PPG signals and blood glucose levels. This exploration enables the system to learn and make accurate predictions based on the collected data. Ms. Bidya Debnath's contribution of the raw PPG dataset significantly contributes to the advancement of the GLUCO-AID project. The availability of this dataset facilitates the development of a robust and reliable blood glucose monitoring system, offering potential benefits for individuals with diabetes in managing their condition effectively.

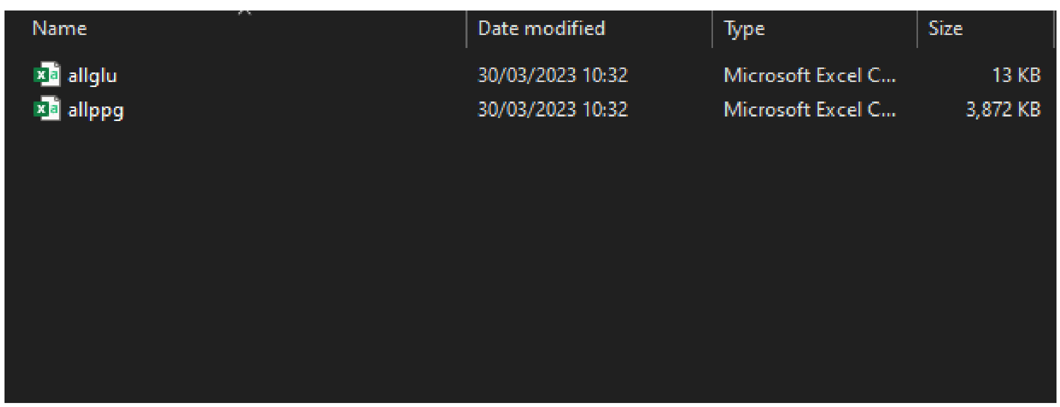

Figure 15. CSV File Names of the Training and Testing Data

4.2.2 Devices Used in Deployment

The mobile application developed for the GLUCO-AID project serves as a user-friendly interface that can be accessed on any mobile device. This application provides a seamless and intuitive experience for users to interact with the GLUCO-AID system.

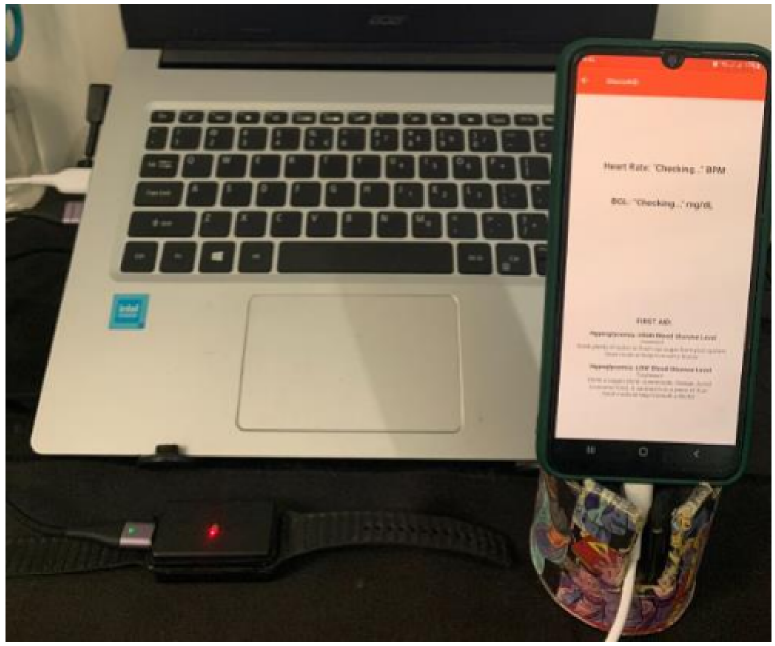

Figure 16. Researcher’s Own Laptop and Mobile Phone used in Deployment.

To ensure accessibility for participants who may not have their own mobile devices, the researchers utilized their personal mobile phones for the deployment of the mobile application. This approach ensures that participants can still benefit from the system and contribute to the study, regardless of their device availability.

By leveraging the researchers' mobile phones, the deployment process becomes more inclusive and allows a wider range of individuals to participate in the study. This approach aligns with the goal of the GLUCO-AID project, which aims to develop a practical and widely accessible blood glucose monitoring system.

The utilization of personal mobile phones for deployment showcases the researchers' dedication to overcoming potential barriers and maximizing the reach of the GLUCO-AID system. It enables a diverse pool of participants to benefit from the system's capabilities and contributes to the overall success of the research study.

4.3 Experimental Results and Data Analysis

A metrics table of a Feedforward Neural Network, specifically the Multilayer Perceptron (MLP), provides a systematic evaluation of performance metrics to assess the effectiveness of the network model. The table typically includes metrics such as mean square error (MSE), root mean square error (RMSE), and mean absolute error (MAE), among others. These metrics quantitatively measure the network's prediction accuracy and error estimation.

Table 3: Metrics Table of the Feedforward Neural Network (Multilayer Perceptron - MLP)

Metric	Mean Square Error (MSE)	Root Mean Square Error (RMSE)	Mean Absolute Error (MAE)
Train	15.24564	3.904567	3.378315
Test	10.17256	3.189444	2.756367

This metric above reveals a Mean Square Error (MSE) of 10.17 mg/dL. These values fall within the typical ranges observed for regression tasks used in this field, and in general, the MSE ranges from 10 to 30 mg/dL. The study by Li et al. (2019) reported an MSE of 20.2 mg/dL for their random forest model. Another study, by Islam et al. (2020), reported an MSE of 17.02 mg/dL for their PLS model. Also, Zhang et al. (2017) specified a MSE of 25.3 mg/dL for their SVM-based model. The MLP model's performance, as assessed by the MSE, RMSE, and MAE, is favorable, with values better than the stated models and within the expected ranges for accurate BGL prediction. Therefore, this model can be considered a good fit for the tasks at hand.

4.3.1 Machine Learning Model Accuracy Results

Machine learning model accuracy results refer to the measurement of how well a model performs in predicting or classifying outcomes compared to the ground truth or known values. Accuracy is one of the fundamental metrics used to assess the performance of machine learning models. It quantifies the proportion of correct predictions or classifications made by the model out of the total number of samples evaluated.

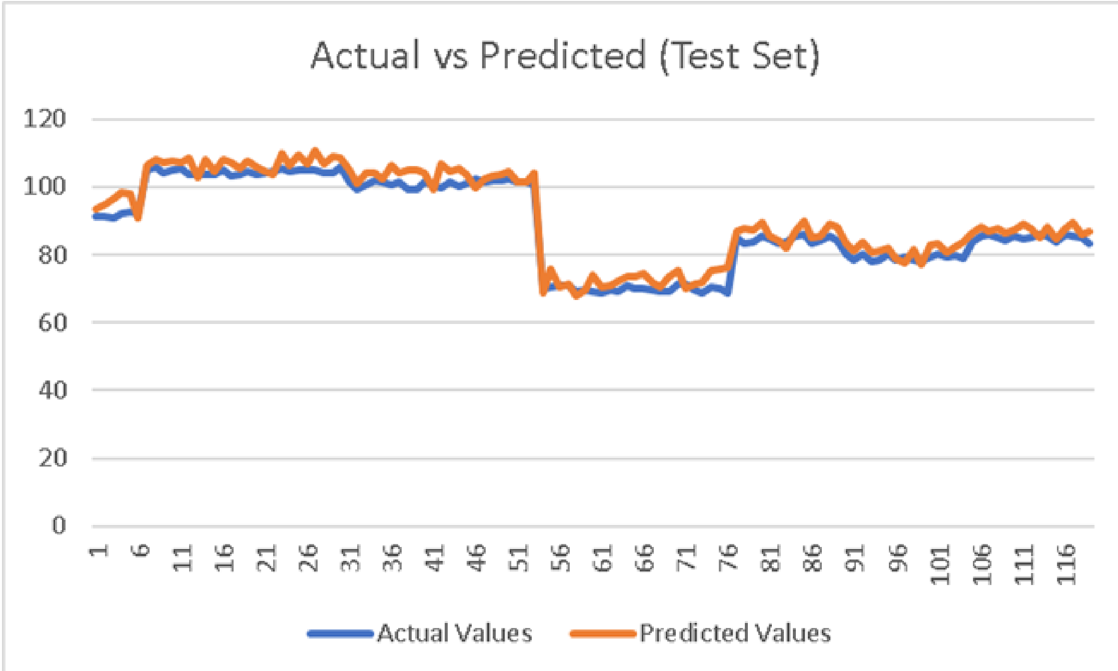

Figure 17. Actual vs. Predicted Line Plot of the Test Set

Figure 17 shown above is a visual representation of the accuracy of the predicted values and actual values of the Test Set of the proposed model. The line plot above can provide valuable insight into the predictive model's performance. Even though most projections are not entirely accurate, they do reveal a small difference from the actual values. This demonstrates that the model often captures the trend and provides estimates of blood glucose levels that are reasonably accurate.

It is important to keep in mind that there are instances where the expected and actual BGL values exhibit considerably big discrepancies. These differences show that the model occasionally struggles to predict blood glucose levels accurately. The chart shows the vast range in forecast accuracy, with some values showing a closer alignment to the actual BGL and others showing higher variances.

4.3.2 Data Results from Deployment

A comparison between actual and predicted blood glucose levels (BGL) involves assessing the accuracy and agreement between the BGL values obtained through measurements and those predicted by a model or algorithm. It aims to evaluate the performance of predictive models or algorithms in estimating BGL levels. This comparison is essential in diabetes management to ensure reliable and accurate predictions, facilitating informed decision-making for patients and healthcare providers.

Table 4: Comparison Between Actual and Predicted Blood Glucose Levels (BGL)

Patient No.	Actual BGL (mg/dL) (Measured with Finger Pricking Test)	Predicted BGL (mg/dL) (Measured with PPG Signals)
14	164	170.09
15	101	101.12
16	113	110.62
17	107	116.65
18	116	112.2

Table 4 represents the comparison between the actual blood glucose levels of the participants during the deployment which was obtained using a medical grade glucometer through finger prick testing and the predicted blood glucose levels of the patient using the proposed model (Gluco Aid) through PPG signals. This offers valuable insights into the performance of the predictive model. While most predictions are not accurately predicted, most of the values exhibit a very small difference, indicating that the model generally captures the trend and provides reasonably close estimations of blood glucose levels.

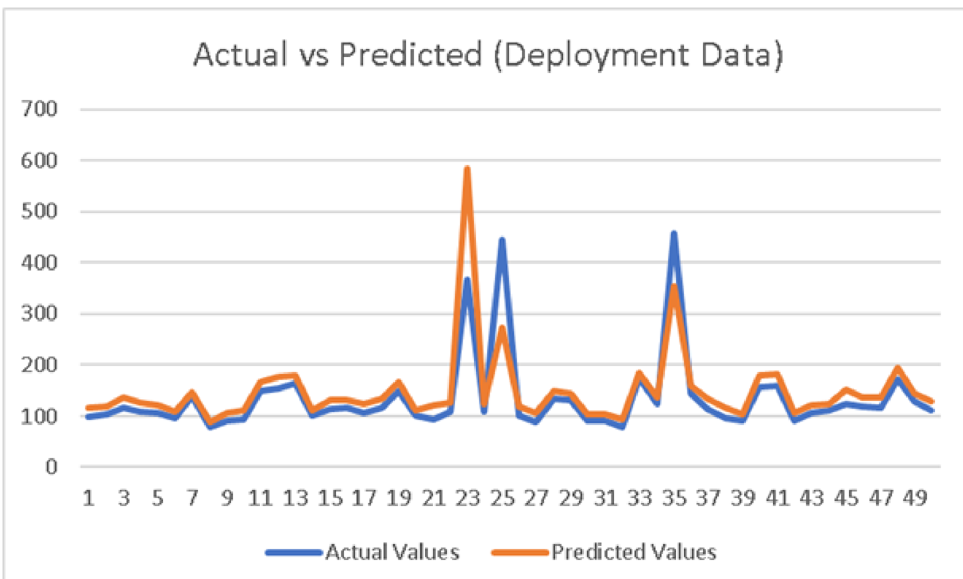

Figure 18. Line Plot of Comparison Between Actual and Predicted BGL

Figure 18 shown above is a visual representation of the comparison of the predicted values and actual values from the project testing (deployment) of the MLP model. The line plot above reveals interesting insights about the performance of the predictive model. While most of the predictions are not entirely accurate, they exhibit a small difference from the actual values. This indicates that the model generally captures the trend and provides reasonably close estimations of blood glucose levels.

However, it is important to note that there are instances where the deviations between the predicted and actual BGL values are significantly high. These deviations suggest that the model encounters challenges in accurately predicting blood glucose levels in certain cases.

The plot highlights the variability in the accuracy of the predictions, with some values demonstrating closer alignment to the actual BGL and others showing larger discrepancies. It indicates that while the model generally performs well, there are specific scenarios or factors that contribute to higher deviations. The 3 highest spikes in the actual values represent the blood glucose levels of the diabetic patients which are higher among most, ranging from 300 to 400. It is notable that the MLP model's prediction deviates the highest from the actual value which is expected because individuals with diabetes can often have altered heart rate variability (HRV).

Table 5: Comparison Between Actual and Multiple Predicted Blood Glucose Levels (BGL)

	Multiple Trial Predictions (BGL)	

Patient No.	Actual (BGL)	Trial 1	Trial 2	Trial 3	Trial Average
14	164	173.09	169.12	166.09	169.43
15	101	104.12	100.12	98.12	100.79
16	113	113.62	109.62	106.62	109.95
17	107	119.65	115.65	112.65	115.98
18	116	115.2	111.2	108.2	111.53

Table 5 represents the comparison between the actual blood glucose levels of the participants during the deployment and their predicted blood glucose levels in multiple trials. It is clear from reviewing the data that the Trials Average values typically differ marginally from the matching actual BGL values. The Trials Average varies depending on whether the actual BGL is higher or lower than it.

Comparing the first row, for instance, the actual BGL is 164 and the trials average is 169.43. This shows that the trials generally produced BGL values that were a little bit higher than the actual number. The trials produced somewhat lower BGL values than the real number, as seen in the second row where the actual BGL is 101 and the trials average is 100.79. It is crucial to remember that the variations between the Trials Average numbers and the real values are generally quite minor. The fourth row, where the actual BGL is 107 and the trials average is 115.98, shows the largest disparity, which is around 9 units. With an average difference of between 1 and 9 units, this shows that, overall, the trials are quite near to the actual values.

4.4 Project Evaluation

The evaluation of the system's overall performance through the involvement of Barangay Healthcare Workers (BHWs) has been challenging due to two primary factors. Firstly, the clustering of health centers in Barangays in Imus limits access to BHWs in Barangay Medicion II-B and its neighboring barangays. Secondly, there is a shortage of healthcare workers available in these areas.

As a result, the proponents have not been able to conduct a comprehensive assessment of the system's performance through the participation of BHWs. The limited availability and proximity of healthcare facilities and personnel have hindered the planned evaluation process.

Despite these limitations, alternative methods for evaluating the system's performance are being explored to ensure a comprehensive analysis. The proponents are actively seeking alternative strategies to gather relevant feedback and data from healthcare professionals and community members to supplement the evaluation process.

By addressing these challenges and employing alternative evaluation approaches, the study aims to obtain a comprehensive understanding of the system's performance and effectiveness in Barangay Medicion II-B and its neighboring barangays, ultimately contributing to the improvement of healthcare services in the area.

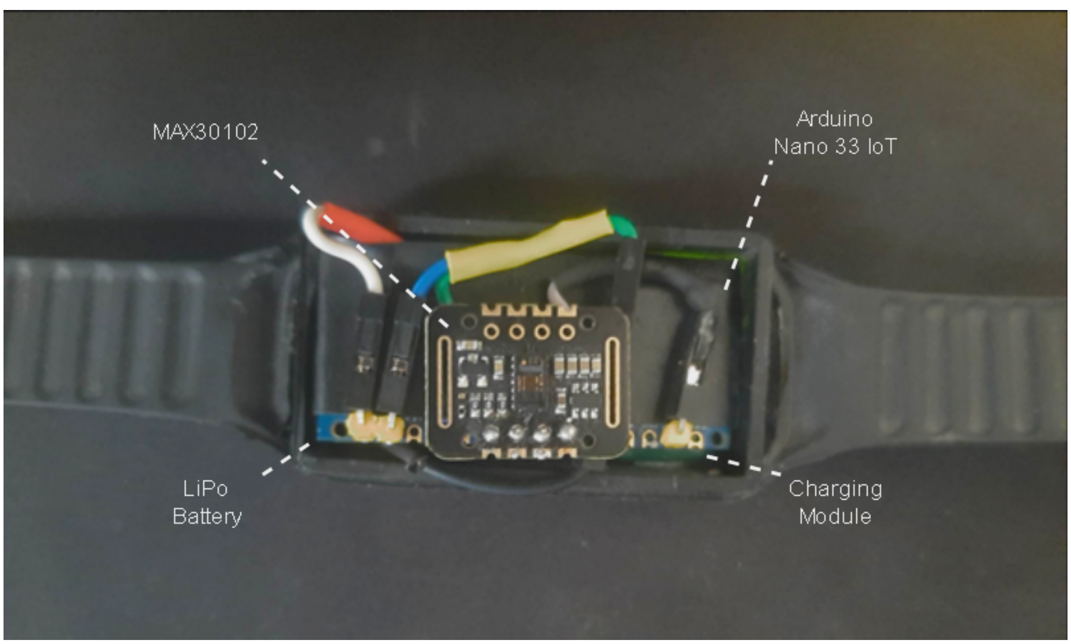

Figure 19. Final Output

4.5. Technical Evaluation (Participants)

The results of the technical evaluation accomplished by the participants after testing is shown below.

	Mean
Effectiveness	13.52
Efficiency	4.56
Satisfaction	22.62
Freedom from Risk	13.5
Content Coverage	13.7

Total Mean	13.58

Table 6. Technical Evaluation Results

Table 6 above shows the calculated mean of the five criteria and their overall mean. This shows that on average, the participants have a moderately positive usage and experience of the mobile application.

Effectiveness: This criterion achieved a mean rating of 13.52 which suggests that the mobile application is rated highly in terms of providing a straightforward diagnosis analysis of the patient after 3 minutes of wearing the device, storing user inputs to their mobile phone, and updating the organization/institution's database based on user inputs.

Efficiency: This criterion achieved a mean rating of 4.56 which suggests that mobile application is perceived as accurate and supported by statistical diagrams, indicating that the information provided is reliable and useful for monitoring blood glucose levels.

Satisfaction: This criterion achieved a mean rating of 22.62 which suggests that users find the mobile application helpful, as it provides a guide and introduction for first-time use, is useful for monitoring blood glucose levels, carries out tasks as discussed, guarantees saved diagnosis analysis accessible to authorized personnel, and has a user-friendly and visually pleasing layout.

Freedom from Risk: This criterion achieved a mean rating of 13.5 which suggests that the use of the mobile application is seen as reducing the need for other invasive blood glucose monitoring techniques, and it only requires wearing the device to predict patients' blood glucose levels. It also takes less than 5 minutes to display the patients' blood glucose levels.

Context Coverage: This criterion achieved a mean rating of 13.52 which suggests that the mobile application is accessible without an internet connection, can be used by individuals with limited knowledge about HRV, and provides its database for future researchers and organizations/institutions for further studies.

Overall, the ratings show that the IoT-based HRV device-based mobile application for continuous glucose monitoring is highly rated in terms of effectiveness, efficiency, satisfaction, risk-free operation, and context coverage. According to the positive reviews, customers believe the application to be helpful, dependable, easy to use, and supportive of their requirements for blood glucose monitoring.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

This chapter summarizes the findings of the study, discusses the conclusions that can be drawn from the results, and makes recommendations for how the study could be improved in the future.

5.1 Summary of Findings

The following are the key findings of the study, directly aligned with the research objectives, illustrating the achievements and outcomes of each objective:

1. **Wearable Device:** The developed cost-effective smartwatch, consisting of an Arduino Nano 33 IoT, MAX30102 sensor, TP4056, Li-Po battery, plastic enclosure, and rubber strap, successfully achieved non-invasive monitoring of blood glucose levels and provided accurate prediction results. It also integrated with the mobile application, allowing for real-time notifications and relevant information delivery to the patient.
2. **Machine Learning Model:** The feedforward neural network (MLP) demonstrated effectiveness in predicting blood glucose levels using HRV signals. The algorithm provided accurate analysis of the results, indicating its potential as a reliable HRV-based glucose monitoring system.
3. **Mobile Application:** The IoT-based mobile application, called "GLUCO-AID," successfully generated relevant information regarding blood glucose levels and provided accurate results in mg/dL. The

application categorized the results as high, normal, or low, enabling comprehensive monitoring and management of blood glucose levels.

4. **Device and Application Connectivity:** The study achieved successful connectivity between the IoT-based wearable device and the mobile application using BLE. This milestone allows for real-time transmission of data, enabling continuous monitoring of the patient's blood glucose levels and seamless integration with the mobile application.
5. **Test Metrics Results:** The system achieved an approximate 10.17256 Mean Square Error and 3.189444 Root Mean Square Error. Furthermore, the system produced a total mean of 13.58 which represents the average rating across all criteria.

5.2 Conclusion

The proponents of the study concluded that the findings and results of their research support the following claims:

1. The cost-effective smartwatch demonstrated interoperability and benefits in non-invasive blood glucose monitoring, accurate prediction results, and real-time notifications through the mobile application.
2. The feedforward neural network (MLP) proved effective in predicting blood glucose levels using HRV signals, offering accurate analysis and showcasing its potential as a reliable HRV-based glucose monitoring system.

3. The IoT-based mobile application, "GLUCO-AID," successfully generated relevant information on blood glucose levels, delivering accurate results in mg/dL and categorizing them as high, normal, or low for comprehensive monitoring and management.
4. The establishment of connectivity between the IoT-based wearable device and the mobile application via BLE was a significant milestone, enabling real-time data transmission and continuous monitoring of blood glucose levels.
5. The machine learning model achieved results which demonstrated promising metrics, while the system evaluation suggests that on average, the participants have a moderately positive usage and experience of the mobile application.

The GLUCO-AID Project introduces a novel non-invasive blood glucose monitoring system that utilizes a deep learning algorithm. This system predicts blood glucose levels by analyzing heart rate variability (HRV) signals collected from a smartwatch. The system underwent testing on a small group of 50 patients, selected through simple random sampling. It is worth noting that the system focuses on predicting blood glucose levels rather than addressing underlying patient conditions such as Diabetes.

The results of the testing phase demonstrated promising accuracy and proximity to actual blood glucose levels, as indicated by the achieved values of Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). These values align with the typical ranges observed in regression tasks, with MSE falling within

10-30, RMSE within 3-5, and MAE within 2-5. This performance underscores the system's capability to accurately predict blood glucose levels. The GLUCO-AID Project holds transformative potential in the field of blood glucose monitoring. Unlike current methods that require finger pricking for blood collection, which can be painful, inconvenient, and carry the risk of infection, the GLUCO-AID Project offers a more convenient and accurate alternative. By enabling individuals with diabetes to monitor their blood glucose levels non-invasively, this project has the capacity to enhance their quality of life.

While still in its early stages of development, the GLUCO-AID Project presents an opportunity to significantly impact the lives of millions worldwide. Its success holds the potential to improve health outcomes for individuals with diabetes and reduce the risk of associated complications. Continued research and development of the GLUCO-AID Project can pave the way for advancements in blood glucose monitoring and contribute to the well-being of individuals affected by diabetes.

5.3 Recommendations

The project was successfully completed, but the proponents would like to make the following recommendations to improve it further:

1. It is recommended to further explore the cost-effectiveness and scalability of the smartwatch system by conducting larger-scale trials and evaluating its performance in real-world settings. Additionally, user feedback should be gathered to assess the usability and user experience of the mobile application and ensure it meets the needs of patients in managing their blood glucose levels effectively.

2. Considering the effectiveness of the feedforward neural network in predicting blood glucose levels using HRV signals, it is recommended to continue refining and optimizing the neural network algorithm. Further research can focus on enhancing the model's performance by incorporating additional features or exploring different neural network architectures that may provide even more accurate and reliable predictions.

3. Considering the successful performance of the IoT-based mobile application in reporting and generating accurate blood glucose level results, it is recommended to conduct user acceptance tests and gather feedback from patients and healthcare professionals. This will help identify areas for improvement and ensure that the application meets the usability and functionality requirements of its intended users.

4. With the successful establishment of connectivity between the wearable device and the mobile application via BLE, it is recommended to conduct field tests and user trials to assess the reliability and stability of the connection in various real-world scenarios. Additionally, considering the real-time monitoring capability, further investigation can be done to explore potential alerts or notifications that can be sent to healthcare providers or caregivers in case of critical blood glucose level fluctuations.

5. To further evaluate the overall performance of the system through the Barangay Healthcare Workers and overcome the challenges of clustering health centers and shortage of healthcare workers, it is recommended to collaborate with local healthcare authorities and organize a comprehensive evaluation plan. This may involve training and engaging healthcare workers to use the system, collecting feedback on its accuracy and usability, and assessing its impact on diabetes management within the community.

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Sherwani, S. I., Khan, H. A., Ekhzaimy, A., Masood, A., & Sakharkar, M. K. (2016). Significance of HbA1c Test in Diagnosis and Prognosis of Diabetic Patients. Retrieved from https://doi.org/10.1155/2020/9628281

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(n.d.). Diabetes Care. American Diabetes Association.

Zhi, K. Y., Faust, O., & Yu, W. (2014). Wavelet based machine learning techniques
for electrocardiogram signal analysis. J. Med. Imaging Heal. Informatics, 4(5), 737–742. doi: 10.1166/jmihi.2014.1314

ANNEX I

BILL OF MATERIALS

BILL OF MATERIALS

Item No.	Item Description	Qty.	Unit	Unit Cost	Total Cost
1	Arduino Nano IOT	1	pc	1700.00	1700.00
2	MAX30102	1	pc	149.00	149.00
3	TP4056	1	pc	29.00	29.00
4	Plastic Enclosure	1	pc	60.00	60.00
5	Rubber Strap	1	pc	109.00	109.00
6	3.7V Li-Po Battery	1	pc	250.00	250.00

ANNEX II

GLUCO-AID CODES

Mobile Application

```
import 'dart:async';
import 'package:flutter/material.dart';
import 'package:flutter_blue/flutter_blue.dart';
import 'dart:io';
import 'package:csv/csv.dart';
import 'package:path_provider/path_provider.dart';
import 'package:charts_flutter/flutter.dart' as charts;
import 'package:tflite_flutter/tflite_flutter.dart';



void main() => runApp(MyApp());

class MyApp extends StatelessWidget {
  @override
  Widget build(BuildContext context) {
    return MaterialApp(
      title: 'Gluco Aid',
      theme: ThemeData(primarySwatch: Colors.red),
      home: BluetoothScreen(),
    );
  }
}
```

```
class BluetoothScreen extends StatefulWidget {
  @override
  _BluetoothScreenState createState() => _BluetoothScreenState();
}

class _BluetoothScreenState extends State<BluetoothScreen> {
  FlutterBlue flutterBlue = FlutterBlue.instance;
  BluetoothDevice? device;
  bool isConnected = false;
  bool isTransmitting = false;
  bool isWritingData = false;
  int? bgl;
  List<charts.Series<dynamic, int>>? bloodGlucoseData = [];
  bool isBglValueDisplayed = false;
  StreamSubscription<List<int>>? dataSubscription;
  List<List<dynamic>> rows = [];
  bool isPhotoVisible = false;
  String? photoPath;
  Interpreter? interpreter;


  @override
```

```
void initState() {
  super.initState();


  flutterBlue.state.listen((state) {
    if (state == BluetoothState.on) {
      startScanning();
    }
  });


  bloodGlucoseData = [
    charts.Series<dynamic, int>(
      id: 'BloodGlucose',
      colorFn: (_, __) => charts.MaterialPalette.red.shadeDefault,
      domainFn: (_, index) => index ?? 0,
      // Use the index as the domain value
      measureFn: (dynamic data, _) => data,
      // Use the data value as the measure
      data: [], // Add the actual blood glucose data here
    ),
  ];


  // Load the TensorFlow Lite model
  loadModel();
```

```
  startDataTimer();
}

void loadModel() async {
  try {
    String modelPath = 'path/to/your/final.tflite';
    interpreter = await Interpreter.fromAsset(modelPath);
  } catch (e) {
    print('Error loading model: $e');
  }
}

// Function to start scanning for devices
void startScanning() {
  flutterBlue.scan(timeout: Duration(seconds: 4)).listen((scanResult) {
    if (scanResult.device.name == 'Gluco Aid 00') {
      setState(() {
        device = scanResult.device;
      });
    }
  });
}
```

```
// Function to connect to the device
void connectToDevice() async {
 if (device != null) {
   await device!.connect();
   setState(() {
    isConnected = true;
   });

   List<BluetoothService> services = await device!.discoverServices();
   services.forEach((service) {
    if (service.uuid.toString() == '0000180d-0000-1000-8000-00805f9b34fb') {
      service.characteristics.forEach((characteristic) {
       if (characteristic.uuid.toString() ==
           '00002a37-0000-1000-8000-00805f9b34fb') {
         characteristic.setNotifyValue(true);
         dataSubscription = characteristic.value.listen((value) {
          setState(() {
            isTransmitting = true;
          });
          processData(value);
         });
       }
```

```
        });
      }
    });

    startDataTimer();
  }
}

void startDataTimer() {
  Timer.periodic(Duration(minutes: 1), (timer) async {
    // Read the latest row from the CSV file
    String? latestData = rows.isNotEmpty ? rows.last[0] : null;

    if (latestData != null) {
      try {
        // Preprocess the input data (if needed)
        List<double> inputData = preprocessData(latestData);

        // Perform the inference
        List<List<double>> input = [inputData];
        List<List<double>> output = List.filled(1, [0.0]);
        // ignore: undefined_method
        interpreter!.runForMultiple(input: input, output: output);
```

```
      // Process the output (if needed)
      double predictedValue = output[0][0];


      setState(() {
        bgl = predictedValue.toInt();


        bloodGlucoseData![0].data.add(bgl); // Update the blood glucose data


        rows.add([]);
      });


      await saveDataToFile();
      print('Writing Data...');
    } catch (e) {
      print('Error during inference: $e');
    }
  }
 });
}



List<double> preprocessData(String data) {
```

```
  // Convert the received data to a list of doubles
  List<String> dataValues = data.split(',');
  List<double> inputData = dataValues.map((value) => double.parse(value)).toList();

  return inputData;
}

double postprocessData(List<List<double>> output) {
  // Process the model output to obtain the predicted value
  double predictedValue = output[0][0];

  return predictedValue;
}


Future<void> saveDataToFile() async {
  setState(() {
    isWritingData = true;
  });

  final directory = await getExternalStorageDirectory();
  if (directory != null) {
    final file = File('${directory.path}/ppg.csv');
```

```
    String csv = const ListToCsvConverter().convert(rows);
    await file.writeAsString(csv);


    setState(() {
      isWritingData = false;
    });


    print('Data saved to CSV file.');
    print('File path: ${file.path}');
    // You can also show a toast or snackbar message here
  } else {
    print('External storage directory is not available.');
  }
}


void processData(List<int> data) {
  String receivedData = String.fromCharCodes(
      data); // Convert the list of integers to a string


  setState(() {
    rows.add([
      receivedData
    ]); // Add receivedData as a single-element list to the rows list
```

```
    print('Received data: $receivedData');
  });
}

void showPhoto(String imagePath) {
  setState(() {
    isPhotoVisible = true;
    photoPath = imagePath;
  });
}

void hidePhoto() {
  setState(() {
    isPhotoVisible = false;
    photoPath = null;
  });
}

  @override
void dispose() {
  dataSubscription?.cancel();
  interpreter?.close();
```

```
  super.dispose();
 }

 // Function to determine the color based on the value of bgl
 Color _getContainerColor() {
  if (bgl != null) {
   if (bgl! < 70) {
    return Colors.yellow;
   } else if (bgl! > 140) {
    return Colors.red;
   } else {
    return Colors.green;
   }
  }
  return Colors.green; // Default color
 }

// Function to determine the text based on the value of bgl
 String _getContainerText() {
  if (bgl != null) {
   if (bgl! < 70) {
    return 'LOW';
   } else if (bgl! > 140) {
```

```
      return 'HIGH';
    } else {
      return 'NORMAL';
    }
  }
  return 'NORMAL'; // Default text
}

@override
Widget build(BuildContext context) {
  return Scaffold(
    appBar: AppBar(title: Text('Gluco Aid'),
    ),
    body: Stack(
      children: [
        Column(
          children: [
            SizedBox(height: 64.0),
            Container(
              decoration: BoxDecoration(
                color: Colors.red,
                borderRadius: BorderRadius.circular(20.0),
              ),
```

```
  padding: EdgeInsets.symmetric(vertical: 8.0, horizontal: 16.0),
  child: Text(
    'BGL (mg/dL): ${bgl != null ? bgl.toString() : '...'}',
    style: TextStyle(fontSize: 24.0,
        fontWeight: FontWeight.bold,
        color: Colors.white),
  ),
),
SizedBox(height: 32.0),
Container(
  decoration: BoxDecoration(
    color: _getContainerColor(), // Use a function to determine the color
    borderRadius: BorderRadius.circular(20.0),
  ),
  padding: EdgeInsets.symmetric(vertical: 8.0, horizontal: 16.0),
  child: Text(
    _getContainerText(), // Use a function to determine the text
    style: TextStyle(fontSize: 18.0, color: Colors.white),
  ),
),
SizedBox(height: 32.0),
Expanded(
  child: Center(
```

```
child: Column(
  mainAxisAlignment: MainAxisAlignment.center,
  children: [
    SizedBox(height: 16.0),
    SizedBox(
      width: double.infinity,
      height: 300.0,
      child: Padding(
        padding: EdgeInsets.all(16.0),
        child: charts.LineChart(
          bloodGlucoseData!,
          animate: false,
          defaultRenderer: charts.LineRendererConfig(
            includePoints: true,
          ),
          primaryMeasureAxis: charts.NumericAxisSpec(
            tickProviderSpec: charts
                .BasicNumericTickProviderSpec(
              desiredTickCount: 5,
            ),
          ),
        ),
      ),
```

```
        ),
      ],
    ),
  ),
),
Container(
  margin: EdgeInsets.only(left: 50.0),
  child: Row(
    mainAxisAlignment: MainAxisAlignment.spaceEvenly,
    children: [
      FloatingActionButton(
        onPressed: () => showPhoto('assets/images/first_aid.png'),
        child: Icon(Icons.medical_services),
      ),
      SizedBox(width: 16.0),
      ElevatedButton(
        onPressed: connectToDevice,
        child: Icon(Icons.bluetooth),
        style: ElevatedButton.styleFrom(
          shape: CircleBorder(),
          padding: EdgeInsets.all(16.0),
        ),
      ),
```

```
          SizedBox(width: 16.0),
          FloatingActionButton(
            onPressed: () => showPhoto('assets/images/blood_image.jpeg'),
            child: Icon(Icons.favorite),
          ),
          SizedBox(width: 32.0),
        ],
      ),
    ),
    SizedBox(height: 32.0),
    Text(
      isConnected
          ? 'BLE Connection: ${isTransmitting
          ? "Connected and Transmitting"
          : "Connected"}'
          : 'BLE Connection: Not Connected',
      style: TextStyle(fontSize: 12.0),
    ),
    Text(
      isWritingData ? 'Writing Data...' : '',
      style: TextStyle(fontSize: 18.0),
    ),
  ],
```

```
      ),
      if (isPhotoVisible) ...[
        GestureDetector(
          onTap: hidePhoto,
          child: Container(
            color: Colors.black.withOpacity(0.5),
            child: Center(
              child: Image.asset(
                photoPath!,
                height: 500,
              ),
            ),
          ),
        ),
      ],
    ],
  ),
 );
}
}
```

Machine Learning Model

```
# -*- coding: utf-8 -*-
"""FINAL_MLP


Automatically generated by Colaboratory.
"""


import numpy as np
import pandas as pd
from keras.optimizers import RMSprop
from scipy.signal import find_peaks
from scipy.signal import filtfilt
from keras.models import Sequential
from keras.layers import Dense
from keras import regularizers
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split


# Load the data
data = pd.read_csv('NEW.csv')


# Cleaning the data
data = data.dropna()  # Remove rows with missing values
```

```
# Separate the input features (PPG) and labels (BGL)
X = data.iloc[:, 1:].values
y = data.iloc[:, 0].values


sampling_rate = 115.2  # Hz
low_cutoff_freq = 0.4  #Hz Low cutoff frequency for bandpass filter
high_cutoff_freq = 4  #Hz High cutoff frequency for bandpass filter


# Preprocessing
def preprocessing(X):
    preprocessed_signal = []
    for row in X:
        # Apply bandpass filter to the row
        filtered_row = bandpass_filter(row, low_cutoff_freq, high_cutoff_freq,
sampling_rate)


        # Extract features from the filtered row
        feature_vector = extract_features(filtered_row, sampling_rate)


        preprocessed_signal.append(feature_vector)


    return np.array(preprocessed_signal)
```

```
def bandpass_filter(signal, low_cutoff_freq, high_cutoff_freq, sampling_rate):
    order = 4  # Filter order
    nyquist_freq = 0.5 * sampling_rate
    low = low_cutoff_freq / nyquist_freq
    high = high_cutoff_freq / nyquist_freq
    b, a = butter(order, [low, high], btype='band', analog=False, output='ba')

    filtered_signal = filtfilt(b, a, signal)

    return filtered_signal

def extract_features(filtered_signal, sampling_rate):
    # Peak detection to identify R-peaks
    peaks, _ = find_peaks(filtered_signal, distance=int(0.5 * sampling_rate))

    # Calculate RR intervals
    rr_intervals = np.diff(peaks) / sampling_rate

    # Calculate SDNN (standard deviation of RR intervals)
    sdnn = np.std(rr_intervals)

    # Calculate RMSSD (root mean square of successive differences)
```

```
    rmssd = np.sqrt(np.mean(np.diff(rr_intervals) ** 2))

    # Calculate mean RR interval
    mean_rr = np.mean(rr_intervals)

    # Calculate pNN50 (percentage of adjacent RR intervals differing by more than 50
ms)
    pnn50 = np.sum(np.abs(np.diff(rr_intervals)) > 0.05) / len(rr_intervals) * 100

    # Calculate TINN (triangular interpolation of RR intervals)
    tinn = np.max(peaks) - np.min(peaks)

    # Return the extracted features as a list
    feature_vector = [sdnn, rmssd, mean_rr, pnn50, tinn]

    return feature_vector

# Apply preprocessing to the data
X_preprocessed = preprocessing(X)
"""
print("preprocessed_features dimensions:", X_preprocessed.shape)
print()
print(X_preprocessed)
```

```
print()
"""

#Set random state
random_state = 57

# Split the data into training, validation, and test sets
X_train, X_test, y_train, y_test = train_test_split(X_preprocessed, y, test_size=0.10,
random_state=random_state)
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.10,
random_state=random_state)

"""# Print the shapes of the resulting sets
print("X_train shape:", X_train.shape)
print("X_test shape:", X_test.shape)
print("y_train shape:", y_train.shape)
print("y_test shape:", y_test.shape)
print()
"""

# Define the MLP model
model = Sequential()
model.add(Dense(64, input_shape=(5,), activation='relu'))
```

```
model.add(Dense(96, activation='relu'))

model.add(Dense(208, activation='relu'))

model.add(Dense(64, activation='relu'))

model.add(Dense(1))


# Specify your desired learning rate and optimizer

optimizer = RMSprop(learning_rate=0.001)


# Compile the model

model.compile(loss='mean_squared_error', optimizer=optimizer)


# Train the model

history = model.fit(X_train, y_train, epochs=100, batch_size=1, verbose=1)


# Evaluate the model on the test set

loss = model.evaluate(X_test, y_test)

print("Test loss:", loss)


# Retrieve the training loss from the history object

training_loss = history.history['loss']

print("Training loss:", training_loss)
```

Arduino Code

```
#include <Wire.h>

#include "MAX30105.h"

#include <ArduinoBLE.h>


// Create objects for the MAX30102 sensor and BLE

MAX30105 particleSensor;

BLEService hrService("180D");  // Heart Rate Service UUID

BLECharacteristic dataCharacteristic("2A37", BLERead | BLENotify, 10, false);  //
Data Characteristic UUID


bool fingerSteady = false;  // Flag to indicate if finger is steady

unsigned long steadyTimer = 0;  // Timer for checking finger stability

const int minRawDataThreshold = 50000;  // Minimum raw data threshold

const unsigned long fingerTimeout = 2000;  // Finger timeout duration (in milliseconds)


void setup() {

  Serial.begin(9600);

  while (!Serial);


  // Initialize I2C communication

  Wire.begin();
```

```
// Initialize MAX30102 sensor
if (!particleSensor.begin(Wire, I2C_SPEED_FAST)) {
  Serial.println("MAX30102 sensor not found. Please check wiring or power!");
  while (1);
}

// Initialize BLE
if (!BLE.begin()) {
  Serial.println("Failed to start BLE module!");
  while (1);
}

// Set the local name and appearance
BLE.setLocalName("Gluco Aid 00");
BLE.setAdvertisedService(hrService);

hrService.addCharacteristic(dataCharacteristic);

// Add HR service to the BLE
BLE.addService(hrService);

// Start advertising
BLE.advertise();
```

```
  Serial.println("Gluco Aid 00 is now advertising over Bluetooth Low Energy
(BLE)...");
}

void loop() {
  // Update BLE connection
  BLE.poll();

  // Check finger stability for 2 seconds
  if (!fingerSteady) {
    if (millis() - steadyTimer >= 2000) {
      if (particleSensor.getIR() > minRawDataThreshold) {
        fingerSteady = true;
        Serial.println("Finger is steady. Starting IR readings...");
      } else {
        Serial.println("Finger is not steady yet. Waiting...");
        steadyTimer = millis(); // Reset the timer
      }
    }
  }
  if (fingerSteady) {
    // Read raw data from MAX30102
```

```
    uint32_t irValue = particleSensor.getRed();


    if (irValue > minRawDataThreshold) {
      // Update IR characteristic value and notify subscribers
      String dataString = String(irValue);
      dataCharacteristic.writeValue(dataString.c_str(), dataString.length());


      // Print IR data to serial monitor
      Serial.print("IR: ");
      Serial.println(irValue);
      // Reset the steadyTimer since we received valid data
      steadyTimer = millis();
    } else {
      // Check if finger timeout has occurred
      if (millis() - steadyTimer >= fingerTimeout) {
        fingerSteady = false;
        Serial.println("Finger timeout. Waiting for a steady finger...");
      }
    }
  } else {
    Serial.println("Waiting for a steady finger...");
  }
}
```

ANNEX III

Progress Documentation

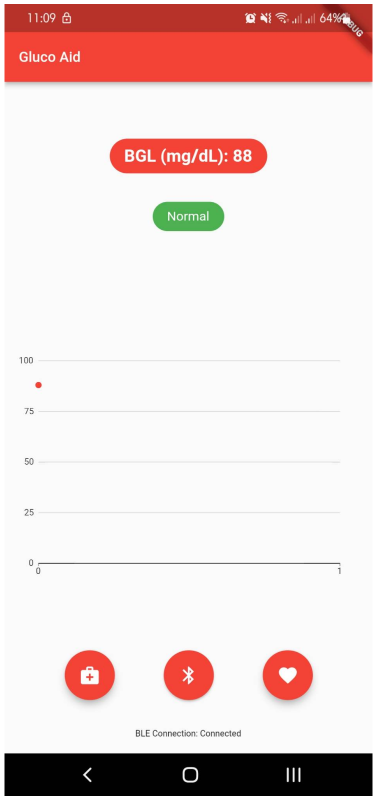
PRE-DEPLOYMENT

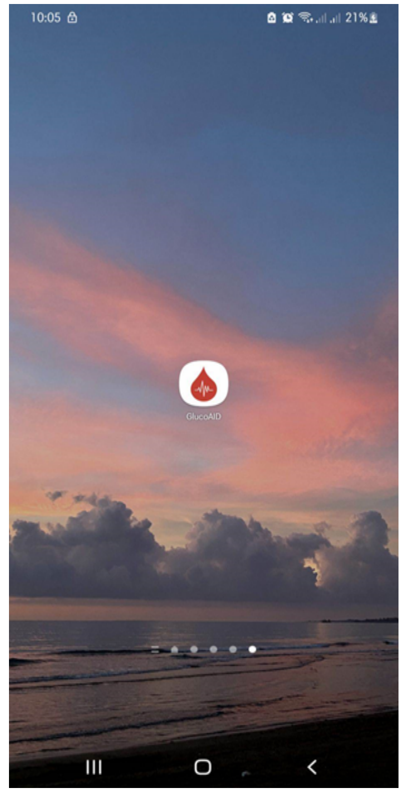
Calibration of Arduino Nano IOT

Building Core Prototype

Calibration of the Sensor

Finished Prototype





Mobile

Application Homepage and Icon

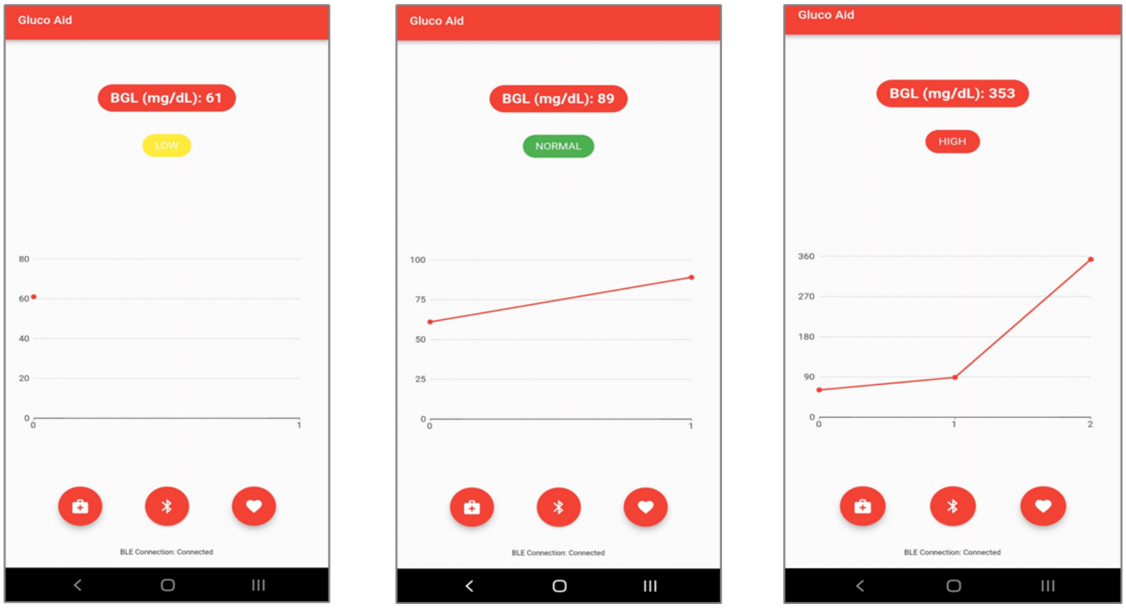
```
# Define the MLP model
model = Sequential()
model.add(Dense(64, input_shape=(5,), activation='relu'))
model.add(Dense(96, activation='relu'))
model.add(Dense(208, activation='relu'))
model.add(Dense(64, activation='relu'))
model.add(Dense(1))

# Specify your desired learning rate and optimizer
optimizer = RMSprop(learning_rate=0.001)

# Compile the model
model.compile(loss='mean_squared_error', optimizer=optimizer)

# Train the model
history = model.fit(X_train, y_train, epochs=100, batch_size=1, verbose=1)

# Evaluate the model on the test set
loss = model.evaluate(X_test, y_test)
print("Test loss:", loss)

# Retrieve the training loss from the history object
training_loss = history.history['loss']
print("Training loss:", training_loss)
```

```python
def extract_features(filtered_signal, sampling_rate):
    # Peak detection to identify R-peaks
    peaks, _ = find_peaks(filtered_signal, distance=int(0.5 * sampling_rate))

    # Calculate RR intervals
    rr_intervals = np.diff(peaks) / sampling_rate

    # Calculate SDNN (standard deviation of RR intervals)
    sdnn = np.std(rr_intervals)

    # Calculate RMSSD (root mean square of successive differences)
    rmssd = np.sqrt(np.mean(np.diff(rr_intervals) ** 2))

    # Calculate mean RR interval
    mean_rr = np.mean(rr_intervals)

    # Calculate pNN50 (percentage of adjacent RR intervals differing by more than 50 ms)
    pnn50 = np.sum(np.abs(np.diff(rr_intervals)) > 0.05) / len(rr_intervals) * 100

    # Calculate TINN (triangular interpolation of RR intervals)
    tinn = np.max(peaks) - np.min(peaks)

    # Return the extracted features as a list
    feature_vector = [sdnn, rmssd, mean_rr, pnn50, tinn]

    return feature_vector
```

```python
# Preprocessing
def preprocessing(X):
    preprocessed_signal = []
    for row in X:
        # Apply bandpass filter to the row
        filtered_row = bandpass_filter(row, low_cutoff_freq, high_cutoff_freq, sampling_rate)

        # Extract features from the filtered row
        feature_vector = extract_features(filtered_row, sampling_rate)

        preprocessed_signal.append(feature_vector)

    return np.array(preprocessed_signal)

def bandpass_filter(signal, low_cutoff_freq, high_cutoff_freq, sampling_rate):
    order = 4  # Filter order
    nyquist_freq = 0.5 * sampling_rate
    low = low_cutoff_freq / nyquist_freq
    high = high_cutoff_freq / nyquist_freq
    b, a = butter(order, [low, high], btype='band', analog=False, output='ba')

    filtered_signal = filtfilt(b, a, signal)

    return filtered_signal

def extract_features(filtered_signal, sampling_rate):
```

```
Training Set Metrics:
Mean Square Error (MSE): 15.24564
Root Mean Square Error (RMSE): 3.904567
Mean Absolute Error:  3.378315

Test Set Metrics:
Mean Square Error (MSE):  10.17256
Root Mean Square Error (RMSE):  3.189444
Mean Absolute Error:  2.756367
```

Training and Testing using Python

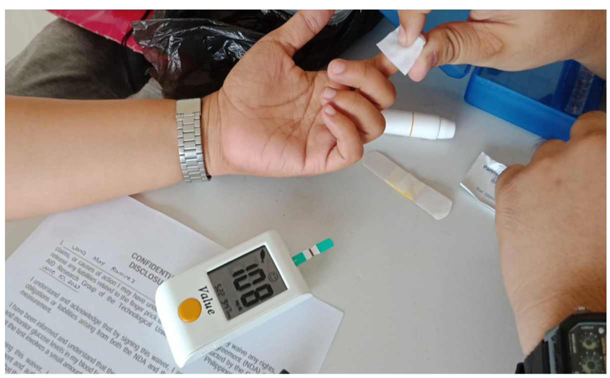


Mobile Application UI and Results

DEPLOYMENT

Discussion of the Deployment Plan of Project in Barangay Medicion II-B

Deployment Day



Measuring Blood Glucose by using Glucometer and GLUCO-AID Prototype

Technical Evaluation Form:

Mobile Application for Continuous Glucose Monitoring using IoT-based HRV Device Proponent Survey					
Introduction: The students involved prior to this study need to conduct a survey for evaluation of different aspects of the proponent, entitled "**Continuous Glucose Monitoring using IoT-Based HRV Device utilizing Deep Learning Algorithms for Smart Healthcare**".					
Instruction: Please rate whether you strongly disagree or strongly agree. Check one response for the following statements. Rate **1** - if Strongly Disagree **2** - Disagree **3** - Neither Agree nor Disagree **4** - Agree **5** - if Strongly Agree					
Survey Statements	**Rating**				
	1	2	3	4	5
Effectiveness					
1. The mobile application results a straightforward diagnosis analysis of the patient after 3-minutes of wearing the device.					
2. The mobile application stores the user's inputs to his/her mobile phone.					
3. The mobile application updates the database of the organization/institution based on the inputs of their users.					
Efficiency					
4. All information provided by the mobile application is accurate and supported by statistical diagrams.					
Satisfaction					
5. The mobile application provides the users a guide and introduction to the mobile application on their first-time use.					
6. The mobile application is very useful in patients' monitoring of their blood glucose level.					
7. The mobile application carried out its tasks as discussed.					
8. The mobile application guarantees diagnosis analysis to be saved and can be accessed anytime by any authorized personnel.					
9. The overall layout of the mobile application is very user-friendly and pleasing to the eyes.					
Freedom from Risk					
10. Using the mobile application helps in reducing the use of other invasive blood glucose monitoring techniques.					
11. Using the mobile application only needs the wearing of the device to predict the patients' blood glucose level.					
12. Using the mobile application takes less than 5 minutes to show the patients' blood glucose level.					
Context Coverage					
13. The mobile application can be accessed without internet.					
14. The mobile application can be used by someone who does not have much knowledge about HRV.					
15. The mobile application can provide the future researchers and organizations/institutions its database for further studies.					

Technical Evaluation Form

ANNEX IV

Photos from Previous Defense

Topic Defense 2022

Title Defense

Progress Defense 2022

Pre-Final Defense 2023

Final Defense 2023

ANNEX V

USER MANUAL

User's Manual: Gluco-Aid

Gluco Aid is a smart device designed to monitor and track your blood sugar levels. This user's manual will guide you through the setup and usage of Gluco Aid.

Turning on the Smart Watch:

- Locate the power button on the smartwatch and press it to turn on the device.
- Wait for the red light (sensor) on the bottom of the watch to turn on, indicating that it is ready to measure blood sugar levels.

Wearing the Smart Watch:

- Put on the smartwatch, ensuring that it is comfortable and not too tight on your wrist.

Opening the App:

- Launch the Gluco Aid mobile application on your smartphone or tablet.

Enabling Bluetooth and Location Services:

- Make sure that the Bluetooth and location services of your phone are turned on.
- You can usually find these options in the settings of your phone.

Connecting the App to the Device:

- On the Gluco Aid app, locate and press the Bluetooth button located below the screen.
- The app will automatically search for and connect to the Gluco-Aid device.
- A status message will appear below the Bluetooth button, changing from "Not Connected" to "Connected and Transmitting" when the connection is established.

Waiting for Results:

- After the device is connected, wait for approximately 1 minute to allow Gluco Aid to measure your blood sugar levels.
- The results will be displayed on your phone's screen and graphed for easy visualization.

First-Aid Tips:

- To access first-aid tips related to blood sugar management, locate and press the first-aid button, located to the left of the Bluetooth button.
- The app will provide you with helpful information and guidelines on managing blood sugar levels effectively.

Blood Sugar Levels Chart:

- If you want to view a chart of your blood sugar levels over time, locate and press the heart button, located to the right of the Bluetooth button.

- The app will display a graphical representation of your blood sugar levels, allowing you to track and monitor changes and trends.

****Please note that Gluco Aid is intended for informational purposes only and should not replace professional medical advice. If you have any concerns or questions regarding your blood sugar levels, consult with your healthcare provider.***

ANNEX VI

PROTOTYPE DUPLICATION

MANUAL

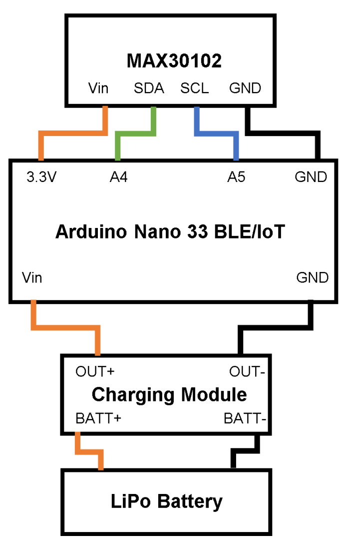
GLUCO-AID: Manual for Duplication of Prototype

Thank you for your interest in duplicating the Gluco Aid project. To successfully replicate the Gluco Aid system, you will need to follow the steps outlined below, which include building the smartwatch, developing the machine learning model, and creating the mobile app.

Smartwatch Assembly:

Gather the following materials: LiPo Battery (5V or higher), Arduino Nano 33 BLE/IoT, multi-cell charging module, MAX30102 (or any other PPG sensor), and a smartwatch chassis.

Assemble the smartwatch components according to the provided schematics or instructions specific to the smartwatch chassis you are using.



Smartwatch Schematics

Ensure that all connections between the components are secure and properly wired.

Double-check the assembly to ensure it matches the design and configuration of the original Gluco Aid smartwatch.

Machine Learning Model Development:

- Download the provided code for the machine learning model from the specified link.
- Set up your development environment with the necessary dependencies and libraries.
- Review the code and understand its structure and functionality.
- If required, modify the code to adapt it to your specific hardware configuration or make improvements as needed.
- Train the machine learning model using appropriate datasets to ensure accurate blood sugar level prediction.
- Test the model thoroughly to verify its performance and adjust parameters if necessary.
- In case you want to develop your own machine learning model, make sure it's converted to ***tflite*** format to be able to integrate it into the flutter app below. Further instructions of integrating the model into the app is stated below.

Mobile App Development (Android):

- Download the provided project folder for the mobile app from the specified link.
- Set up your development environment for mobile app development (Recommended: Android Studio).

- Open the project folder using your preferred IDE.
- Review the code and understand its structure and functionality.
- Install any required dependencies or libraries as specified in the code documentation.
- Customize the app's user interface (UI) and user experience (UX) if desired.
- Ensure that the app integrates with the smartwatch via Bluetooth communication, as outlined in the original Gluco Aid functionality.
    - Modify the service and UUID characteristics to your requirement.
- Test the app thoroughly to ensure it properly connects to the smartwatch, receives and displays blood sugar level data, and provides additional features such as first-aid tips and blood sugar level charting.
- In case you developed your own machine learning model, convert it into ***tflite*** format and then replace the existing model in the “assets” folder located in the root folder. Make sure that the file name of the model matches the file name inside the main.dart file for it to be called properly.

Integration and Testing:

- Connect the smartwatch to the mobile app by following the Bluetooth pairing process outlined in the original Gluco Aid system.
- Verify that the app successfully communicates with the smartwatch and receives real-time blood sugar level data.
- Test the application’s additional features, such as displaying first-aid tips and blood sugar level charting, to ensure they function as intended.

- Conduct comprehensive testing to validate the overall system's functionality and reliability.

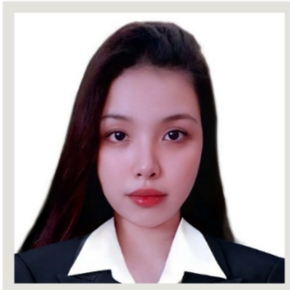
Project Link (Gluco Aid Project Source Files & Codes):

https://drive.google.com/drive/folders/1T_FMxuo74P1T4mjRlXk6shRicoyHtoJu?usp=sharing

Please note that duplicating the Gluco Aid project requires technical knowledge in hardware assembly, software development, and machine learning. It is essential to understand the code and adapt it to your specific requirements and hardware configuration. If you encounter any difficulties or have questions during the duplication process, refer to the documentation provided in the code or seek assistance from relevant communities or forums. Good luck!

ANNEX VII

Proponents' Information



CHERRILYN ALCAÑICES

ELECTRONICS ENGINEER

About Me

I am seeking for a company that will definitely improve my skills and knowledge regarding on my chosen field. Exploring more experiences and new ways on how to live within this industry.

Education

Bachelor of Science in Electronics Engineering
June 2018 - August 2023
Technological University of the Philippines - Manila

Science, Technology, Engineering, & Mathematics
June 2016 - April 2018
Cavite National High School

Contact

Cavite City

+63 977 031 6726

cherrilyn.alcanices@gmail.com

Trainings and Seminars

1st Electrical and Electronics Engineering Summit
May 2021

Emerging Technologies: 5G & Its Spectrum
April 2021

Unleashing Innovative Minds: Preparing Future Engineers for the Challenges of Societal Advancements
December 2020

Real-Life Application of Mathematics and Physics
October 2020

TechEx: Fundamentals of Data Science
October 2020

Skills

- **Basic Programming**
- **Digital and Verbal Communication**
- **Creative Intelligence and Critical Thinking**
- **Computer and Application Knowledge**
- **Administrative Management and Quality Assurance**
- **Technical Writing**

ANDREI **BARERRA**

ELECTRONICS ENGINEER

Contact

Cavite City

+63 961 258 2614

andrei.barerra@tup.edu.ph

Skills

- **Proficient in Mathematics**
- **Computer Literate**
- **Experience in Multisim**
- **Experience in Proteus**
- **Basic knowledge in IP addressing and Subnetting**

About Me

I am seeking for a job that will allow me to apply and practice my knowledge and build my personality as a professional while employing my skills.

Education

Bachelor of Science in Electronics Engineering

June 2019 - August 2023

Technological University of the Philippines - Manila

Science, Technology, Engineering, & Mathematics

June 2017 - April 2019

San Sebastian College-Recoletos de Cavite

Trainings and Seminars

IP Addressing and Subnetting for CCNA by Mnet IT

May 2022

Cisco Basic Routing by Mnet IT

May 2022

Cybersecurity: Cybercriminals and Social Media

September 2020

Real-Life Application of Mathematics and Physics

October 2020

Excel VBA

September 2020

JULIANE EMBREY **CRUZ**

ELECTRONICS ENGINEER

Contact

Las Piñas City

+63 927 858 1321

www.linkedin.com/in/juliane-embrey-cruz

julianeembreycruz@tup.edu.ph

Skills

- Knowledgeable in Canva and CapCut
- Knowledgeable in Photoshop and Lightroom
- **Proficient in Microsoft Applications:** Word, Excel, Presentation, Teams, OneNote
- **Proficient in Google Workspace:** Docs, Sheets, Slides, Forms, Sites, Meet, Drive
- **Livestream Softwares:** OBS Studio, Facebook LIve, Zoom, MS Teams
- **Programming:** MATLAB and Octave
- **Network Simulation:** CISCO Packet Tracer
- **Circuit Simulation:** NI Multisim, LTSPICE, DesignSpark

About Me

Committed to continuous learning and professional growth, I aim to leverage my strong work ethic and passion for delivering exceptional results to drive organizational growth and exceed objectives. Seeking a collaborative and innovative work environment that values creativity, fosters growth, and offers opportunities for advancement.

Education

Bachelor of Science in Electronics Engineering

June 2015 - August 2023

Technological University of the Philippines - Manila

Work Experience

Dai-Ichi Electronics Manufacturing Corporation
November 2022

Cadet Engineer

- Make Engineering Change Notices, Bill of Materials, Registration of Documents
- Woofer and Ribbon Tweeter Assembly
- Tweeter Quality Control, Rub and Buzz Testing, and SPL Testing using CLIO
- Answer calls and set meetings
- Performs other duties that may be assigned from time to time

College of Engineering, TUP Manila
Supervised Industrial Training (SIT) Program
November 2022 - December 2022

Student Research Assistant

- Gained hands-on experience in handling paper works and small-scale research projects under the research and extension of the college and the department.

ROY BENEDICT DE GUZMAN

ELECTRONICS ENGINEER

Contact

Obando, Bulacan

+63 920 698 3675

linkedin.com/in/roydeguzman

roybenedictdeguzman@gmail.com

Work Experience

Dai-Ichi Electronics Manufacturing Corporation
August 2022 - October 2022

Cadet Engineer

- Completed and documented model-project folders.
- Performed assembly, troubleshooting, and testing PCB/crossover networks.

About Me

Organized and dependable candidate successful at managing multiple priorities with a positive attitude, great work ethic, and excellent skills in communication and problem-solving.

Education

Bachelor of Science in Electronics Engineering

June 2019 - August 2023

Technological University of the Philippines - Manila

Skills

Technical Skills

- Proficient in Electrical and Electronic Circuit Analysis & Design
- Proficient in computer hardware, software, and networking - related applications.
- Intermediate knowledge and experience in Python especially its usage in Data Science and Machine Learning.
- Basic knowledge in Java, R, SQL, PHP, HTML and JavaScript.
- Substantial knowledge in network engineering such as: Router
- Configuration, Enabling SSH on Network Devices, Packet Tracing, IP Addressing and Subnetting, and Utilizing Network Simulation Tools (Cisco Packet Tracer).
- Proficient in both English and Filipino

Interpersonal Skills

- Highly organized and efficient
- Excellent in working independently and with others
- Excellent in both written and oral communications

LAWRENCE ANDRE **RODRIGUEZ**

ELECTRONICS ENGINEER

Contact

Parañaque City

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lawrenceandrerodriguez@gmail.com

Skills

Technical and Programming Skills

- Proficient in Electrical and Electronic Circuit Analysis & Design, including assembly, troubleshooting, and repair of circuit panels and board.
- Proficient in computer hardware, software, and networking - related applications.

Computer Programs

- Microsoft Office Applications
- Google Suite Applications
- DesignSparkPCB, NI Multisim, DOST-ASTI Electric & LTSpice
- Adobe Photoshop, Illustrator, InDesign

Language

- Proficient in both English and Filipino

Communication

- Excellent written and oral communication skills, strong work ethic, social media management, with ability to work cooperatively in a team.

About Me

Engineering student committed to developing skills in biomedical engineering, and data science. Knowledgeable at exploratory data analysis and applying machine learning techniques using R and Python.

Education

Bachelor of Science in Electronics Engineering

June 2018 - August 2023

Technological University of the Philippines - Manila

Science, Technology, Engineering, & Mathematics

June 2016 - April 2018

Olivarez College

Work Experience

College of Engineering, TUP Manila
Supervised Industrial Training (SIT) Program
November 2022 - December 2022

Student Research Assistant

- Gained hands-on experience in handling paper works and small-scale research projects under the research and extension of the college and the department.

Philippine Genome Center, UP Diliman
June 2022 – July 2022

Intern

- Experienced interactive training in introductory biology, genomics, and Bioinformatics, and gained supervised, hands-on experience doing research or infrastructure development of real Bioinformatics projects.