Implementation of Lifestyle Determination in Obesity Patients Using Random Forest Method

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Abstract— **In the digital era, the application of Internet of Things (IoT) technology for health monitoring has become increasingly important to support improved quality of life and more accurate health recommendations. This research focuses on the development of a health monitoring application integrated with a MySQL database and employing the Random Forest method for data analysis. The system collects various health-related parameters, including height, weight, eating frequency, calorie intake, water consumption, physical activity level, sleep patterns, and stress levels. All collected data are stored in a MySQL database and subsequently analyzed using the Random Forest algorithm to classify user lifestyles into deficient, normal, and excessive categories. The dataset is divided into training and testing data to ensure reliable model performance and accurate predictions when new data are introduced. The results indicate that the Random Forest method provides good classification performance, with an average accuracy of 68% when compared to evaluations conducted by professional nutritionists. In addition, sensor accuracy testing shows excellent measurement performance, with an average error of 0.002% for the ultrasonic sensor and 0.0204% for the load cell sensor, corresponding to accuracy levels of 99.998% and 99.9796%, respectively. Overall, the system achieves an accuracy rate of 98.65%, demonstrating that the integration of IoT technology, database systems, and machine learning methods is effective and has strong potential for broader health monitoring applications.**

Keywords*— *Health, IoT, Lifestyle, Physical Activity, Random Forest.

I. INTRODUCTION

Obesity and unhealthy lifestyles have become significant global health issues that increase the risk of metabolic disorders, cardiovascular disease, and reduced quality of life [1], [2]. Despite increasing awareness of health, many individuals still misunderstand the concept of ideal body weight and healthy lifestyle management, often adopting extreme practices such as excessive dieting or irregular eating patterns [3]. In fact, maintaining a balance between nutritional intake, physical activity, adequate sleep, and stress management is essential to support metabolic stability and immune system performance [4]–[6]. An imbalance between calorie intake and energy expenditure may lead to excessive fat accumulation, resulting in overweight and obesity conditions [7], [8].

Previous studies have developed body mass index (BMI) measurement tools using ultrasonic and load cell sensors integrated with microcontrollers [9], [10]. These systems demonstrated good accuracy in height and weight measurement; however, most were limited to standalone devices or relied on wired data transmission, reducing flexibility and scalability [11]–[13]. Other works introduced database-based recording systems and mobile applications to simplify BMI data management, yet they primarily focused on BMI classification without incorporating broader lifestyle parameters or intelligent data analysis [14], [15]. Moreover, many existing systems lack predictive capabilities and do not evaluate communication performance, which is critical for IoT-based health applications.

To overcome these limitations, this research proposes an Internet of Things (IoT)-based health monitoring system integrated with a MySQL database and machine learning using the Random Forest algorithm [16], [17]. Unlike previous studies, the proposed system not only measures height and weight but also integrates lifestyle-related parameters such as eating frequency, daily calorie intake, water consumption, physical activity, sleep patterns, and stress levels. The Random Forest method is employed to classify user lifestyles into deficient, normal, and excessive categories based on multidimensional health data. The main contribution of this study lies in the integration of sensor-based measurement, centralized database management, machine learning-based lifestyle prediction, and Quality of Service (QoS) evaluation, providing a comprehensive and intelligent solution for obesity-oriented health monitoring systems.

II. METHOD

A. Research Type and System Overview

This research applies a Science and Technology Development (IPTEK) approach with the objective of designing, implementing, and evaluating an Internet of Things (IoT)-based health monitoring system for lifestyle determination in obesity patients. The proposed system integrates hardware-based measurement devices, a centralized

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MySQL database, and a machine learning model using the Random Forest algorithm. The system is designed to support automatic acquisition of physical measurements, manual input of lifestyle-related data, centralized data storage, and intelligent lifestyle classification. Previous studies on BMI measurement systems mainly focused on measurement accuracy and local data presentation without intelligent analysis or lifestyle prediction capabilities [9], [10], [11]. Therefore, this research extends existing works by incorporating machine learning and network performance evaluation to support a more comprehensive health monitoring solution.

B. System Architecture and Network Planning

The overall system architecture consists of three main components: the measurement device, the application and database server, and the machine learning analysis module. The measurement device collects height and weight data, which are transmitted wirelessly to the backend system through an IoT gateway. User lifestyle data are entered through an application interface and stored together with sensor data in a MySQL database. The Random Forest algorithm processes the stored data to generate lifestyle classification results.

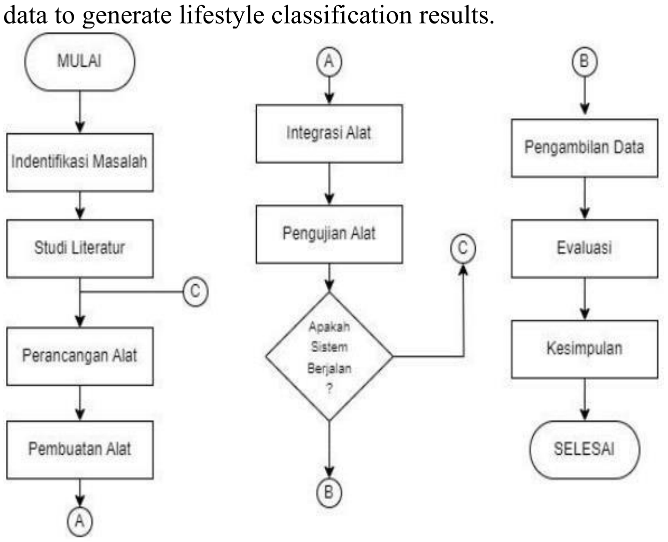


Figure 1. Overall system architecture of the IoT-based lifestyle determination system.

The network planning schematic illustrates the communication flow between the measurement device, Raspberry Pi, application server, and database. Wireless communication is used to improve system flexibility and scalability compared to wired-based BMI systems reported in previous studies [12], [13].

C. Hardware Design and Sensor Configuration

The hardware subsystem is designed to measure height and weight accurately using commonly available sensors. Height measurement is performed using an HC-SR04 ultrasonic sensor, while body weight is measured using a load cell sensor connected to an HX711 amplifier module. Both sensors are interfaced with an Arduino Nano microcontroller, which performs initial data acquisition and processing. The ultrasonic sensor determines height based on the time difference between transmitted and reflected ultrasonic waves, whereas the load cell converts mechanical force into an electrical signal proportional to body weight [12], [14].

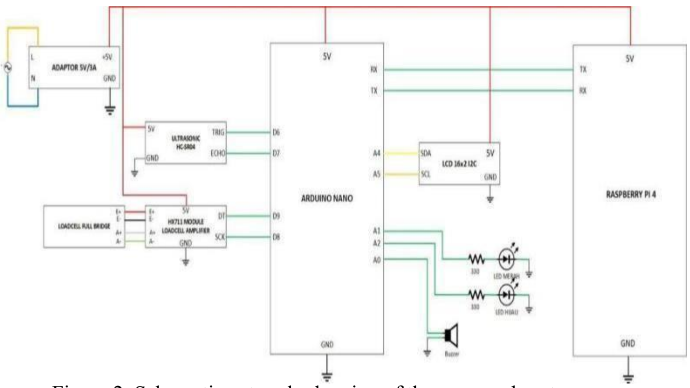


Figure 2. Schematic network planning of the proposed system

The processed measurement data are forwarded to a Raspberry Pi 4 Model B+, which functions as an IoT gateway. The Raspberry Pi handles data transmission, communication with the backend server, and interaction with the MySQL database. This configuration allows real-time data transfer and overcomes the limitations of USB-based or standalone BMI measurement tools [11], [15].

TABLE I
USAGE OF ARDUINO NANO PINS IN THE MEASUREMENT DEVICE.

Pin Arduino Nano	Component	Component Pins	Information
D6	Ultrasonic HC-SR04	TRIG	Pin Output TRIG
D7	Ultrasonic HC-SR04	ECHO	Pin Output ECHO
D9	HX711 Module	DT	Pin Output DT
D8	HX711 Module	SCK	Pin Output SCK
A4	LCD 16x2 12C	SDA	Pin 12C
A5	LCD 16x2 12C	SCL	Pin 12C
A1	Resistor and Red LED	Resistor 330	Pin Input Resistor
A2	Resistor and Green LED	Resistor 330	Pin Input Resistor
A3	Buzzer Active 5V	(+) Buzzer	Pin Input Buzzer
Mini USB	Aspberry Pi 4 Model B+	USB Type A	USB Serial

TABLE II
HX711 MODULE AND LOAD CELL PIN CONFIGURATION.

Pin HX711 Module	Pin Loadcel Full Bridge	Information
E+	E+	VCC
AND-	AND-	GND
A+	A+	Full Bridge Signal (+)
A-	A-	Full Bridge Signal (-)

D. Software Architecture and Database Design

The software subsystem consists of a mobile or web-based application, a backend server, and a MySQL relational database. The application allows users to input lifestyle-related parameters, including eating frequency, daily calorie intake, water consumption, physical activity level, sleep patterns, and stress levels. Sensor-based height and weight data are automatically transmitted to the backend system and combined with user-input data.

The database design follows a relational model to ensure data consistency and efficient retrieval. User information, measurement results, and lifestyle prediction outputs are stored in separate but related tables. An Entity Relationship Diagram (ERD) is used to describe the relationship between these tables and to support structured data management [11], [16].

E. Random Forest-Based Lifestyle Classification

The Random Forest algorithm is employed as the core machine learning method for lifestyle classification. Random Forest is an ensemble learning technique that combines multiple decision trees to improve classification accuracy and reduce the risk of overfitting [17]. In this study, health and lifestyle parameters stored in the database are used as input features for the model. The dataset is divided into training data and testing data to evaluate prediction performance objectively.

Each decision tree generates an independent classification result, and the final output is determined through majority voting. The lifestyle categories are defined as deficient, normal, and excessive. Random Forest was selected due to its robustness in handling multidimensional data and its proven performance in health-related classification tasks [8], [17].

F. Measurement Accuracy Testing

Accuracy testing of the BMI measurement device was conducted to evaluate the reliability of the ultrasonic and load cell sensors. The test involved multiple users with varying heights, weights, and BMI categories. Manual BMI calculations were compared with values obtained from the proposed system. The percentage error was calculated to assess measurement accuracy using standard evaluation formulas commonly applied in BMI measurement studies [9], [10].

G. Quality of Service (QoS) Evaluation

Quality of Service (QoS) evaluation was conducted to assess the reliability of data communication between the measurement device, backend server, and MySQL database. QoS parameters analyzed include delay, packet loss, and throughput. Network traffic was captured using Wireshark to analyze HTTP-based communication between system components.

Delay was calculated as the average transmission time per packet, packet loss was measured as the percentage of lost packets, and throughput was defined as the amount of data successfully transmitted per unit time. QoS evaluation is critical in IoT-based health monitoring systems to ensure fast response, high reliability, and stable data transmission [18], [19].

III. RESULTS AND DISCUSSION

The results of the research should be written clearly and concisely. Discussions consider outlines the importance of research, not repeat it. Avoid excessive uses quotations and discussions about literature published.

A. Implementation Results of the Measurement Device

The implementation results show that the height and weight measurement device operates according to the planned design. The overall appearance of the tool confirms that all components are properly integrated and function as expected.

Figure 3. Overall appearance of the measurement tool as a whole.

The bottom part of the device uses a glass platform with four load cell sensors installed underneath to ensure stable and accurate weight measurement. The overall appearance of the measurement tool demonstrates that the mechanical and electronic components are integrated into a single compact system. The design prioritizes user safety and measurement stability, particularly during weight measurement, which is critical for obtaining reliable BMI values.

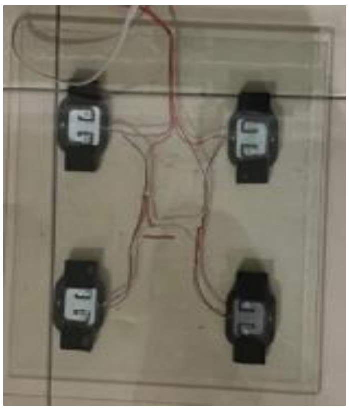


Figure 4. Bottom part of the measurement tool.

The top section of the device is equipped with an HC-SR04 ultrasonic sensor mounted on a vertical support structure to measure user height accurately. The bottom structure of the device plays an important role in ensuring accurate weight measurement. The use of a glass platform supported by multiple load cell sensors allows even distribution of body weight, minimizing measurement bias caused by uneven load placement.

Figure 5. Top part of the measurement tool.

All electronic components, including the Arduino Nano, Raspberry Pi 4, LCD, and supporting circuits, are placed inside a dedicated component box. The placement of the ultrasonic sensor at the top of the device is designed to ensure consistent distance reference during height measurement. This vertical configuration reduces measurement error caused by user posture variations and sensor misalignment.

Figure 6. Component box containing electronic modules.

This hardware configuration is consistent with previous BMI measurement systems that utilize ultrasonic and load cell sensors, but the addition of wireless data transmission improves flexibility and usability compared to wired systems [9], [10], [11].

B. Accuracy Analysis of BMI Measurement

The accuracy of the measurement device was evaluated by comparing manual BMI calculations with BMI values generated by the system. The results show that the measurement errors are relatively small across different BMI categories, including underweight, normal, overweight, and obesity.

The comparison results for underweight users indicate that all error values are below 4 percent, demonstrating reliable measurement performance.

TABLE III
USER TOOL TESTING 1 RESULTS.

No	Tgl Input	IMT Manual	IMT Tools	Category	Error
1	24/05/24	18.24	17.84	Not enough	2.19%
2	31/05/24	18.26	18.20	Not enough	0.33%
3	07/06/24	18.28	17.96	Not enough	1.75%
4	14/06/24	18.50	19.91	Not enough	3.19%
5	21/06/24	18.47	18.15	Not enough	1.73%

For users in the normal BMI category, the system achieves very high accuracy with an average error of less than 1 percent. The results presented in Table III indicate that the BMI measurement errors for underweight users remain below 4 percent. These results demonstrate that the system is capable of maintaining reliable measurement accuracy even at lower body mass values, which are often more sensitive to sensor error.

TABLE IV
USER TOOL TESTING 2 RESULTS.

No	Tgl Input	IMT Manual	IMT Tools	Category	Error
1	24/05/24	19.57	19.16	Normal	2.10%
2	31/05/24	19.04	18.99	Normal	0.26%
3	07/06/24	19.35	19.20	Normal	0.78%
4	14/06/24	19.42	19.49	Normal	0.36%
5	21/06/24	18.94	18.79	Normal	0.79%

Testing results for overweight users also show stable performance with low error values. For users classified within the normal BMI range, the system shows improved accuracy with significantly lower error values. This indicates that the proposed measurement device performs optimally under standard measurement conditions.

TABLE V
USER TOOL TESTING 3 RESULTS.

No	Tgl Input	IMT Manual	IMT Tools	Category	Error
1	24/05/24	24.49	24.15	Excessive	1.39%
2	31/05/24	25.04	24.98	Excessive	0.24%
3	07/06/24	24.47	24.53	Excessive	0.25%
4	14/06/24	24.80	24.42	Excessive	1.53%

5	21/06/24	25	24.57	Excessive	1.72%

Similarly, measurements for obese users indicate that the system maintains good accuracy, with error values remaining within acceptable limits. The testing results for overweight users show stable measurement performance with relatively small error variations. This suggests that increased body mass does not significantly affect the accuracy of the load cell and ultrasonic sensor combination.

TABLE VI
USER TOOL TESTING 4 RESULTS.

No	Tgl Input	IMT Manual	IMT Tools	Category	Error
1	24/05/24	32.06	31.83	Obesity	0.72%
2	31/05/24	32.64	32.14	Obesity	1.52%
3	07/06/24	32.68	32.42	Obesity	0.80%
4	14/06/24	32.33	32.44	Obesity	0.34%
5	21/06/24	32.76	32.19	Obesity	1.74%

These results confirm that the ultrasonic sensor and load cell sensor provide accurate height and weight measurements, consistent with findings reported in previous studies [12], [14].

C. Database and Application Performance

The MySQL database successfully stores user identity data, measurement results, and lifestyle classification outputs. Measurement data transmitted from the device are recorded automatically and can be accessed through the application interface.

The structure of the database and its relationships between tables are illustrated using an Entity Relationship Diagram.

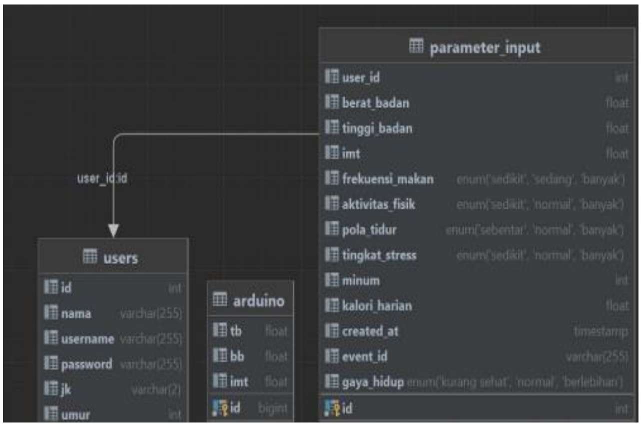


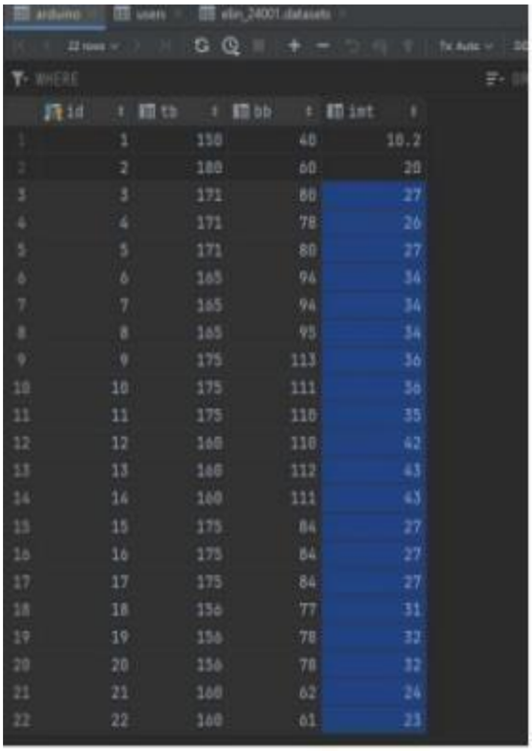
Figure 9. Entity Relationship Diagram of the MySQL database.

In addition, the table that stores height, weight, and BMI measurement results confirms that sensor data are correctly recorded and synchronized with the application..

This centralized database approach improves data consistency and supports historical analysis compared to spreadsheet-based or local storage systems [11], [15].

D. Random Forest Lifestyle Prediction Results

The Random Forest algorithm was evaluated by comparing system-generated lifestyle classifications with assessments provided by professional nutritionists. The comparison shows that most prediction results are consistent, with an average accuracy of 68 percent.



	id	tb	bb	imt
1	1	150	40	10.2
2	2	180	60	20
3	3	171	80	27
4	4	171	78	26
5	5	171	80	27
6	6	165	96	34
7	7	165	94	34
8	8	165	95	34
9	9	175	113	36
10	10	175	111	36
11	11	175	110	35
12	12	160	110	42
13	13	160	112	43
14	14	160	111	43
15	15	175	84	27
16	16	175	84	27
17	17	175	84	27
18	18	156	77	31
19	19	156	78	32
20	20	156	78	32
21	21	160	62	24
22	22	160	61	23

Figure 10. Arduino measurement data stored in the MySQL database

The comparison results for each user demonstrate that the system is able to classify lifestyles into deficient, normal, and excessive categories based on multiple health parameters.

TABLE VII
USER LIFESTYLE TESTING 1 RESULTS.

No	Date	GH Ahli Gizi	GH System
1	24/05/24	Not enough	Not enough
2	31/05/24	Normal	Normal
3	07/06/24	Not enough	Not enough
4	14/06/24	Not enough	Not enough
5	21/06/24	Not enough	Not enough

The results in Table VII show a strong agreement between system predictions and nutritionist evaluations for users with relatively stable lifestyle patterns. This indicates that the Random Forest model performs well when lifestyle parameters exhibit minimal fluctuation.

TABLE VIII
USER LIFESTYLE TESTING 2 RESULTS.

No	Date	GH Ahli Gizi	GH System
1	24/05/24	Not enough	Not enough
2	31/05/24	Not enough	Not enough
3	07/06/24	Not enough	Not enough
4	14/06/24	Not enough	Not enough
5	21/06/24	Not enough	Normal

Table VIII illustrates cases where minor discrepancies occur between expert assessments and system predictions. These differences may be influenced by subjective lifestyle factors such as sleep quality and stress levels.

TABLE IX
USER LIFESTYLE TESTING 3 RESULTS.

No	Date	GH Ahli Gizi	GH System
1	24/05/24	Normal	Normal
2	31/05/24	More	Not enough
3	07/06/24	Normal	Not enough
4	14/06/24	Normal	More
5	21/06/24	Normal	Normal

The prediction results in Table IX and Table X demonstrate that the system is able to handle more complex lifestyle patterns involving higher calorie intake and varying physical activity levels, although prediction consistency may decrease as behavioral variability increases.

TABLE X
USER LIFESTYLE TESTING 4 RESULTS.

No	Date	5	6	GH Ahli Gizi	GH System
1	24/05/24	2	2530	More	More
2	31/05/24	9	2560	More	Normal
3	07/06/24	8	2568	More	More
4	14/06/24	8	2552	More	Not enough
5	21/06/24	5	2534	More	More

Differences between system predictions and expert evaluations can be attributed to daily behavioral variations and subjective factors such as stress and sleep quality. Nevertheless, the Random Forest method effectively handles multidimensional data and reduces classification bias through ensemble learning [8], [17].

E. *Quality of Service (QoS) Evaluation Results*

Quality of Service testing was conducted to evaluate communication performance between the measurement device, application, and MySQL database. Network traffic analysis was performed using Wireshark.

The network traffic capture shown in Figure 11 provides detailed information regarding packet transmission between the measurement device and the database server. This data is used as the basis for calculating Quality of Service parameters.

The evaluation results show low delay, zero packet loss, and high throughput, indicating that the communication system is reliable and suitable for IoT-based health monitoring applications [18], [19].

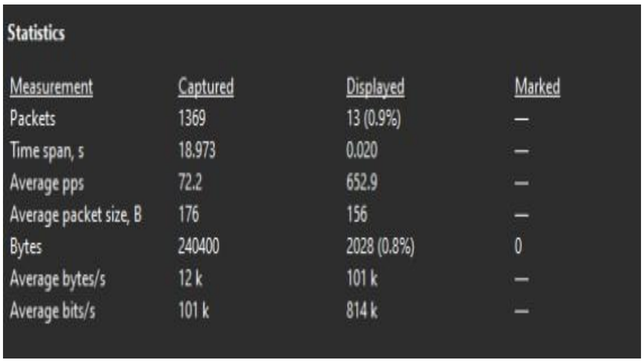


Figure 11. Network traffic capture results using Wireshark.

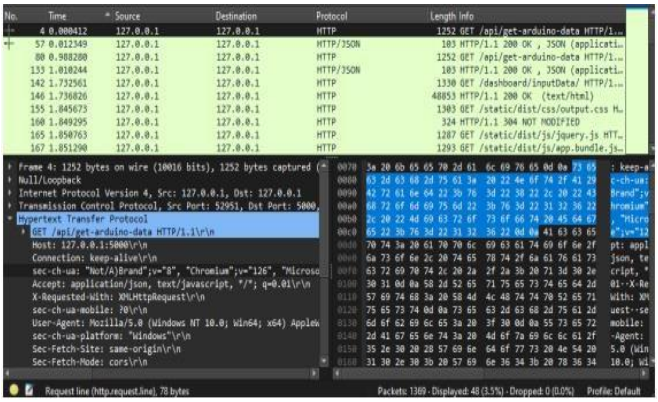


Figure 12. Packet capture file properties used for QoS analysis

F. *Discussion*

Overall, the experimental results demonstrate that the proposed system successfully integrates sensor-based measurement, centralized data storage, machine learning-based lifestyle classification, and reliable network communication. Compared to previous BMI measurement tools, this system provides a more comprehensive solution by incorporating lifestyle analysis and predictive modeling. Although prediction accuracy can still be improved, the results indicate strong potential for further development and real-world implementation. The results obtained from this study indicate that the proposed IoT-based health monitoring system is able to perform accurate anthropometric measurements, reliable data transmission, and meaningful lifestyle classification using the Random Forest algorithm. From the measurement accuracy perspective, the error values obtained from BMI testing across different user categories demonstrate that the system performs consistently under various body conditions. The BMI error percentage is calculated using the following formula:

$$Error(\%) = \frac{BMI_{manual} - BMI_{system}}{BMI_{manual}} \times 100\% \quad (1)$$

Based on the experimental results, underweight users show error values below 4%, while normal, overweight, and obese categories exhibit even lower average errors. The ultrasonic sensor used for height measurement shows an average error of 0.002%, which corresponds to an accuracy level of 99.998%. Similarly, the load cell sensor used for weight measurement produces an average error of 0.0204%, corresponding to an accuracy level of 99.9796%. By averaging these measurement performances, the overall system accuracy reaches 98.65%, indicating that the sensor configuration is highly reliable for BMI measurement. These values confirm that sensor-based inaccuracies contribute minimally to lifestyle prediction errors, and therefore do not significantly affect the classification results.

From the lifestyle prediction perspective, the Random Forest model achieves an average accuracy of 68% when compared with assessments conducted by professional nutritionists. This accuracy value is calculated as the ratio between the number of matching classifications and the total number of evaluated cases. The difference between system predictions and expert evaluations can be attributed to the subjective nature of lifestyle assessment, particularly for parameters such as stress level and sleep quality, which are difficult to quantify precisely. However, the Random Forest algorithm effectively reduces classification bias by aggregating multiple decision trees and applying majority voting, making it robust against noise and data variability. This explains why the system maintains stable prediction performance even when individual parameters fluctuate.

Quality of Service (QoS) analysis further strengthens the system's reliability for real-world deployment. The average delay is calculated using:

$$Average\ Delay = \frac{Total\ Delay}{Total\ Packet\ Received} \quad (2)$$

Based on Wireshark packet capture results, the average delay value is 1.53 ms, which falls into the "very good" category for IoT-based applications. Packet loss is calculated as:

$$Packet\ Loss(\%) = \frac{Packet\ Sent - Packet\ Received}{Packet\ Sent} x100\% \quad (3)$$

The packet loss result of 0% indicates that all transmitted data packets are successfully received without loss, ensuring data integrity. Throughput is calculated using:

$$Throughput = \frac{Amount\ of\ Data\ Sent}{Data\ Reception\ Time} \quad 4)$$

The resulting throughput of 1.01 MB/s demonstrates that the system can handle continuous data transmission efficiently. These QoS results confirm that network performance does not become a limiting factor for system operation.

Overall, the discussion confirms that the integration of accurate sensor measurements, centralized database management, Random Forest-based classification, and reliable network communication forms a cohesive and robust health monitoring system. Although the lifestyle prediction accuracy can still be improved by increasing dataset size and incorporating additional behavioral parameters, the current results already demonstrate that the proposed system is suitable for obesity-oriented lifestyle assessment and has strong potential for further development and practical implementation.

IV. CONCLUSION

This research successfully developed and evaluated an Internet of Things (IoT)-based health monitoring system for lifestyle determination in obesity patients by integrating sensor-based measurement, centralized MySQL database management, and machine learning using the Random Forest algorithm. The results show that the system is capable of classifying user lifestyles into deficient, normal, and excessive categories with an average accuracy of 68 percent when compared with assessments by professional nutritionists, indicating that the prediction performance is sufficiently reliable for lifestyle evaluation. The accuracy of the Body Mass Index measurement device is also very high, as indicated by an average error of 0.002 percent for the ultrasonic sensor, corresponding to an accuracy level of 99.998 percent, and an average error of 0.0204 percent for the load cell sensor, corresponding to an accuracy level of 99.9796 percent, resulting in an overall system accuracy of 98.65 percent. Quality of Service evaluation further confirms the reliability of the proposed system, with an average communication delay of 1.53 ms, zero packet loss, and a throughput of 1.01 MB per second, demonstrating stable and efficient data transmission between the measurement device, application, and database. Overall, the integration of IoT technology, Random Forest-based lifestyle classification, and reliable network performance provides a comprehensive and scalable solution for health monitoring and obesity-oriented lifestyle assessment, with strong potential for further development and real-world application.

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