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College of Science and Technology

AFRICAN CENTER OF EXCELLENCE IN INTERNET OF THINGS

Design of a Non-invasive IoT-Based System for Prediction and Early Detection of Type 2 Diabetes using Fuzzy Logic

A dissertation submitted in partial fulfillment of the requirements for the award of masters of science degree in internet of things: Embedded computing system

Submitted By:

Kipngetich Godfrey (Ref. No: 221000067)

December, 2022

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Supervised by:

- Dr. Gatare Ignace

- Dr. Gerard Rushingabigwi

December, 2022

DECLARATION

I KIPNGETICH Godfrey, Masters' student from African Center of Excellence in internet of things, at University of Rwanda. I declare that this research thesis is my own original work and it has never been presented before anywhere in the world.

KIPNGETICH Godfrey

Ref: 221000067

Signed: ………………………….

Date: ……/……/……

BONAFIDE CERTIFICATE

This is to certify that this submitted Research Thesis work report is a record of the original work done by **KIPNGETICH Godfrey** (**Ref. No: 221000067**), MSc. IoT-ECS Student at the University of Rwanda / College of Science and Technology / African Center of Excellence in Internet of Things, the Academic year 2021/2022.

This work has been submitted under the supervision of Dr. Ignace GATARE and Dr. Gerard RUSHINGABIGWI.

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ABSTRACT

Diabetes is a chronic, metabolic disease characterized by elevated levels of blood glucose, which leads over time to serious damage to the heart, blood vessels, eyes, kidneys, and nerves. The most common is Type 2 Diabetes Mellitus (T2DM), usually found in adults, which occurs when the body becomes resistant to insulin or doesn't make enough insulin. Mostly it is a consequence of poor diet and poor lifestyle but in some cases hereditary. Diabetes can be effectively managed or avoided if it is diagnosed early. With the current trends and great strides made in technology, a lot of approaches are proposing solutions that will prevent long-term fatal conditions associated with diabetes type-2 from happening. The available solutions are mostly invasive type of testing which are uncomfortable as they require drawing blood samples for testing and is costly also to carry out as it requires constant change of consumables like test strips and needles. In this research, we use photoplethysmography (PPG) signals to get sample for blood glucose testing in a non-invasive way from the patient’s fingertip. The use of fuzzy logic system in the health domain is very beneficial as it incorporates the knowledge and experience of the medical experts which is transformed into fuzzy sets and rules. The fuzzy logic system will take the information collected from the patients in form of datasets as inputs. It then applies the rules stored in the knowledge base, which is developed by using parameters and symptoms stated by the experts who are specialist doctors in this domain to provide the prediction and early detection rates of diabetes mellitus type 2 disease. With this solution, there will be increased diabetes type 2 disease awareness among the population and improved healthy living.

Keywords: Blood glucose, Fuzzy logic, Internet of Things, Type 2 Diabetes mellitus

LIST OF ACRONYMS

AI – Artificial Intelligence

BMI - Body Mass Index

CDC – Centers for Disease Control and prevention

DM – Diabetes Mellitus

FIS – Fuzzy Inference System

HBA1C -Glycated hemoglobin

IDF - International Diabetes Federation

IoT - Internet of Things

IR - InfraRed

LED - Light Emitting Diode

MCU- Micro Controller Unit

ML - Machine Learning

OLED – Organic Light Emitting Diode

PPG - Photoplethysmography

RAM – Random Access Memory

ROM – Read Only Memory

T2DM - Type two Diabetes Mellitus

WHO - World Health Organization

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CHAPTER ONE

GENERAL INTRODUCTION

1.1 Introduction

The World Health Organization (WHO) estimates that diabetes is the most commonly reported endocrine disorder in the world, accounting for 4 million deaths annually. It also predicts that the worldwide incidence of diabetes and other blood sugar-related problems will rise from 171 million in 2000 to 366 million by the year 2030 [1]. From the statistics done in Africa, 1 in 24 adults (24 million) people are living with diabetes and it is predicted to increase by 129% to 55 million by the year 2045 [2]. Among these, over 1 in 2 (54%) of the people are living with diabetes undiagnosed and the diseases is responsible for 416,000 deaths in the year 2021 [3]. In fact, it is the fourth leading cause of death in developing countries, according to WHO and it is among the top killer conditions in Kenya [4]. Like other lifelong conditions, treatment for type 2 diabetes management involves not only medications but also identified lifestyle adjustments as the key factor to delay progression to, and/or prevent other long-term complications. This research will be focused on Type 2 diabetes mellitus which mostly affects people over 35 years of age and is mostly associated with lifestyle and hereditary factors.

The most available and widely used testing method is the invasive type of measurement whereby the fingertip is pricked to get the blood sample for testing [5]. Fingerpicking is a painful and inconvenient method and it is the main reason why a lot of people are not measuring enough to manage their blood sugars. Apart from the pain on the patient, it is also susceptible to infection and, is not readily available at all the hospitals and it is not affordable too. There are three categories of diabetes type 2 measurement ranges: normal within prescribed ranges, pre-diabetic where the blood glucose levels are slightly elevated, and diabetic ranges where blood sugar levels are high. When random glucose test is done, a blood glucose level of below 200mg/dL is considered normal while diabetic ranges is above 200 mg/dL level. For fasting glucose test the normal range is below 100 mg/dL, pre-diabetic ranges are between 100 – 125 mg/dL and diabetic ranges being above 126 mg/dL [6]. Using these ranges, a person will be diagnosed accordingly depending on the test output results and advised accordingly.

With advancement of modern technology and IoT, it is now possible to use non-invasive methods to diagnose and predict various ailments and events. The use of a signal generated by a device equipped with a photoplethysmography (PPG) sensor to get patient glucose level measurement is gaining momentum in the medical field mainly due to it is non-invasive method of sample collection, affordability and availability as it is currently being used to check heartbeat rates in our hospitals [7], [8]. The PPG signal records the change in blood volume based on the variation in the intensity of light that passes or is reflected by human organs. For this purpose, a LED and photodetector will be used to achieve it.

In this study, we use a non-invasive PPG biosensor device which is used to collect the patient's data samples. From the acquired data, a blood glucose measurement system is developed. To measure the blood glucose level, the PPG signal features are extracted and then machine learning model, in this case fuzzy logic, is used to develop an algorithm to test and analyze the data and generate a result.

1.2 Problem statement

According to World Health Organization (WHO) statement, diabetes mellitus is a chronic disease and if it goes unchecked for a long period, one develops complications from related illness [9], [10]. According to International Diabetes Federation (IDF), about 537 million people worldwide have diabetes, with 24 million from Africa and the majority living in low-and middle-income countries, and over 1.5 million deaths are directly attributed to diabetes each year [10]. According to a study done in Kenya, the prevalence of diabetes is at 3.3 % and by the year 2025 it is expected to rise to 4.5% [11]. Due to the unawareness among Kenyans, two third of diabetic patients are undiagnosed and this is quite a big challenge to the health sector [11].

With so many undiagnosed diabetics, the country's progress towards fighting and possibly eradicating diabetes becomes a difficult task. The increase in prevalence is mainly due to change in lifestyle leading to increased consumption of unhealthy diets, physical inactivity and subsequently obesity [11]. Also challenges in access and the cost of health procedures, lack of medication, population growth, etc [12], [13].

There are only two mostly used testing methods for diabetes in Kenya, random/fasting blood glucose testing and the hemoglobin A1c (HbA1c) test which gives a three months history of blood glucose. They are both invasive methods of sample collection where the finger is pricked to get the blood sample for testing, which is very uncomfortable and prone to infections[14].

Due to these factors, prediction and early detection is required to remind the unaware people of the signs and symptoms so that they can be screened and get proper medication. The most common symptoms of type 2 diabetes include increased thirst (polydipsia), increased urination (polyuria), increased hunger (polyphagia), fatigue, dry mouth, blurred vision, numbness or tingling in feet and hands, sores that do not heal and unexplained weight loss, etc [15]. Most cases of diabetes type 2 can be detected early and predicted using personal life indicators and this can go in a long way to saving lives [16].

Many people do not frequently check their sugar levels due to the invasive nature of the procedures. There is a discussion towards the non-invasive procedures and the current trends which hope will positively impact the need for frequent checkups [17].

There is also need for solutions that are standalone, that is they can operate fully without being dependent on other factors in giving results like internet and direct power. Our solution is an edge-based solution that will fully operate and provide output results using the inbuilt software and rechargeable battery which can also be recharged using solar energy. With this, we hope to reduce the challenges we have in Africa, where internet connectivity is a big challenge and stood at 28 % in the year 2020 [18] and other factors which include affordability in terms of devices and service charges, lack of infrastructure to unreliable/no electricity connection [19].

1.3 Research Questions

The following three questions are the baselines which guided this study;

1. Are there non-invasive methods of testing blood glucose levels of patients?

2. Are there diabetes detection symptoms/models that can be learned and trained using ML models to automate the process?
3. Can machine learning be incorporated with IoT to develop a system which can predict and detect early signs of a person who is pre-diabetic and give recommendations or alerts in case of detection?

1.4 Study Objectives

1.4.1 General Objective

This project aims to provide an affordable, cost-effective and convenient smart healthcare solution to be used in healthcare facilities to help in prediction and early detection of type 2 diabetes disease, mostly in the unaware population.

1.4.2 Specific Objectives

To achieve the general objective of this project, the following specific objectives are used as guiding points;

1. To use a PPG signal device, which is non-invasive method of sample collection to measure patient glucose level
2. Use existing machine learning models/algorithms to receive, process, cluster, train, build and analyze the input data to predict output values.
3. Apply fuzzy system logic in collected and selected online open datasets to train and automate prediction and detection process in real-time and be able to give recommendations and alerts depending on the output results.

1.5 Hypothesis

The hypothesis is that an embedded edge-based device can be integrated with fuzzy logic system and merged with internet of things to develop diabetes type-2 testing and awareness system to be used in health facilities with minimal expert involvement.

1.6 Study Scope

This study focused on using fuzzy logic system to early detect and predict the possibility of a person being diabetic using symptomatic parameters provided by the health experts. The parameters include random glucose level, age and BMI. The system will analyze and provide results depending on the feedback from the patient and give recommendations as well. However, this study is only applicable to diabetes type 2 disease and not any other type of diabetes.

1.7 Significance of the Study

As stated by the World Health Organization (WHO), there is a very high prevalence rate of diabetes type 2 disease and this calls for urgent actions and solutions to curb the adverse effects on the population. With this in mind and in line with the Sustainable Development Goals (SDG) number three on health, which is about ensuring healthy lives and promoting well-being at all ages[20], this solution will greatly help improve the health wellbeing of many people and in the end reduce avoidable health issues. The solution will offer the following benefits;

1. Possibility of doing frequent tests at an affordable cost as the device is reusable.
2. Convenience and comfortability in taking samples as it is non-invasive method.
3. The results will be provided in real-time.
4. Patients will get results and recommendations after their tests.
5. It will also help the government to know the general health of it is citizens and plan accordingly in terms of medicine, food and other lifestyle requirements.
6. As a researcher, I will be able to use my knowledge and experience to develop solutions that will improve the welfare of the society.

1.8 Organization of the Document

Chapter one gives the introduction of the research problem and the objectives that we are going to achieve after completion of the study. Chapter two discusses the literature review and the gaps identified from it. In chapter three we discuss the research methodology adopted, the research process and the methods of data collection used. Chapter four discusses the system design and implementation which includes architectural design, system design, embedded design, hardware components and system flow charts. Chapter five discusses the results and findings of the study and finally chapter six discusses challenges, recommendations and conclusions from the research study.

1.9 Summary

This chapter has presented an introduction of the study and the problem statement. From it we have seen that diabetes type 2 is a very common and serious lifestyle disease which affects a lot of people in the world. A bigger percentage of these people are unaware that they are developing the disease and this is mainly due to the challenges in testing and diagnostic gadgets available in most health facilities. The study, upon implementation, will contribute towards the achievement of the sustainable development goal number three on health by providing cheap and affordable device for testing and prediction of diabetes type 2 disease.

CHAPTER TWO

RELATED LITERATURE

2.1 Literature Review

In this chapter, we look at the existing methods of diabetes mellitus testing and management solutions currently available and future works towards providing better improved solutions.

2.1.1 Use of AI and ML in Diabetes Management

Machine learning techniques has been applied in health systems to do predictive models and it includes diabetes disease. The ML techniques were applied and it was able to predict various types of diabetes and it also showed the relationship to the future risk level of the patient and the type of treatment that can be provided [21]. It was found out that prediction analytics when applied to health data can help make critical choices and predictions whereas machine learning techniques are used to perform prediction analysis.

There are regular factors that determine diabetes which include Glucose, BMI, Age, blood pressure, etc. and with these factors a predictive model using logistic regression and gradient boosting machine techniques can be applied. The model has the ability to predict diabetes using commonly available laboratory results with satisfactory sensitivity [22]. However, this system is recommended for online use to assist physicians in predicting future occurrence of diabetes and provide necessary prevention interventions.

The analysis of the detection, diagnosis, and self-management techniques of diabetes depend mainly from six different parameters which are datasets of diabetes namely; pre-processing, methods, feature extraction methods, machine learning-based identification, classification, and diagnosis of diabetes [23]. These factors are applied in machine learning and artificial intelligent algorithms to develop machine learning and artificial intelligent algorithms for detection and self-management systems.

Machine Learning approaches seek to predict and classify patient features by recognizing patterns in large dataset. These approaches produce decision trees to help guide clinical interventions which have higher sensitivity and specificity than traditional regression models for risk predictions. The biggest challenge with this approach is the application of strategies to communicate how machine learners are generating their prediction [24]

Artificial Intelligence and Machine Learning are transforming all spheres of life and it includes the health sector system. With application of Machine Learning and Artificial Intelligence, there is a potential to vastly enhance the reach of diabetes care by making it more efficient, and it is increasingly becoming very useful in the management of chronic diseases which include diabetes [25].

However, researchers and developers face two main challenges when building diabetes type 2 Machine Learning models. The first challenge is due to considerable heterogeneity in previous studies regarding the techniques used which makes it challenging to identify optimal technique to use. Secondly is the lack of transparency about the features being used in the models thus reducing interpretability. However, these challenges are addressed by informing the selection of Machine Learning techniques and feature to create novel type 2 diabetic predictive models [26]

2.1.2 Use of IoT and ML in Diabetes Management

A lot of research has been done on incorporation of IoT and machine learning/artificial intelligence techniques with different approaches applied.

A survey was done to give the status of research in determining diabetes and the proposed frameworks. It was found that the use of IoT with Machine Learning/ Artificial Intelligence greatly assists in detection and monitoring of diabetic patients in that high volume of medical information is produced and it is important to gather, store, learn and predict the health of such patients using continuous monitoring and technological innovations. The benefit is of using IoT include simultaneous reporting and monitoring between doctor and patient, end-to-end connectivity, data assortment and analysis. [27].

Internet of Things has brought a lot of positive trends in the health domain. An IoT application framework can be integrated with Machine Learning techniques to design an advanced automation system which will be used to monitor diabetic patients and make decisions for proper diagnosis [28].

Diabetes management in ambient assisted living environment is very difficult since many factors affect the patients' blood sugar levels. These factors include different illnesses, treatments, physical & psychological stress, physical activity drugs, change in meals etc. cause unpredictable and potentially dangerous fluctuations in blood sugar levels. Personal device is developed based on IoT, with patient support profile management architecture based on RFID card and connectivity between the developed patient personal device to the nurses'/doctor's desktop application to manage personal health cards at patient web portal [29]. However, for future work, they recommend to include extended security privacy to ensure anonymous consultations from external nurses or doctors.

Health wearable devices improves the effectiveness of monitoring life threatening conditions. This effectiveness increases with addition of IoT component with a wearable device [28], [30]. A study done found out that for individuals with early type 2 diabetes, lifestyle intervention using wearable monitoring system and remote health guidance improved diabetic control in middle-aged company workers [31].

It has also been established that by applying intelligent data analysis techniques, many interesting patterns are identified for early and onset detection and prevention of several fatal diseases, diabetes being among them [32].

There is also a discussion about a new system for monitoring diabetic patients and predictive analytics using different Machine Learning algorithms and a node microcontroller [33]. With addition of IoT, it was able to monitor blood glucose level, body temperature and location of the patient.

2.1.3 Use of Fuzzy Logic in Diabetes Management

Internet based innovations are being used to share and circulate information. People around the world can be assisted by using online platforms to manage diabetes mellitus, whereby the patients can check their diabetes risk and the doctors can also access the same. Fuzzy logic approaches can be utilized to achieve this by using variables and setting of fuzzy rules for the decision-making logic[34].The paper proposes the future work to be extended further by adding more sets for diabetes symptoms and complication as well as the rule base be added with expert system modules for diabetes diagnosis and it is management.

Implementation of a method that can help in detection of diabetes is a very important step towards the prevention and control of illness, especially in early stages. By using adaptive neural fuzzy inference system, it is shown that it is able to predict the illness with high accuracy levels even by using real data sets [35]

Early diagnosis of diabetes aids patients to start timely treatment and eliminates risk of severe complications. Fuzzy logic can be used to develop an interpretable model to perform early detection of diabetes [36]. This is done by combining various methods and fuzzy rules on the identified classifiers and evaluated using available diabetes datasets. It is recommended to be used to diagnose other diseases in future works.

There are various optimization techniques used for classification of diabetes, which is a process of attaining the most effective result under specified conditions by maximizing the desired values and minimizing undesired ones depending on blood glucose level and fuzzy logic system [37]. This classification will help the doctors confirm whether the patient is diabetic, pre-diabetic or non-diabetic. However, the study recommends enhancement of recognition efficiency to improve accuracy levels in future.

Diagnosis of diabetes is complicated and time-consuming process. By using fuzzy system in medical condition diagnosis, it is possible to efficiently deal with human logic. Fuzzy logic creates chances for easy checking of the system, adding or deleting more inputs and changing fuzzy conditional statements. In this study, the proposed methodology presented an effective and efficient diagnostic system for diabetes disease with the use of fuzzy logic toolbox of Matlab and it showed 97% accuracy when compared with other diagnostic systems [38] The study recommends that for future works the number of inputs to be increased in order to include more information about patient diagnostic process, apply fine tuning techniques to optimize membership function parameters, other types of diabetes be included and improve the knowledge base for improved performance analysis.

By using available datasets and fuzzy system, it can be demonstrated that performance assessment methodology is very effective in improving the accuracy of diabetes application [39]. Various input variables are selected as per the dataset and membership functions are identified. Probability values for fuzzy rules are set which will be used to develop the rule-base. The developed system was able to show a high accuracy of 90.38% compared to past methods and this was mainly attributed to the use of fuzzy assessment methodology which evaluates the number of membership function, correlation fuzzy logic to identify area overlap between fuzzy numbers and membership and the probability to manage uncertainty in rules.

A study was done that developed a fuzzy expert system that was based on the concepts of fuzzy logic, using fuzzy verdict mechanism for the diagnosis of diabetes by analyzing the data of the patients and compared the result of the expert system with the previously available mechanisms in the year 2011 [40].

2.1.4 Invasive Methods of Diabetes Testing

According to Centers for Disease Control and Prevention (CDC), there are several tests which are done by taking of blood samples by way of pricking to test for blood glucose level measurements [41]. The available clinically approved invasive testing methods are;

1. **A1C test** which measures the average blood sugar level over the past 2-3 months. An A1C below 5.7% is normal, between 5.7 and 6.4% indicates you have prediabetes, and 6.5% or higher indicates you have diabetes.
2. **Fasting Blood Sugar Test** which is used to measure blood sugar level after overnight without eating. A fasting blood sugar level of 99 mg/dL or lower is normal, 100 to 125 mg/dL indicates you have prediabetes, and 126 mg/dL or higher indicates you have diabetes.
3. **Glucose Tolerance Test** which is used to measure blood sugar level before and after drinking a liquid which contains glucose. This is done after fasting overnight and samples will be checked after 2 hours period. At 2 hours, a blood sugar level of 140 mg/dL or

lower is considered normal, 140 to 199 mg/dL indicates you have prediabetes, and 200 mg/dL or higher indicates you have diabetes.

4. **Random Blood Sugar Test** which measures the blood sugar at the time it is tested. This can be taken anytime and don't need to fast. A blood sugar level of 200 mg/dL or higher indicates you have diabetes.

2.1.5 Non-Invasive Methods of Diabetes Testing

Most of the existing research shows a positive trend towards developing non-invasive methods of glucose testing. Among the most promising technologies is the spectroscopy which involves the study of objects based on their wavelengths when they are emitting or absorbing light [42], [43].

Existing methods of extraction of samples in addition to indicators of blood glucose level towards the development of an innovative non-invasive extraction technology is gaining momentum. These include analysis of support methods towards customized, automated and intelligent diabetic management systems[17], [44].

A simple screening method was established for diabetes based on myoinositol (MI) in urine samples collected at home and it showed that it is possible to measure sugar levels using non-invasive methods [45].

There is also a lot of research focusing on the use of Photoplethysmography (PPG) signal to collect blood glucose measurement from the finger sensor using photodiode and nearby infra-red-light technology [43], [46], [47].

2.2 Summary

From the mentioned researches done on detection and prediction of diabetes type 2 as well as other diseases, most of them use clinical data (blood glucose level), which is collected invasively from the patients directly with the help of health personnel. This normally presents the patients with hard choices due to the inconveniences of the method used, the cost of the service, and the need to have a medical expert to take and interpret the results. Also, the aforementioned solutions mostly present the prediction results only and leaves the decision of the next action to the health personnel. Others provide the non-invasive testing methods only and leaves the diagnosis part to the medics. The non-invasive testing methods are currently undergoing research by various researchers, and we hope to add our findings too to this noble cause. The high cost of medical care in Africa coupled with limited number of medical personnel calls for a solution which is cheap in cost considering it is consumables, re-usable, easy to use, smart to give automatic recommendations and stand-alone device which can be used without the help of medical expert. Finally, the solution is edge-based solution which means that it can be used to test and get results in real-time without the need of external factors like internet connectivity.

CHAPTER THREE

RESEARCH METHODOLOGY

In this chapter the methods and approaches used to conduct the study are outlined. This includes the steps undertaken to complete the study, the system design methodology, fuzzy logic concept and tools used in prototyping of the proposed solution.

3.1 Research Process

The research process began with an idea that prompted further interrogation by undertaking of a comprehensive literature review. This led to the topic of the study that was formulated based on the identified gaps from literature and existing solutions. The research proposal was then prepared and presented for approval. On approval the steps that followed included;

1. State of the art analysis
2. Identifying prototyping resources (dataset, AI platform, software tools)
3. Setting up a prototyping tools and resources
4. Fuzzy Inference System (FIS) design and testing
5. System design and prototype setup
6. System testing and debugging
7. Thesis preparation and publication of results.

3.2 Research Design

Even in it is early stages, diabetes can cause changes to the blood vessels and how blood flows through them, often referred to as vascular changes. These changes in features will be extracted and machine learning models, in this case using fuzzy logic system, will be used to improve an existing algorithm to analyze the data and give an output. This leads to the design and implementation of a prototype device.

The solution will incorporate the Photoplethysmography (PPG) sensor, which is an uncomplicated and inexpensive optical measurement method that is often used for pulse rate monitoring purposes. PPG is a non-invasive technology that uses a light source and a photodetector at the surface of skin to measure the volumetric variations of blood circulation. Other parameters that will be incorporated into the fuzzy logic system are the age of the patient and BMI. This will enable the training to be effective and increase the prediction accuracy.

The data will be processed and analyzed at the edge whereby the IoT device will use fuzzy system logic to detect, analyze and do the comparison with the datasets provided.

3.3 Data Collection

3.3.1 Data Collection Methods

In this study, we implement the solution in two phases;

1. Phase 1 where we collect data from people to create an algorithm with the Max30102 biosensor.
2. Phase 2 where we build the artificial intelligence detection and prediction system using fuzzy logic system where we acquire data from experts and build a knowledge base to analyze and infer the output results.

3.3.1.1 Phase 1: Sample Data Collection

To effectively create a correlation between a person's blood glucose level and Max30102 sensor IR readings, we collected raw data directly from one hundred volunteers and analyzed both readings in order to map them together.

This study used clinically approved glucometer (CodeFree) manufactured by SD BIOSENSOR healthcare PVT LTD company to take blood samples from the volunteers [48]. We then recorded this value and the same person places his/her finger on the Max30102 sensor and the IR readings are recorded as well.

These two readings are later analyzed and correlation coefficient is calculated and an algorithm is developed which will enable the blood glucose testing using only the Max30102 sensor which is non-invasive method of testing.

3.3.1.2 Phase 2: Knowledge-Base Development

To effectively train and test our detection and prediction model, we considered defined parameters from previous literatures [49], [50] and verified online websites, i.e. Center for Disease Control (CDC) and World Health Organization (WHO) [51]–[53], to create a knowledge base and create rules that will determine the probability of the disease occurring. These online websites were selected because they offer accurate, analyzed and reliable information and data in terms of data integrity and accuracy. Center for Disease Control (CDC) applies scientific standards to ensure the accuracy and reliability of their research results and routinely seeks inputs of highly qualified peer reviewers on the propriety, accuracy, completeness and quality of it is materials [54]. World Health Organization (WHO) also has very strong policies concerning the information and data they share on their platform. They have a technical and communications team who work together to ensure that all communications are accurate and deliver consistent messages. The team follow procedures to ensure the technical accuracy and appropriate presentation of their information and always keep fact sheets up to date [55].

We identified three basic input parameters which have big impact on diagnosis and detection to build our system. These are Random Blood Glucose level, Body Mass Index (BMI) and Age of the person. These input parameters will be analyzed and it will produce one output known as Diabetes prediction. These parameters will help come up with diagnosis and rules for the fuzzy inference system.

3.4 System Development Approach

3.4.1 Waterfall Model

For this study, waterfall software development methodology is used. Waterfall methodology is a linear-sequential life cycle model, in which each phase must be completed before jumping to the next phase [56]. The selection of this model is guided by the need to understand the needs of health officers which include ease of device use, easy interpretation of results, fast and reliable device, and the application areas of the device. The steps involved in waterfall methodology are as shown in figure 3.1.

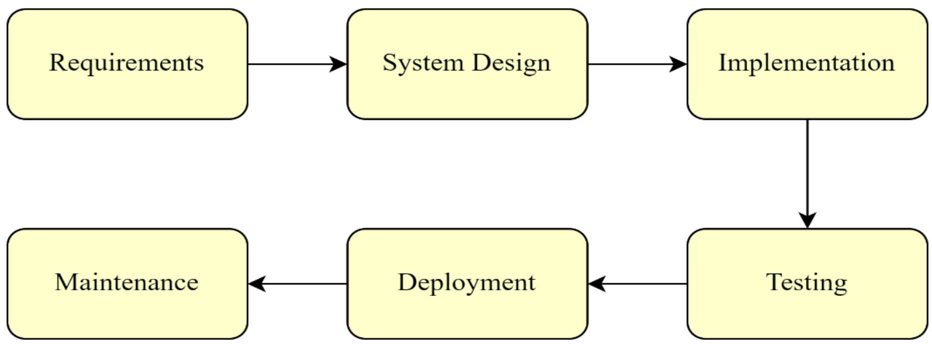


Figure 3.1: System Development cycle

This model was chosen because;

The system requirements for prediction and detection of diabetes type 2 disease are clearly documented and are not expected to change.

- The technologies to be applied are well understood and are static, it cannot change over time.
- There are no ambiguous requirements for the system.

The project implementation time is short and with a fixed deadline.

The advantages of using the waterfall model are;

- It is simple and easy to understand
- It makes the system management simple as each phase has a specific outcome

- The phases are done systematically and in order.
- It works perfectly with smaller projects with fixed timelines
- The outcome of each step is clearly documented and can be easily referenced.

3.4.2 System Development Steps

The following are the sequential steps which are followed using the waterfall model development.

1. Requirements

In this phase, we collect all the requirements based on the problems statement and get feedback from the stakeholders and other service providers involved in this study. These requirements are analyzed and the system requirements documented.

2. System Design

This is the phase where the system level design is done. This includes the system architecture, block diagram and prototype design.

3. Implementation

This is where we combine the input data and output data to create a complete system. It involves the sample collection from the patient and the artificial intelligence section where all the parameters will be analyzed. This section involves both the hardware configuration and software programming to create a working prototype device.

4. Testing

This is the phase where the system is put into real use and results expected as per the user requirements.

5. Deployment

This is the stage where the finished product will be available to be used in medical facilities to do the testing, diagnosis and recommendation functions.

6. Maintenance

This is the last phase where the system will be undergoing regular checks and maintenance case by case and in some cases upgrades.

3.5 The System Design Process Flow

The system process flow starts with the system initialization where the system boots up and comes to the ready state for the process to start. When the system is ready, the patient glucose level measurement is taken and then it is processed and analyzed with other parameters defined to predict the possibility of being affected by the disease. Once this is completed successfully, the fuzzy inference logic is done, but if not, the system goes back to analysis stage to start the process all over again. After performing the inference logic, the system automatically checks again if all the rules were considered and if it is done, the results will be displayed on the Oled screen with recommendations on the next cause of action to be taken. If the rules were not considered the system returns to performing the inference logic again until it is successful. To avoid continuous looping in the system, we will use recursion technique where a function will call it itself. The figure 3.2 shows the design process flowchart of the system.

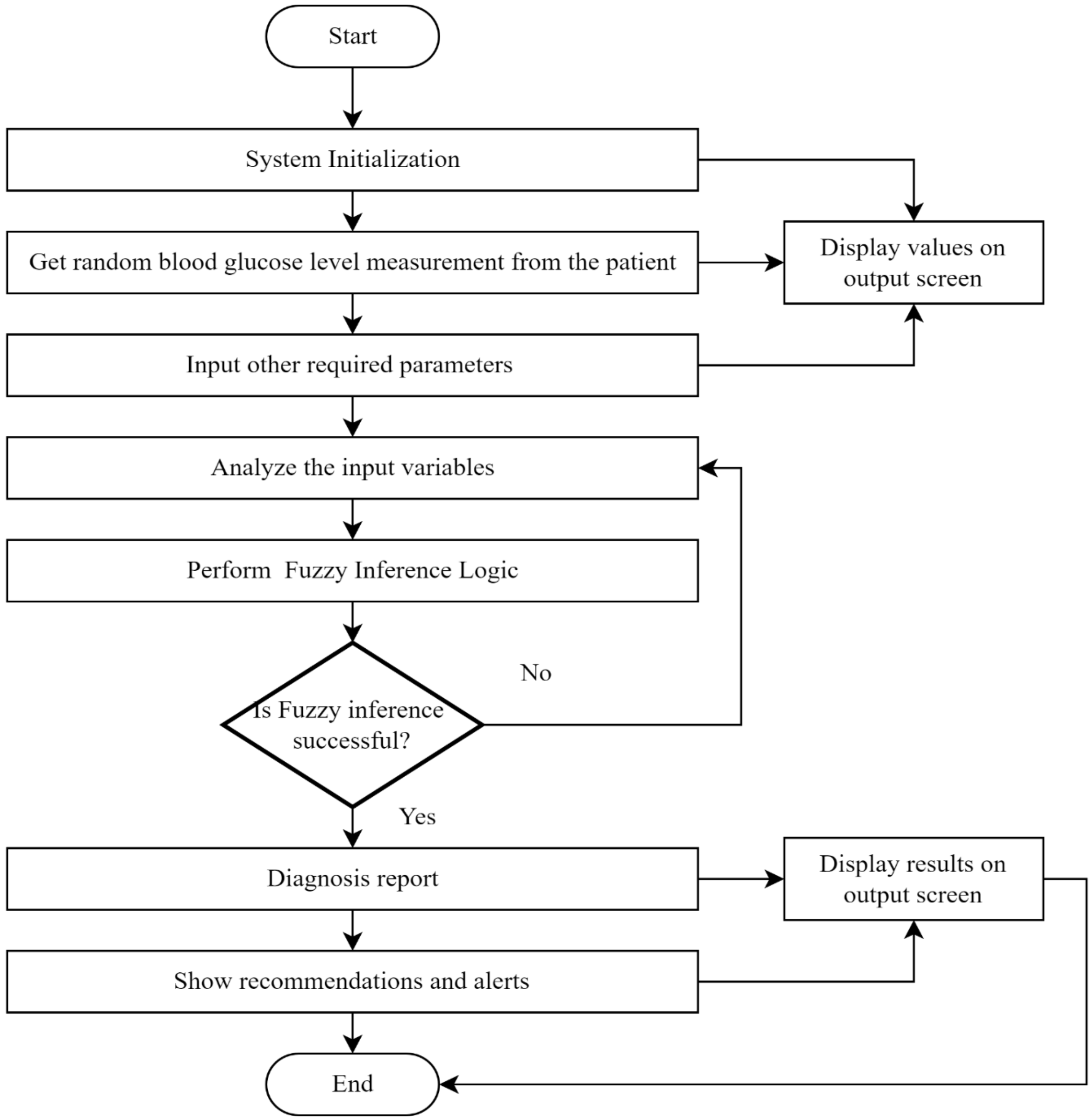


Figure 3.2: System design flowchart

3.6 The Fuzzy Logic System Concept

Once the data has been collected, a Fuzzy expert system model is developed in order to process and analyze the data. Matlab fuzzy logic toolbox is used to develop the prediction and detection model using rules implemented in a fuzzy inference system. Fuzzy Logic is a method of reasoning that resembles human reasoning. This model will later be converted into an Arduino compatible model to be implemented on an embedded device.

The Fuzzy Logic consists of four mains parts which are; fuzzifier which transforms the system inputs into fuzzy sets, knowledge base which stores the knowledge from experts and the rules to be applied to analyze the parameters. Another part is the fuzzy inference engine which will simulate the human reasoning process by making inference on the inputs and rules and finally the Defuzzifier to transform the fuzzy sets from inference engine back to crisp values [57].

The fuzzy logic system is preferred in most cases due to it is flexibility where rules can be modified by adding or deleting. It is also easy to understand and construct the architecture of fuzzy logic system to accommodate imprecise, distorted and noisy input information. It also provides solution to complex problems in many fields of life including medical domain where it resembles human reasoning and decision making. Figure 3.3 shows the architecture of the fuzzy logic system structure.

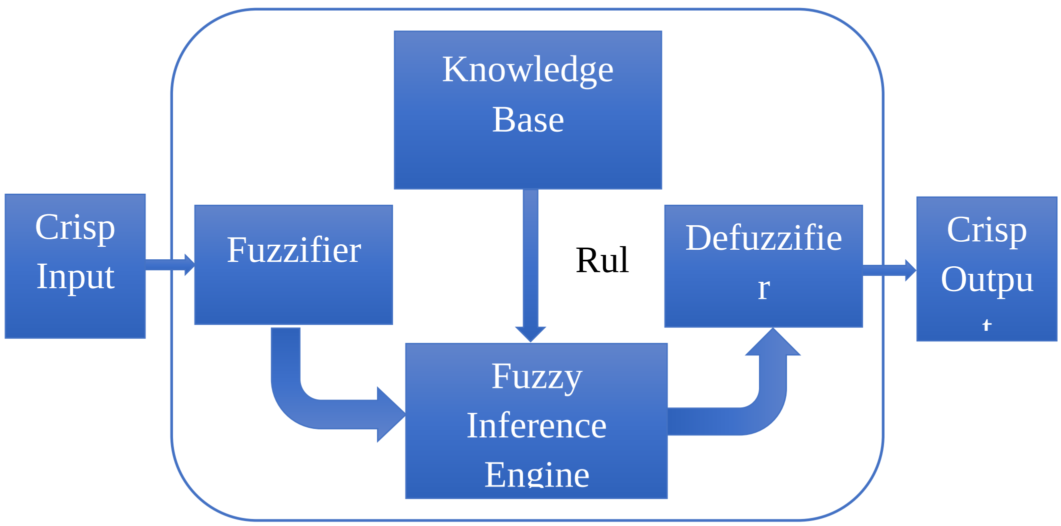


Figure 3.3: Block diagram for Fuzzy Inference System

3.7 Dataset Preparation for Fuzzy Logic System

The solution is based on fuzzy inference system to analyze and predict the possibility of a person developing diabetes type 2 disease based on three input parameters. These input parameters are Blood Glucose Level (BGL), Body Mass Index (BMI) and Age of the person and the outcome will be one output parameter Diabetes (DM). The fuzzy logic system is based on Mamdani type fuzzy inference system [58]. Table 1 shows the details of the parameters used.

Table 1: Linguistic variables for input and output parameters

No	Linguistic variable	Type	Membership Functions	Numerical ranges
1	Random Blood Sugar Level (BGL)	Input	Normal	Less than 140 mg/dl
			Prediabetes	140 mg/dl – 199 mg/dl
			Diabetes	Above 200 mg/dl
			Source:[59]	
2	Body Mass Index (BMI)	Input	Underweight	Less than 18.5
			Healthy	18.5 – 24.9
			Overweight	25.0 – 29.9
			Obese	Above 30
			Source:[60]	
3	Age	Input	Child	(5 – 12) years
			Teen	(13 - 19) years
			Adult	(20 - 39) years
			Middle age adult	(40 - 59) years
			Senior adult	Above 60 years
			Source:[61]	
4	Diabetes (DM)	Output	Very Low	0 – 0.25
			Low	0.22 – 0.4

			Medium	0.38 – 0.56
			High	0.50 – 0.74
			Very High	0.73 - 1
			Source:	

3.8 The Fuzzy Rules

Fuzzy rules are used to analyze and evaluate the output variable membership functions that are later used in the inference process. These rules are represented by IF-THEN statements and in our case, we use the AND operator to decide on the outcome.

Fuzzy rules are created using knowledge from relevant domain experts and from verified available online guidelines and procedures from World Health Organization (WHO), Centre for Disease and Control (CDC) and International Diabetes Federation (IDF) websites [52], [53], [59], [62], [63]. The input variables are identified and the resulting output variable. Depending on the ranges and weights assigned to each membership function, an outcome will be anticipated.

3.9 Software Tools

To successfully implement the study, several software tools are used to achieve the objective. The softwares outputs are later combined to produce a complete system. The following software tools are used in this study;

3.9.1 Arduino IDE

Arduino IDE is an open-source Arduino Integrated Development Environment software which contains a text editor to write code, a message area, a text console to display output and a toolbar with buttons for common functions and a series of menus. It is used to connect to the Arduino hardware to upload programs and communicate with them [64].

3.9.2 MATLAB Software

MATLAB is a programming platform designed specifically for engineers and scientists to design and analyze systems and products as well as create models [65].

3.9.3 MakeProto

This is an online tool used to convert a Matlab generated Fuzzy Inference System (FIS) file to an Arduino executable C code. We use it to convert the fuzzy model (fis) file to make it executable on the Arduino board so as to enable edge-based inference [66].

CHAPTER FOUR

SYSTEM DESIGN AND IMPLEMENTATION

In this chapter the system design architecture and implementation are discussed. These include the three level of architectures used, which are the perception layer composed of data/ sample collection process, network layer where the gathered data is processed and lastly the application layer which is the interaction point for the doctor and patient to check the results. Also, the embedded system level design is presented and it consists of all the hardware devices that makes up the gadget. Finally, is the system flow chart which shows the process of data collection from the patient, the fuzzy logic process and generation of output results.

4.1 System Design

The solution incorporates the Photoplethysmography (PPG) sensor which will be integrated with a microcontroller to form the sensing unit part of the system. The collected data is then aggregated and integrated with manually inputted data, which is BMI and age to create a prediction and detection algorithm by using fuzzy logic system. The Fuzzy Logic System discussed in Section 3.6 is used to diagnose and predict diabetes type 2 disease. It starts by converting crisp values into fuzzy values using fuzzification technique and fed as input to the fuzzy inference system to apply the rule base algorithms to generate the results based on the knowledge base provided by the human experts. The final output which is fuzzy set will again be converted into crisp values using defuzzification technique to produce output values [57]. From the output results, the system will be able to automatically give recommendations depending on results and results will be displayed on the device using Oled screen. The output data is also transmitted to a ThingSpeak platform for future analysis and storage if need be. The system is composed of both hardware and software tools. Figure 4.1 shows the high-level system architecture of the design where the process starts from the lowest level called the perception layer which is the patient sample collection stage. The next phase is the network layer where the analysis and communication take place between the device and storage options available. The final layer is the application layer where the results are displayed and interpreted to the patient and health care givers.

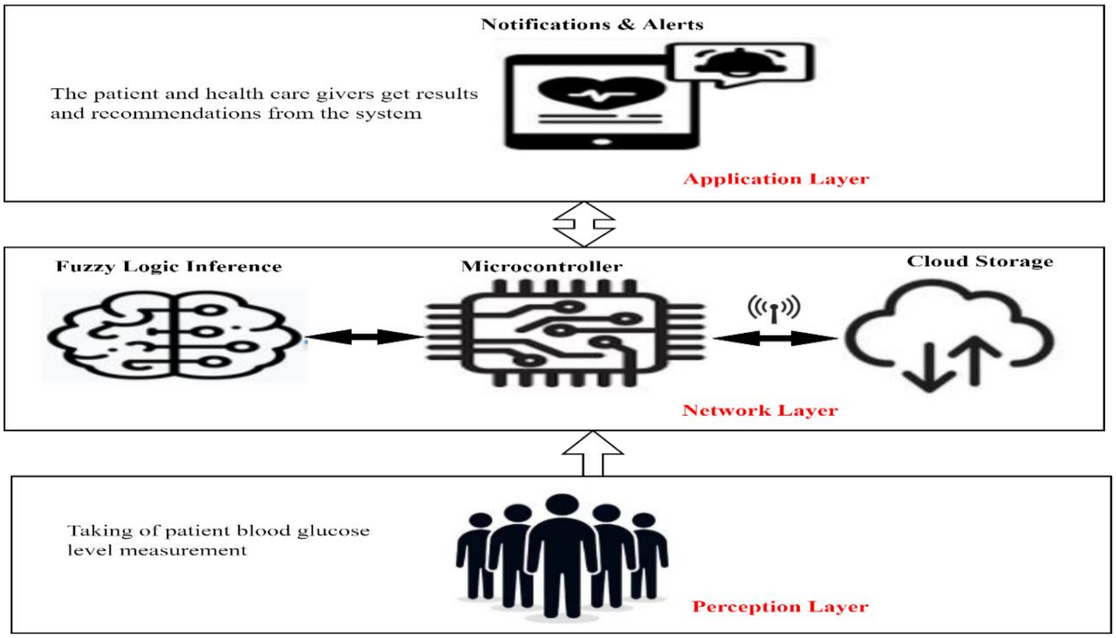


Figure 4.1:High Level System Architecture.

4.2 Embedded System Level Design

The embedded system consists of a PPG signal biosensor for taking patient blood glucose measurement using the fingerprints as the input. The input values are fed into an ESP32 Microcontroller for data processing and will be connected with an Oled display to show the results. Also, there is an LED and a buzzer to indicate when the blood glucose level measurement is taken. The microcontroller has an inbuilt WI-FI module which will be used to send data to the cloud for storage and further analysis when required. Figure 4.2 shows the embedded system design of the prototype.

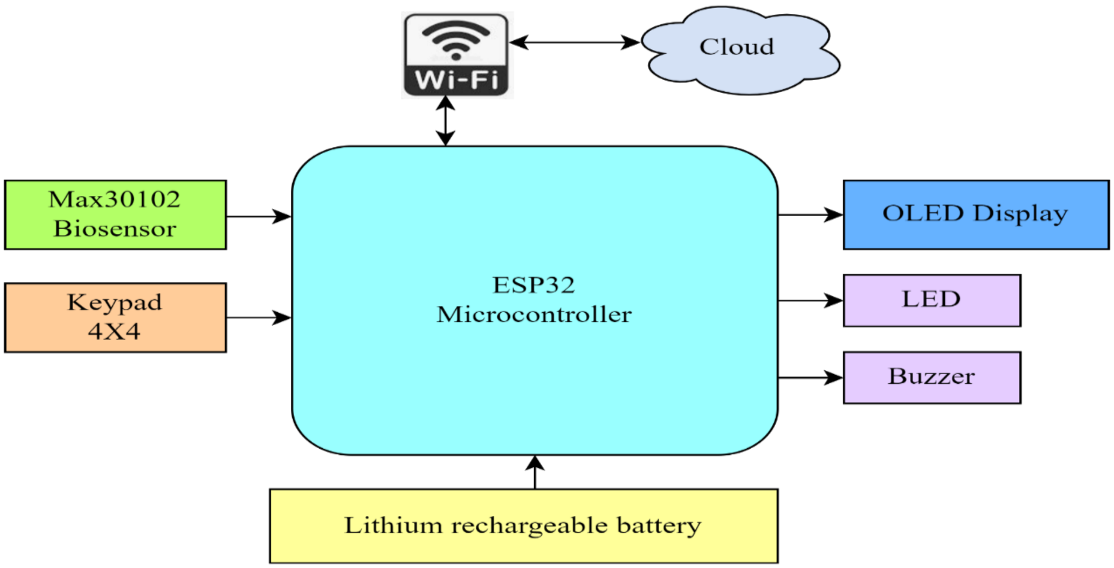


Figure 4.2: Prototype block diagram

4.3 Hardware Components

The system consists of hardware components which include ESP32 microcontroller, Integrated biosensor max30102 for collecting sample from patients, LED to display different system statuses, buzzer to provide system alerts, Oled display to show messages and results and a rechargeable battery for powering the device.

4.3.1 ESP32 Microcontroller

ESP32 is a very powerful ultra-low power, low cost MCU built on Tensilica Xtensa 32-bit LX6 microprocessor with some variants having up to two cores and supports pinning tasks to cores and this makes it very powerful to run multiple tasks simultaneously. It also boasts of inbuilt WI-FI and dual-mode bluetooth capabilities which makes it very ideal for IoT project development and is developed by Espressif Systems [67]. It is integrated with RF components like Power Amplifier, Low-Noise Receive Amplifier, Antenna Switch, Filters and RF Balun. This makes designing hardware around ESP32 very easy as you require very few external components. Among it is specifications are single/dual-Core 32-bit LX6 Microprocessor with clock frequency up to 240 MHz, 520 KB of SRAM, 448 KB of ROM and 16 KB of RTC SRAM, Motor PWM and up to 16-channels of LED PWM, secure boot and flash encryption and cryptographic hardware acceleration for AES, Hash (SHA-2), RSA, ECC and RNG. For an understanding of the ESP32 module with pin out configurations, the reference is made from Electronic Hub (https: www.electronicshub.org/getting-started-with-esp32/).

4.3.2 Integrated maxim Biosensor (MAX 30102)

The MAX30102 is a very versatile biosensor that can also measure body temperature other than heart rate and blood oxygen level. It features two LEDs (one Infrared and one Red), a photodetector, optics, and low-noise signal processing unit to detect pulse oximetry (SpO2) and heart rate (HR) signals [68]. The main idea is that you shine a single LED at a time and check the amount of light that is getting reflected back to the sensor. Based on the reflection you can determine the blood oxygen level and heart rate. This module has 7 pins VCC, SCL, SDA, INT, IRD, RD, and GND. All the pins of this sensor module are digital, except VCC and Ground. More information about this sensor and configurations is found at Maxim integrated website on (https://www.maximintegrated.com/en/products/interface/sensor-interface/MAX30102.html)

4.3.3 Oled Display (128X64)

OLED is a low-power, self-luminous display module board compatible with Arduino. It is specifications include 128x64 OLED Display size: 0.96", built-in controller SH1106, interface 6800, 8080, SPI, I2C communication [69]. For reference and more about the OLED display configuration, check on (https://lastminuteengineers.com/oled-display-arduino-tutorial/).

4.3.4 Buzzer

This is a piezo electronic buzzer which is used to give a sound to indicate a condition. It has two terminals, a positive (VCC) and Negative (GND) terminals. This reference can be checked from the seeed studio website on (https://www.seeedstudio.com/blog/2020/12/22/introduction-to-buzzers-piezo-and-magnetic-buzzers/).

4.3.5 LED

A light-emitting diode (LED) is a semiconductor light source that emit is light when current flows through it. It is used to indicate the state of the system at a given time and also status of an output. There are many different kinds and types of coloured LEDs. This information is found at Reichelt company website: (https://www.reichelt.com/de/en/led-5-mm-standard-green-led-5mm-st-gn-p6823.html).

4.3.6 Lithium Rechargeable Battery

Lithium Polymer ion battery is a rechargeable battery that is used to provide power to the prototype. It is used as a stand-alone power supply for the device and can be recharged using solar energy. More information and specifications about this battery is found at Amazon website (https://www.amazon.com/EEMB-3700mAh-Rechargeable-Connector-certified/dp/B08215B4KK).

4.4 System Analysis

4.4.1 System functional requirements

This project aims to deliver a high-quality product at the end of study. The functional requirements of this project include product features and functions that must be implemented to enable users to accomplish their tasks. The functional requirements for the system are as follows:

- The system should be able to test the blood sugar level of the patient.
- The health officials should be able to enter BMI and Age of the patient to the system
- The system should be able to predict the diabetic health status of the patient.
- The system should be able to automatically give recommendations after the results
- The system should be able to send the collected data and the prediction to an open source IoT cloud platform for storage and further analysis if need be.

4.4.2 Non-functional requirements

Non-functional requirements are quality attributes that describe the ways the system should behave. They include the following:

- Availability: the system's functionality and services should be available for use with all operations 99.99% of the time.
- Usability: the system should be easy to use by the medics and patients.
- Reliability: The system should work without failure for at least 5 years
- Scalability: The system must grow without negative influence on it is performance.
- Power consumption: It should be in a position to consume as low power as possible to conserve energy and the environment. Ultra-low power devices should be used in the implementation.
- Data Integrity: the system should be in a position to secure access to confidential data for the users.
- Performance: the system should ensure optimal responsiveness to various user interactions with it at all times
- Recoverability: In case of failure, the system should have a self-recovery backup procedure
- Flexibility: Flexible service-based architecture will be highly desirable for future extension
- Security: ensure that the software is protected from unauthorized access to the system and it is stored data.
- Size: the system should be designed using miniaturized devices for portability
- The system should be powered through a renewable energy source, and in this case solar power.

4.5 Flow Charts

4.5.1 Data Processing Flow Chart

The process of data processing starts with initialization of the system. Once the system is running, patient data is acquired as per system prompts and sent to the microcontroller for processing. Figure 4.3 shows the process flow chart used for acquiring the data from the patients.

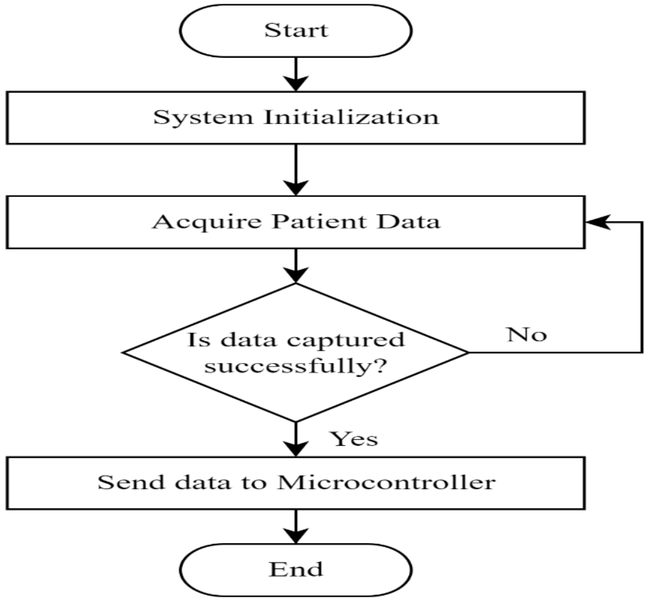


Figure 4.3: Data collection flow chart

4.5.2 Fuzzy Inference Logic Flowchart

The fuzzy logic system begins with identifying the input parameters and the output parameters. This is decided by the problem to be solved and the type of data to use. After identification of the inputs and outputs, we assign ranges to the parameter membership functions which will be used as border lines to define the belongingness to an input. Expert knowledge acquired from domain experts is now used to generate the rules to be used in determination of the output. Next step is passing this data through the fuzzy inference engine where all the data and rules are analyzed. From here, the fuzzy output is defuzzified to give crisp output. This crisp output is then checked if all rules were applied successfully to give output results, otherwise it goes back to fuzzy rule generation stage. This system flow is shown in figure 4.4

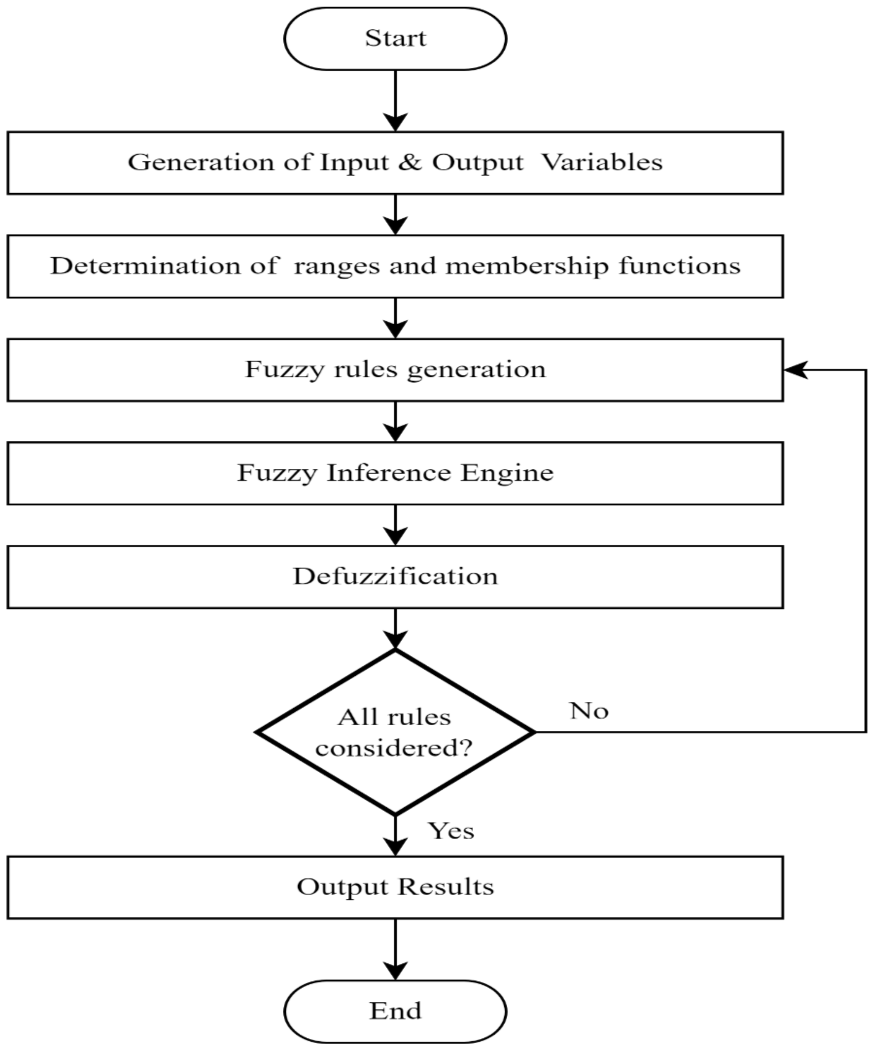


Figure 4.4:Fuzzy Inference Logic flowchart

CHAPTER FIVE

RESULTS AND ANALYSIS

This section discusses the results and analysis of the research study. This includes the data collected during the research process and the results obtained and how it affects the outcome of the research findings. Also, the results and analysis of the fuzzy logic machine learning method used to train and analyze the parameters to give out the outcome are discussed. A prototype was also developed and we discuss the performance and the results here as well.

5.1 Data Analysis

This section discusses the analysis of the data collected in details and how it affects the system output.

5.1.1 Random Blood Glucose Level (BGL) as an Input

In this study, we collected a sample size of one hundred volunteers and it was observed from the analysis shown in figure 5.1 that there is a strong linear relationship between the two measurements. This is done by calculating the Pearson correlation coefficient, which is a measure of the strength of a linear association between two variables and is denoted by r. When the correlation coefficient is between 0 and 1, it is referred to as positive correlation, which in this case is 0.66 and this means that it has a large correlation in that when one variable changes, the other variable changes in the same direction [70]. Table 2 shows the Pearson correlation coefficient calculation of the two parameters.

Table 2: Pearson correlation coefficient

Pearson Correlation Coefficient		
	Glucometer	*IR*
Glucometer	1	
IR	0.66209122	1

From this observation, it is justified that even with more data, the relationship will still remain the same hence the sample size was enough to calculate the multiplication factor.

After data collection process as explained in section 3.3.1 A, the readings from the glucometer and biosensor module are mapped to create a formula to test blood glucose non-invasively. To get the difference between the two parameters an average of the two values is calculated, i.e., (glucometer/ IR value) for the whole data collected. From the resulting average values of the two parameters, the mean is calculated and a value of 1.23 is obtained, which we then use it in the formula as a multiplication factor to get blood glucose level measurement non-invasively using Max30102 biosensor.

So, the formula is: Random Blood Glucose Level = IR Value x 1.23. This formula is then integrated in the code for blood glucose testing using max30102 biosensor module.

Figure 5.1 shows the comparison of the data collected using glucometer and Max30102 biosensor module.

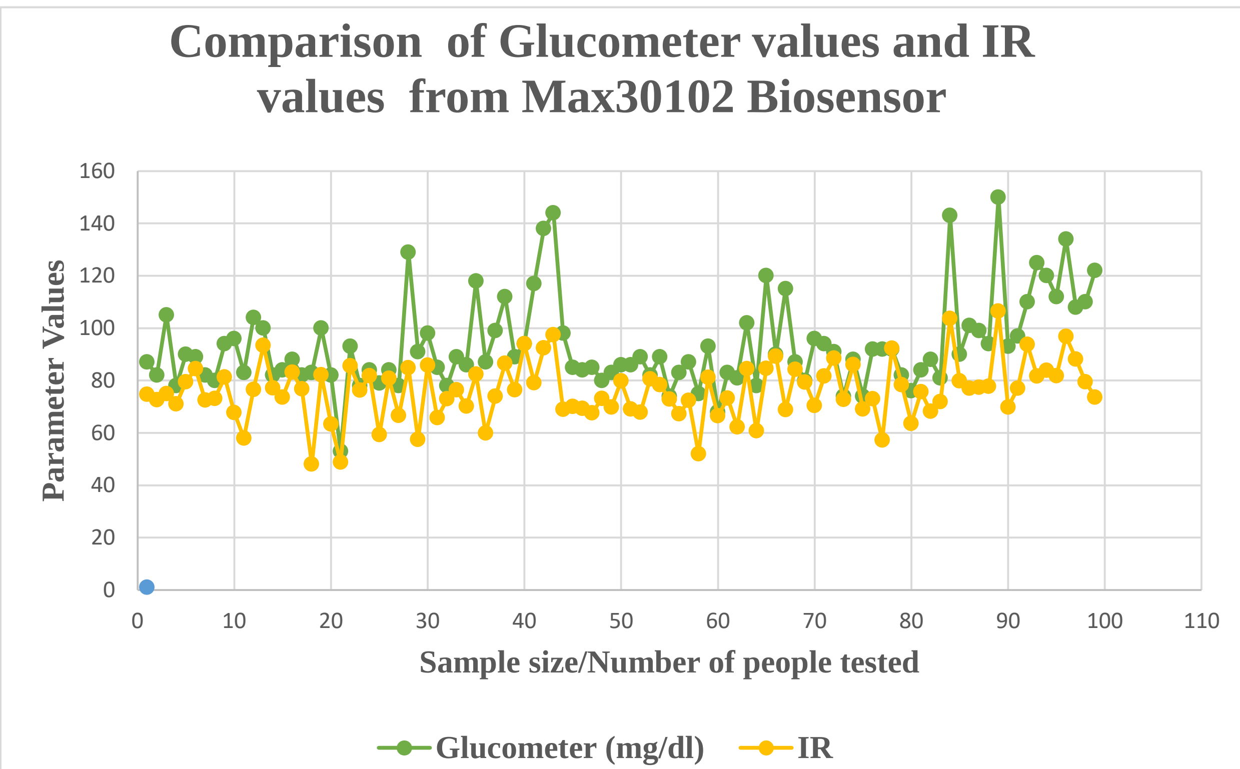


Figure 5.1: Glucometer Vs InfraRed values

5.1.2 Body Mass Index (BMI) as an Input

The body mass index (BMI) is the measure of the body fat based on the height and weight of an individual. This is done by taking the person weight in kg and dividing with the height in metres squared (kg/m^2). Obesity is defined by BMI and it is a complex health condition that involves an excessive amount of body fat, and is evaluated in terms of fat distribution via the waist-hip ratio. Abdominal fat in the body increases inflammation which decreases insulin sensitivity by disrupting the function of beta-cells. This will in turn cause insulin resistance condition which leads to the prevalence of type 2 diabetes[60], [71], [72]. This figure is calculated and the result is keyed into the system as an input parameter. This parameter has been shown to determine the possibility of a person being diabetic depending on the level [60].

5.1.3 Age as an Input

Aging increases the risk of metabolic syndrome and chronic diseases including diabetes type 2 [73]–[75]. It also increases chronic inflammation in an elderly individual leading to insulin resistance. Aging is considered a triggering factor between independent risk factors and risk factors of diabetes and mostly increases the chances in overweight and obese senior adults. In this study, age is used as an input parameter where the patient is asked his/her age and it is keyed into the system. This parameter also determines the possibility of a person developing diabetes type 2 disease [73], [74]

5.1.4 Diabetes Prediction as an Output

This is the resulting output after undergoing the fuzzy inference system and it is the outcome of the prediction. This result contains weighted averages between 0 and 1, with 0 being the lowest and 1 being the highest probability.

The output predicted results will categorize the probability of a person developing or being diabetic into five categories namely; Very Low, Low, Medium, High and Very High with each category with recommendation on the next step to take.

5.2 The Fuzzy Inference System (FIS)

The fuzzy inference system will consist of three input parameters and one output parameter as shown in figure 5.2. The main task of the fuzzy logic system is to predict the possibility of a person developing diabetes type 2 disease based on the input parameters which are random blood glucose level, BMI and the age of the person.

The fuzzy logic system is based on Mamdani-type of fuzzy inference system and has four main steps which are fuzzification, formulation of fuzzy inference rules, defuzzification and finally model evaluation.

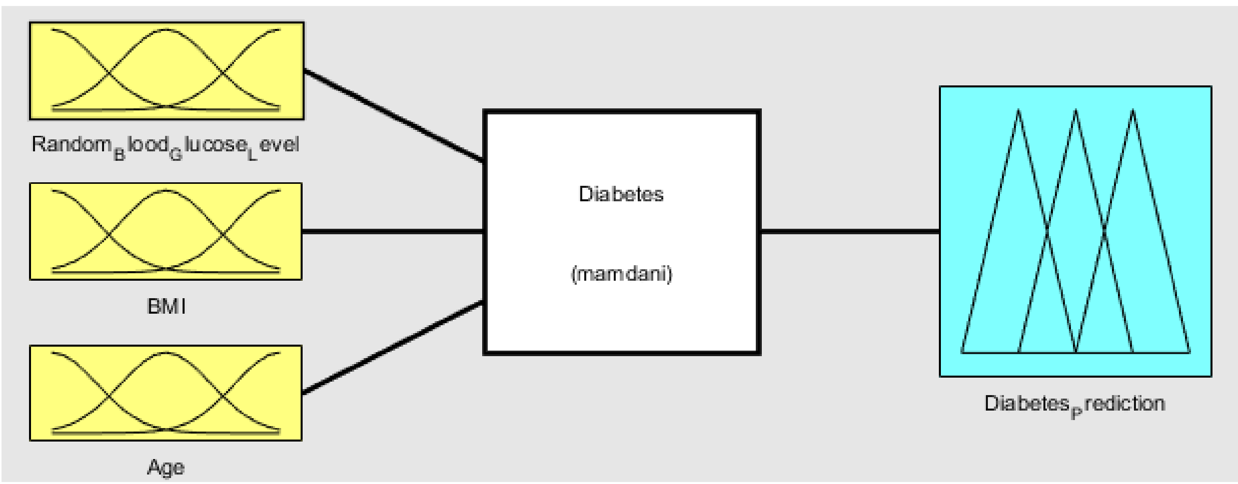


Figure 5.2: Design of Diabetes Type2 Prediction model.

The next step is to create the membership function with the fuzzy sets for the fuzzification process as shown in table 3. To do this, the identified membership functions with identified numerical ranges are used as shown in table 1.1. The membership functions define how each point in the input space is mapped to a membership value/ fuzzy set. The fuzzy sets show how much a parameter is bounded/ belong to a set and are set in the ranges given by domain experts. The type of a set is considered by the number of membership functions and the intervals of a linguistic variable. The membership function has a curve that shows the degree of membership and is represented as either a trapezoidal type which has a collection of four points forming a trapezium or a triangular type having a collection of three points forming a triangle shape.

Table 3: List of linguistic variables with membership functions and fuzzy sets

No	Linguistic variable	Membership function	Type	Fuzzy sets
1	Random Blood Glucose Level (BGL)	Normal	Trapezoidal	[60,60,140,140]
		Prediabetes	Triangular	[141,170,199]
		Diabetes	Trapezoidal	[200,200,500,500]
2	BMI	Underweight	Trapezoidal	[0,0,18.5,18.5]
		Healthy	Triangular	[18.5,21.79,25.1]
		Overweight	Triangular	[25.2,27.65,30.1]
		Obese	Trapezoidal	[30,30,100,100]
3	Age	Child	Trapezoidal	[5,5,12,12]
		Teen	Triangular	[13,16,19]
		Adult	Triangular	[20,29.5,39]
		Middle age adult	Triangular	[40,49.5,59]
		Senior adult	Trapezoidal	[60,60,150,150]
4	Diabetes	Very Low	Trapezoidal	[0,0,0.1,0.25]
		Low	Triangular	[0.22,0.25,0.4]
		Medium	Triangular	[0.38,0.45,0.56]
		High	Triangular	[0.50,0.62,0.74]
		Very High	Trapezoidal	[0.73,0.82,1,1]

The setup of the fuzzy inference system (FIS) parameters is shown Figure 5.3. It consists of the three inputs (Random blood glucose level, BMI and Age) and output (Diabetes prediction).

For random blood glucose level variable, it has three membership functions (Normal, prediabetes and Diabetes) which has set ranges between 0 and 500 i.e., minimum and maximum values of the membership function. The system will use these ranges to allocate the belongingness of a value to the respective membership function.

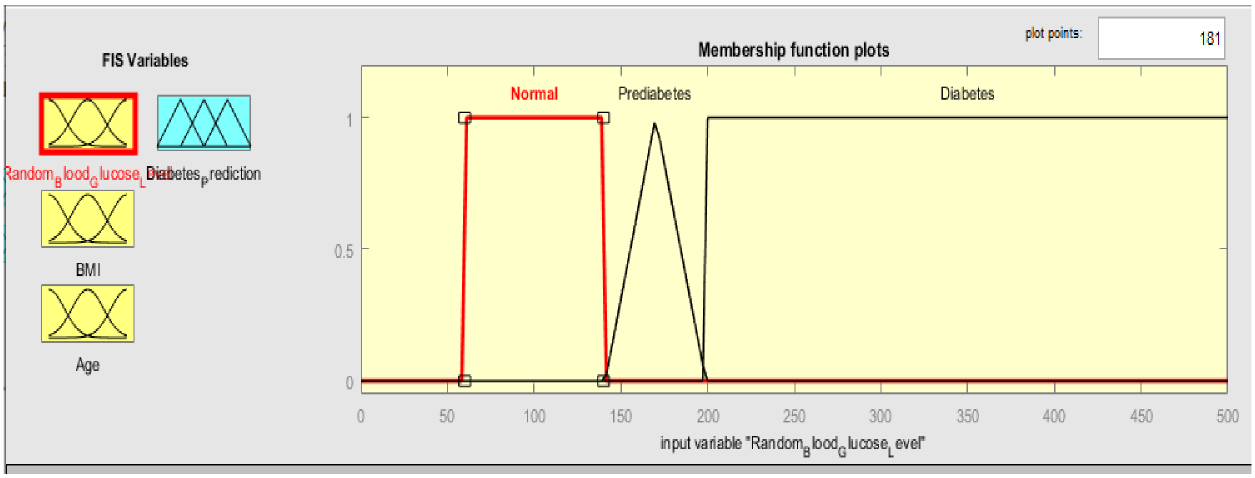


Figure 5.3: Random Blood Glucose Level Variable

Body Mass Index (BMI) input variable setup is shown Figure 5.4, and has four membership functions (Underweight, Healthy, Overweight and Obese) which has set ranges i.e., minimum and maximum values each membership function. The system will use these ranges between 0 and 100 to allocate the belongingness of a value to the respective membership function.

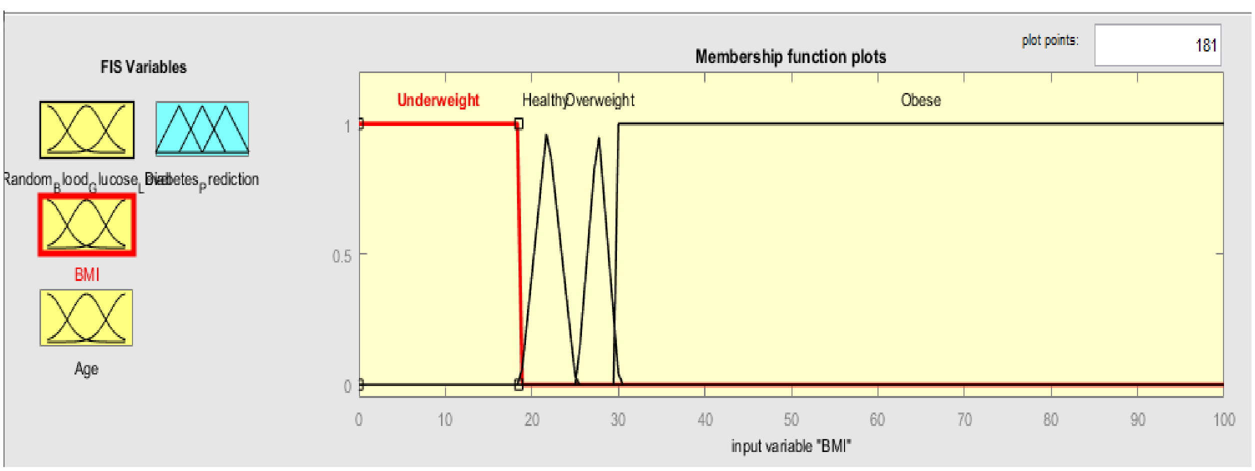


Figure 5.4:BMI Input Variable.

The Age input variable has five membership functions (child, teen, adult, middle age adult and senior adult) as shown in figure 5.5, each membership function having minimum and maximum range values between 0 and 150.

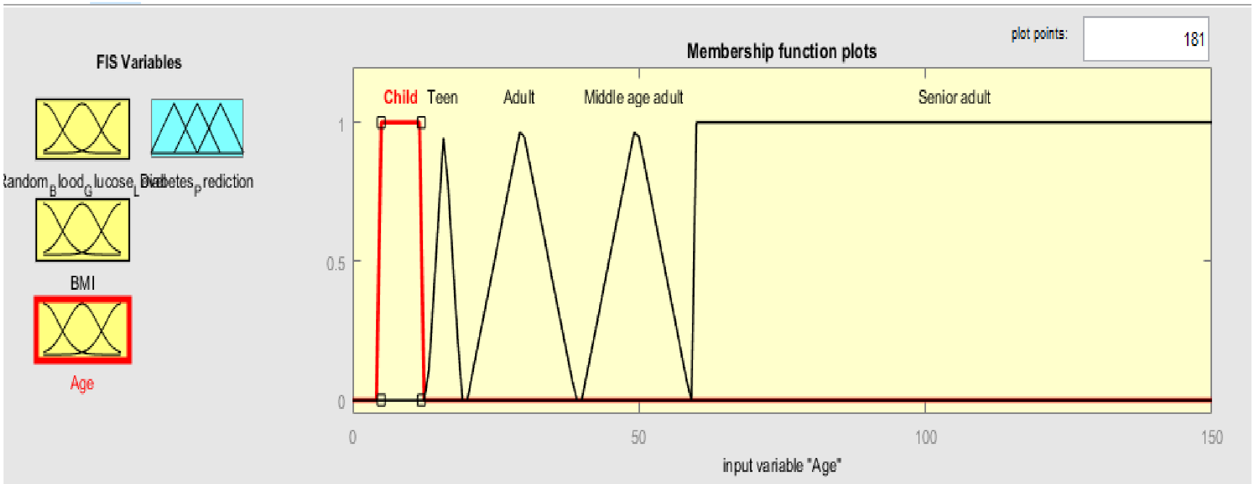


Figure 5.5: Age Input Variable.

The fuzzy logic system has one output variable, diabetes prediction as shown in figure 5.6. It contains five membership functions (Very low, Low, Medium, High and Very High). Each membership function contains minimum and maximum ranges between 0 and 1 to be used in determining the belongingness of the prediction to a membership function.

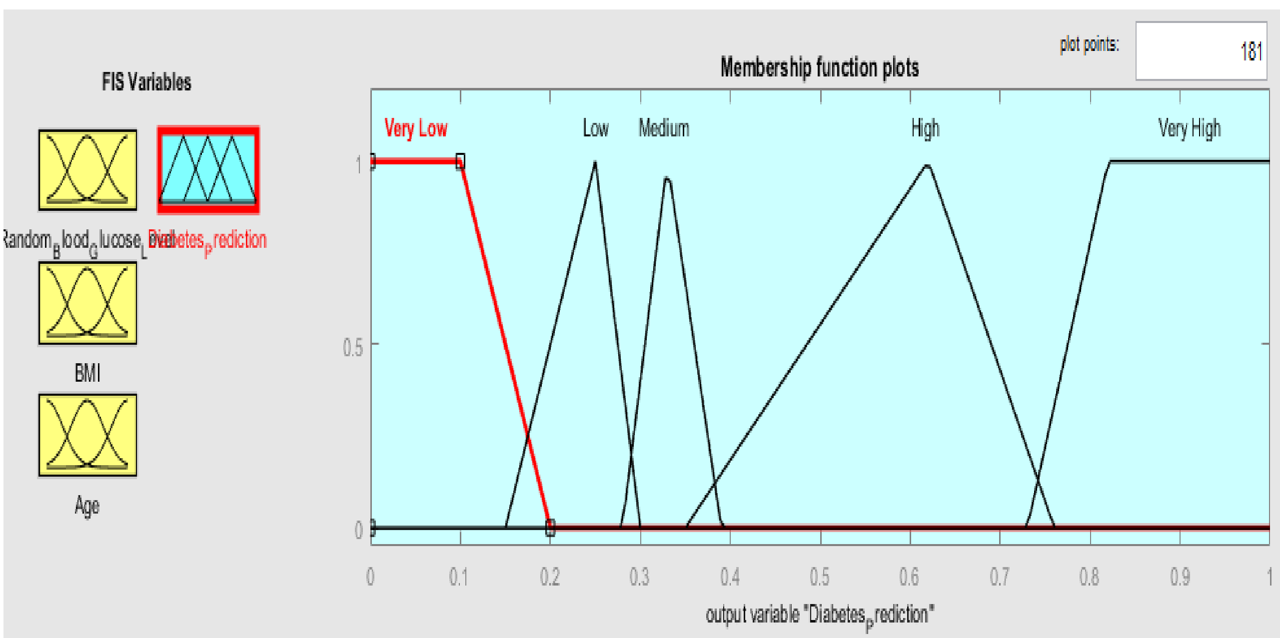


Figure 5.6: Diabetes Prediction Output Variable.

5.3 Formulation of Fuzzy Rules

This project has three input linguistic variables, Random Blood Glucose Level, BMI and Age. For the Blood Glucose Level linguistic variable, it contains three membership functions normal, pre-diabetic and diabetic with each membership function linked to fuzzy sets of linguistic variable BMI (underweight, healthy, overweight and obese) which are four, and linguistic variable Age (child, Teen, adult, middle age and senior adult) which are five resulting in generation of twenty fuzzy rules. So, a total of sixty rules were created to cover all the membership functions as shown in appendix 1. After the development of the rules, we implemented them on MATLAB as shown in figure 5.7.

To create the rules, input variable membership functions are selected and use “AND” operator to join them to give an output using “THEN” operator. The rules can be adjusted or removed by using the buttons provided i.e., Delete, add and Change rule options.

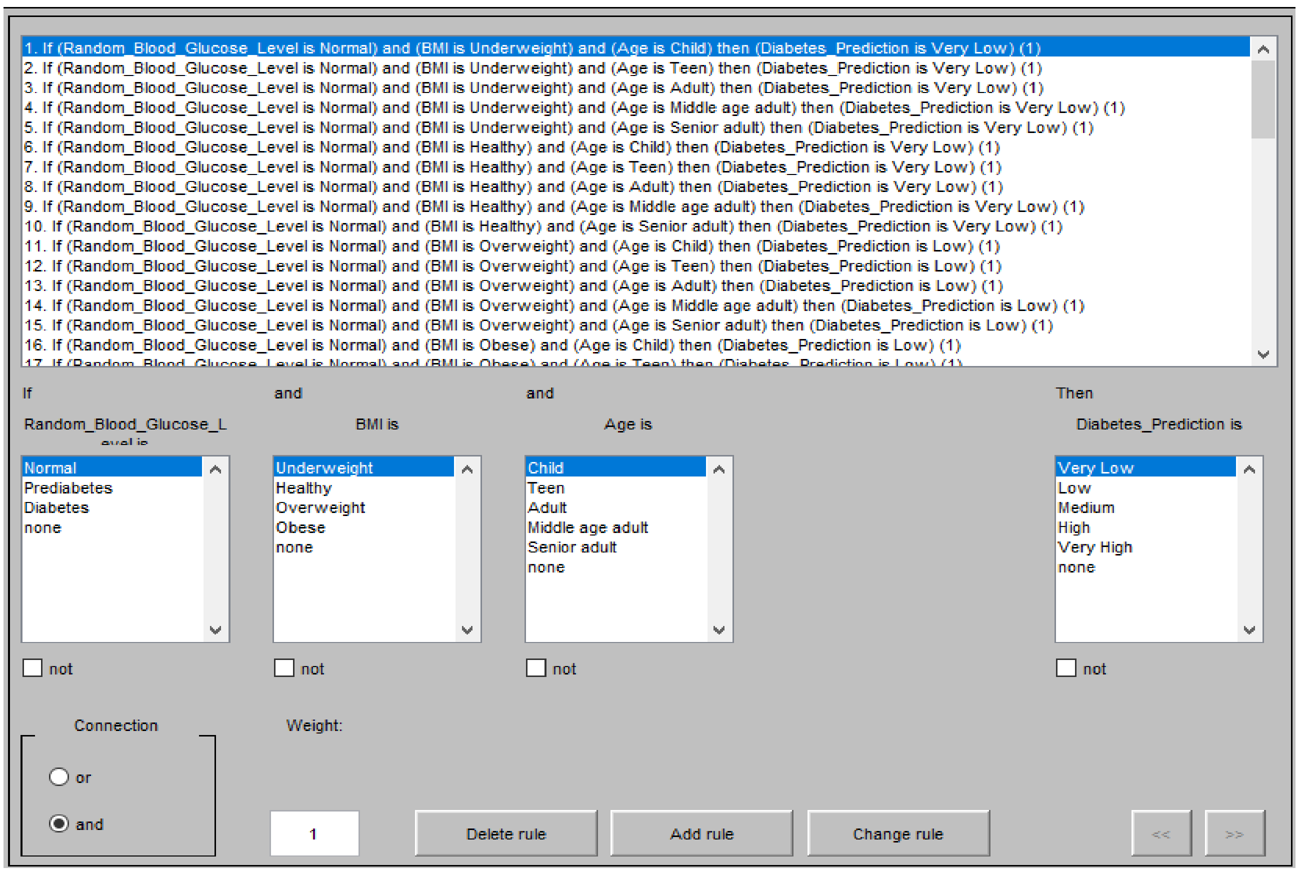


Figure 5.7: Fuzzy rules setup in MATLAB environment

5.4 Results and interpretation of results

From the study and prototype development, we came up with results and this will be discussed in this section.

5.4.1 Rule viewer

In fuzzy logic systems, the rule viewer is used to analyze how individual membership functions will impact on the output variable. The input variables are set to desired values and the output is displayed depending on the output membership functions assigned.

For the input variables, the selected points are shown by a red vertical line which cuts across all the membership functions. A membership function found within the selected value will be highlighted in yellow trapezoidal or triangular shape depending on the type of membership set during fuzzification process. For the output variable, the affected membership function is indicated by a blue color shading. These are shown in figure 5.8.

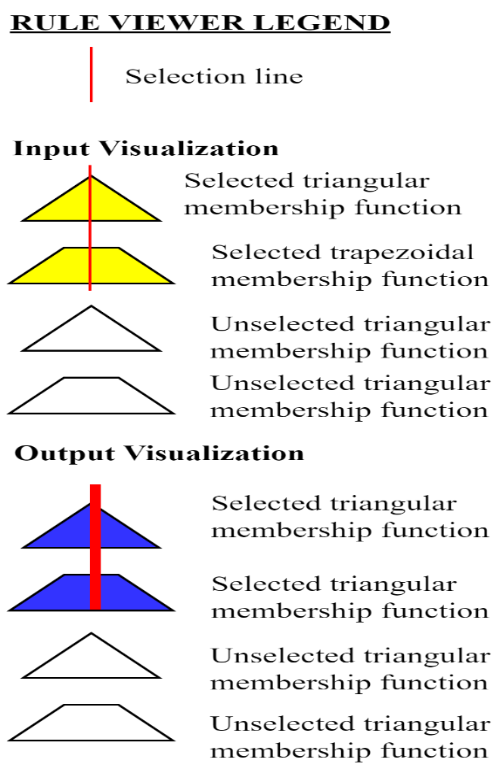


Figure 5.8:Rule viewer legend

In figure 5.9, it is shown that when random blood sugar level is at 80 mg/dl, which is in normal range and BMI is at 22 which is also normal range and age is at 35 years who is an adult, the diabetes prediction will be at 0.0873 which falls at a very low level of being diabetic.

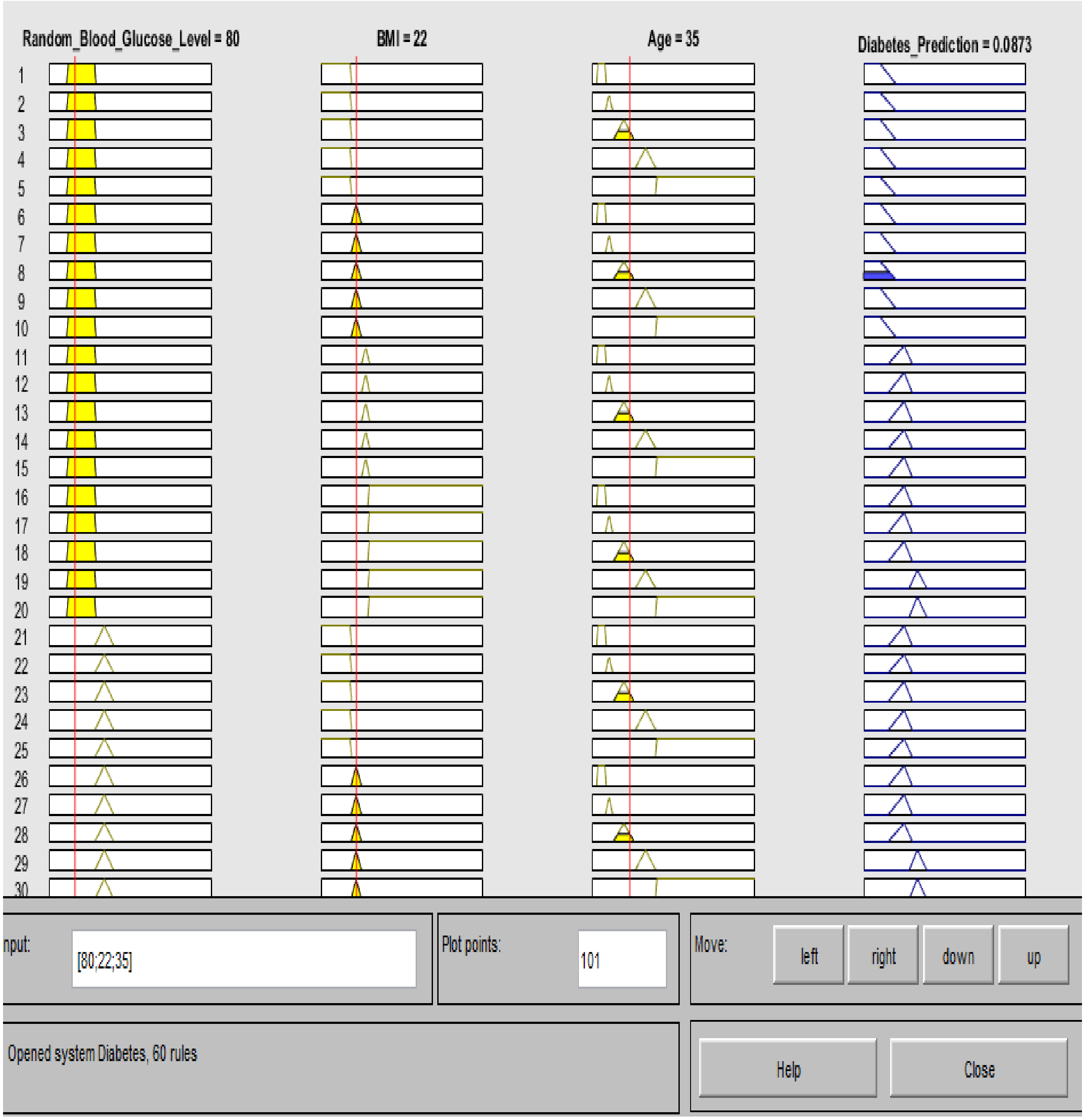


Figure 5.9: Rule viewer for very low output.

When random blood sugar level is at 130 mg/dl, and is in normal range but almost maximum level and BMI is at 28 which is in overweight range and age is at 45 years who is a middle age adult, the diabetes prediction will be at 0.231 as shown in Figure 5.10, falls at a low level of being diabetic.

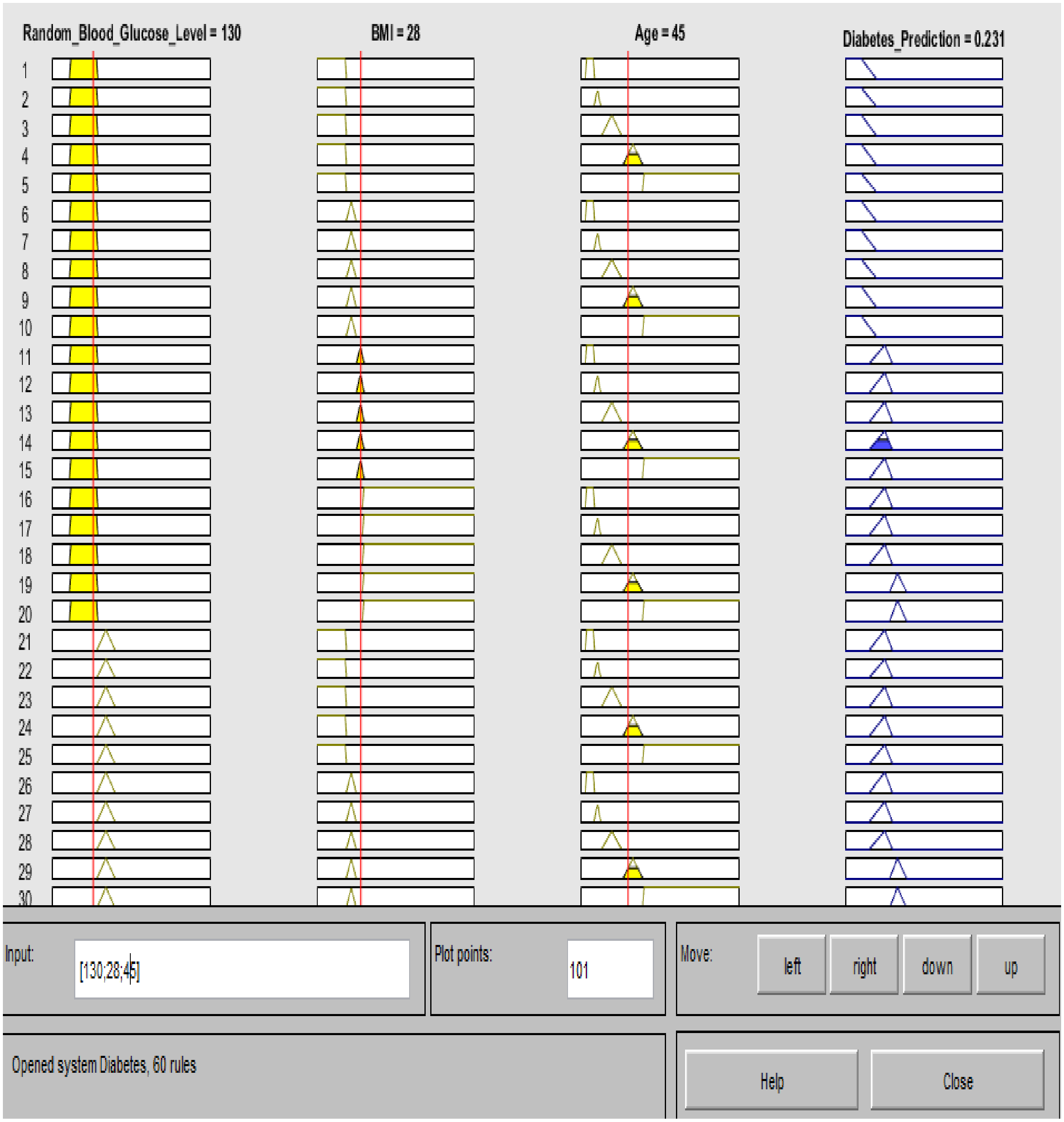


Figure 5.10:Rule viewer for Low output.

Figure 5.11 shows that when random blood sugar level is at 180 mg/dl, which is in pre-diabetic range and BMI is at 35 which is in obese range and age is at 45 years who is a middle age adult, the diabetes prediction will be at 0.57 which falls at a high level of being diabetic.

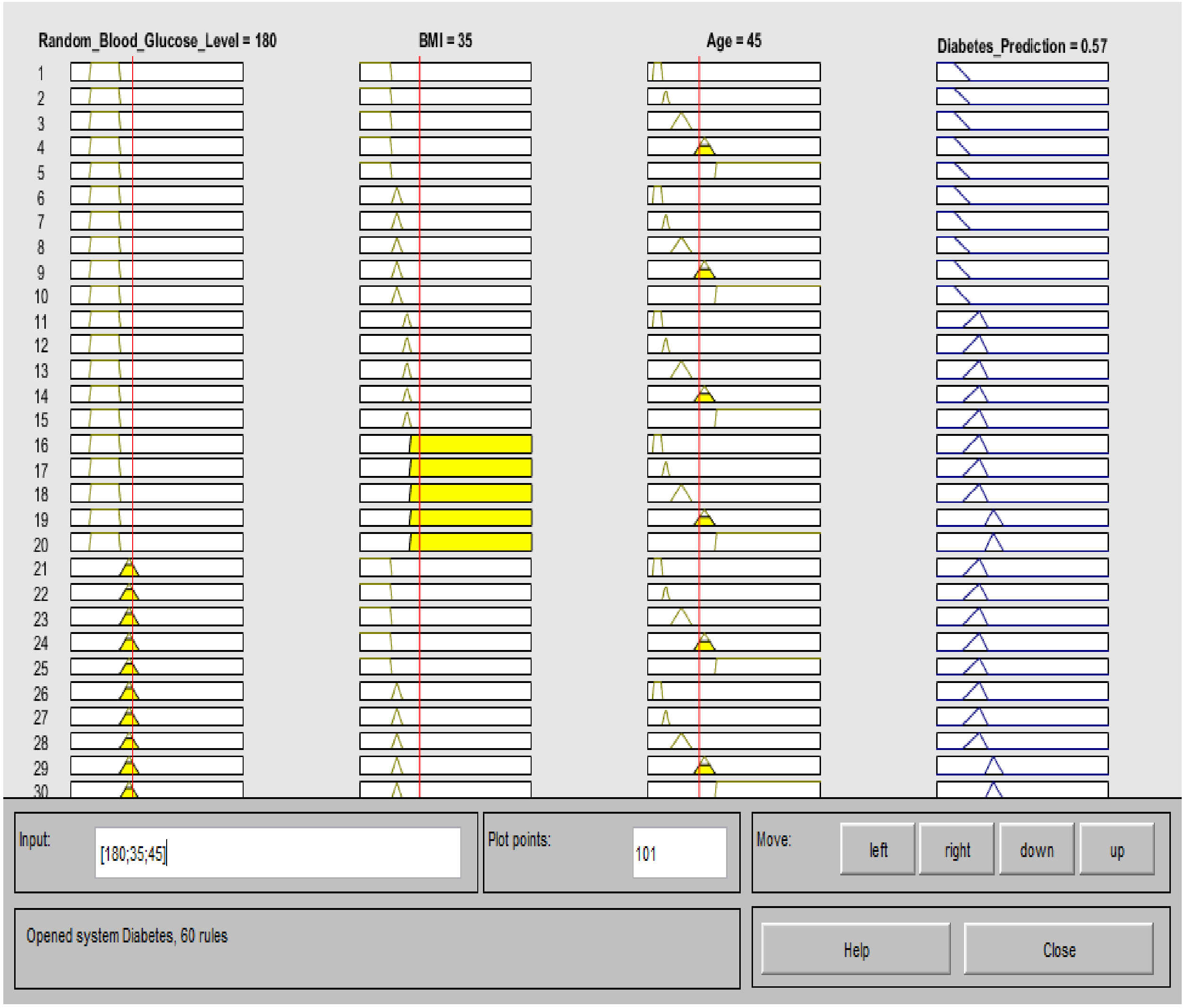


Figure 5.11:Rule viewer for medium output.

Figure 5.12 shows that when random blood sugar level is at 220 mg/dl, which is in diabetic range and BMI is at 35 which is in obese range and age is at 62 years who is a senior adult, the diabetes prediction will be at 0.889 which falls at a very high level of being diabetic.

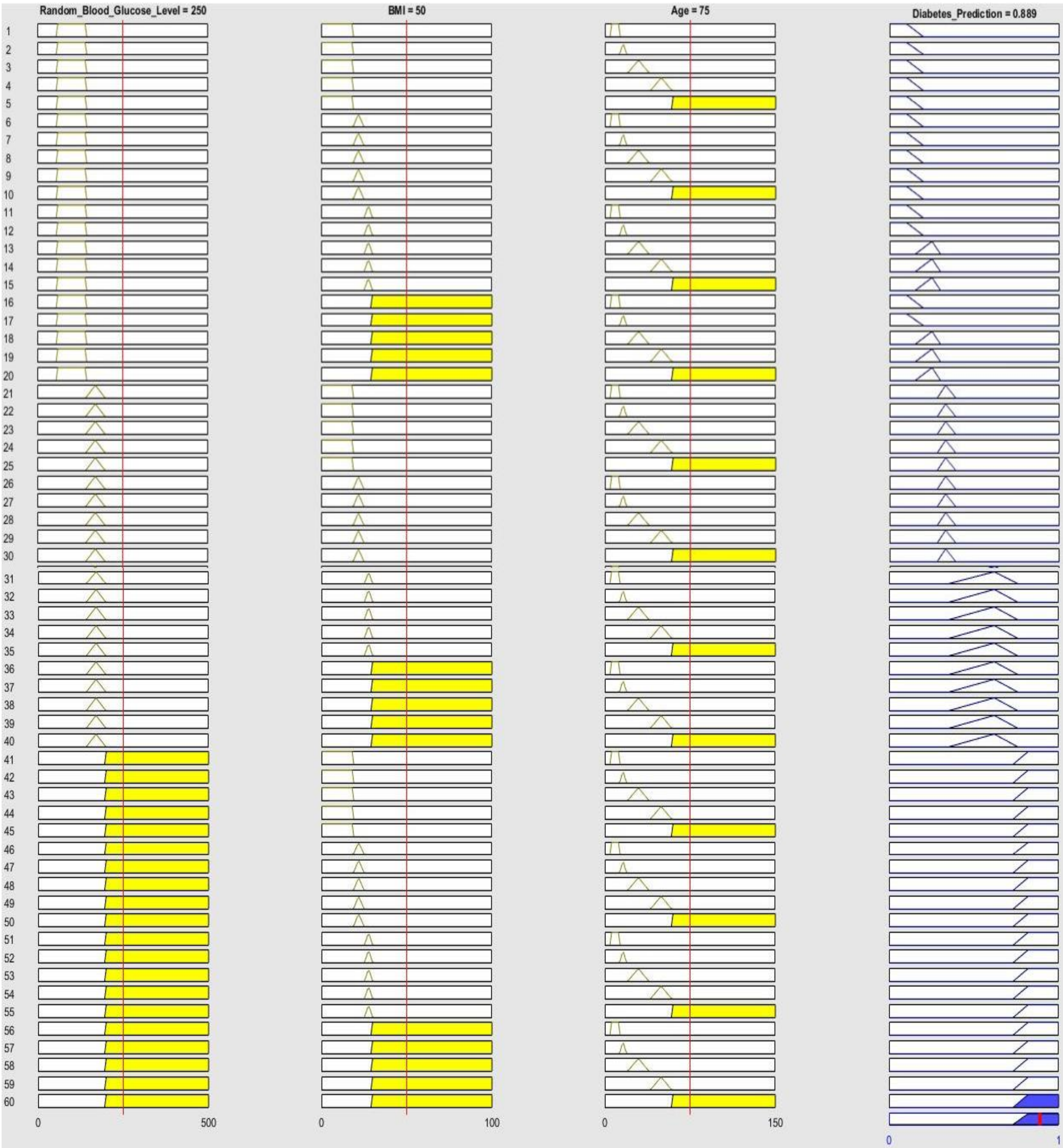


Figure 5.12: Rule viewer showing very high output.

5.4.2 Surface Viewer

The surface viewer is used to show how the output generated depends on one or more inputs. The surface viewer produces and plots an output surface map for the developed model.

In figure 5.13, it shows how the output Diabetes prediction depends on the two inputs, BMI and Random Blood Glucose level. It clearly shows that a larger BMI value and aging increases the diabetes prediction value. Any change in any of the inputs will affect the output.

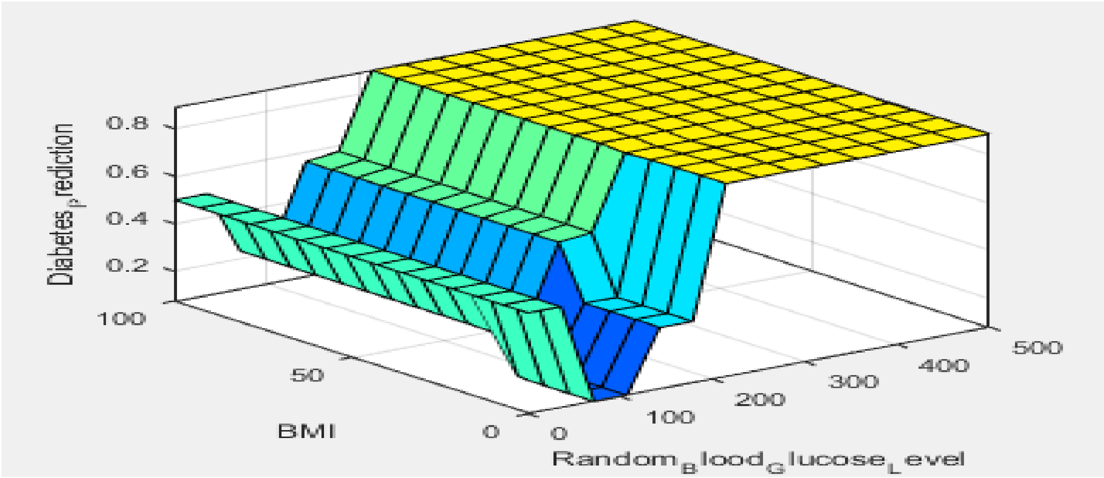


Figure 5.13: Surface viewer showing how blood glucose and BMI inputs affect output.

As shown in Figure 5.14, the output Diabetes prediction when two inputs, Age and Random Blood Glucose level are considered, it shows that high blood glucose levels and aging increases the diabetes prediction level.

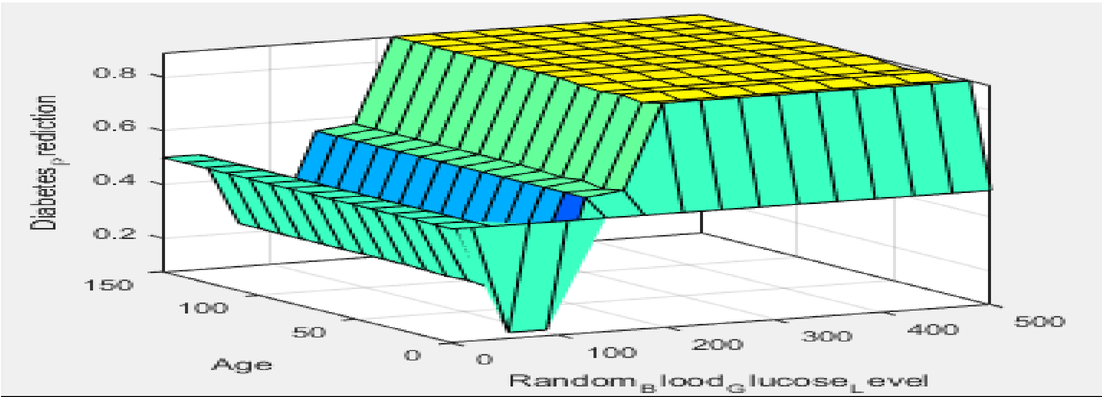


Figure 5.14:Surface viewer showing how blood sugar level and Age blood sugar level and Age inputs affect the output.

The analysis of random blood glucose level to diabetes prediction is shown in Figure 5.15. It shows that diabetes type 2 prediction is very low when the value is below 100 mg/dl. From (100 – 140) mg/dl the prediction level is still low at less than 0.5. Between (140 – 180) mg/dl the prediction rate is medium at a range between 0.5 – 0.6. Above 200 mg/dl blood glucose level, the prediction level is high above 0.6.

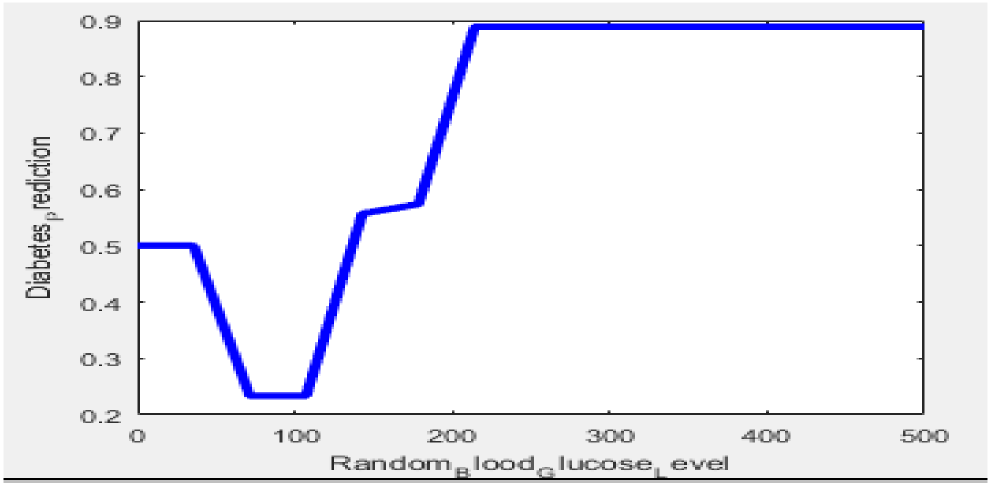


Figure 5.15: Random blood glucose level vs Diabetes prediction.

For BMI vs diabetes prediction rate shown in figure 5.16, it shows that at the range of normal BMI i.e. below 25 the prediction rate is very low. The prediction rate starts increasing between the overweight range (25 - 30) and very high at the obese range which is above 30.

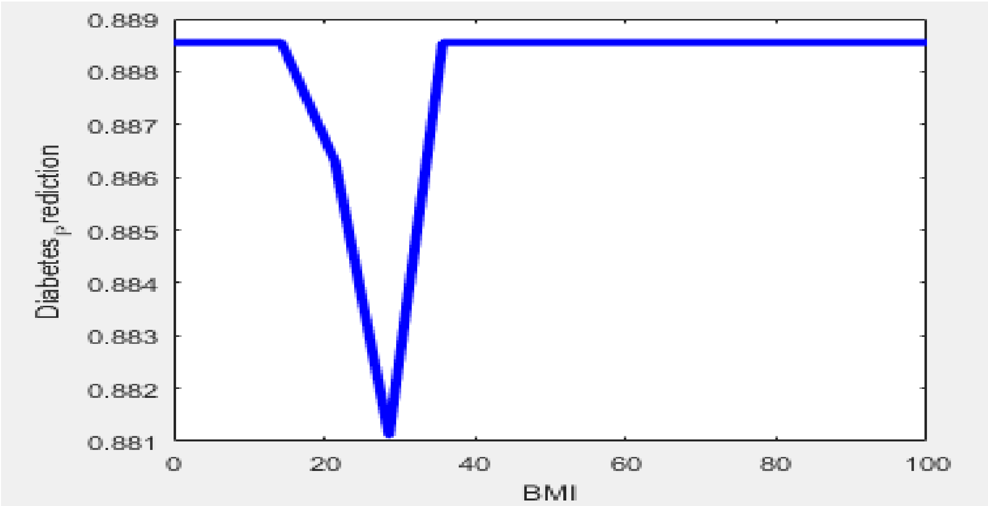


Figure 5.16: BMI vs Diabetes prediction.

For age vs diabetes prediction, as shown in figure 5.17 diabetes prediction increases with aging, i.e., above the age of 30 years the risk is very high.

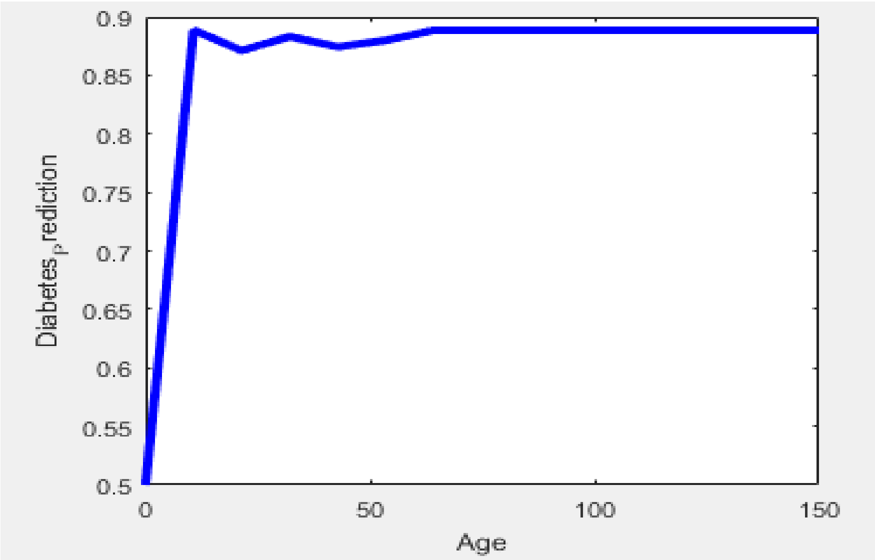


Figure 5.17: Age vs Diabetes prediction.

5.5 Prototype Results and Analysis

This study resulted in development of a prototype device. The hardware components are interconnected and programming done to provide the software to operate and control the system. The prototype devices include Max30102 biosensor and keypad as an input and Oled display, three LEDs (Green, Blue & Red) to show different system statuses. These devices are controlled by ESP32 microcontroller which is programmed as per system requirements. The connections are done using jumper cables and a breadboard.

5.5.1 Prototype Implementation

The prototype device designed and developed is shown in Figure 5.18 with all connections and components connected.

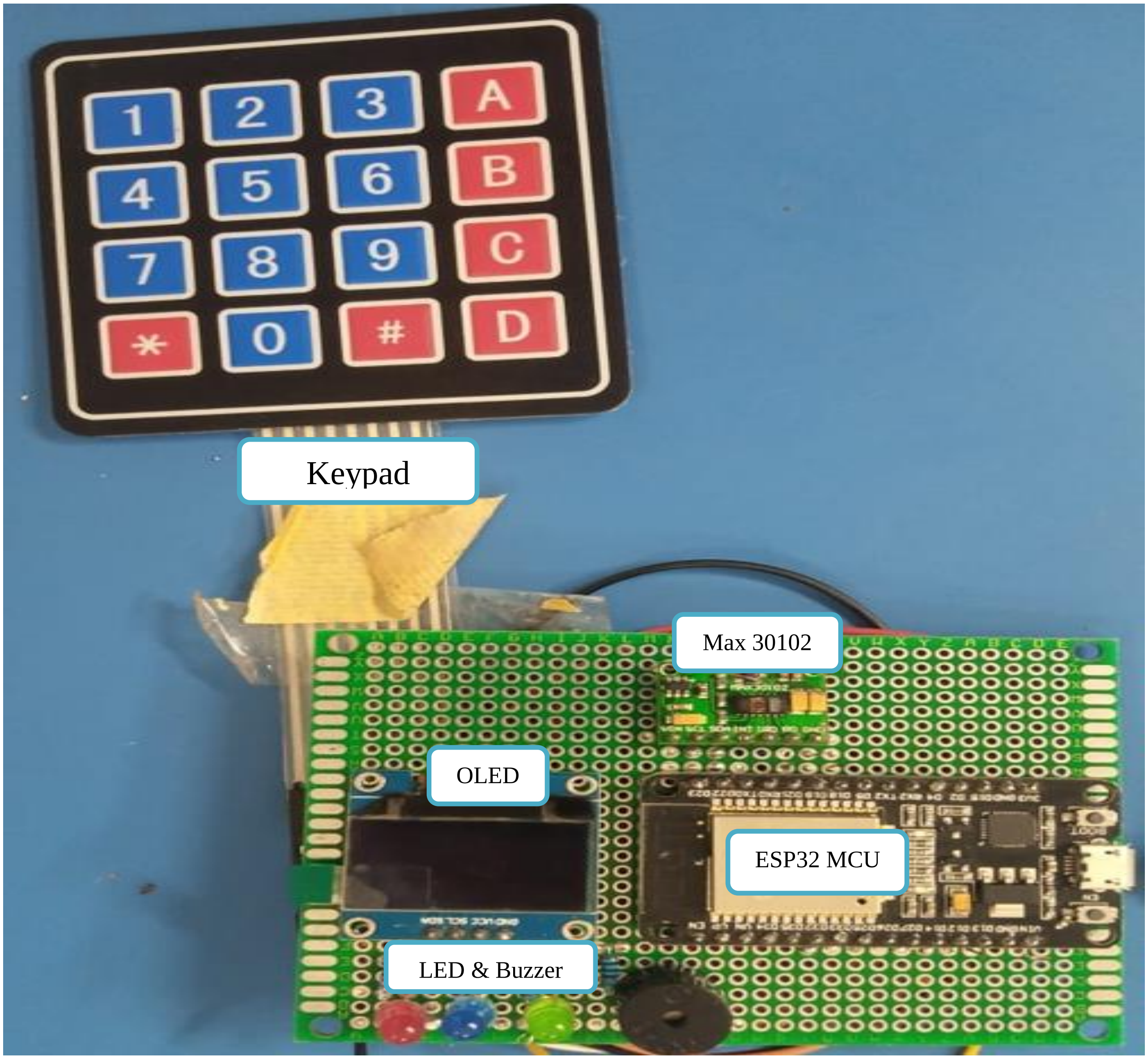


Figure 5.18:Prototype Setup.

When the system is powered on it displays the system function and step-by-step procedure for prediction by prompting for inputs until final result as shown in figure 5.19.

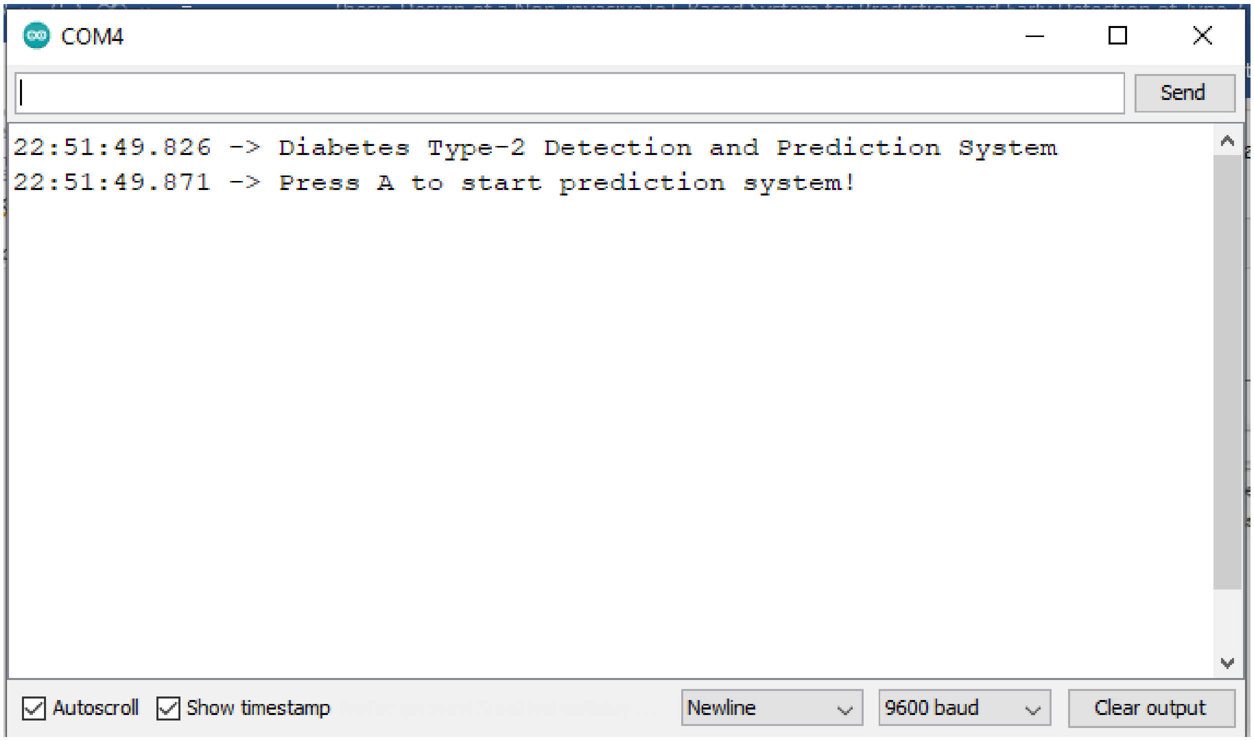


Figure 5.19: Initialization screen on terminal monitor during system start up.

5.5.2 Prototype results

The system was tested and the results from the prototype display screen and serial output monitor is as explained in this section.

5.5.2.1 Very Low Predictivity for Diabetes Type 2 occurrence

Random blood glucose level was measured using the max30102 sensor and the other two inputs, BMI and age were keyed into the same and results were obtained. A blood glucose level reading of 135.76 mg/dl was obtained which is on normal range, BMI of 35.71 which is on obese range and the age of 65 years which is on senior adult age range. The probability level of getting diabetes is Very Low according to the rules in the fuzzy set and the patient is recommended to eat balanced diet and exercise regularly as shown in figure 5.20.

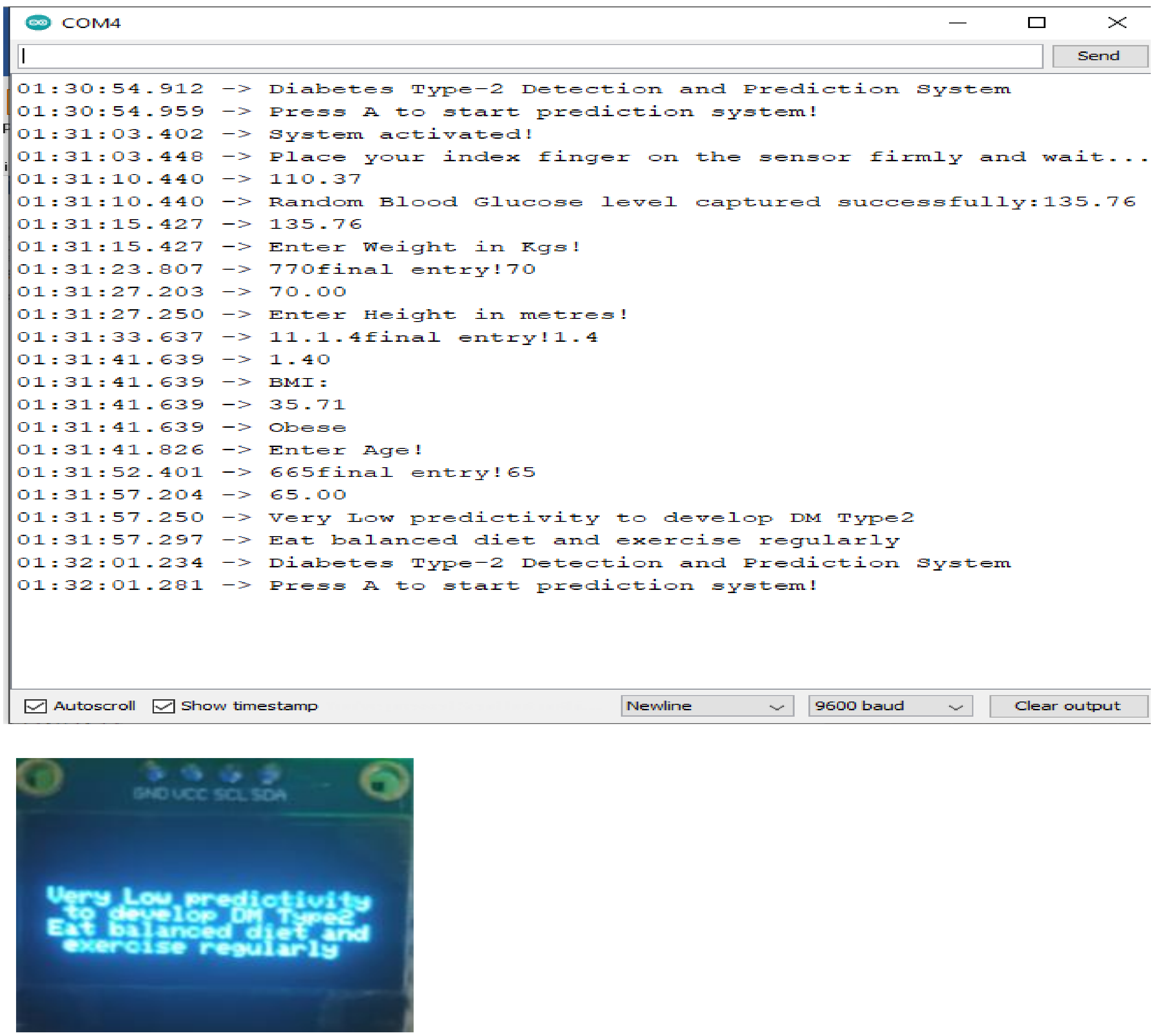
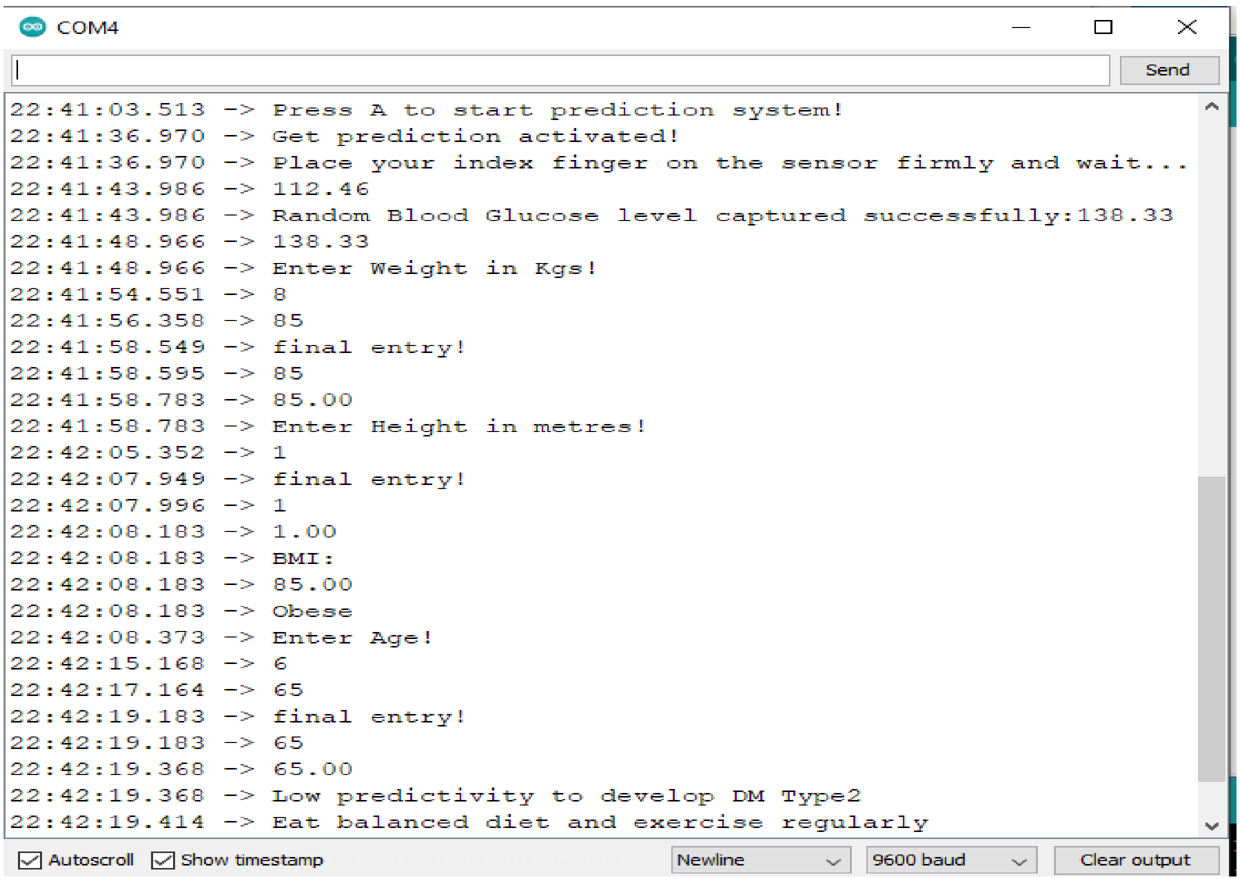


Figure 5.20: Very low prediction results.

5.5.2.2 Low Predictivity for Diabetes Type 2 occurrence

Another test was done as shown in figure 5.21. A random blood glucose level test was 138.33 still on normal range, BMI of 85 which is in obese range and age of 65 years old on senior adult range, the prediction result is Low predictivity of being diabetic. The patient is advised to eat balanced diet and exercise regularly.



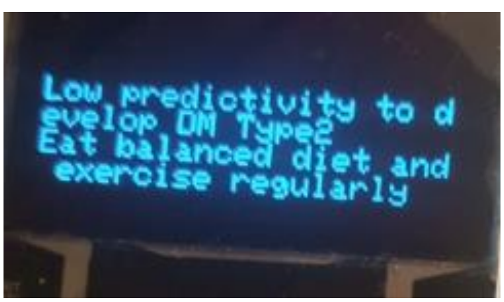


Figure 5.21: Low Prediction results.

5.5.2.3 Medium Predictivity for Diabetes Type 2 occurrence

When random blood sugar level is at 180 mg/dl, which is in prediabetic range and BMI is at 25.95 which is in overweight range and age is at 65 years who is a senior adult, the diabetes prediction is medium of being diabetic as shown in figure 5.22. The patient is recommended to reduce starch, lose weight and do physical exercises regularly.

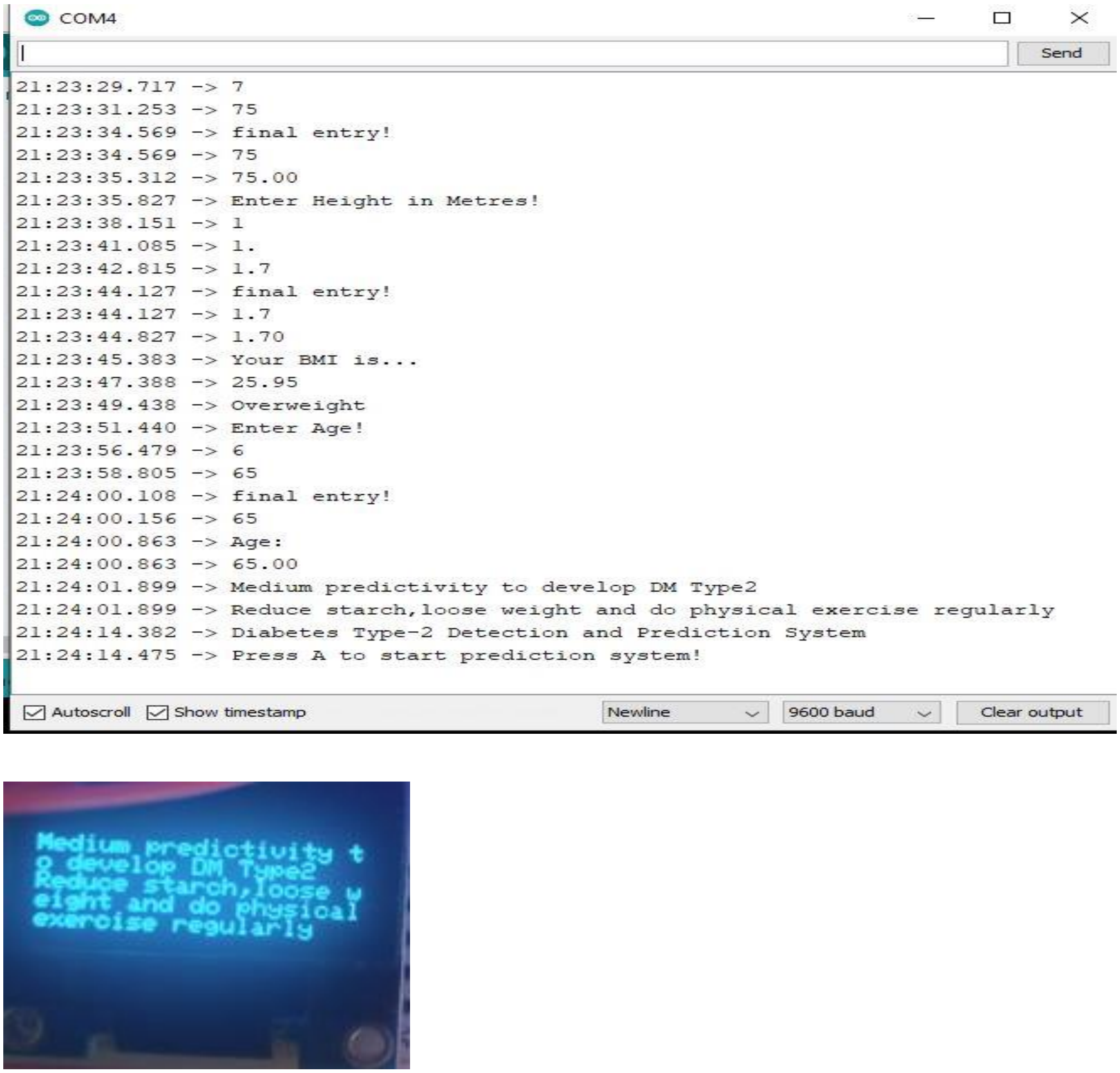


Figure 5.22:Medium prediction results.

5.5.2.4 High Predictivity for Diabetes Type 2 occurrence

When the random blood sugar level is at 201 mg/dl, which is in the diabetic range and BMI is at 29 which is in the overweight range and the age is at 35 years who is a young adult, the diabetes prediction will be at high level of being diabetic as shown in figure 5.23.

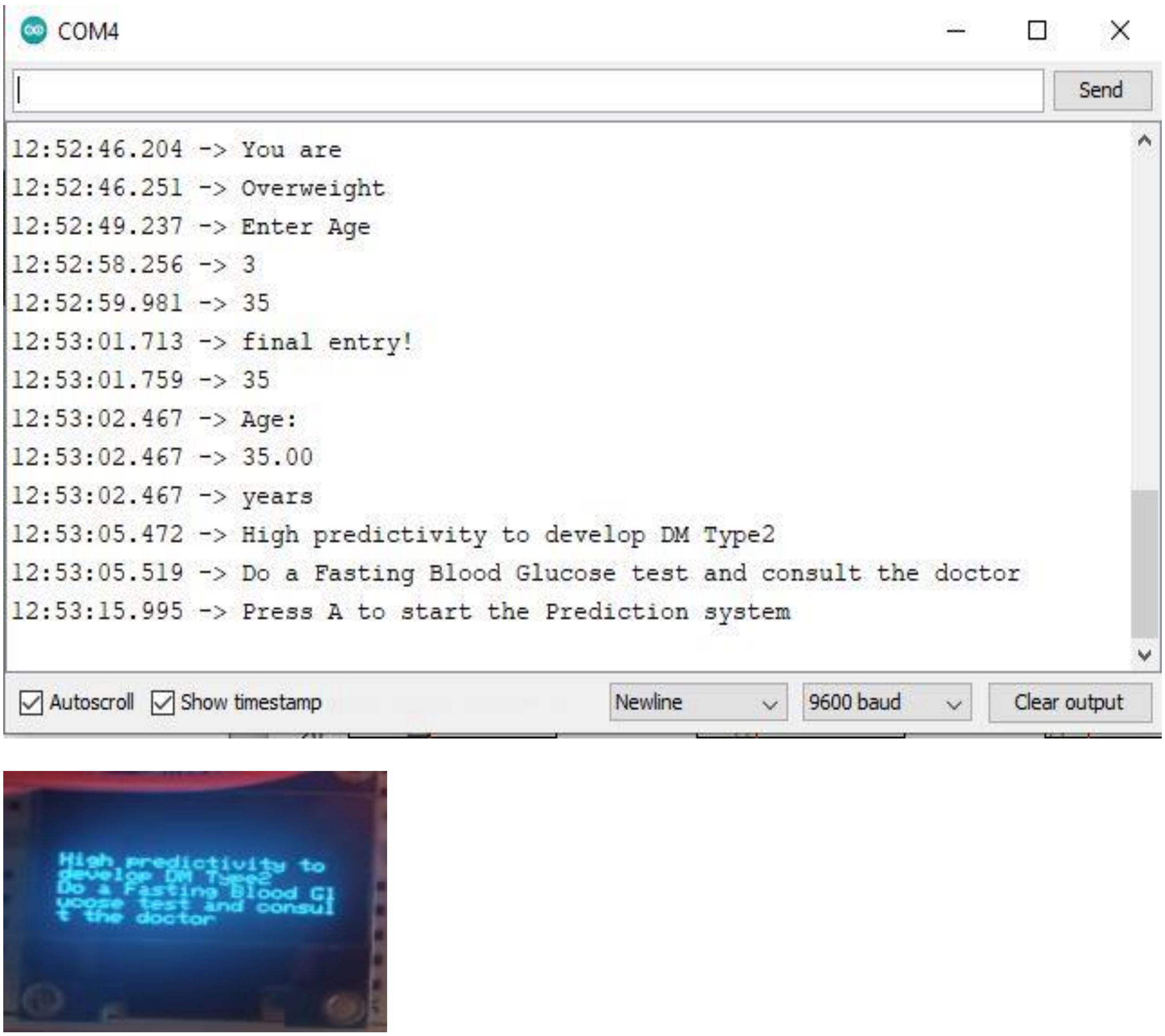


Figure 5.23:High prediction result.

5.5.2.5 Very high Predictivity for Diabetes type 2 occurrence

When the random blood sugar level is at 220 mg/dl, which is in the diabetic range and BMI is at 35 which is in the obese range and the age is at 38 years who is a middle adult, the diabetes prediction will be at a very high level of being diabetic as shown in figure 5.24.

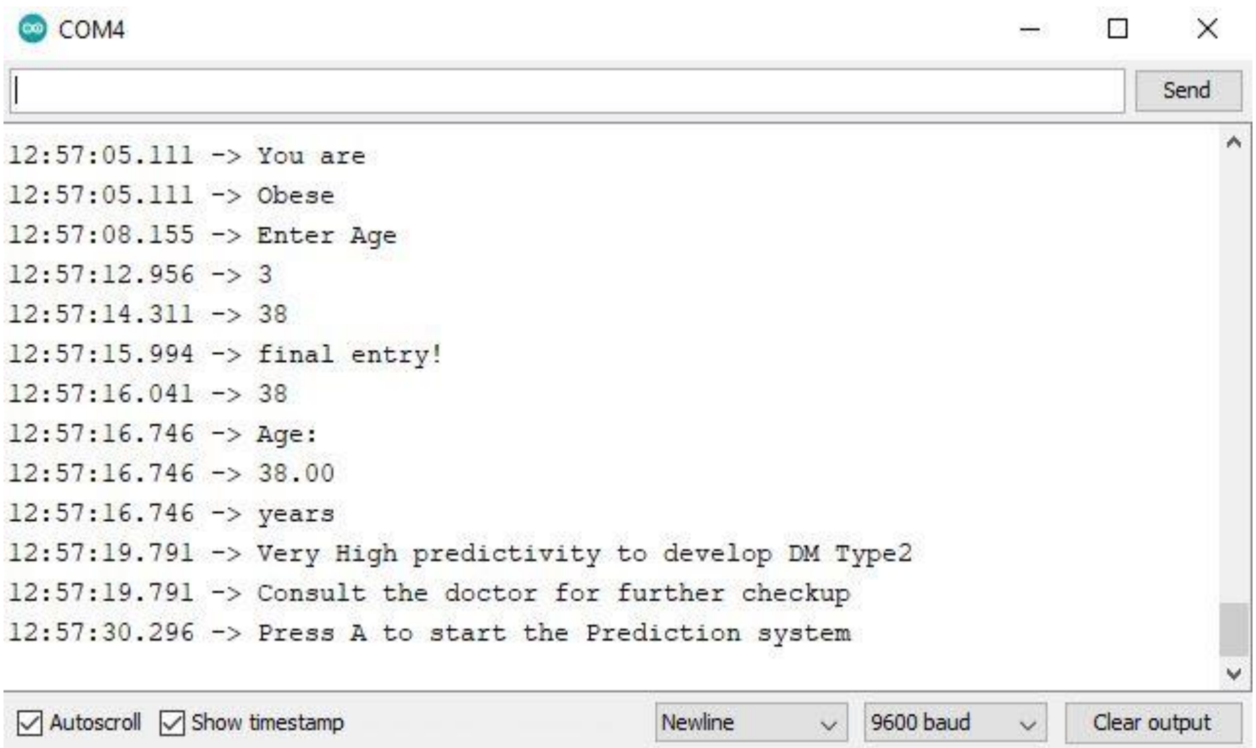


Figure 5.24:Very high prediction result.

5.5.3 Cloud Storage

The device is a complete edge-based device, which means that it operates fully without the need of internet connection or external support from other devices. However, for storage and data analysis it is integrated with thingspeak.com which is an Internet of Things (IoT) platform used for real-time sensor data collection, storage, analysis and visualization. This platform does advance cloud analytics and instant visualizations of data posted by the sensors. Figure 5.25 shows the data as captured from the ThingSpeak platform. The charts show the three inputs, Glucose level, BMI, and Age with one output Prediction Value done in a day between 20:00 hrs and 21:00 hrs period for five people. It contains four fields, with field 1 chart capturing the glucose level measurements during that particular period. Field 2 shows the BMI values of the patient tested for the same period of time. Field 3 shows the ages of the patients tested. Finally, field 4 shows the prediction value output of the patients during the same period after processing. The reason for this data being available online is for future use in research and create awareness about the disease.

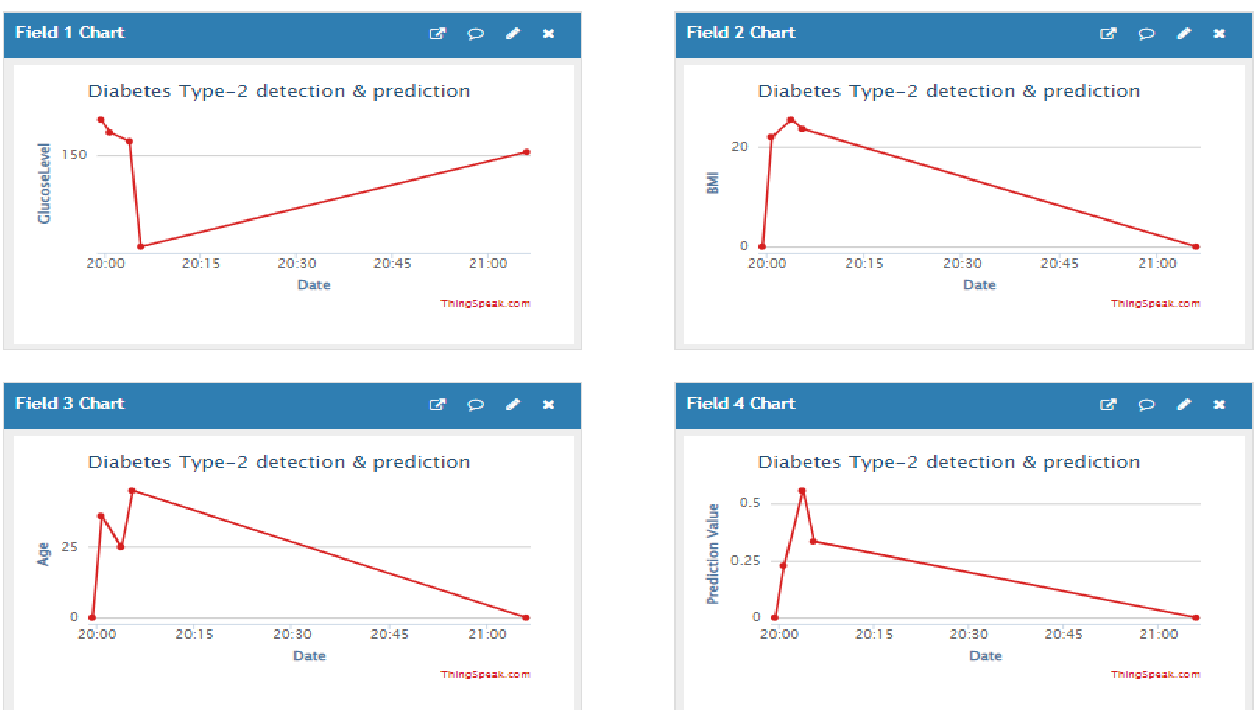


Figure 5.25: Thingspeak data

5.5.4 Sensor Significance

In this study, integrated Max30102 sensor was used to take patient sample using fingertip to collect random blood glucose level non-invasively. Figure 5.26 shows the results from fifteen volunteers done using glucometer and Max30102 biosensor taken after calibration. The comparison was done by comparing the blood glucose measurements taken using CodeFree glucometer and Max30102 sensor. It is seen that there is a very small error rate margin for normal range glucose values and a slightly bigger error rate for higher glucose level value ranges.

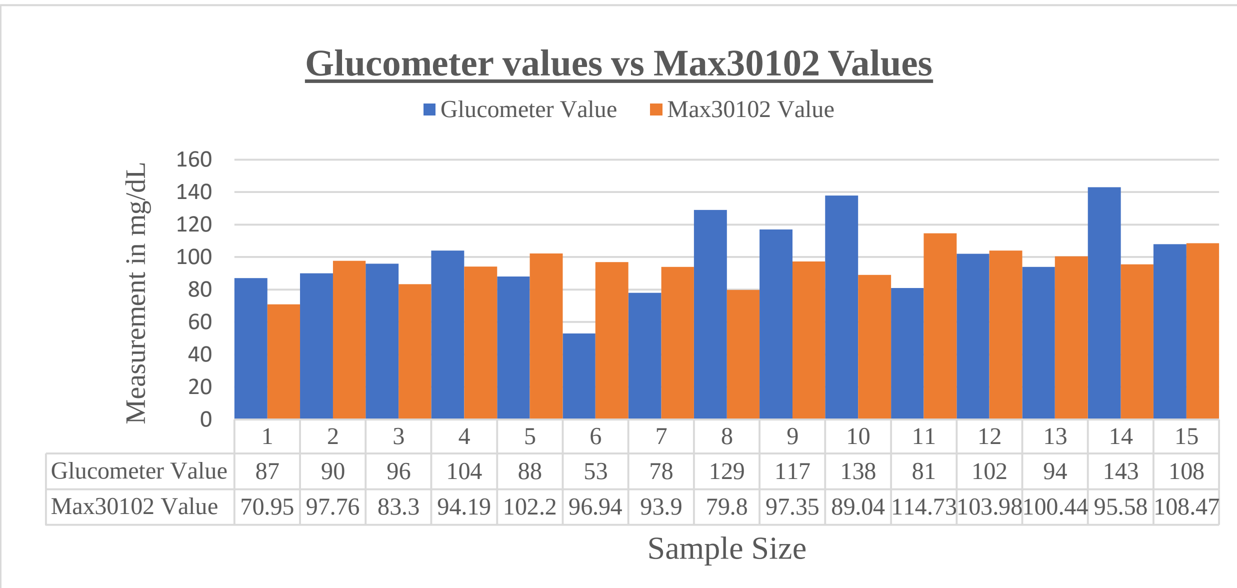


Figure 5.26: Glucose test comparison chart.

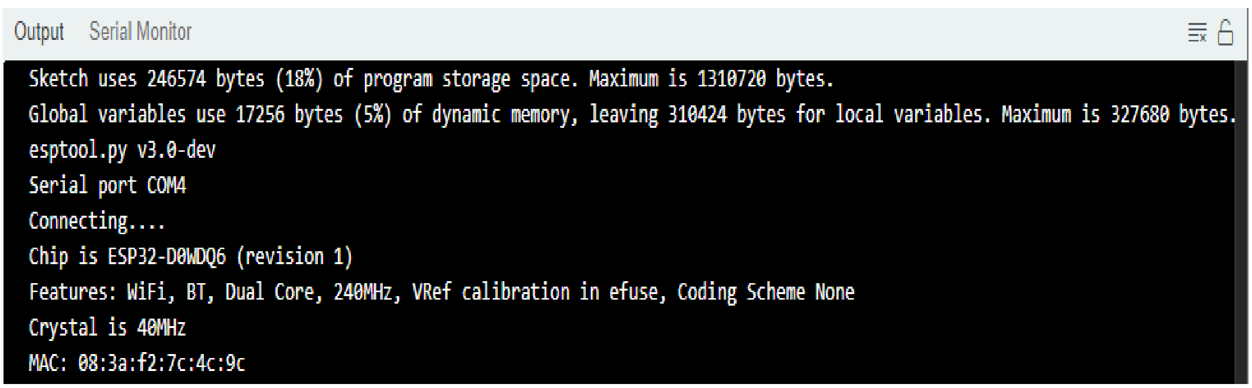
From the collected samples, we note that there are some factors which also affect the use of Infrared light technology in acquiring accurate and precise values. These factors include;

- The pressure applied on the sensor can produce different values and for this, the sensor needs to be placed on a steady and controlled housing.
- The amount of light absorbance is affected by the angle of finger placement. This can be improved by having an enclosure covering the sensor for placing the finger.

- Max30102 sensor has an Infrared wavelength of 800 nm and it has good glucose absorbance. However, other studies recommend the use of higher wavelength Infrared sensors of above 940-1800 nm for increased accuracy due to the fact that attenuation of optical signals at these ranges is minimum, hence maximum penetration is achieved [76].

5.5.5 Device Performance

The device resources required by the model to successfully run on an embedded device were loaded and analyzed to check it is feasibility. The on-device performance of the model on an embedded device as shown on Arduino ide serial output is that it uses 18% of ROM out of a maximum of 1310Kb and 5% of RAM usage out of a maximum of 327Kb as shown in figure 5.23. These results show that the required resources are using very minimal resources and the model can be used on any available embedded devices that have minimum capacity of 320Kb RAM and 448Kb ROM.



Output   Serial Monitor

```
Sketch uses 246574 bytes (18%) of program storage space. Maximum is 1310720 bytes.
Global variables use 17256 bytes (5%) of dynamic memory, leaving 310424 bytes for local variables. Maximum is 327680 bytes.
esptool.py v3.0-dev
Serial port COM4
Connecting....
Chip is ESP32-D0WDQ6 (revision 1)
Features: WiFi, BT, Dual Core, 240MHz, VRef calibration in efuse, Coding Scheme None
Crystal is 40MHz
MAC: 08:3a:f2:7c:4c:9c
```

Figure 5.27: Device resources performance

CHAPTER SIX

CONCLUSION, RECCOMENDATION AND FUTURE WORKS

6.1 Conclusions

This study proposes non-invasive testing of diabetes type 2 disease and also uses fuzzy logic system to do early detection and prediction. This solution aims to increase awareness and reduce the cost of doing the tests by providing real-time results and re-usable device. This solution will also help in areas where there are no or limited number of medical experts to assist in diagnosis and medical recommendations.

The model was tested on an embedded device and it showed that it is possible to get blood glucose level measurement non-invasively. It is also possible to integrate expert knowledge with other parameters to create artificial intelligence systems using fuzzy logic to operate independently and give diagnosis and recommendations to patients thereby overcoming the challenges of shortage of medical personnel in rural areas. However, there is need to acquire enough expert knowledge to build the knowledge base in order to improve the accuracy of the system to give out the correct diagnosis and recommendation. On the selection of the biosensor to collect patient data, there are no data available to be used in sensor calibration. Here, a lot of data is required to get high precision and accuracy by collecting the data using different type of sensors and devices. The collected data provided very insightful information on the relationship between invasive glucometer device data and max 30102 biosensor data, however more data is required from all conditions of diabetes classification ranges in order to improve accuracy and build a robust and precise system. From the collected data, it can be seen that the relationship between the InfraRed values form biosensor is directly proportional to the glucose level measurement from glucometer.

Considering that this is ongoing research, the next phase is to implement this solution. This will lead to improving the health conditions of the community by creating diabetes type-2 awareness and thus assist the government in planning the needs of it is citizens depending on the reports generated. To do this, there is strong need to collect both the sensor data and knowledge base data in a clinical setup environment. The use of this device will reduce the dependence of health personnel and reduction in medical examination cost due to reusability of the device.

A lot of challenges are experienced during sample data collection due to ethical clearances issues and this calls for the need to have policy change to allow flexibility for innovative solutions, mainly in health domain because a lot of ideas die off before implementation due to lack of data collection.

6.1.1 Nullifying the Hypothesis.

The hypothesis was if an embedded edge-based device can be integrated with fuzzy logic system and merged with Internet of Things to develop diabetes type-2 testing and awareness system to be used in health facilities with minimal expert involvement.

From the results obtained from the prototype, it is proven that fuzzy logic system can be seamlessly integrated with an embedded machine learning device with Internet of Things technology, a robust non-invasive testing and diabetes type-2 prediction and early detection system can be developed. The blood sugar level can be tested non-invasively and categorized in the ranges recommended by the world health organization (WHO) guidelines without blood sample requirement and in addition get the probability of being affected by the disease based on provided parameters. The data can be optimized further for prediction and early detection by collecting more data in a clinical setting and by adding more parameters / symptoms associated with the onset of diabetes type -2 to improve the accuracy levels. With all these factors considered, the system should be able to perform and produce results and recommendations with very minimal professional involvement unless otherwise deemed necessary to do more investigations.

6.2 Recommendations

From the findings and experiences during the study, the following recommendations are given to improve the performance of the solution;

- Patient sample data collection for all blood glucose level ranges i.e., normal, pre-diabetic and diabetic should be considered during biosensor calibration.

- A biosensor module with a higher InfraRed wavelength should be considered. A study has shown that Infrared wavelength at the range of 940 nm has the best glucose absorbance peak and can be used to get better results because the attenuation of optical signals by other blood constituents like water, platelets and blood cells is minimum at that level, hence desired depth of penetration can be achieved and actual blood glucose levels can be predicted [76].
- Other factors that affect the accuracy of testing should be considered. These include the pressure applied on the sensor, thickness of the skin and the light exposure to the sensor.

Do the research in a medical setup to acquire more information and knowledge from medical experts for knowledge base development for improved prediction accuracy.

Due to limited time and resources, we were not able to perform the validation process. We therefore recommend validation of the device during testing stage to ascertain the functional and non-functional requirements performance as per the specifications defined.

6.3 Future Works

This work introduced non-invasive sample collection for diabetes type-2 testing and the use of fuzzy logic system to create early detection and prediction system using biosensor and expert knowledge. A prototype was developed on embedded development board ESP32 and biosensor max30102 and tests conducted with volunteers to evaluate the performance of the solution. Future works will involve more data collection for sensor calibration and working with medical experts to develop the knowledge base and finally implement the solution. Also, using the same setting, a different biosensor module with higher wavelength can be used considering the recommendations given in section 6.2 to get the peak glucose absorption range wavelength and improve the prediction values.

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APPENDICES

Appendix 1: Fuzzy Knowledge base development/ Rule Base

Condition	IF	AND	AND	THEN
Rule	**Random Blood Glucose Level**	**BMI**	**Age**	**Diabetes Prediction**
1	Normal	Underweight	Child	Very Low
2	Normal	Underweight	Teen	Very Low
3	Normal	Underweight	Adult	Very Low
4	Normal	Underweight	Middle age ...	Very Low
5	Normal	Underweight	Senior adult	Very Low
6	Normal	Healthy	Child	Very Low
7	Normal	Healthy	Teen	Very Low
8	Normal	Healthy	Adult	Very Low
9	Normal	Healthy	Middle age ...	Very Low
10	Normal	Healthy	Senior adult	Very Low
11	Normal	Overweight	Child	Very Low
12	Normal	Overweight	Teen	Very Low
13	Normal	Overweight	Adult	Low
14	Normal	Overweight	Middle age ...	Low
15	Normal	Overweight	Senior adult	Low

16	Normal	Obese	Child	Very Low
17	Normal	Obese	Teen	Very Low
18	Normal	Obese	Adult	Low
19	Normal	Obese	Middle age ...	Low
20	Normal	Obese	Senior adult	Low
21	Prediabetes	Underweight	Child	Medium
22	Prediabetes	Underweight	Teen	Medium
23	Prediabetes	Underweight	Adult	Medium
24	Prediabetes	Underweight	Middle age ...	Medium
25	Prediabetes	Underweight	Senior adult	Medium
26	Prediabetes	Healthy	Child	Medium
27	Prediabetes	Healthy	Teen	Medium
28	Prediabetes	Healthy	Adult	Medium
29	Prediabetes	Healthy	Middle age ...	Medium
30	Prediabetes	Healthy	Senior adult	Medium
31	Prediabetes	Overweight	Child	High
32	Prediabetes	Overweight	Teen	High
33	Prediabetes	Overweight	Adult	High
34	Prediabetes	Overweight	Middle age ...	High
35	Prediabetes	Overweight	Senior adult	High

36	Prediabetes	Obese	Child	High
37	Prediabetes	Obese	Teen	High
38	Prediabetes	Obese	Adult	High
39	Prediabetes	Obese	Middle age ...	High
40	Prediabetes	Obese	Senior adult	High
41	Diabetes	Underweight	Child	Very High
42	Diabetes	Underweight	Teen	Very High
43	Diabetes	Underweight	Adult	Very High
44	Diabetes	Underweight	Middle age ...	Very High
45	Diabetes	Underweight	Senior adult	Very High
46	Diabetes	Healthy	Child	Very High
47	Diabetes	Healthy	Teen	Very High
48	Diabetes	Healthy	Adult	Very High
49	Diabetes	Healthy	Middle age ...	Very High
50	Diabetes	Healthy	Senior adult	Very High
51	Diabetes	Overweight	Child	Very High
52	Diabetes	Overweight	Teen	Very High
53	Diabetes	Overweight	Adult	Very High
54	Diabetes	Overweight	Middle age ...	Very High
55	Diabetes	Overweight	Senior adult	Very High

56	Diabetes	Obese	Child	Very High
57	Diabetes	Obese	Teen	Very High
58	Diabetes	Obese	Adult	Very High
59	Diabetes	Obese	Middle age ...	Very High
60	Diabetes	Obese	Senior adult	Very High