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Design of an IoT-Based Body Mass Index (BMI) Prediction Model

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Msc. Internet of Things- Embedded Computing Systems

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Design of an IoT-Based Body Mass Index (BMI) Prediction Model

MASTER'S DISSERTATION

Submitted in partial fulfilment of the requirements for the award of

MASTER OF SCIENCE IN INTERNET OF THINGS (IoT)- EMBEDDED COMPUTING SYSTEMS (ECS)

Submitted by:

Glorious Musangi Mark (Reg: 220012800)

Under the supervision of:

Prof. Chomora Mikeka

Dr. Pierre Bakunzibake

DECEMBER 2021

DECLARATION

I’m making an affirmative declaration that this Dissertation contains my own original work except in some areas which have been categorically and positively acknowledged.

Glorious Musangi Mark. REG No. 220012800

Signature: ....

13/12/2021

Date: ……………………..........................

BONIFIDE CERTIFICATE

This is to certify that the research entitled "IoT-Based Body Mass Index (BMI) Prediction Model" is a record of original work done by Glorious Musangi Mark with registration number 220012800 in partial fulfilment of the requirement for the award of Master of Science in Internet of Things (IoT)- Embedded Computing Systems (ECS) in College of Science and Technology, University of Rwanda.

This work has been submitted under the guidance of Prof. Chomora Mikeka and Dr. Pierre Bakuzibake.

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ABSTRACT

Overweight and obesity have a significant economic and social implications in terms of low productivity, high mortality rate and increased health care needs. Overweight and obesity have become a major health concern associated with diseases such as cardiac arrest, type 2 diabetes, stroke, high blood pressure, and other non-communicable diseases (NCD) and are the leading risks for deaths globally, killing more people than underweight. Body Mass Index (BMI) is a measure that uses weight and height to work out a person's nutrition status. Research throughout to calculate BMI is based on traditional manual methods which are time consuming, error prone and they are not cloud-based. Few systems have incorporated machine learning yet with low accuracy. Existing literature is based on areas with high number of overweight and obese cases, however, lacking information from regions in transition. Based on these findings this research takes a technological approach of calculating BMI among the residents of Kitengela town Kajiado County in Kenya men and women (aged between 5 and 50 years) using an IoT based BMI system. This system consists of a NodeMCU microcontroller for computations with an inbuilt ESP8266 WiFi module for connectivity to the internet, load cell sensor for body weight measurement, a HX711 load cell amplifier module and HC-SR04 ultrasonic sensor for height measurement. Values are displayed on a 16x2 LCD and sent to ThingSpeak for storage and analysis. ThingSpeak is integrated with MATLAB Machine Learning to make the prediction based on height and weight sensory data. This research uses Supervised Exponential Gaussian Process Regression algorithm to predict whether a person is underweighted, normal weight, overweight or obese. The designed IoT Based BMI computation system achieves an accuracy of 99.18% with a time reduction of 1.1 % per person while the ML model achieves an accuracy of 98%. The system was more time efficient in that the 45 residents were measured in 15minutes while the manual system took 4 hours 5 minutes, a time saving factor of 3 hours 50 minutes.

Keywords: IoT, Body Mass Index (BMI), Machine Learning, Prediction, Overweight, Obesity

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LIST OF ACRONYMS AND ABBREVIATIONS

BMI: Body Mass Index

CIDP: County Integrated Development Plan

CNN: Convolutional Neural Network

GPR: Gaussian Process Regression

IoT: Internet of Things

KDHS: Kenya Demographic and Health Survey

KHSSP: Kenya health sector strategic plan

KPHC: Kenya Population and Housing Census

LCD : Liquid Crystal Display

LED: Light Emitting Diode

ML: Machine Learning

NCD: Non-Communicable Diseases

RMSE: Root Mean Square Error

STEPS: Kenya STEPwise survey for non-communicable diseases risk factors 2015 report

SVM: Support Vector Machines

WHO: World Health Organization

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CHAPTER ONE

INTRODUCTION

1.1 INTRODUCTION

Internet of Things (IoT) has gained a lot of popularity in different sectors such as, smart homes, smart agriculture, smart cities due to its capability of connecting different devices and sensors, allowing them to connect to each other and communicate over the internet. IoT in health sector has not been left behind with applications to monitor patients' health being adopted. In Internet of Things (IoT), healthcare is an important application area because it helps save on cost and improve the quality of service. IoT has influenced healthcare positively in terms of real time communication, real time data processing, use of cloud services for data storage and analysis and ubiquitous connectivity between devices and health professionals [1]. Wearable devices have been used by patients to monitor things like sugar levels, blood pressure, heart rate etc. However, with these devices in place, human health is still deteriorating.

Rapid urbanization, economic transition and life style changes have given rise to high body mass index (BMI) levels with urbanization being the key driver of obesity and overweight [2]. Obesity and overweight have a significant economic and social implications in terms of low productivity, high mortality rate and increased heath care needs [3]. 2018 WHO report showed that almost two billion people were overweight in year 2016 with 650 million of them being obese[4]. Obesity and overweight are the leading risks for deaths globally, killing more people than underweight[4] and therefore being a global epidemic[5][6].

Sub-Saharan Africa (SSA) is experiencing high rate of overweight and obesity with females being more affected in regards to gender while urban areas suffer more compared to rural areas [7]. With an increasing number of urban migration throughout SSA, high levels of BMI continue to rise attributing to increased risk of cardiovascular diseases, diabetes, hypertension and other non-communicable diseases (NCD) across SSA [7]. These conditions have led to increased premature deaths and disabilities[8][9].

Kenya accounts for 7.7% global obesity levels [10], and continues to face an increase in obesity and overweight in the past twenty years with an immense burden of hypertension, diabetes, cardiovascular diseases and NCDs[11]. Kenya health sector strategic plan 2014–2018 (KHSSP) report shows an increase in overweight and obesity by region with Nairobi and Central region having a prevalence rate of over 50%; Coast, eastern and Nyanza regions with prevalence of between 30% & 40% and North-eastern, Western, Rift valley regions with prevalence of below 30% [12]. 2015 STEP report shows that overweight and obesity prevalence in urban areas is 1.6 times more than prevalence in rural areas [12]. Research throughout has been conducted to determine the causes of overweight and obesity. These studies have been regional targeting Nairobi County and focusing on women or among people living in slums [2], [13], [14], [15]. Nairobi County has been selected by most of the researchers because it has a high number of overweight and obese women, however, lacking information from regions in transition.

This research focuses on Kitengela town in Kajiado county as the most urbanizing area in Kenya. Research done earlier in [16] shows high levels of hypertension and diabetes associated with high BMI levels among the residents of Kajiado County. According to KPHC 2019 census the town's population inflow has tripled since 2009 with urban population of 154,436 people [17], [18]. Kitengela town being within Nairobi metropolitan area and in Rift Valley region, is experiencing a rapid urbanization and a rapid lifestyle change.

Table 1: Kitengela Population projection

Urban Centers	**2009 projections**			**2018 projections**			**2020 projections**			**2022 projections**		
	Male	Female	Total	Male	Female	Total	Male	Female	Total	Male	Female	Total
Kitengela	30088	28079	58167	48715	45463	94178	54221	50601	104822	60350	56320	116670

Source: *Kenya National Bureau of Statistics*[18]

Table 2: Kitengela Town Population.

Name	**County**	**1999 population Census**	**2009 population Census**	**2019 population Census**
Kitengela	Kajiado	9327	56987	154436

Source: *Kenya National Bureau of Statistics*

To combat the challenges of battling with overweight and obesity, WHO have developed a standard way of measuring person's nutrition status. BMI is used as an indicator of a person's nutrition status[19]. It's defined as persons weight in kilogram divided by the square of the person's height in meters (kg/m2)[19]. Irrespective of the sex, gender and ethnicity BMI is widely used as a measure of adiposity in both grownups and children [20]. An ideal BMI as per the World Health Organization should be between 18.5 and 24.9 Kg/m^2. BMI below 18.5 is defined as underweight. BMI between 25.0 and 29.9 is Pre obesity while Obesity class I is BMI of between 30.0 and 34.9. Obesity class II is a BMI between 35.0 and 39.9 while Obesity class III is BMI above 40 kg/m^2 [19].

This research incorporates both internet of things (IoT) and machine learning (ML) to compute BMI data and predict person's nutrition status in real time. Traditionally, BMI data is calculated using mathematical formula. This method is time consuming, error prone due to human associated errors and the data is locally stored. In this research, BMI computation method will be implemented using IoT devices to capture height and weight sensor data and compute for BMI data. The sensor data will be stored in ThingSpeak cloud storage. This system is expected to be time efficient and accurate. The sensor data will then be used to predict BMI nutrition status based on the trained ML model. Machine learning focuses on the use of data to train machines, identify patterns, and make decisions with minimal human interventions. With statistical methods, algorithms are trained to make classifications or predictions[21]. Machine learning is essential in this research due to the need to predict persons nutrition status based on their BMI parameters in real time without relying on rules-based programming.

1.2 PROBLEM STATEMENT

The growing number of research to calculate BMI is based on traditional methods. This is done either through measuring tapes, height boards or weighing scale [2], [22], [23]. There are also charts and tables that are used to assess the health risks of obesity [24]. These methods are time consuming in calculating adiposity and most of the time they give inaccurate data due to human errors. These methods requires the researcher to record the height and weight values somewhere and later feeds the values into a device [2]. Other methods requires the researcher to calculate BMI manually using the BMI mathematical formula [25]. A few automated system have been developed in the existing literature however, these systems are not cloud based, they are expensive, they require high level of expertise to operate and are not user friendly[26], [27], [28].

Therefore, this research will employ an IoT based BMI system and a machine learning model to calculate BMI value and predict persons nutritious status in real time. Here, the user will not be required to input any data manually, but rather step on the system which will intern calculate the BMI value automatically. With a press on a button, the data will be sent to the cloud for storage and analysis. The proposed system is easy to use, requires no expertise to use and its accurate.

1.3 AIMS OF THE RESEARCH

This research aims at designing and implementing and IoT based BMI system that is not only fast, accurate and easy to use but also one that enables real time storage, analysis and predicts persons nutrition status based on height and weight sensory data.

1.4 GENERAL OBJECTIVE

To design and develop an IoT based BMI system that will replace the traditional methods of calculating BMI and predict BMI nutrition status using ML.

1.4.1 SPECIFIC OBJECTIVES

a) To design an embedded system that will incorporate the weight, height, and microcontroller functions.
b) To create database for data storage and a machine leaning model for data prediction.
c) To evaluate the accuracy, ease of use and reliability of the system.

1.5 HYPOTHESIS

The hypothesis was that Internet of things and machine learning can be integrated to enable fast and accurate body mass index calculation and nutrition status prediction in real time.

1.6 SIGNIFICANCE OF THE STUDY

a) Hospitals and medical facilities will have better system to automatically measure patients' BMI. This system will lessen the work of health professionals and make a quicker response to patients and offer better nutrition care and support.

b) This IoT based BMI prediction model can be used anywhere in the world where there is internet access. The adoption of this system will help in eliminating queues and errors associated with manual calculations. This system can be used in hospitals, gym, schools etc.
c) Implementation and findings of this study will help in setting priorities and designing interventions to provide health care needs to underweight, overweight and obese persons. It will also educate the public on their nutrition status since most of them don’t realize when they got to such levels of weight.

1.7 ORGANIZATION OF THE STUDY

This paper is structured as follows: Chapter 1 comprises of the introduction, problem statement, aims and objectives of the research. Chapter 2 presents the literature review, Chapter 3 describes the methodology applied, system and hardware requirements, description of components, Chapter 4 presents the system design and development. Chapter 5 discusses the results and system test; Chapter 6 summarizes conclusion and the recommendations.

CHAPTER TWO

LITERATURE REVIEW

IoT based devices are increasingly used in the healthcare sector due their ability to monitor and analyze health conditions. This chapter focus on reviewing state of the art related to IoT in healthcare with respect to BMI. It aims at increasing an understanding of what has been done, strengths and weaknesses of the existing literature.

2.1 EXISTING BMI SYSTEMS

A MATLAB based height and weight measurement is proposed in [26] to replace the traditional ways of measuring height and weight. To measure the height, shots of images of a person are taken using a webcam and later the MATLAB toolbox is used in processing the image to compute a person's height. First you capture the background with no person, which must be white. The image of the person whose height is to be measured is then captured. You then subtract the image with no person with the image with person. Next step you apply threshold to the subtracted image to get a black and white image. Scan the black and white image to obtain the pixels then calculate the height of a person. A weight sensor is used to obtain weights. The height and weight are then used to calculate the BMI. This system requires expertise to understand, it is not user friendly, time consuming and expensive to implement.

In [29] a microcontroller based system that uses the weight and height parameters to calculate the body mass index is proposed. A weighing scale is used to capture the weight of individuals with a light dependent resistor being used to capture height measurements. The use of light dependent resistor in measuring height can lead to inaccuracies hence a need for improvement.

A BMI calculator based on an android device is proposed in [30]. A user enters the weight and height measurements which is then used by the system to calculate the body mass index and subsequently the person's adiposity. This system involves manual entries that may not only be time consuming but are also prone to human errors.

A digital weighing and alert system is presented in [31]. The system has the capability of measuring the weight of a person and sending an alert to the user on a mobile based application.

The system automatically weighs a person and sends the data to a cloud database. The user enters their height manually through the mobile application. The weight and the height measurements are then used to compute the BMI. The manual entry of heights is a major drawback as it slows the proses and is prone to errors.

A system that can automatically calculate and display a person BMI was developed in [32] . This system showed quick and more accurate results in comparison to the traditional methods of BMI calculation. However, the system is limited to weights up to 90kgs which may not be the case for all persons therefore a need for an all-inclusive system.

A voice feature based system is also proposed in [27]. The system uses voice feature and a logic regression algorithm to predict if a person has a normal weight, is underweight, is overweight or obese. There is still a need to carry out further studies on this system to verify the feasibility of its application on African population.

In [28] a microcontroller based system that can measure the weight and height of a person and use those values to automatically calculate the BMI is designed. The weights are measured using a load cell with an ultrasonic sensor being used to measure heights. This system proves that sensing technologies can be used to capture real time data and calculate the BMI of a person automatically. The data from this system however cannot be shared with health professionals as its not cloud-based and, it's not readily available to the African population hence the need for a cheap and cloud-based system.

In Kenya studies have only targeted limited number of counties in Kenya with most research using secondary data from 2014 Kenya Demographic and Health Survey (KDHS). To determine the BMI among women, the 2014 KDHS takes height and weight measurements among women aged 15-49. Weight measurements are made using seca electronic scale. Height measurements are made using Shorrboards [22]. The 2014 KDHS data shows that 33% of Kenyan women are either overweight or obese with 10% of them being obese [22].

In [33] the authors proposes the use of an IoT based smart mirror to help users monitor their body mass index and body fat percentage. Ultrasonic sensor and load sensors are used to obtain height and weight values respectively. Electrode plates were implemented on the weight scale to estimate fat percentage in a user's body. The research proves to accurately compute BMI of a user with an accuracy of 92.5%.

2.2 MACHINE LEARNING PREDICTION

This section gives a review of the state of the art of research involving machine learning in healthcare, with respect to overweight and obesity.

In [34] authors utilize ML to investigate the association between parameters related to psychological variables such as depression and BMI. The forecasted unobserved BMI values was able to predict BMI with an accuracy of 80%.

In [35] Deep Neural Network and structural brain imaging is used to predict BMI of an individual. Their research showed convolutional neural network (CNN) proved that there is a relationship between brain structure and BMI.

In [36] authors proposes a method of predicting normal, overweight and obese classes based on voice features, independently of weight and height. They use logistic regression algorithm and bagging & random forest classification algorithms. Results showed that classification model build using logistic regression algorithm gave better results.

In [37] a ML model is constructed to predict the risk of becoming overweight or obese among the young people. Authors employs several ML algorithms to accurately predict adolescents at the risk of becoming overweight or obese at teenage stage. Their model achieves an accuracy of 90%.

2.3 SUMMARY AND GAPS IDENTIFIED

The review of the state of the work proves that sensing technologies can be used to capture real time data and calculate the BMI of a person automatically. Likewise, studies have showed that use of machine learning to predict overweight and obesity is achievable. However, this research has found that, some of the existing BMI system utilize manual entry of data leading to poor accuracy and consuming more time, other systems lack a real time cloud storage. Other systems are quite expensive [38][39], while others require high level of expertise. Limited studies have incorporated machine learning with respect to body mass index yet with lower accuracy.

Therefore, this research implements an IoT-based BMI prediction model that is accurate, easy to use with real time storage, low-cost and a better accuracy in predicting BMI classes. The proposed system does not replace the healthcare systems put in place but rather acts as a support tool for healthcare.

CHAPTER THREE

METHODOLOGY

3.1 SYSTEM METHODOLOGY

Prior to designing the proposed system, the existing manual system were analyzed. Two methodologies were used in collecting data: qualitative method and experimental method. Qualitative method was used to understand the challenges faced by health practitioners when collecting BMI data and how they would want the system improved. In this method, Interviews were used to collect data from four different hospitals within Kitengela town. Two hospitals were private, and two were public hospital. Interviews questions included the following.

- What is the current method used in calculating BMI?
- When is BMI measured?
- What are the challenges faced?
- How much time does it take to measure BMI for one patient?
- How is the BMI data stored and retrieved?
- How would the current system have improved?

Experimental method was used to ascertain the time lost during the process.

BMI data was collected in Triage room for all patients. It was mandatory to determine if patients needed emergency care or not. Each patient was asked to remove shoes then step on the weighing scale (SECA and Charder) which was fixed with height board. Patients were asked to stand straight after which a head rest was placed on their head. The data was manually recorded in the hospitals record book or system and later used the BMI chart (height against weight ratio) to classify the patients BMI as either underweight, normal, overweight, or obese. These hospitals stated that they would opt for a system that could improve their current operations and save on time if it existed.

3.2 SYSTEM DEVELOPMENT PROCESS

The research journey commenced with an idea which triggered a full literature review around the topic of interest. This was led by formulation of the research topic based on the gaps identified from the literature review. This was followed by a research proposal write-up which was presented for approval by the University. The sequential steps that followed upon research proposal approval are as shown in figure 1. This research employed prototyping model in the design and development of the system from initiation to completion. In this model the prototype was build, tried, reworked until a satisfactory product was achieved.

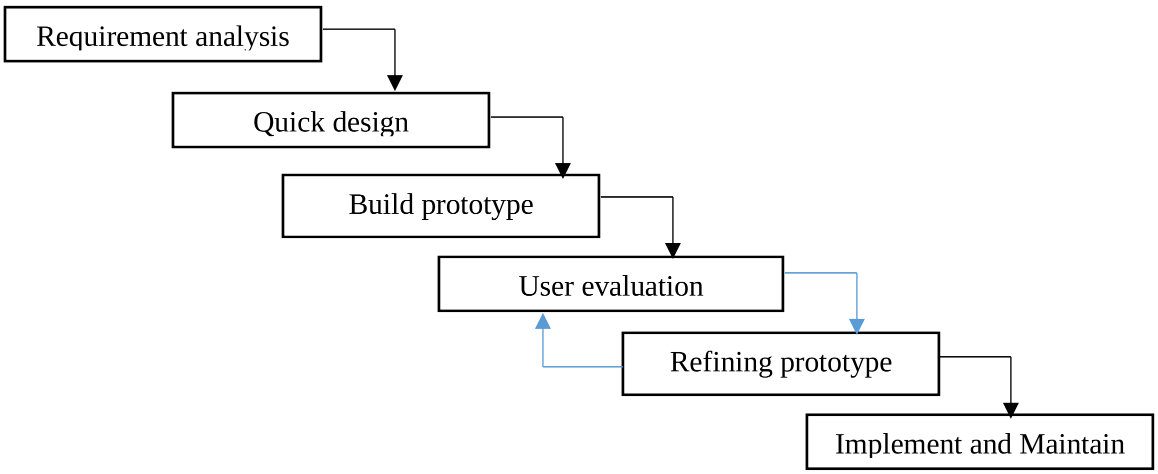

Figure 1. System development process

Requirement gathering and analysis- In this stage, the prerequisites of the system were defined. We interviewed health practitioners from Kitengela town to get their pain points of the traditional methods they were using and get their views on how they would want the proposed system function.

Quick design- In this stage a quick design of the system was created. This incorporated the structural design of the proposed system which gave a brief idea of the system framework to the user.

Build prototype- In this stage an actual prototype was build dependent on the data assembled from quick design. This stage incorporated all the system requirements gathered and the expectations of the user.

User evaluation- In this stage we presented the proposed framework to the end user for an initial evaluation. This stage helped in discovering the strengths and weaknesses of the proposed system and areas of the framework which needed improvement.

Refining prototype- In this stage we incorporated the changes made by end user into the system until the end user was happy with the system. This was in terms of system accuracy, ease of use, reliability, and time efficiency of the system.

Implement and maintain- This was the last stage in which the system was fully tested and rolled out to be used among the 45 residents of Kitengela town. The system was maintained to prevent any system failure.

3.3 USABILITY EVALUATION METHOD

The developed prototype was tested by 5 users. Interviews was used as an evaluation method. Users were interviewed to share their experiences and expectations. In this method, scaled questioner was used to allow users gauge the ease of use, reliability, accuracy, and time efficiency of the system.

3.4 MACHINE LEARNING (ML) PROCESS

This research employed the use of machine learning to predict a person's nutrition status based on height and weight sensor data without relying on rules-based programming. To train the ML model, the following steps were followed as shown in Figure 2.

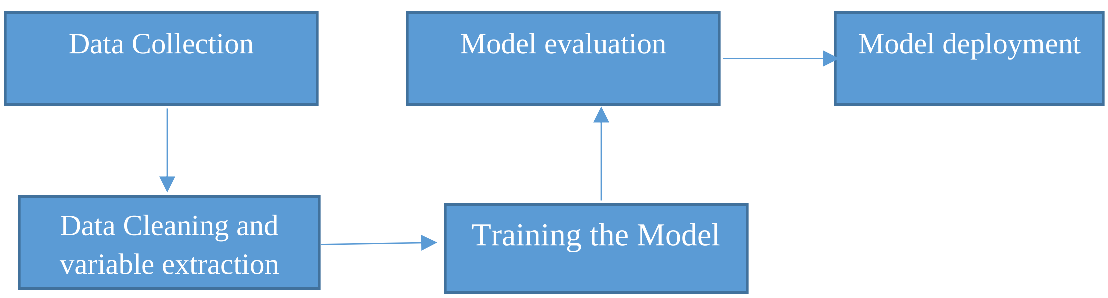

Figure 2. Machine Learning process

1. Data collection- The dataset used was "500-person-gender-height-weight-body mass index", an open-source dataset from kaggle.com [40]. Kaggle is one of the largest data science community that publishes datasets and allows users to build models in a web-based data-science environment. The dataset contained 500 rows x 5 columns. We were only interested with height and weight data to train the model.
2. Data Cleaning and variable extraction- We explored the dataset to remove any duplicates, dealt with missing values, data conversion and randomized the data to remove any order in which data was collected and any relevant relationship between

variables. Preprocessing was followed by variable extraction from the dataset. Essential variables were extracted leaving behind non-essential variables. The extracted variables were saved on a different file.

3. Training the Model- This research employed supervised machine learning algorithms. We trained the algorithms using Regression Learner app in MATLAB and opted for the one which had lower Root Mean Square Error (RMSE). We split the dataset into training set (80%) and evaluation set (20%). We used under-sampling technique to balance the dataset by reducing the size of the abundant class. Over-sampling technique was used to increase the size of the rare samples.
4. Model evaluation- We then evaluated the model and tested it using evaluation data set.
5. Model deployment- The final step was to deploy our trained model to make prediction of a person's nutrition status by providing the model with sensor data.

3.5 SYSTEM REQUIREMENTS

Different requirements are incorporated in the design of the system from inception to its completion. The IoT based BMI system consists of different requirements. The NodeMCU microcontroller is the main part of the system. It does all the computations required for the system to run smoothly. Sensors are used to measures the weight and height of a person and sent the data to the microcontroller. LCD is used to display the weight, height, and BMI status to the user. Power supply powers the whole system. Internet connectivity is used to enable connectivity between the Cloud storage and the microcontroller. Thingspeak cloud storage is used to store and analyze data. MATLAB software is integrated with Thingspeak cloud storage to make nutrition status prediction based on the trained model. Data is visualized through a web application.

3.5.1 HARDWARE AND SOFWARE REQUIREMENTS

The proposed system consists of the following hardware components to meet the objectives of this research.

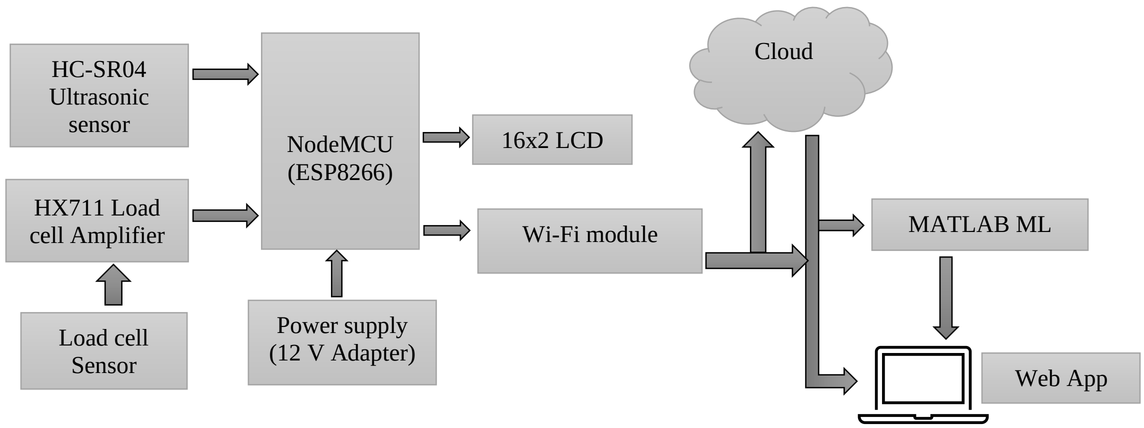

Figure 3. Proposed system block diagram

HC-SR04 Ultrasonic Sensor

Ultrasonic sensor is an electronic device that emit sound waves at a high frequency of 40 KHz at regular intervals. Ultrasonic sensor has a transmitter which emits the sound waves and the receiver which receives the reflected sound waves. To measure the distance of an object, the sensor measures the time it takes between the emission and reception of the sound waves, and it's calculated as D = ½*T*S. The HC-SR04 ultrasonic sensor is used in this project because it can measure distance from 2cm to 450cm with a accuracy of 3mm[41].

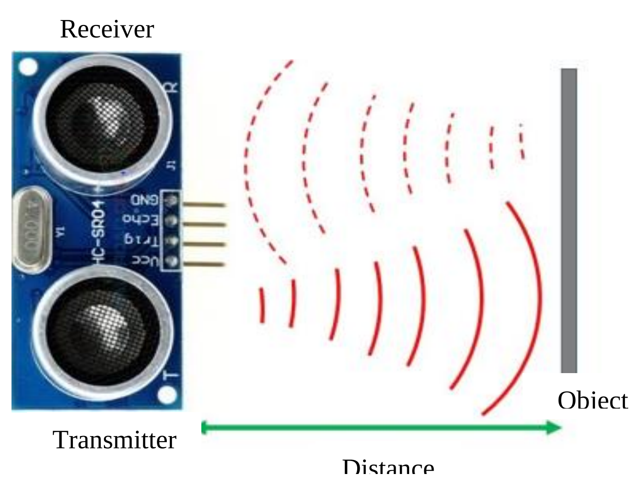

Figure 4. The HC-SR04 ultrasonic sensor

Load cell Sensor and HX711 Load cell Amplifier

Load cell is a force transducer that converts pressure, tension, or comprehension into electrical output. The force applied is directly proportional to the electrical output. The strain gauge load cells are arranged in a Wheatstone bridge configuration. The signals produced by the load cell are in mV (millivolt). HX711 is a 24-bit Analog-to-Digital Converter (ADC) that amplifies the small electrical signal generated by the load cell into 24-bit changes in voltage (0-5V) [42]. This allows the microcontroller to resolve the weight changes and get a measurable data out of the load cell. In this research we used a 4x50Kg body load cell weighing sensor as shown in figure 4 [43]. The load cells were mounted to a 30x30 cm wooden surface using a 3D mounting frame as shown in Figure 6.

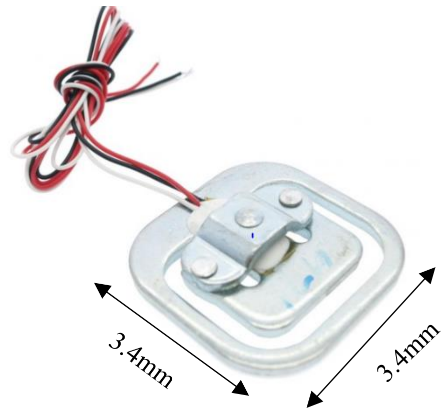

Figure 5. 50Kg Body Load Cell

Figure 6. 3D Load cell Mounting frame

NodeMCU (ESP8266)

It's a low-cost development board designed for IoT applications. The hardware is based on ESP-12E module, and the firmware runs on ESP8266 Wi-Fi SoC. The processor supports real time operation system (RTOS) operating at a clock frequency of between 80MHz and 160 MHz. It has 128 KB RAM and 4MB of Flash memory for data and program storage. It has a high processing power and deep sleep operating feature that's makes it perfect for IoT applications [44].

Figure 7. ESP8266 NodeMCU [47]

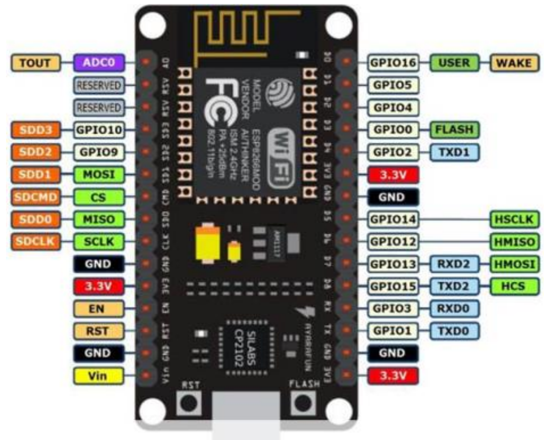

Figure 8. ESP8266 NodemCU PinOut [47]

16x2 LCD

Figure 9. LCD display

16x2 LCD (Liquid Crystal Display) device displays characters and symbols. It has 16 columns and 2 rows. It is cheap, easy to program and readily available. 16x2 LCD is used to display the weight and height values and weight status.

Power Supply

Regulated DC power supply is used in this project as it's more sustainable compared to use of battery.

Other hardware that was used included wires, bolts and nuts, metal plates etc.

The following are the software requirements for the project.

a. Window 10- an operating system for personal computers.
b. Arduino IDE- is an open-source Arduino software where you write and upload code.
c. C programing language- The programming language used in writing the code.

d. ThingSpeak cloud storage- is an open-source cloud platform that allows users to communicate with internet enabled devices. Users can store, visualize, analyze, and retrieve live data streams in the cloud.
e. MATLAB- is a high-level performance language used for computation, data analysis and visualization, algorithm development, application development including graphical user interface and many more.

CHAPTER FOUR

SYSTEM DESIGN AND DEVELOPMENT

4.1 SYSTEM ARCHITECTURE

The following figure 10 presents a high-level architectural design of the proposed prototype system. The system is composed of four main parts: sensing part, data storage & analyses, BMI status prediction using MATLAB and data visualization. Sensors sense data and send it to NodeMCU for computations. The computed data is sent to ThingSpeak data storage through Wi-Fi. The data at this point can be analyzed and visualized. ThingSpeak is integrated with MATLAB using API keys to make prediction using the real time data from sensors.

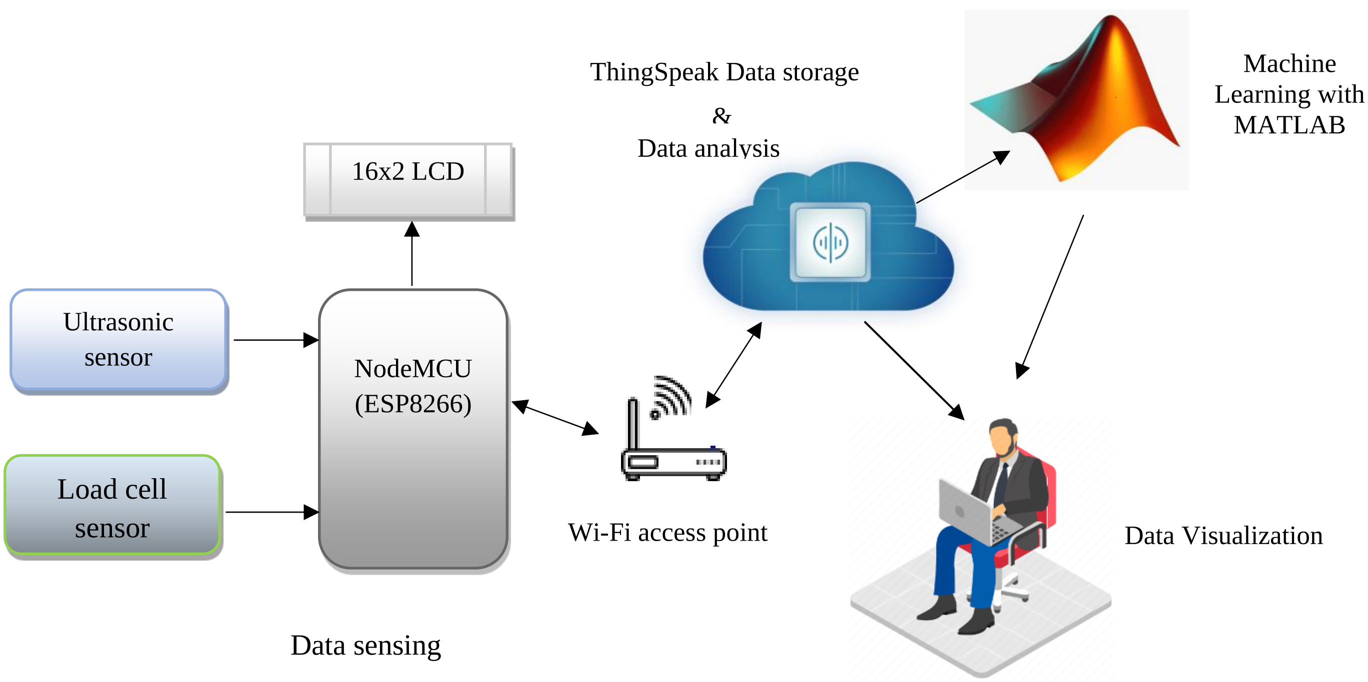

Figure 10. Proposed system

The proposed system is built based on a three-layer architecture proposed by researchers in the field of internet of things (IoT) [45]. The architecture has three layers namely, perception, network, and application layer.

Perception layer- is a physical layer which has sensors for sensing and gathering data. This layer comprises of ultrasonic sensor and load cell sensors for capturing height and weight data of a person.

Network layer- is used for connecting with other smart devices, network devices and is also used for transmitting and processing sensor data. The IoT devices are connected to each other or to cloud via network layer.

Application layer- used for delivering application specific services to the user. Web application is used to provide predicted nutrition status and data stored in the cloud.

4.2 HARDWARE DESIGN

The development of an IoT based BMI system consists of Load cell sensor, Ultrasonic sensor, HX711 amplifier and NodeMCU microcontroller. The ultrasonic sensor and load cell sensor sent the data into the microcontroller which does the computations and sends the computed data to the LCD. Load cell sensors are arranged in a Wheatstone bridge configuration to measure the weight. A Wheatstone bridge is a configuration of four resistors with a known voltage applied as shown in figure 11.

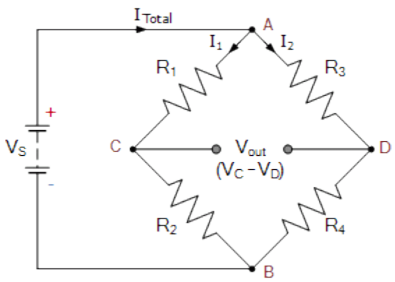

Figure 11: Wheatstone bridge Circuit

With a known constant voltage, V_s, V_{out} is measured. V_{out} is 0 if *R1/R2* = *R3/R4*. A change in any of the resistors means a change in $V_{out.}$ This is governed by the Ohm's law as shown in equation (1).

$$Vout = \left[\left(\frac{R3}{R3 + R4} - \frac{R2}{R1 + R2}\right)\right] * Vin \qquad (1)$$

If we replace the Wheatstone bridge resistors with a strain gauge, V_{out} can easily be measured which intern will help assess the amount of force applied. The electrical resistance of the Wheatstone bridge changes on the direct application of a force on the load cell and thus generates electrical output in millivolts (mV). The HX711 amplifier, then amplifies the small electrical signal generated by the load cell into 24-bit changes in voltage (0-5V) [42]. This allows the microcontroller to resolve the weight changes and get a measurable data out of the load cell. The HX711 uses a two-wire interface (Clock and Data) for communication with NodeMCU.

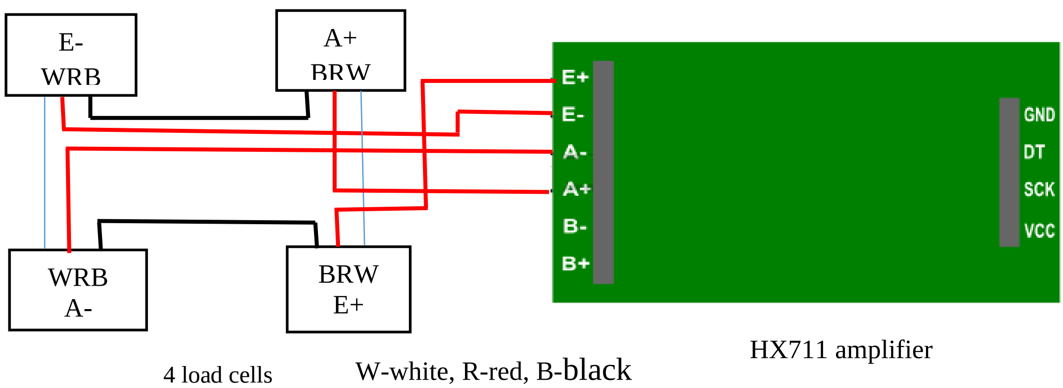

Figure 12. Load cell connection with HX711 amplifier

NodeMCU hardware is based on ESP-12E module, and the firmware runs on ESP8266 Wi-Fi SoC. Wi-Fi module connect to internet to upload or fetch data. The input and output pins have a different mapping on NodeMCU. Unlike other Arduino boards that are powered with 5Volts, ESP8266 chip requires 3.3V power supply voltage. However, NodeMCU ESP-12E development board can be connected to 5V using micro-USB connector or Vin pin available on board. In this project we made a 5 V regulated power supply for NodeMCU Esp8266 so that it can be easily powered using a 12 V adaptor, a solar panel, a 12 V battery, or any dc voltage source. The input voltage should be less than 35 Volts and greater than 5 Volts as we are using a 7805-voltage regulator.

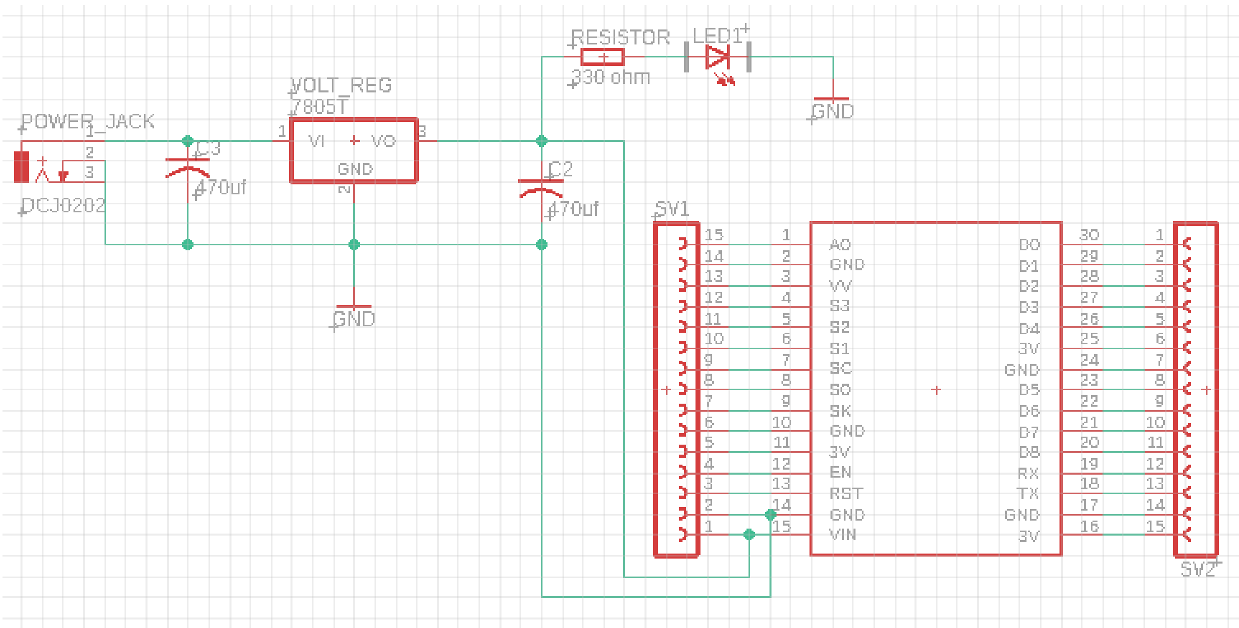

Figure 13. NodeMCU power supply Schematic diagram

Power jack is a female dc socket which is connected to either 12 V adaptor, 9 V battery or 12 V battery. The power is regulated using L7805 voltage regulator. One 470µf capacitor is connected to the input of the voltage regulator and the other is connected to the output of the voltage regulator. A 330Ω current limiting resistor is connected in series with a 2.5 V LED. To power up the NodeMCU, we connected the output of the voltage regulator to the Vin pin of NodeMCU and connected ground to the ground of NodeMCU. SV1 and SV2 are female header pins that are used for interfacing with other electronic circuits.

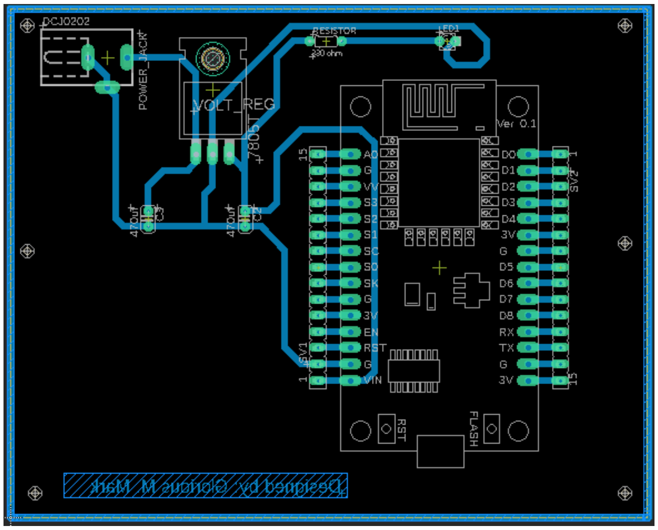

Figure 14. NodeMCU power supply PCB

The next step was to design and print the NodeMCU power supply PCB as shown in figure 14 that would later be interfaced with ultrasonic sensor, LCD and Load cell sensors.

Circuit Explanation

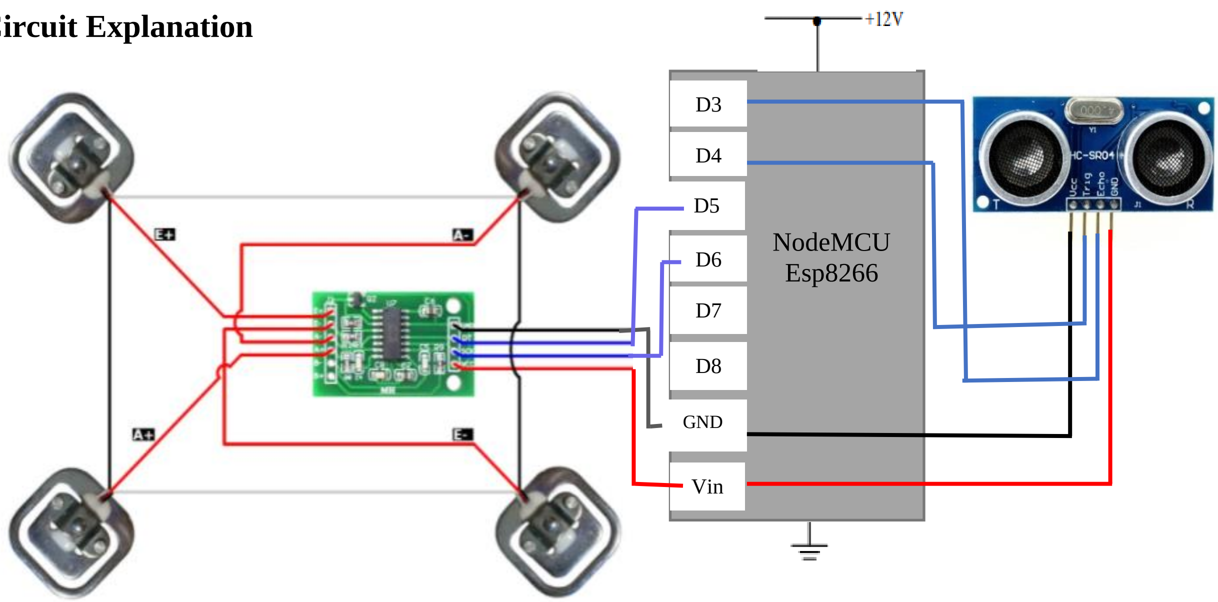

Figure 15. Interfacing load cells and ultrasonic sensor to NodeMCU

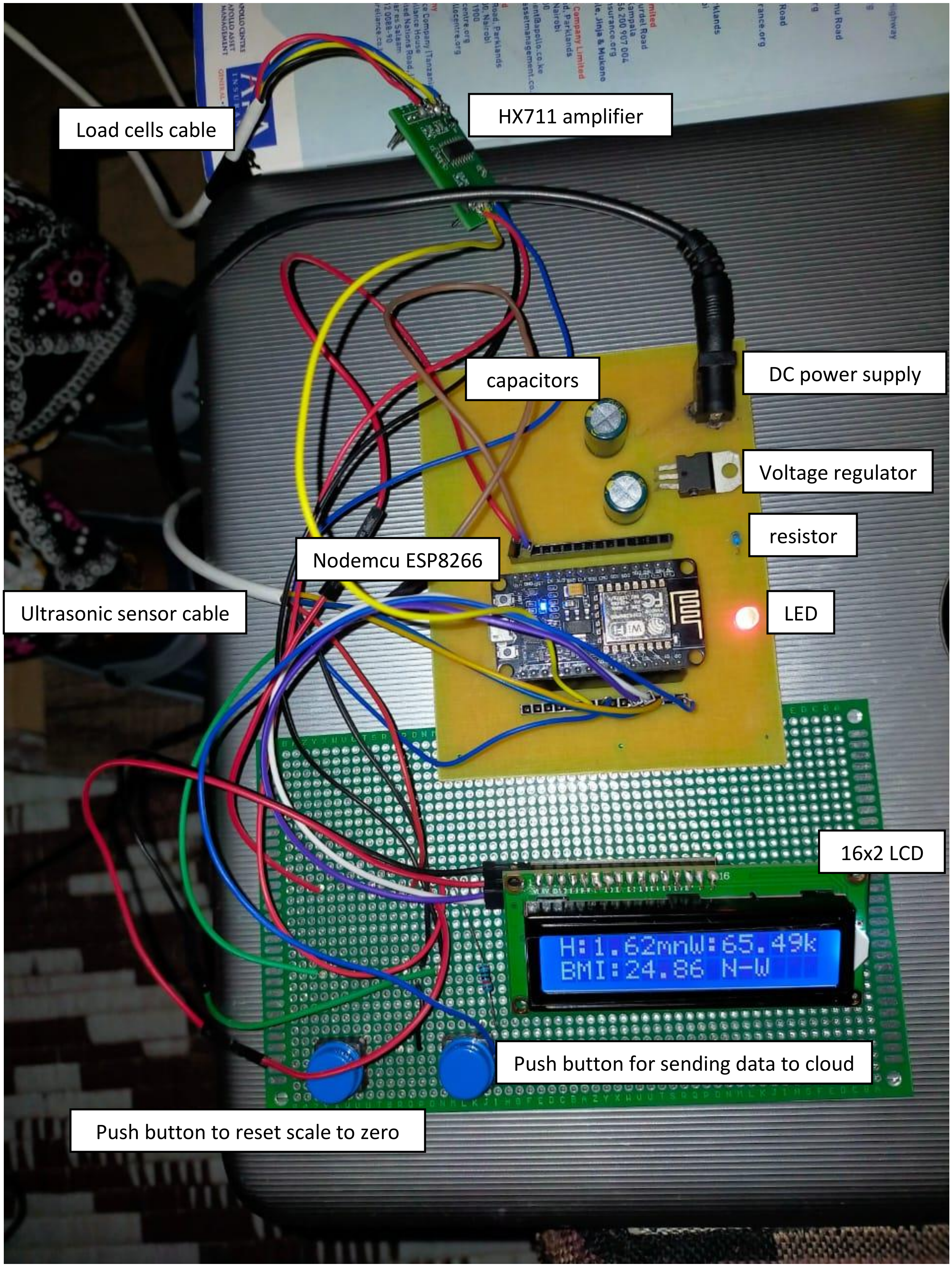

Figure 16. Experimental setup of the prototype

LCD pins GND, VDD, SDA and SCL were connected to pin number GND, Vin, D1, and D2 of NodeMCU respectively. HX711 Module's DT and SCK pins are directly connected with pin D5 and D6 respectively. Ultrasonic sensor trig pin and echo pin are connected to D4 and D3 respectively. One push button for sending data to the cloud was connected to D0 while the other for resetting the scale was connected to D7. The NodeMCU Vin pin and Ground pin were extended to a Vero board to support more devices.

4.3 SOFTWARE DESIGN

This phase involved installation of Arduino IDE from Arduino.cc, ESP8266 board manager, HX711 library, ThingSpeak library, Liquid Crystal I2C library and coding. Figure 16 shows the flow chart of the system.

To get the correct measurements from the weight sensor, we first calibrated the system. First, we powered up the system and removed any weight from the scale. After the readings began, we placed a known weight on the scale and send its weight via the serial monitor to obtain the calibration factor. Once the calibration factor was obtained, we could simulate any weight up to 200kg. The calibration factor was later used in the main code.

To get the height of a person, ultrasonic sensor was fixed on a known height of 2.4m from the weight sensor as shown in figure 19. The height of a person was abbreviated with letter H, and the ultrasonic distance with letter D. To calculate H the formula was, H=2.4m-D.

From our code, the system was able to display the height and weight of a person with their BMI status on a 16x2 LCD. With a press of a push button the computed data was send to ThingSpeak for storage and analysis.

Pseudocode

Start
    Input weight in kilograms
    Input height in meter

Compute BMI=weight\(height*height)

If BMI<18.50
    Print = Under weight

Else if BMI <=24.9
    Print =Normal weight

Else if BMI <=29.9
    Print = Pre-obesity

Else if BMI <=34.9
    Print = Obesity class I

Else if BMI <=39.9
    Print = Obesity class II

Else
    Print= Obesity class III

End if

End

Flowchart

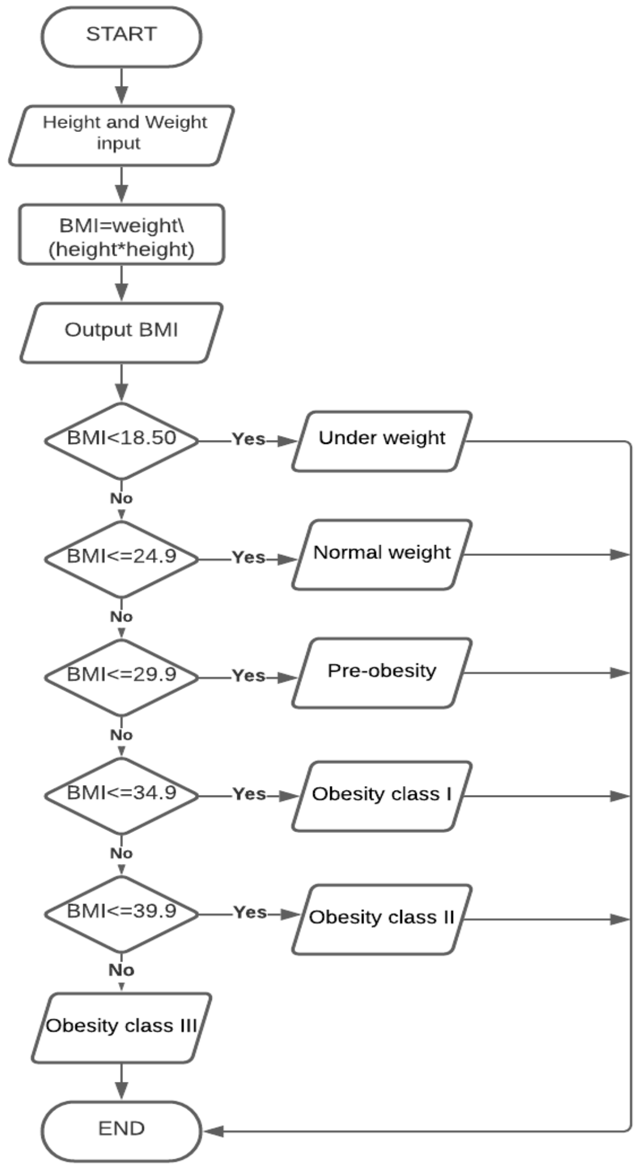

Figure 17. BMI Flow chart

Creating the ThingSpeak database

ThingSpeak is a cloud platform that provides an easy way of storing the sensory data collected at the device level. It bridges the gap between server-side programming and non-programmers. ThingSpeak allows aggregation, visualization, and analysis of live data in the cloud. ThingSpeak offers a tone of features including collecting and storing data in private channel for the privacy of your data. We chose ThingSpeak because it's an open-source cloud platform that lets you store your data to the cloud at no cost so you can sync it across all devices or share it among multiple users. It has a comprehensive set of security rules to help manage access. It works in near real time, automatically fetching changes from your database as they occur. ThingSpeak was integrated with MATLAB using Channel ID and Read API key to enable data to be read.

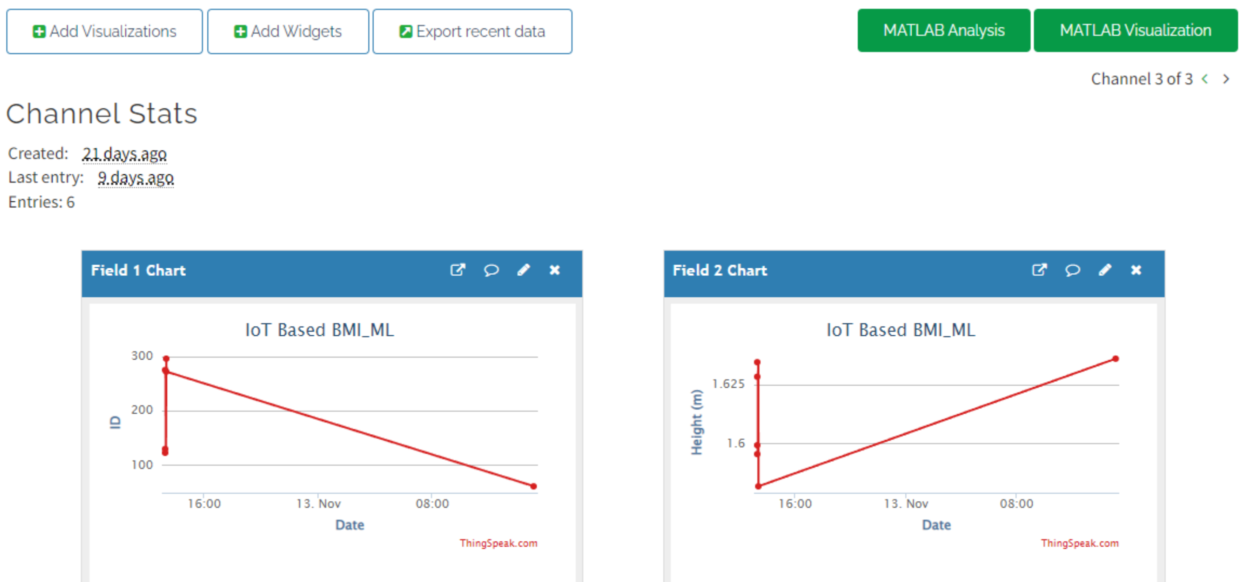

Figure 18. ThingSpeak Experimental setup

4.4 IoT-BASED BMI STRUCTURAL DESIGN

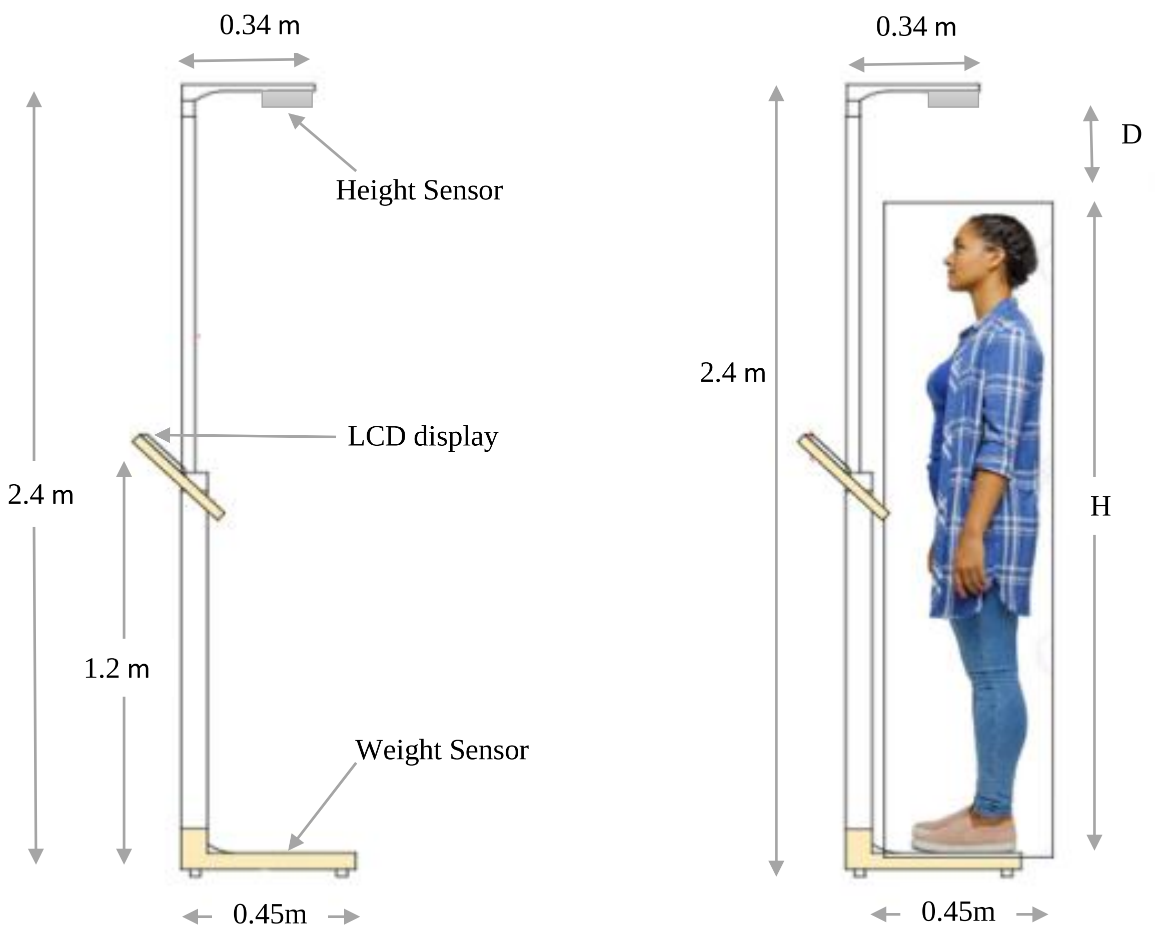

Figure 19. BMI structural design

The structural design of the system was made up of stainless steel. The load cell sensors were mounted on a 0.30x0.30m wooden surface and then mounted on top of the metal base. The height sensor was fixed at 0.34m with a height of 2.4m from the weight sensor. The metal base carrying the weight sensor was 0.45m long. The overall system weighed 5.9kg which is portable compared to other exiting system which weighed 52 kg[39].

4.5 MACHINE LEARNING (ML) ALGORITHM IMPLEMENTATION

The objective was to train our system using low data sets for our system to be able to make prediction of BMI nutrition status.

4.5.1 DATASET DISCOVERY

The BMI dataset used was an open-source dataset from kaggle.com. The dataset was 500 rows x 5 columns containing gender, height (cm), weight, and BMI. To the original dataset we calculated BMI, index (0-5), added a status column, and converted the height in centimeters to height in meters.

index 0= Underweight: BMI<18.50

index 1=Normal weight: BMI <=24.9

index 2 = Pre-obesity: BMI <=29.9

index 3 = Obesity class I: BMI <=34.9

index 4= Obesity class II: BMI <=39.9

index 5= Obesity class III: BMI >=40.0

Table 3. BMI dataset

Height(m)	Weight (Kg)	BMI	Index	Status
1.74	96	31.7083	3	Obesity Class I
1.89	87	24.3554	1	Normal Weight
1.85	110	32.1402	3	Obesity Class I
1.95	104	27.3504	2	Pre-Obesity
1.49	61	27.4762	2	Pre-Obesity
1.89	104	29.1145	2	Pre-Obesity
1.47	92	42.5749	5	Obesity Class III
1.54	111	46.8038	5	Obesity Class III
1.74	90	29.7265	2	Pre-Obesity
1.69	103	36.0632	4	Obesity Class II
1.95	81	21.3018	1	Normal Weight
1.59	80	31.6443	3	Obesity Class I
1.92	101	27.398	2	Pre-Obesity
1.55	51	21.2279	1	Normal Weight
1.91	79	21.6551	1	Normal Weight
1.53	107	45.7089	5	Obesity Class III
1.57	110	44.6266	5	Obesity Class III
1.4	129	65.8163	5	Obesity Class III
1.44	145	69.9267	5	Obesity Class III

To the original dataset, data analysis and visualization was performed to make the data easier to understand as shown in Figure 20.

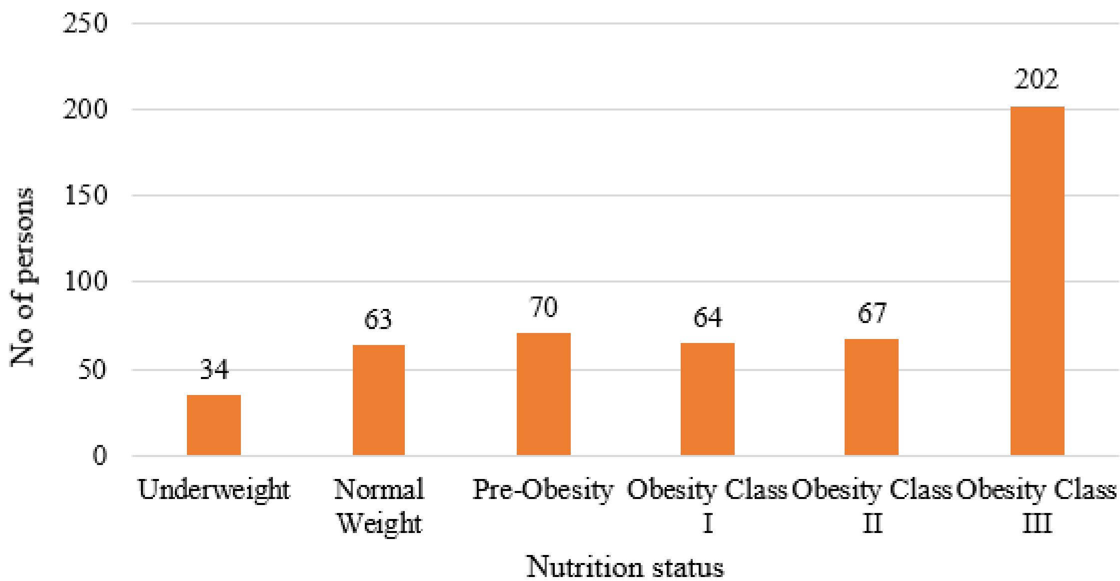

Figure 20. Nutrition status of 500 persons

4.5.2 MACHINE LEARNING STEPS

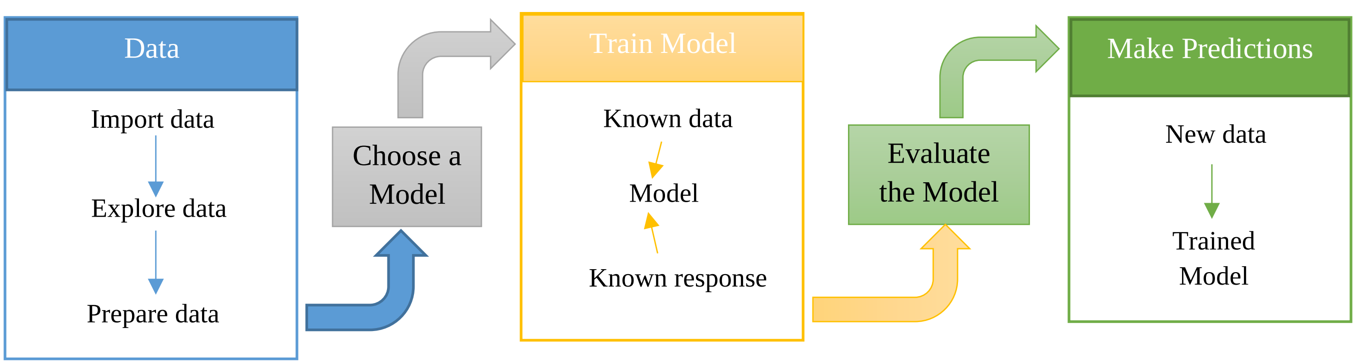

Figure 21. Machine learning steps

The first step of ML was to import the dataset into MATLAB software. We explored the data to remove any duplicates, deal with missing values, data conversion and randomized the data to remove any order in which data was collected. The data was not balanced and so we needed to equalize the data from our dataset as shown in figure 22. Leaving the dataset as it was meant that we'll be overfeeding the model and it will only perform prediction on obesity class III and underfeed on underweight. We used both under-sampling and over-sampling techniques to balance the dataset. Data preparation was done by visualizing the data to detect any relevant relationship between variables and split the dataset into training (80%) and evaluation set (20%). To our dataset as shown in table 4, we took the index column as the response variable y, while height and weight columns as the predictor variables x.

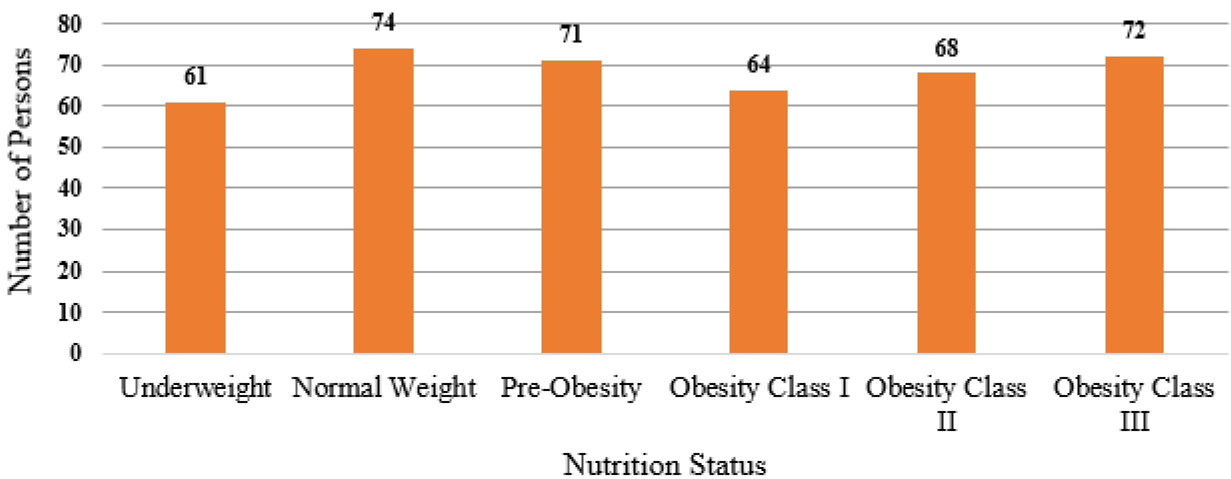

Figure 22 . Equalized BMI dataset

The next step was to choose a model. This research employed supervised machine learning using exponential gaussian process regression algorithm. Before settling for this algorithm, we trained multiple algorithms using Regression Learner App in MATLAB and settled for the one with lower Root mean Square Error (RMSE) as shown in figure 23. RMSE is used to measure the

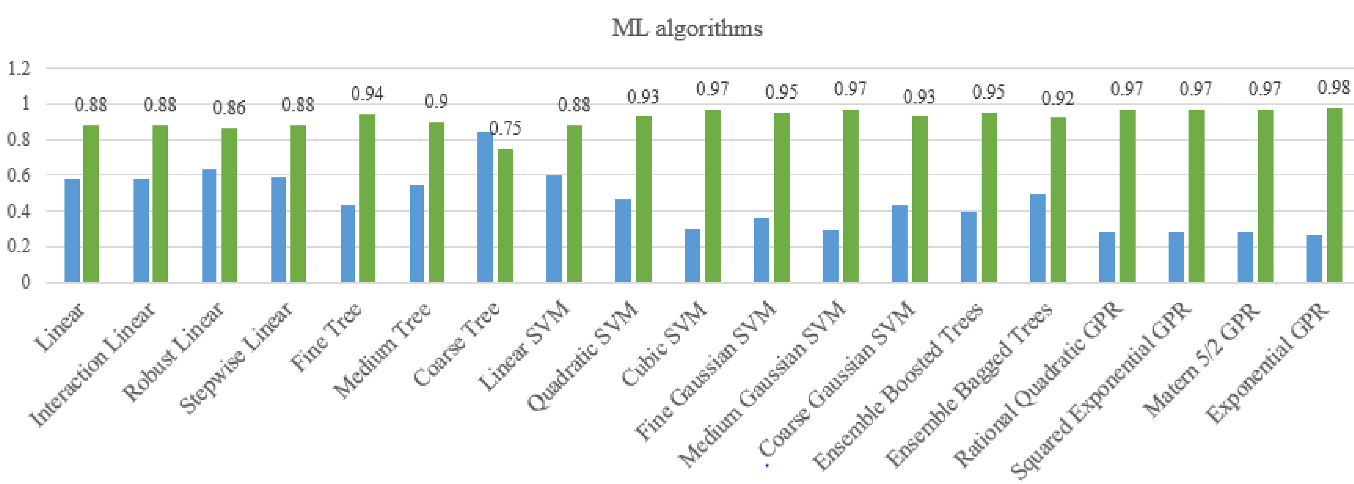

Figure 23. ML supervised algorithms

error of a prediction model. Exponential Gaussian Process Regression algorithm had a RMSE of 0.26823 with an accuracy score of 0.98.

The final step was to make prediction of a person's nutrition status based on the accuracy of the model. We fed our trained model with completely new data, and it made accurate prediction as shown in table 4.

Table 4. Predictions based on trained model

Height(m)	Weight (Kg)	BMI	Known output	Predicted output
1.62763	78.85477	29.7657	2	2.4457
1.63243	73.27403	27.4967	2	1.9987
1.64238	79.025	29.2966	2	2.1829
1.65267	76.83383	28.1307	2	1.933
1.62146	72.30511	27.5015	2	1.9914
1.16767	23.67251	17.3622	0	-0.0002
1.17453	23.95582	17.3653	0	0.0004
1.15635	24.15566	18.0651	0	0.0002
1.15189	23.92203	18.0292	0	0.0002
1.3155	69.02853	39.8884	4	4.0006
1.67977	68.3281	24.2158	1	1.0018
1.70378	67.37347	23.2093	1	1.0002
1.26302	66.98612	41.9918	5	4.9987
1.59745	71.85576	28.1583	2	2.0011
1.61426	70.41376	27.0216	2	1.9817
1.61323	73.87621	28.3865	2	2.0769
1.61426	71.83728	27.5679	2	1.9937
1.62866	77.24644	29.1218	2	2.2435

```
>> yfit = trainedModel2.predictFcn(newdata)

yfit =

    2.4457
    1.9987
    2.1829
    1.9330
    1.9914
   -0.0002
    0.0004
    0.0002
    0.0002
    4.0006
    1.0018
    1.0002
    4.9987
    2.0011
    1.9817
    2.0769
    1.9937
    2.2435
```

CHAPTER FIVE

RESULTS AND SYSTEM TEST

5.1 PROTOTYPE IMPLEMENTATION

A lightweight IoT-based BMI system was designed and developed in this research with figure 24 showing the completed system. The completed system weighed 5.9 kg.

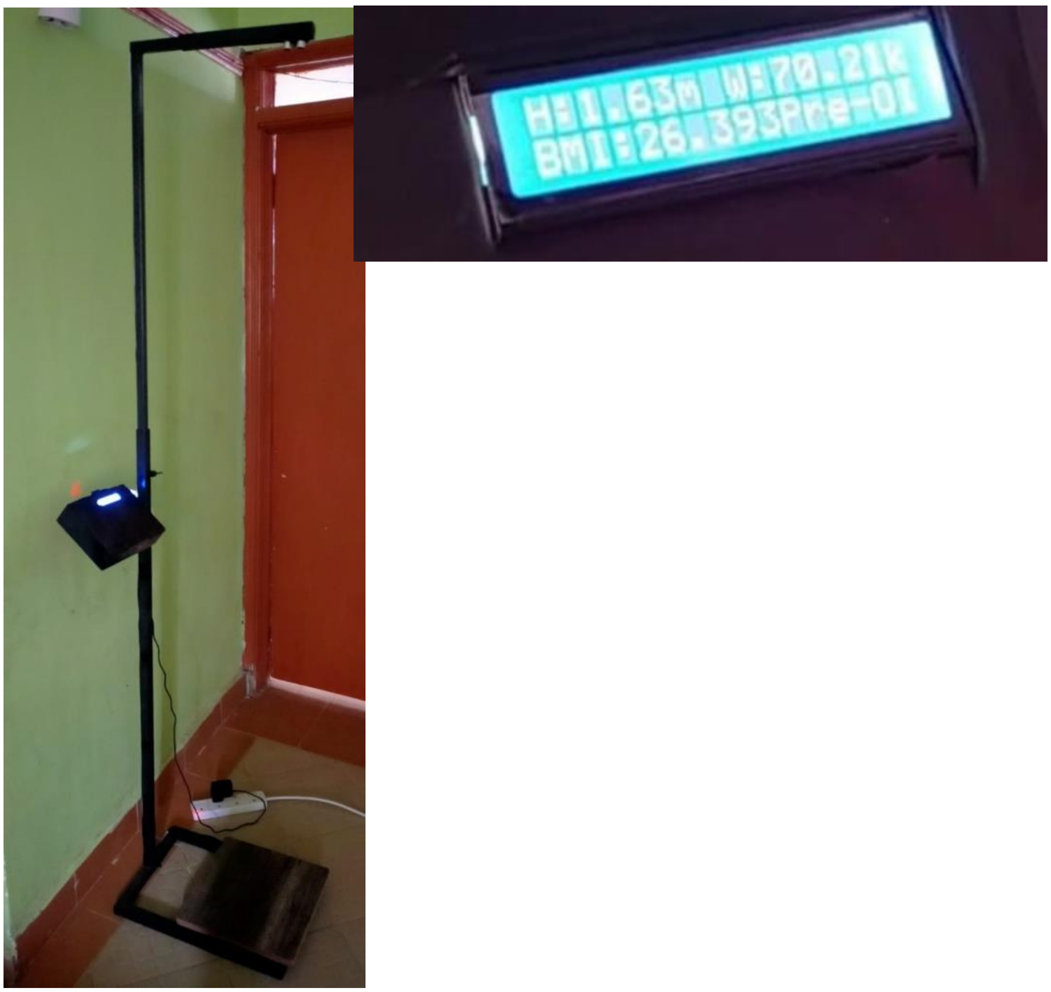

Figure 24. IoT based BMI prototype

Each component associated with the PCB was tested to verify if it was working correctly with no short circuits. As a result, the reliability of the microcontroller-based unit was confirmed.

5.2 PROTOTYPE ACCURACY

The accuracy of the weighing scale was tested using different objects of known weight measured using existing commercial Ramtons digital scale. The known weights were compared against the proposed IoT based BMI system weighing scale. Table 5. shows the output of measuring different object based on 3 trials with an accuracy of 99.8 % obtained from equation (2) and (3).

Table 5. IoT based Weighing scale output data

Object weight (kg)	1st Trial	2nd Trial	3rd Trial	Average Trial
0.1	0.12	0.11	0.12	0.116
5kg	5.02	5.02	5.01	5.016
10kg	10.01	10.02	10.02	10.016
20kg	20.01	20.01	20.02	20.013

$$Error\ rate = \big((Observed\ value - Actual\ value)/Actual\ value\big) * 100 \qquad (2)$$

$$Accuracy = \ 100\% \ - \ Error\ rate \qquad (3)$$

The next step was to verify the accuracy of the height sensor and the weight sensor among 7 persons. The ultrasonic sensor was placed on a 2.4m height and 0.34m from the metal post. We verified the 2.4m by letting the ultrasonic sensor measure the distance from its location to the bottom where the weighing scale was located. We later used the manual height boards to measure height of 7 people and compared the values with the ultrasonic sensor value. We also used existing commercial digital scale to measure person’s weight. Figure 25 shows the comparison between the ultrasonic data and the manual height board data. The IoT-based height proved to have better accuracy while the manual method had an accuracy difference of 2cm. The results of the ultrasonic sensor satisfied the expected output. The IoT based digital scale proved to be accurate as the commercial digital scale as shown in figure 26.

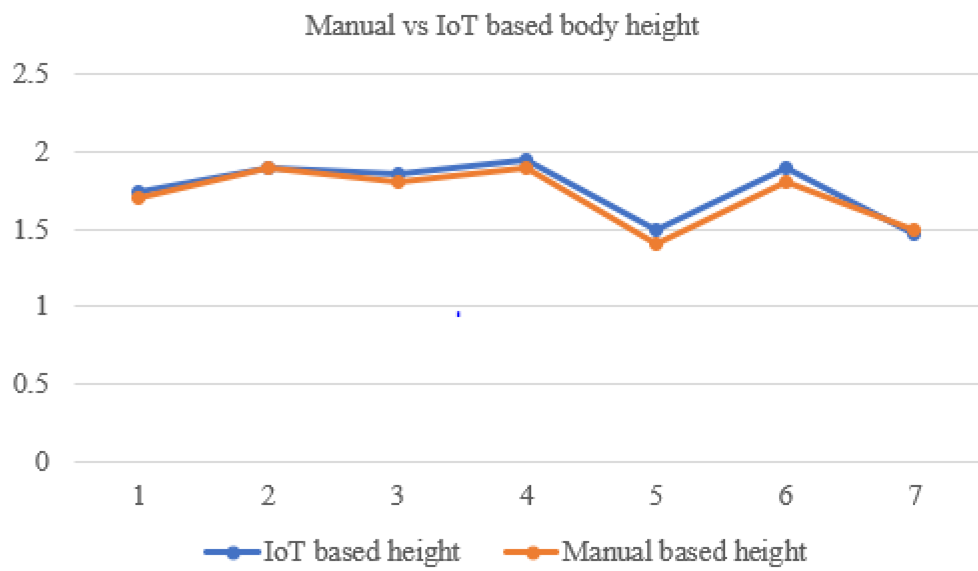

Figure 25. Manual height vs IoT based height

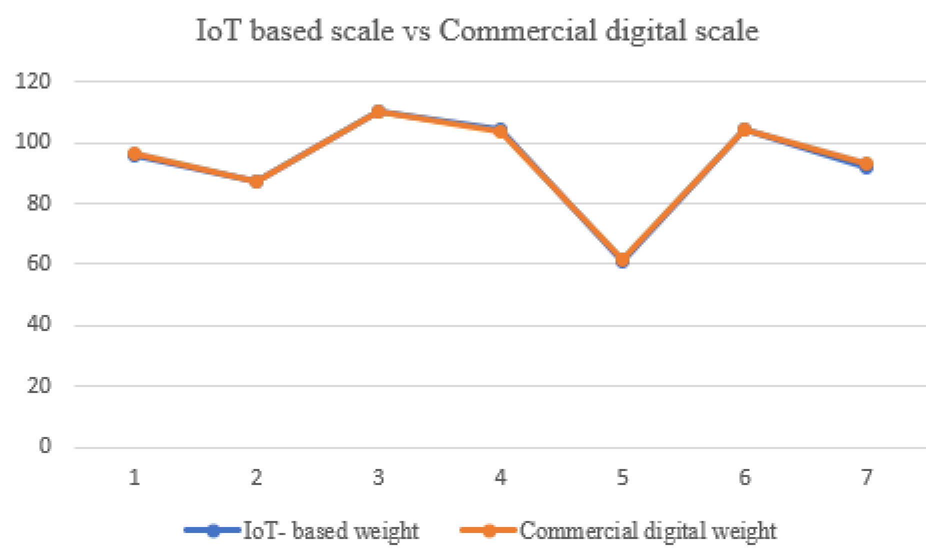

Figure 26. Commercial digital weight vs IoT based weight

We then compared the accuracy of BMI data between the IoT based BMI and the manual BMI using 7 subjects as shown in figure 27. The IoT based BMI was found to be more accurate as compared to the manual method which had accuracy errors leading to overall inaccurate BMI data. The manual method consumed more time in reading height data, weight data, recording the data on a record book and using BMI chart to classify persons nutrition status. The whole process had a lot of distractions leading to more delays. It took an average time of 6 minutes per person to calculate and classify BMI in manual method while in IoT based BMI method it only took 4 seconds per person to calculate and classify BMI.

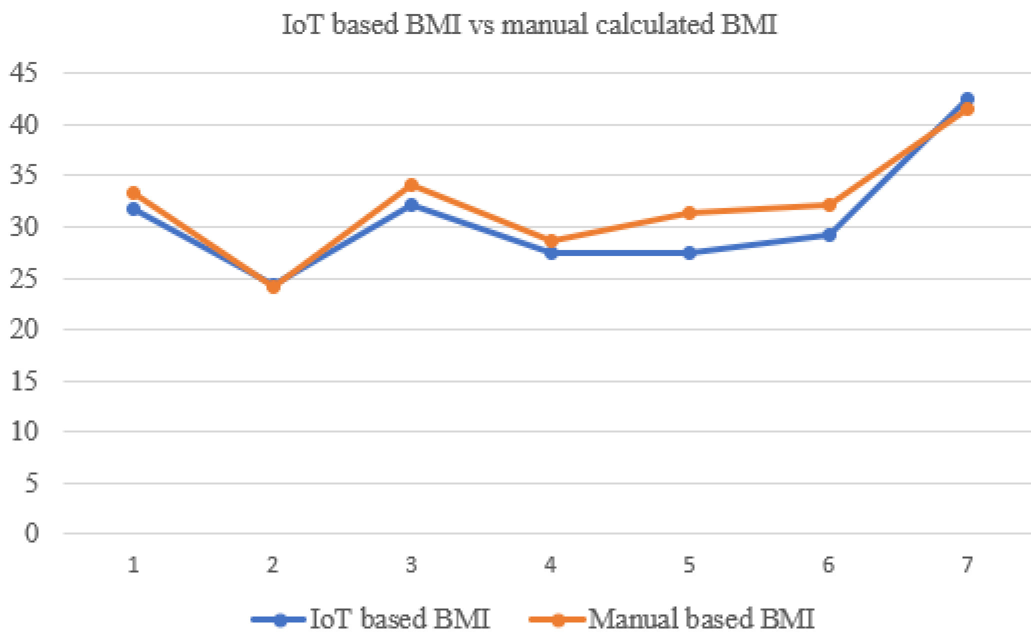

Figure 27. Manual vs IoT based BMI

5.3 REAL TIME DATA

The next step was to collect real time data from persons aged between 5 and 50 years in Kitengela town and sent data to the cloud for storage and analysis. We managed to collect BMI data from 45 persons. The proposed IoT based BMI system calculated each person's BMI and displayed their nutrition status on LCD and send the data to ThingSpeak for storage and analysis as shown in figure 28. Figure 29 visualizes the nutrition status of 45 Kitengela residents stored in ThingSpeak. Out of the 45 people 20% were underweight, 22% were normal weight, 42% were pre-obese, 7% were obesity class I, Obesity class II were 2% and finally obesity class III were 2%.

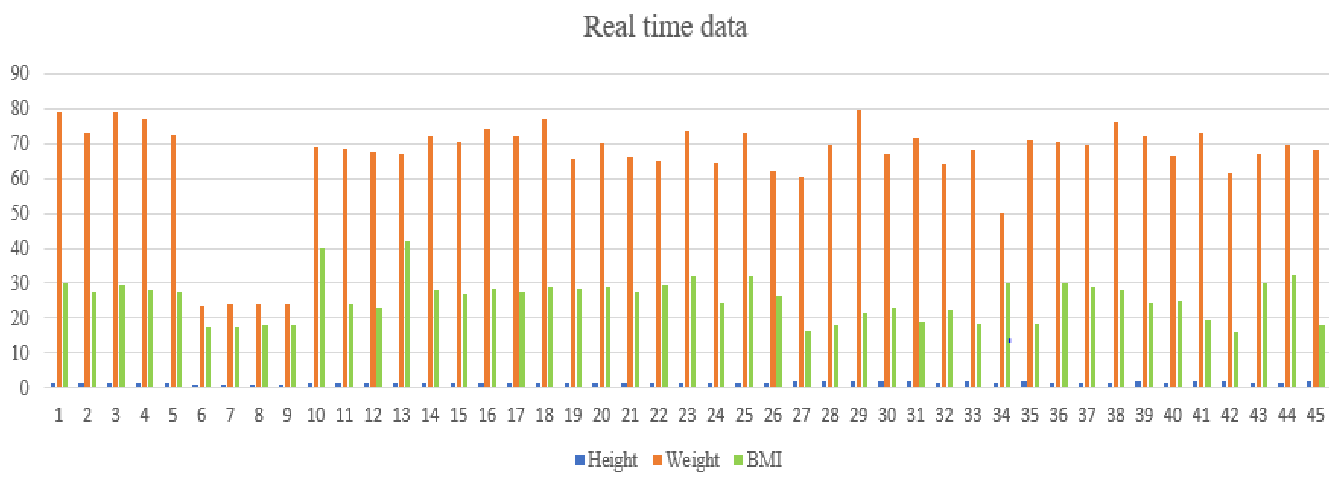

Figure 28. Real time BMI data

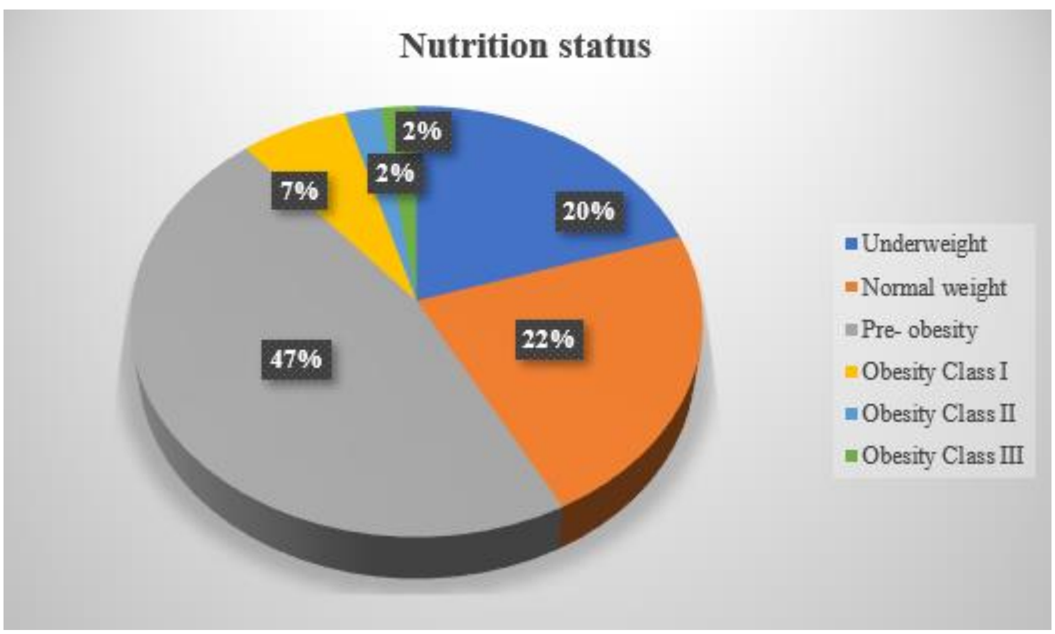

Figure 29. Nutrition status of Kitengela residents

5.4 BMI NUTRITION STATUS PREDICTION

The final step was to predict BMI nutrition status of the 45 residents of Kitengela town using our trained ML model based on real-time height and weight values from the sensors. Our model confirmed to predict the nutrition status with an accuracy of 98%. as shown in Table 6 and figure 30.

Table 6. Real time data Prediction

Height (m)	Weight (kg)	BMI	Nutrition status
1.62866	77.24644	29.12176	2
1.51204	65.66135	28.71992	2
1.5508	69.96604	29.09214	2
1.54634	65.93472	27.57428	2
1.48323	64.9644	29.52966	2
1.51033	73.44036	32.1952	3
1.61391	64.39516	24.72263	1
1.51136	73.09657	32.00082	3
1.53742	62.16444	26.30007	2
1.92947	60.49493	16.24961	0
1.95108	69.31336	18.20819	0
1.92639	79.45034	21.40954	1
1.71373	66.87543	22.77098	1
1.69418	64.00394	22.29911	1
1.92742	68.06261	18.32128	0
1.54257	69.34494	29.14238	2
1.64444	75.84915	28.04882	2
1.62935	66.33529	24.9871	2
1.94971	73.12507	19.23651	1
1.94868	61.47428	16.18872	0
1.49901	67.05391	29.84112	2
1.4575	69.54745	32.7389	3

```
>> yfit = trainedModel2.predictFcn(realtime)

yfit =

    2.2523
    1.9954
    2.0724
    1.9759
    2.3475
    3.0157
    1.2031
    3.0036
    1.6369
    0.0067
    0.0472
    0.9542
    1.0115
    0.9567
    0.4234
    2.3139
    1.9893
    1.5887
    0.6547
    0.0061
    2.2203
    3.0343
   -0.0162
```

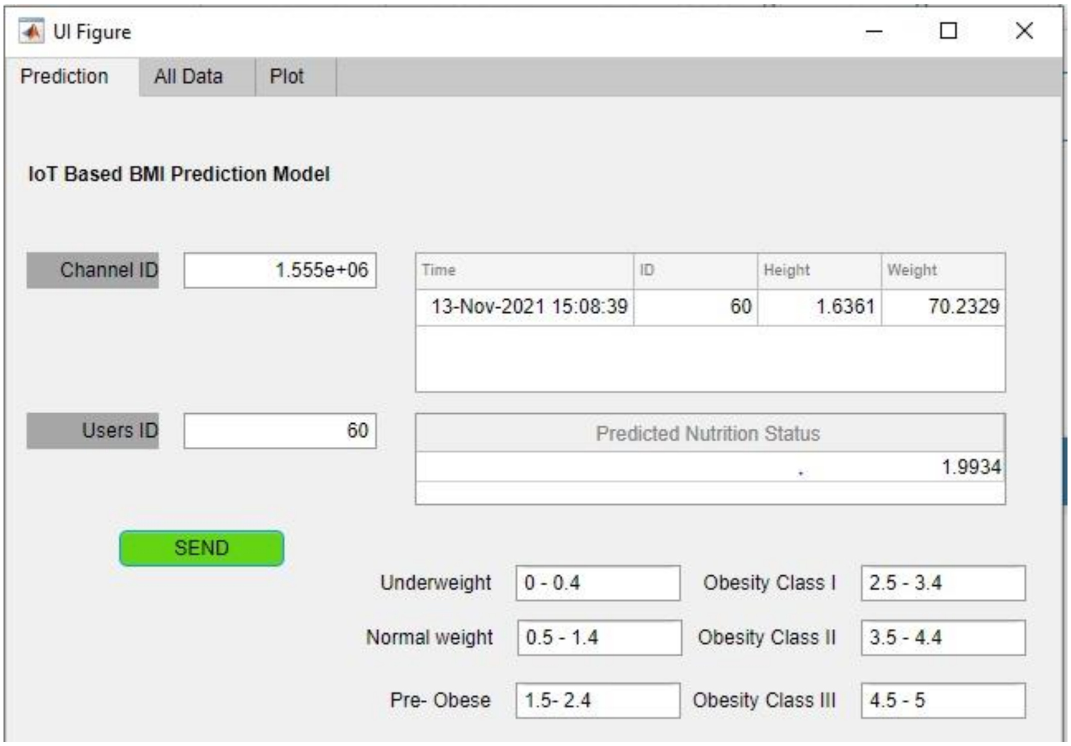

Figure 30. ML user interface

5.5 USER ACCEPTANCE EVALUATION

The final system was evaluated by 5 end users based on accuracy, ease of use, time efficiency and reliability of the system. In a scale of 1-5 where 5 denoted excellent and 1 very poor, the users rated the system as shown in table7. 4.5-5 denoted Excellence, 4- 4.4 denoted very Good, 3.5-3.9, 2.5-3.4 denoted Fair, below 2.4 denoted Poor.

Table 7. User acceptance testing of the system

Accuracy	Evaluation	
Height and weight measurement	5.0	Excellence
BMI measurement	5.0	Excellence
Nutrition status accuracy	5.0	Excellence
Ease of Use		
Power on/Off	4.8	Excellence
Push button press	4.8	Excellence
Time efficiency		
Is the system fast enough to read and display data	4.8	Excellence
Reliability		
Does the system send data to cloud?	4.8	Excellence

CHAPTER SIX

DISCUSSION, CONCLUSSION AND FUTURE WORK

6.1 DISCUSSION

The prediction of a person's nutrition status was accurately achieved in this dissertation. Our ML model employed the use of Exponential Gaussian Process Regression algorithm among other algorithms to predict BMI nutrition status. This nutrition status included underweight, normal weight, pre obesity, obesity class I, obesity class II and obesity class III. We used index as the response variable ranging from 0 to 5. Zero (0) denoted underweight, 1 denoted normal weight, 2 denoted pre obesity, 3 denoted obesity class I, 4 denoted obesity class II and 5 denoted obesity class III. This model required only two variables (height(m) and weight(kg)) to make a prediction of a person's nutrition status. The IoT-based BMI computation system in this dissertation was proved to measure persons height, weight, and compute BMI accurately and automatically hence eliminating systems errors associated with manual calculations. The average time of the system to read height value, weight value, calculate BMI and send data to the cloud was 4 seconds per person

```
18:24:53.683 -> Height: 1.93
18:24:53.732 -> Weight: 68.06
18:24:53.732 -> BMI18.32
18:24:53.732 -> Under Weight1.93 m
18:24:56.348 -> 68.06 kg
18:24:56.348 -> 18.32 kg/m2
18:24:56.348 -> Channel updated successful.
```

```
18:24:35.544 -> Height: 1.69
18:24:35.544 -> Weight: 64.00
18:24:35.591 -> BMI22.30
18:24:35.591 -> Normal Weight1.69 m
18:24:38.312 -> 64.00 kg
18:24:38.358 -> 22.30 kg/m2
18:24:38.358 -> Channel updated successful.
```

Figure 31. Real time data Time stamp

compared to manual BMI method which took an average of 6 minutes per person to read data, calculate and classify BMI. The system first calculated a person's height, weight, BMI data and displayed the data on the LCD. The admin was then asked to press the push button if he or she wanted the data to be sent to the cloud. The system was more time efficient in that the 45 residents were measured in 15minutes while the manual system took 4 hours 5 minutes, a time saving factor of 3 hours 50 minutes.

The IoT based BMI computation system achieved an accuracy of 99.18% as compared to existing research on IoT based BMI system which achieved an accuracy of 92.5% [33], an improvement of 6.68%. The system achieved time reduction of 1.1% per person. The prediction model gave same results as the IoT based computation system therefore can be used interchangeably where the data needs to be shared remotely especially in areas with internet connectivity. The model had an accuracy of 98%. Data was easily stored in cloud. This data can be used further in research therefore improving the body of knowledge. In addition, the data can be used to train future AI models. The overall cost incurred in purchasing the components and building this project is as shown in the appendix 1 which is cheaper as compared to commercial BMI system [46].

ADVANTAGES

The developed system is easy to use, accurate, secure, reliable with fast calculations, it's not hazardous to the environment nor the users, its lightweight and easy to maintain. The system is cloud-based meaning the data can be shared easily anytime from anywhere. It has an adjustable nob to increase or decrease the height distance. Though the system does not replace the existing medical systems in relation to BMI, it acts as a support tool for healthcare. The adoption of this system can help various decision makers and implementers at knowing how healthy or unhealthy the users are. This can help in setting priorities and designing interventions to provide health care needs if need be. The 2018-2022 Kajiado County Integrated Development Plan (CIDP) that aims at making strategic investments in the health and well-being that accelerates economic growth by declining the country's mortality can be realized [18]. Hospitals and medical facilities have a better system to automatically measure patients' BMI.

LIMITATIONS

The developed system can only measure a maximum of 200kg and therefore not suitable for persons weighing above 200 kilograms. The system is not favorable for people with these disabilities: crippled and people with unsound mind. The system also cannot be used by pregnant women or women who are six months postpartum. Children under the age of 5 years cannot use the system. The system can only measure one person at a time and the maximum height the system can measure is 4.5 meters.

6.2 CONCLUSION

An IoT-based BMI prediction model was designed, developed, tested, and validated to successfully achieve the aims and objectives of this research. The prototype was tested and validated using 45 randomly selected residents of Kitengela town. The goal was to design and develop a system that would automatically calculate persons BMI data, display on LCD, and send that data to the cloud for storage and then predict nutritious status using real time data from sensors. The system was proved to accurately calculate the BMI data automatically and predict persons nutritious status based on sensors height and weight parameters. The finished product was lightweight with an average weight of 5.9 kilograms. The IoT based BMI computation system proved to measure persons height, weight, and compute BMI accurately and automatically with an accuracy of 99.18%. This research proved to accurately predict persons nutrition status with an accuracy score of 98%.

6.3 FUTURE WORK

Further research can be used to predict persons health risk in terms of different illnesses by training a ML model with more variables and by using larger datasets. Cardiovascular diseases, diabetes, hypertension, and other non-communicable diseases (NCD) can be predicted. A real time system incorporating different sensors embedded in a person’s body to come up with a chronic disease-based prediction model can be a novel innovation.

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APPENDIX

Item	Qty	Cost (USD)	Total (USD)
Human weight Load Cell - 50kg x 4	1	17.50	17.50
HX711 Load cell Amplifier	1	2.50	2.50
Load Cell 3D Mounting Frame printing	4	4.00	16.00
HC-SR04 Ultrasonic Sensor	1	2.00	2.00
NodeMCU WiFi Development Board - ESP8266	1	8.00	8.00
16x2 LCD	1	4.00	4.00
10k potentiometer	1	1.00	1.00
400-point breadboard	1	2.50	2.50
Electrical wire cable	1	6.00	6.00
Soldering Iron and Wire	1	14.00	14.00
PCB printing	1	45.50	45.50
Miscellaneous Screws, Glue, Wooden base, Metal post, Wiring, Casing, Manpower	1	60.00	60.00
12 V Adapter	1	15.00	15.00
Shipping cost		20.00	20.00
Total			214.00

Appendix 1. System expenditure

Appendix 2. Kitengela residents' Real time data

Height	Weight	BMI
1.62763	78.85477	29.76562
1.63243	73.27403	27.49656
1.64238	79.025	29.29653
1.65267	76.83383	28.13061
1.62146	72.30511	27.50154
1.16767	23.67251	17.36217
1.17453	23.95582	17.36532
1.15635	24.15566	18.06506
1.15189	23.92203	18.02912
1.3155	69.02853	39.88826
1.67977	68.3281	24.21588
1.70378	67.37347	23.20932
1.26302	66.98612	41.99153
1.59745	71.85576	28.15837
1.61426	70.41376	27.0217
1.61323	73.87621	28.38662
1.61426	71.83728	27.56799
1.62866	77.24644	29.12169
1.51204	65.66135	28.71985
1.5508	69.96604	29.09211
1.54634	65.93472	27.57421
1.48323	64.9644	29.52966
1.51033	73.44036	32.19533
1.61391	64.39516	24.72254
1.51136	73.09657	32.001
1.53742	62.16444	26.29994
1.92947	60.49493	16.24956
1.95108	69.31336	18.20815
1.92639	79.45034	21.40963
1.71373	66.87543	22.77109
1.95074	71.59277	18.81355
1.69418	64.00394	22.29925
1.92742	68.06261	18.32138
1.29355	50.10433	29.94389
1.94937	71.06245	18.70049
1.53262	70.33513	29.94347
1.54257	69.34494	29.14242
1.64444	75.84915	28.04882
1.71167	72.17586	24.63502
1.62935	66.33529	24.98716

1.94971	73.12507	19.23651
1.94868	61.47428	16.1887
1.49901	67.05391	29.84119
1.4575	69.54745	32.73867
1.94902	67.87086	17.86689