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Development of an Automatic Body Mass Index Machine with Proposed IoT-Based for Weight Management

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ABSTRACT

Overweight and obesity are major health concerns associated with non-communicable diseases and are the leading causes of death globally. Body mass index (BMI) is a widely used measure for assessing nutritional status. In this work, an automatic BMI machine was designed and constructed using an HC-SR04 ultrasonic sensor for height measurements. Then HX 711 200kg load cells with a load amplifier for weight measurements and an ATMEGA328P microcontroller was employed for computations. A 16x2 LCD was used for displaying the results, and a Wi-Fi module was incorporated for connectivity to the internet. To make the system a smart instrument, an IoT-based approach was proposed. The BMI machine was integrated with Thingspeak, a cloud-based IoT platform, for data storage and analysis. MATLAB Machine Learning was used to analyze the BMI data and make predictions based on height and weight sensory data. A Supervised Exponential Gaussian Process Regression algorithm was employed to predict whether a person is underweight, normal weight, overweight, or obese. The proposed IoT-based BMI system has the potential to provide personalized and real-time

BMI measurement and prediction, which can assist in weight management and promote healthy lifestyles.

Keywords:*Body Mass Index, Internet of Things, Liquid Crystal Display, Machine Learning, Non- Communicable Diseases, Overweight, Obese.*

1.0 Introduction

Obesity and overweight have become significant health concerns worldwide, associated with a high risk of developing non-communicable diseases (NCDs) such as type 2 diabetes, cardiovascular disease, stroke, and some cancers. According to the World Health Organization (WHO), more than 1.9 billion adults worldwide are overweight, with 650 million classified as obese. These numbers are expected to increase in the coming years due to changes in lifestyle and diet, lack of physical activity, and the global pandemic[1,2,3]. Body Mass Index (BMI) is a widely used metric for determining the nutritional status of individuals based on their weight and height. It is calculated by dividing an individual's weight in kilograms by their height in meters squared (kg/m²). A BMI score of less than 18.5 indicates underweight, a score between 18.5 and 24.9 indicates normal weight, a score between 25 and 29.9 indicates overweight, and a score of 30 or higher indicates obesity. BMI is a useful tool for detecting and monitoring overweight and obesity in individuals and populations [4,5,6,7]. Manual measurement of BMI is time-consuming and prone to errors, making it less effective for large-scale monitoring of the population's health. Therefore, there is a need for automated BMI measurement devices that are accurate, efficient, and easy to use.

$$\text{BMI} = \frac{Weight(kg)}{square\ \ of\ the\ height\ (m^2)} \quad (1)$$

In recent years, there has been significant progress in developing automated BMI measurement devices using various technologies such as ultrasonic sensors, load cells, and infrared sensors. However, these devices often lack the ability to communicate data, limiting their potential to be used for population health monitoring [8,9,10]. In this study, proposed the development of an automatic BMI machine that incorporates IoT technology for weight management[11]. The BMI machine design will include an ultrasonic sensor for height measurements and a load cell for weight measurements. The ATMEGA328P microcontroller will be used for computations, and a 16x2 LCD will be used for data display. The machine will also incorporate a Wi-Fi module for internet connectivity, allowing data to be transmitted to a central database for storage and analysis. Thingspeak will be employed, an IoT platform, for data storage and analysis. Thingspeak allows data to be collected and analyzed in real-time, making it ideal for monitoring population health. Also MATLAB Machine Learning will be used to develop a predictive model that can determine an individual's BMI category based on height and weight sensory data. A Supervised Exponential Gaussian process Regression algorithm will be used for the model development.

2.0 System Architecture

Different are incorporated in the design of the system from inception to its completion. The IoT based BMI system consists of different requirements [12]. The node MCU microcontroller will be the main part of the system. It does all the computations required for the system to run smoothly. Sensors will be used to measure the weight and height of a person and sent the data to the microcontroller LCD will be used to display the weight, height, and BMI status to the user. Power supply will power the whole system. Internet connectivity is used to enable connectivity between the cloud storage and the microcontroller. Thingspeak cloud storage will be used to store and analyze data. MATLAB software will be integrated with Thingspeak cloud storage to make nutrition status prediction based on the trained mode. Data is visualized through a web application [13].

Figure 1 presents a high level architectural design of the proposed prototype system.

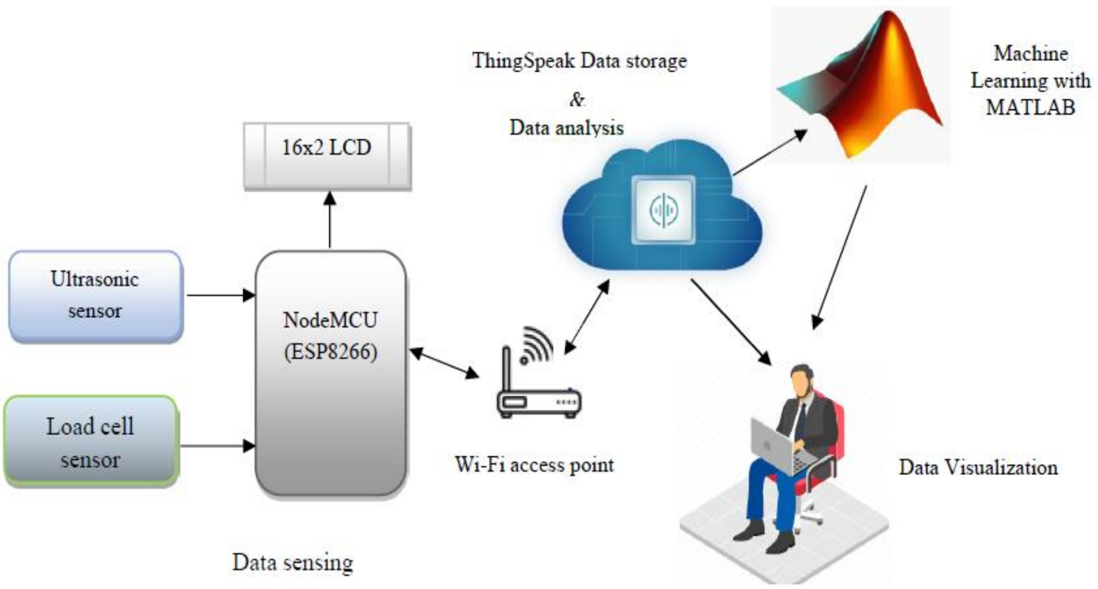

Figure 1: System Architecture

HARDWARE AND SOFWARE REQUIREMENTS

The proposed system will consist of the following hardware components to meet the design specifications.

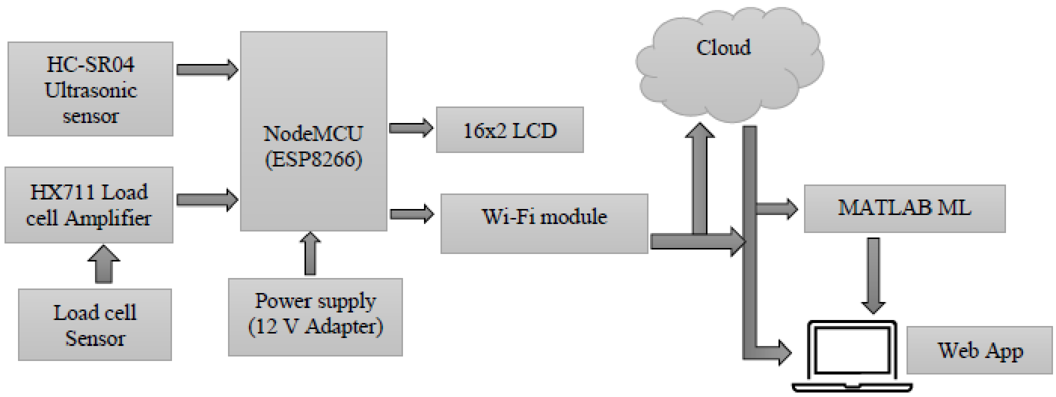

Figure 2: Proposed system Block diagram

2.1 HC-SR04 Ultrasonic Sensor

The ultrasonic sensor is used for height measurement. It emits ultrasonic waves and measures the time taken for the waves to bounce back from the top of the person's head[14]. The sensor has a detection range of 2 cm to 400 cm, with a precision of up to 3 mm. It operates at a frequency of 40 kHz, making it suitable for applications requiring accurate and reliable distance measurements.The HC-SR04 sensor is easy to integrate into electronic circuits, with four pins for connections: V_{CC} (5V), Trig (trigger), Echo (echo), and GND (ground). The trigger pin is used to initiate the ultrasonic pulse, while the echo pin is used to receive the reflected pulse. The V_{CC} and GND pins provide power to the sensor.

Figure 3: Ultrasonic Sensor

2.2 Load Cell

The load cell is used for weight measurement. It measures the weight placed on it and generates an electrical signal proportional to the weight.

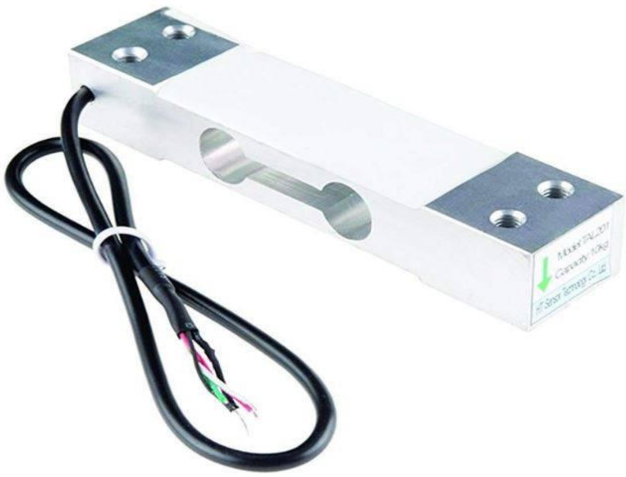

Figure 4: Load Cell

A load cell is a transducer that is used to measure force or weight in a wide range of industrial and commercial applications. It is a highly precise and accurate sensor that is capable of converting mechanical force into an electrical signal. Load cells come in different shapes and sizes, and they can be classified into different categories based on their sensing mechanism.The most common type of load cell is the strain gauge load cell, which uses a metal strain gauge attached to a metal beam or diaphragm. When a force is applied to the load cell, the metal deforms, causing a change in resistance in the strain gauge. The change in resistance is then converted into an electrical signal, which can be measured by a data acquisition system. Load cells are used in many different industries, including manufacturing, aerospace, automotive, and healthcare. They are used for a variety of applications, such as weighing systems, force measurement, and material testing. Load cells can be used in conjunction with other sensors, such as temperature sensors, to provide even more accurate measurements.

2.3 ATMEGA328P Microcontroller

The microcontroller is the brain of the machine. It receives the height and weight measurements from the sensors, performs the necessary calculations, and displays the results on the LCD display. The ATMEGA328P microcontroller is a high-performance, low-power, 8-bit AVR microcontroller that is widely used in a variety of embedded applications[15]. It is based on the Harvard architecture, which means that it has separate memory spaces for program and data, allowing for faster and more efficient processing. The chip has 32KB of in-system programmable flash memory for program storage, 2KB of SRAM for data storage, and 1KB of EEPROM for non-volatile storage. The ATMEGA328P also includes a range of peripherals, such as 10-bit analog-to-digital converters, timers, and serial communication interfaces (UART, SPI, I2C).One of the key advantages of the ATMEGA328P is its low power consumption, making it an ideal choice for battery-powered applications. It also features a wide operating voltage range, from 1.8V to 5.5V, allowing it to be used in a variety of different power supply configurations.

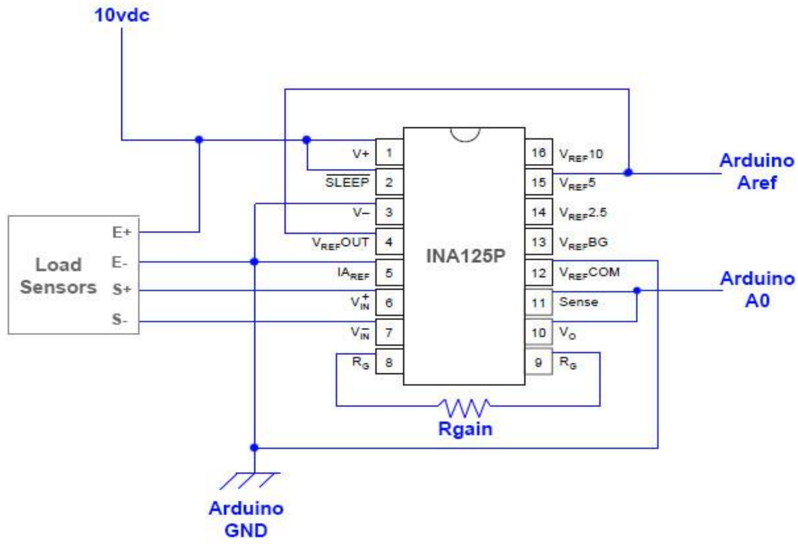

Figure 5: ATMEGA328P Microcontroller

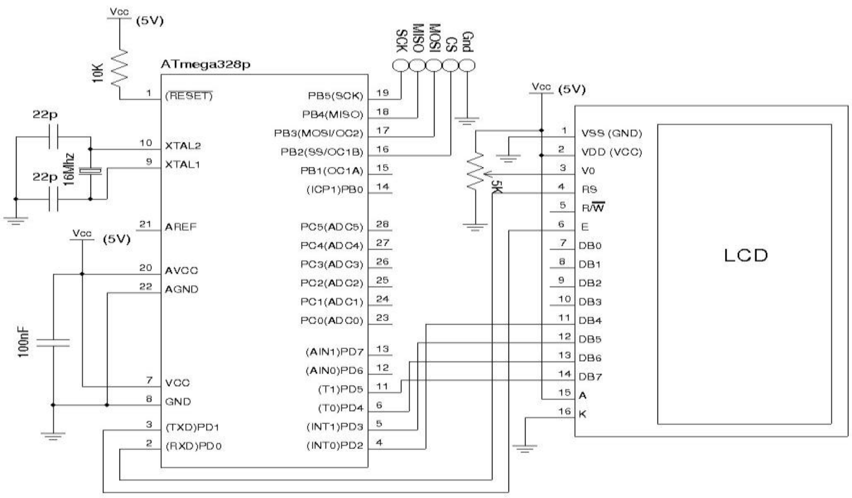

Figure 6: System Circuit Diagram

The LCD display is used to display the calculated body mass index (BMI) value. The WiFi module is used for internet connectivity. It allows the machine to upload the BMI data to a cloud server for analysis. The circuit was designed using the Eagle PCB software and the PCB was manufactured using a CNC machine. The components were then soldered onto the PCB and the machine was assembled. The machine was calibrated using known weight and height values to ensure accurate BMI calculations. The ultrasonic sensor and load cell were tested to ensure they were working correctly and producing accurate measurements.

3.0 The Structural Design

The structural design of the system was made up of stainless steel. The load cell sensors were mounted on a 0.30 x 0.30m 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 35 kg which is portable compared to other exiting system which weighed 52 kg. To the original dataset, data analysis and visualization was performed to make the data easier to understand as shown in Figure 7

Figure 7: BMI Structural Design

3.0 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 7 shows the flow chart of the system. To get the correct measurements from the weight sensor, then calibrated the system. The system was first powered up and removed any weight from the scale. After the readings began, a known weight was placed on the scale and send its weight via the serial monitor to obtain the calibration factor. Once the calibration factor was obtained, 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 7 . 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.

3.1 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

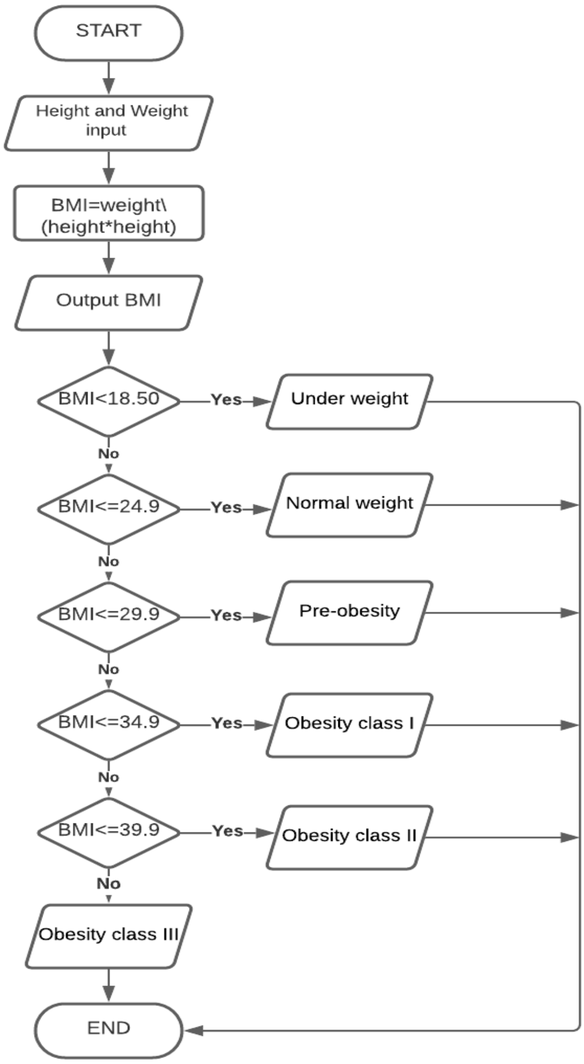

Figure 7: Flowchart

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

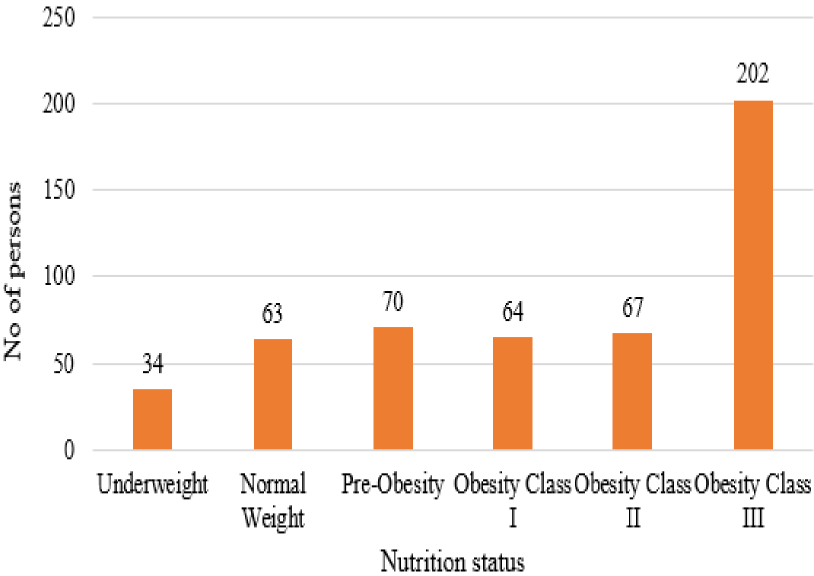

Figure 9: Nutrition status

3.3 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 1. 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

$$Errorrate = ((Observedvalue - Actualvalue)/Actualvalue) * 100 \quad (2)$$

$$Accuracy = 100\% - Errorrate \quad (3)$$

The accuracy of the height sensor and the weight sensor among 7 persons were used for the verification. The ultrasonic sensor was placed on a 2.4m height and 0.34m from the metal post. Verified the 2.4m by letting the ultrasonic sensor measure the distance from its location to the bottom where the weighing scale was located. Later used the manual height boards to measure height of 7 people and compared the values with the ultrasonic sensor value. Also existing commercial digital scale was used to measure person's weight. Figure 9 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.

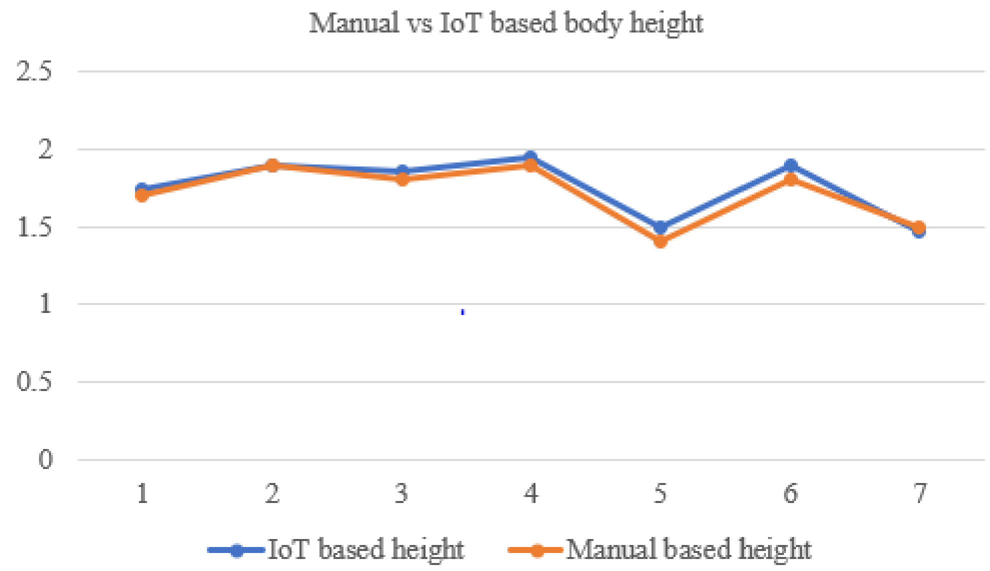

Figure 10. Manual height vs IoT based height

Then compared the accuracy of BMI data between the IoT based BMI and the manual BMI using 7 subjects as shown in figure 10. 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 person's 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.

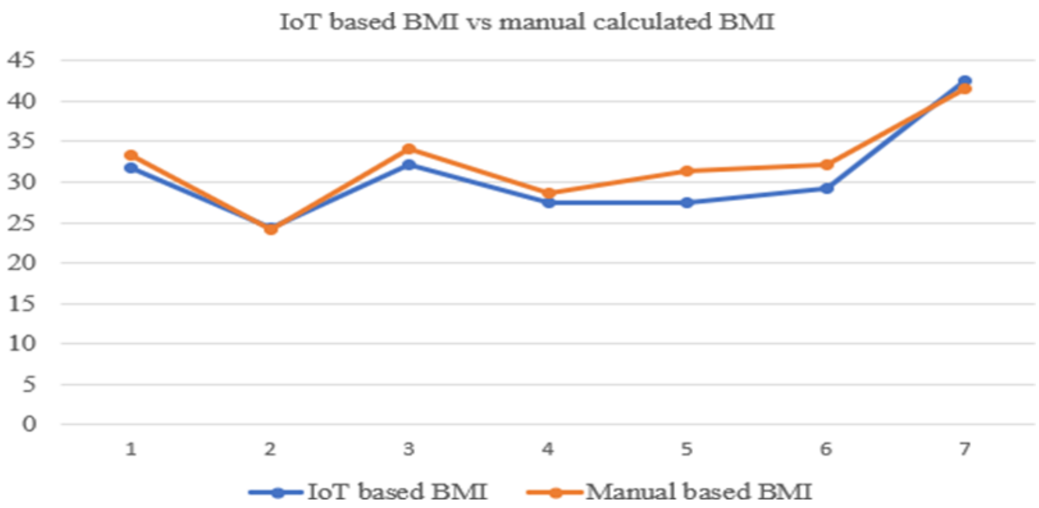

Figure 11: IoT based BMI vs Manual calculated BMI

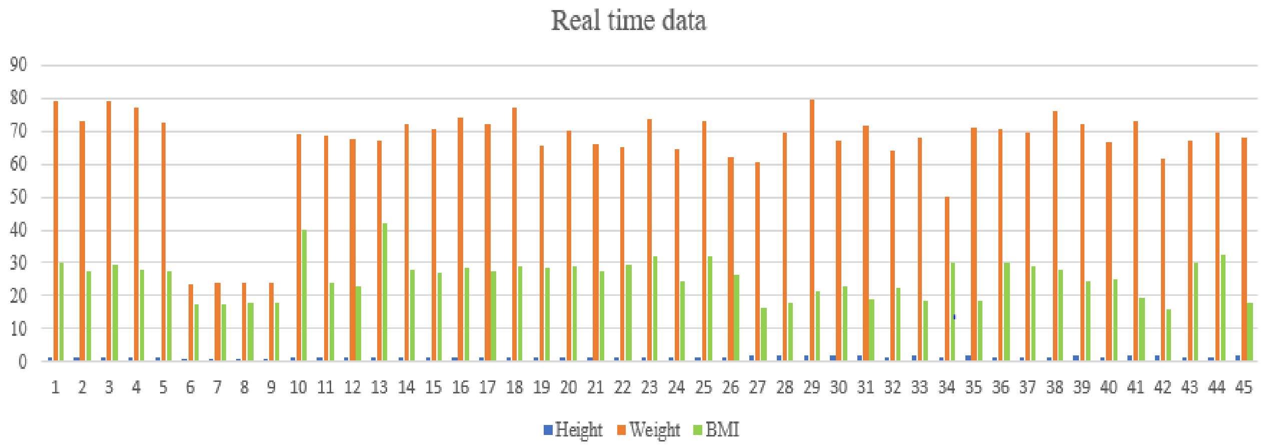

Figure 12: Real Time data

4.0 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 Ogbomoso town. The goal was to design and develop a system that would automatically calculate person's BMI data, display on LCD, and send 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 person's nutritious status based on sensors height and weight parameters. The finished product was light weight with an average weight of 10 kilograms. The IoT based BMI computation system proved to measure person's height, weight, and compute BMI accurately and automatically with an accuracy of 99.18%. This research proved to accurately predict person's nutrition status with an accuracy score of 98%.

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