Website: www.aceiot.ur.ac.rw
Mail: aceiot@ur.ac.rw

College of Science and Technology

AFRICAN CENTER OF EXCELLENCE IN INTERNET OF THINGS (ACEIoT)

Research Thesis Title: IoT-Based Smart Fitness Monitoring System for Personalized Workout Recommendations in Gyms

A dissertation submitted in partial fulfilment of the requirements for the award of masters of science degree in internet of things Embedded computing systems

Submitted By:

Henriette UMUHOZA (Ref. No: 215003284)

August, 2025

Website: www.aceiot.ur.ac.rw
Mail: aceiot@ur.ac.rw

College of Science and Technology

AFRICAN CENTER OF EXCELLENCE IN INTERNET OF THINGS (ACEIoT)

Research Thesis Title: IoT-Based Smart Fitness Monitoring System for Personalized Workout Recommendations in Gyms

A dissertation submitted in partial fulfilment of the requirements for the award of masters of science degree in internet of things Embedded computing systems

Submitted By:

Henriette UMUHOZA (Ref. No: 215003284)

Supervised by:

Dr. Pierre BAKUNZIBAKE

Dr. Emmy MUGISHA

August, 2025

DECLARATION

I, **Henriette UMUHOZA**, Master' student from African Centre of Excellence in Internet of Things, at University of Rwanda. I declare that this research thesis is my own original work, and it has never been presented before anywhere in the world.

Henriette UMUHOZA

Ref: 215003284

Signed:

Date: ……/ ……/ ……

BONAFIDE CERTIFICATE

This is to certify that the research work entitled "**IoT-Based Smart Fitness Monitoring System for Personalized Workout Recommendations in Gyms"** is a record of the original work done by **Henriette UMUHOZA** (Ref. Nu: **215003284**), MSc. IoT-ECS Student at the University of Rwanda /College of Science and Technology / African Center of Excellence in Internet of Things, the Academic year 2023/2025.

This work has been submitted under the supervision of **Dr Pierre BAKUNZIBAKE** and **Dr Emmy MUGISHA**.

Dr Pierre BAKUNZIBAKE	Dr Emmy MUGISHA
Date:	Date: 08/08/2025
Signature:	Signature:

The Head of Masters studies and Trainings

Dr. James RWIGEMA

Signature:

Date:

Signature…………………

ACKNOWLEDGEMENT

I am grateful to **God Almighty** for granting me health throughout my studies and research work.

I sincerely thank the Mastercard Foundation Scholars Program for providing me with the financial support to pursue my studies and research under the African Center of Excellence in the Internet of Things.

I am deeply thankful to my supervisors, **Dr. Pierre BAKUNZIBAKE** and **Dr. Emmy MUGISHA,** who supported me throughout this research journey. Their stimulating suggestions, encouragement, and motivation greatly helped me in conducting the research and writing this thesis.

I thank all ACEIoT's administration especially Director **Prof Damien HANYURWIMFURA**, and our sincere head of the Master's program **Dr James RWIGEMA** for his dedication and guidance throughout my academic journey. Their efforts have greatly contributed to the success of this program and my research. I thank all my fellow students who offered guidance and support during my entire research journey.

Last but not least I would like to thank my family and friends, especially my mother **Julie NYIRASAFARI**, and my husband **Jean De Dieu TWAGIRIMANA** for their continued support and encouragement and for always believing in me.

ABSTRACT

In today's fast-paced world, maintaining a healthy lifestyle poses significant challenges, with many individuals, particularly gym users, requiring efficient tools to monitor and manage key fitness metrics such as height, weight, Body Mass Index (BMI), and heart rate. Traditional methods are often manual, inconvenient, and error-prone, while existing digital solutions frequently lack integration and real-time feedback, limiting their effectiveness in promoting sustained health management.

This project has developed an IoT-Based Fitness Monitoring System that leverages advanced sensors for precise height and weight measurement, ECG for accurate heart rate monitoring, RFID technology for seamless user identification, and an ESP8266 microcontroller for robust data processing and cloud transmission. The system is designed to provide accurate, automated, and user-friendly fitness monitoring, delivering real-time feedback through an LCD display and enabling comprehensive data analysis via a cloud platform. Additionally, machine learning is employed to analyze the parameters, helping gym users and trainers determine the most suitable sports and fitness activities for individuals.

The trained machine learning model achieved an accuracy of 98.8% with an error rate of only 1.2%, demonstrating high reliability in predicting personalized workout recommendations.

By integrating these technologies, the system empowers users to make informed health decisions, track their fitness progress, and achieve their fitness goals more effectively. Furthermore, the system supports gym trainers by providing detailed, individualized data, enabling them to create tailored workout plans for users. The IoT-Based Fitness Monitoring System represents a significant advancement in personal health management, offering a reliable and convenient solution for continuous fitness monitoring and improvement.

Keywords: *IoT, Fitness metrics, RFID technology, Machine Learning, User interface, Personal Health Management.*

TABLE OF CONTENTS

LIST OF ACRONYMS AND ABBREVIATION

ACEIoT: AFRICAN CENTER OF EXCELLENCE IN INTERNET OF THINGS

ECS: Embedded Computing System

BMI: Body Mass Index

IoT: Internet of Things

LCD: Liquid Cystal Display

ECG: Electrocardiogram

RFID: Radio Frequency Identification

ESP: Espressif Module

GYM: Gymnasium

ACSM: American College of Sports Medecine

APP: Application

IDE: Integrated Development Environment

SQL: Structured Query Language

HTML: HyperText Markup Language

CSS: Cascading Style Sheets

ML: Machine Learning

SVM: Support Vector Machine

KNN: K-Nearest Neighbor

CNN: Convolution Neural Networks

TFT: Thin-Film Transistor

LIST OF FIGURES

LIST OF TABLES

LIST OF EQUATIONS

CHAPTER 1. INTRODUCTION

1.1.Overview and Background

Fitness is essential for maintaining overall health and well-being. Regular physical activity helps control weight, reduces the risk of chronic diseases, improves mental health, and enhances the quality of life [1]. Engaging in fitness activities strengthens muscles and bones, boosts the immune system, and increases longevity [2]. For gym users, tracking fitness metrics such as height, weight, BMI, and heart rate is crucial for monitoring progress and tailoring workouts to individual needs.

Keeping up an active way lifestyle in today's fast-paced world poses significant challenges, especially for gym users who require efficient tools to monitor key fitness metrics. Traditional tracking methods are manual, inconvenient, and prone to errors, failing to provide the necessary accuracy and integration. Existing digital solutions often lack real-time feedback, limiting their effectiveness in promoting sustained health management. Effective fitness management requires precise and consistent tracking of these metrics to ensure optimal exercise routines and to prevent potential health risks.

This project aims to develop an IoT-Based Fitness Monitoring System that leverages advanced sensors for precise height and weight measurement, ECG for accurate heart rate monitoring, RFID for seamless user identification, and an ESP8266 microcontroller for robust data processing and cloud transmission. Machine learning will be employed to analyze the collected data, helping gym users and trainers determine the most suitable sports and fitness activities for individuals. This not only enhances the personalization of workout plans but also contributes to better health outcomes. By integrating these technologies, the system empowers users to make informed health decisions, track fitness progress, and achieve their fitness goals more effectively, while also supporting gym trainers in creating personalized workout plans.

1.2.Motivation

The motivation for this research arises from the growing demand for personalized fitness solutions and the limitations of current methods used in gyms. Many gym users find it difficult to accurately track essential metrics like BMI and heart rate, hindering effective progress monitoring. Furthermore, gym trainers often lack access to detailed, real-time information needed to create tailored workout plans. By developing an IoT-based fitness monitoring system, this project aims to offer real-time feedback and personalized recommendations, improving workout efficiency and user experience, while assisting trainers with precise, actionable insights.

1.3.Problem statement

Maintaining a healthy lifestyle has become increasingly challenging in today's fast-paced world. A lot of people, especially those who use gyms, require assistance in order to regularly maintain and monitor fitness metrics like height, weight, BMI, and heart rate. Gym users often struggle to effectively track their progress and receive personalized workout recommendations that match to their individual health needs. This lack of personalized guidance can lead to inefficient workouts, and unsuitable levels of fitness. Additionally, gym trainers often face difficulties in understanding the specific exercise needs of each gym user, making it challenging to provide accurate and personalized workout plans [3].

Current research highlights the effectiveness of personalized exercise programs in enhancing training responsiveness and adaptations. However, there are limited accepted guidelines on how to develop these individualized programs [4]. The American College of Sports Medicine (ACSM) highlights the need for fitness plans that accommodate the diverse responses of individuals to exercise and nutrition, considering factors such as experience, age, lifestyle, and genetics [5]. Additionally, trainers often lack the necessary tools and comprehensive data to create tailored workout plans that reflect individual goals, fitness levels, and preferences. Studies demonstrate that personalized fitness programs significantly improve user satisfaction and help achieve fitness goals more effectively [6].

Therefore, there is a critical need for advanced systems that can provide gym users with real-time, personalized fitness monitoring and recommendations to help them achieve their health and fitness goals more efficiently and safely.

1.4.Study objectives

1.4.1. General Objective

The general objective of this project was to develop an IoT-based smart fitness monitoring system that provides personalized workout recommendations in real-time, enhancing workout effectiveness and safety for gym users while supporting gym trainers with detailed, individualized data for creating tailored workout plans.

1.4.2. Specific objectives

The specific objective of this study is to:

- Design and develop a Prototype that integrates weight, height, ECG, and RFID sensors to monitor fitness metrics like BMI and heart rate in real time.
- Train and evaluate a machine learning algorithm to analyze the collected fitness data and generate personalized workout recommendations for users.
- Integrate an LCD to provide real-time feedback by showing the suggested sports to the users.
- Develop a web application that allows gym users to access their fitness data remotely and receive personalized workout recommendations.

1.5.Hypothesis

After deploying this IoT-based smart fitness monitoring system, gym users will experience improved workout efficiency and safety, leading to better health outcomes, while gym trainers will be able to create more effective personalized workout plans with increased convenience and precision. As a result, both users and trainers will experience enhanced satisfaction, more effective fitness management, and improved overall health outcomes.

1.6.Scope of the study

This project focuses on developing an IoT-based smart fitness monitoring system that provides real-time fitness tracking and personalized workout recommendations. The project will focus on developing a working prototype that displays real-time data on an LCD, sends alerts via a buzzer, and provides personalized insights through a web application. Due to time constraints, the scope is limited to the development and testing of the prototype within a controlled gym environment, with plans for future expansion to include mobile app integration and cloud-based predictive analytics.

1.7.Significance of the study

The System is significant as it revolutionizes how fitness is managed and monitored by integrating advanced technology into everyday routines. By offering personalized, real-time data, it empowers users to achieve their fitness goals with greater precision and efficiency. The system reduces the dependency on traditional methods, making fitness monitoring more accessible and cost-effective for both individuals and gyms. Additionally, it promotes a data-driven approach to fitness, allowing trainers to provide more tailored workout plans based on accurate, up-to-date information.

1.8.Thesis contribution

The system offers an innovative IoT solution for fitness management in gyms. It facilitates real-time monitoring and personalized workout recommendations, contributing to more effective fitness management and empowering users to achieve their fitness goals with greater precision and ease. This system represents a significant advancement in the application of IoT technology in the fitness industry, promoting healthier lifestyles and improved gym experiences

1.9.Organization of the study

Chapter one: Introduction this is an introductory chapter. It describes the background of the study, the problem statement, the objectives of the study, the scope of the study, significance of the study, project interest and the organization of the study.

Chapter two: Literature review this chapter clarifies the work done by the other researchers on the IoT based on health.

Chapter three: Research methodology this chapter clearly shows the writer proposed methodology.

Chapter four: System design and analysis this chapter shows the prototype, corresponding to how the connectivity is done.

Chapter five: Results and Analysis this chapter shows the results of the prototype.

Chapter six: Conclusion and Recommendation this chapter gives the conclusion of the study and recommendations for the future researchers.

CHAPTER 2. LITERATURE REVIEW

2.1. Introduction

Maintaining fitness is essential for a healthy lifestyle, offering benefits like weight control and improved mental health. Gym users face challenges in tracking metrics such as height, weight, BMI, and heart rate due to manual and error-prone methods. Existing digital solutions often lack integration and real-time feedback. There is a pressing need for an advanced system that delivers accurate, real-time data and personalized recommendations, empowering users to make informed health decisions and aiding trainers in creating tailored workout plans for enhanced effectiveness and satisfaction[7].

2.2. Definitions

2.1.1. Internet of Things

The **Internet of Things (IoT)** refers to a system of interconnected devices, equipped with sensors, software, and communication technologies, that collect, exchange, and act on data over the internet. These devices operate in real time, enabling seamless interaction and automation [8]. In the context of this research, IoT plays a crucial role in integrating fitness sensors for tracking and analyzing gym users' health metrics such as heart rate, BMI, and movement. This allows real-time monitoring, data analysis, and personalized workout recommendations to enhance users' fitness experiences and outcomes.

2.1.2. Radio frequency Identification Technology

Radio Frequency Identification (RFID) is a wireless communication technology that uses radio waves to automatically identify and track objects or individuals through embedded tags. Each RFID tag holds electronically stored information that can be read remotely without requiring a direct line of sight [9]. In this research, RFID is used to identify gym users automatically when they enter, linking their fitness data such as heart rate, BMI, and workout routines to their profiles. This enables personalized monitoring, real-time feedback, and tailored workout recommendations, optimizing users' fitness tracking and progress.

2.1.3. Body Mass Index (BMI):

Body Mass Index (BMI) is a common measurement that assesses a person's weight in relation to their height. It is determined by dividing an individual's weight in kilograms by the square of their height in meters. BMI classifies people into categories such as underweight, normal weight, overweight, or obese, making it a useful tool for evaluating overall health. This classification helps fitness experts create customized fitness programs and dietary plans, enabling individuals to reach their health and wellness objectives [10]. Recognizing the significance of BMI is crucial for enhancing awareness about weight management and its effects on overall health.

The formula for calculating Body Mass Index (BMI) is:

$$\text{BMI} = \frac{\text{Weight (kg)}}{\text{Height (m)}^2}$$

Equation 1: BMI formula

Where:

- **Weight is measured in kilograms (kg).**
- **Height is measured in meters (m).**

2.1.4. Machine learning

Machine learning is a subset of artificial intelligence that uses algorithms and statistical models to enable systems to learn from data and make predictions or decisions without being explicitly programmed [11]. There are many ML algorithms, including Decision Trees, Random Forest, Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Naïve Bayes, and Convolution Neural Networks, each suited for different types of tasks. Deep learning techniques have significantly improved human activity recognition using wearable sensors. Research on deep learning in activity recognition highlights how models such as CNNs, RNNs, and Transformer networks can accurately classify movements, detect fitness activities, and provide real-time insights for users[11].

2.2. Related work

Research has consistently highlighted the importance of personalized exercise programs in improving training responsiveness and adaptations. A study demonstrated that individualized fitness plans significantly enhance user engagement and effectiveness, compared to generic workout routines [12][13]. The American College of Sports Medicine (ACSM) underscores the necessity for fitness plans that consider the diverse responses of individuals to exercise and nutrition, taking into account factors such as experience, age, lifestyle, and genetics [5]. However, there are limited accepted guidelines on how to develop these individualized programs, posing a challenge for trainers who aim to provide personalized fitness guidance[14].

Advancements in IoT and sensor technology offer promising solutions to these challenges. IoT-based systems can integrate multiple sensors to provide real-time monitoring and feedback, improving the accuracy and efficiency of fitness tracking. A study highlighted the effectiveness of IoT-enabled fitness devices in providing continuous health monitoring and personalized feedback, leading to better health outcomes [15]. Additionally, the integration of ECG sensors for heart rate monitoring has been shown to provide accurate and reliable data, which is crucial for optimizing workout intensity and ensuring user safety [16]. IoT Based Heart Activity Monitoring Using Inductive Sensors [17] explores different sensor technologies for heart rate monitoring.

Furthermore, RFID technology has been effectively utilized for seamless user identification in various applications, including fitness tracking. Research demonstrated the benefits of RFID in enhancing user experience and data accuracy in gym environments [12]. The use of microcontrollers such as the ESP8266 for data processing and cloud transmission ensures robust and efficient handling of large datasets, facilitating comprehensive data analysis and personalized recommendations [13]. An IoT-Based Framework for Personalized Health Assessment and Recommendations Using Machine Learning [7] further supports the use of IoT for personalized health assessments. Patient Monitoring System Based on Internet of Things: A Review and Related Challenges with Open Research Issues [18] offers a broader context on IoT applications and challenges in healthcare.

However, privacy concerns remain a significant challenge in AI-driven fitness monitoring. Recent studies propose privacy-preserving multi-level deep learning approaches, such as the Privacy-Preserving Personalized Fitness Recommender System (P3FitRec), which enables personalized fitness tracking while ensuring user data security[19]. An adaptive secure internet of things and cloud-based disease classification strategy for smart healthcare industry [20] addresses the importance of data security in such systems. This approach leverages federated learning and encrypted data processing techniques to provide workout recommendations without compromising user privacy. Incorporating such privacy-aware AI models is crucial for IoT-based fitness systems, ensuring secure user data management while maintaining personalized workout experiences.

This project aims to address this gap by developing an IoT-Based Fitness Monitoring System that leverages advanced sensors, ECG, RFID, and an ESP8266 microcontroller to deliver accurate, real-time fitness data and personalized recommendations. A Machine Learning Approach to Predict Customer Usage of a Home Workout Platform [21] highlights the use of machine learning to predict user behavior in fitness. Dynamic Physical Activity Recommendation Delivered through a Mobile Fitness App: A Deep Learning Approach [22] explores the use of deep learning for personalized recommendations. Physical Activity Recommendation System Based on Deep Learning to Prevent Respiratory Diseases [23] further demonstrates the application of machine learning in fitness. By doing so, it seeks to empower users and gym trainers to achieve their fitness goals more effectively and safely.

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 automatically calculate fitness metrics such as BMI and heart rate. Likewise, studies have demonstrated that the use of machine learning to provide personalized workout recommendations is achievable. However, this research has identified several limitations in existing fitness monitoring systems:

- Some systems require manual data entry, which compromises accuracy and is time-consuming[24].
- Many systems lack real-time cloud storage, limiting data accessibility and comprehensive analysis[25].
- Some available systems are expensive, making them less accessible to a broader population[26].

- Limited studies have successfully incorporated machine learning for personalized workout recommendations, and those that do often exhibit lower accuracy[27].

Table 1:Related work summary table

Author(s)	Contribution	Identified Gaps	Feedback
A. Farrokhi et al. (2021)	Surveyed IoT and AI applications in smart fitness systems.	Lack of real-time personalized feedback and integration with gym environments.	Strong foundation, but more real-world prototypes needed
S. K. Jagatheesaperumal et al. (2023)	Proposed IoT-based framework for health assessment using ML.	Limited application to specific fitness metrics like BMI and heart rate.	Promising work; fitness-specific customization needed.
H. Wackerhage and B. J. Schoenfeld (2021)	Highlighted need for personalized exercise programs.	Lacked IoT or smart systems to dynamically personalize programs.	Supports personalized fitness but needs IoT+ML systems for real-time guidance.
Hoelzemann and Van Laerhoven (2023)	Analyzed wearable sensors and annotation methods.	Manual data collection increases error rates and inefficiency.	Need fully automated real-time data collection systems.
Zheng and Liu (2022)	Designed cloud storage-oriented fitness monitoring system.	Limited real-time integration and high system complexity.	Cloud storage is important but must be simplified and fast for gym users.
Seçkin et al. (2023)	Reviewed wearable technologies in sports.	Many solutions are expensive, limiting mass adoption.	Solutions must be cost-effective to reach a wider user.

Fang et al. (2024)	Applied ML for exercise goal personalization.	Low model accuracy in some fitness scenarios.	ML models should be optimized for diverse fitness parameters.

CHAPTER 3. RESEARCH METHODOLOGY

3.1. Introduction

A methodology is a documented process for project management that includes procedures, definitions, and explanations of techniques and tools used to collect, analyze, store, and present data as part of research[28]. This section discusses and gives detailed information on the study area and Scope of the project, the research method to be used, the target population, Sample size and sampling techniques, Data collection tools, and the System Development Approach that will be used to conduct this study and allow findings to be replicated to validate them or deduce a conclusion from that analysis.

3.2. Research Methods

The research methods for developing and evaluating the IoT-Based Fitness Monitoring System involve an experimental and prototype development approach. Experimental research involves implementing and testing the system's hardware and software components to evaluate performance. Surveys and questionnaires will collect feedback from users and trainers. he development of the IoT-Based Smart Fitness Monitoring System integrates various sensors, components, and algorithms to efficiently meet the system’s objectives of personalized workout recommendations. The system features an ESP8266 microcontroller as the core processing unit, integrated with multiple sensors such as an ECG sensor for heart rate monitoring, a weight sensor, and an ultrasonic sensor for height measurement. Additionally, the system incorporates an RFID reader for user identification, enabling personalized data collection and tracking. The data collected by these sensors were processed by the microcontroller and transmitted to a cloud platform for analysis using machine learning algorithms, allowing real-time recommendations and personalized fitness insights. The LCD display will provide real-time feedback to users, displaying fitness metrics such as BMI and heart rate.

3.2.1. Data Collection

Data is collected from various integrated sensors, including:

- **ECG sensor** to capture the user's heart rate.
- **Weight sensor** to track body weight.
- **Ultrasonic sensor** to measure the user's height, used for BMI calculation.
- **RFID reader** to identify users and link data to their personal fitness profiles.

The system automatically calculates the BMI based on the height and weight data collected. The LCD screen displays real-time BMI and heart rate readings. All data collected is transmitted to a cloud-based SQL database for real-time processing and monitoring. Additionally, machine learning models analyze the fitness data, which is trained using the **Dataset 10000 from Kaggle**, to provide personalized workout recommendations. These recommendations help gym users optimize their exercise routines and achieve their fitness goals.

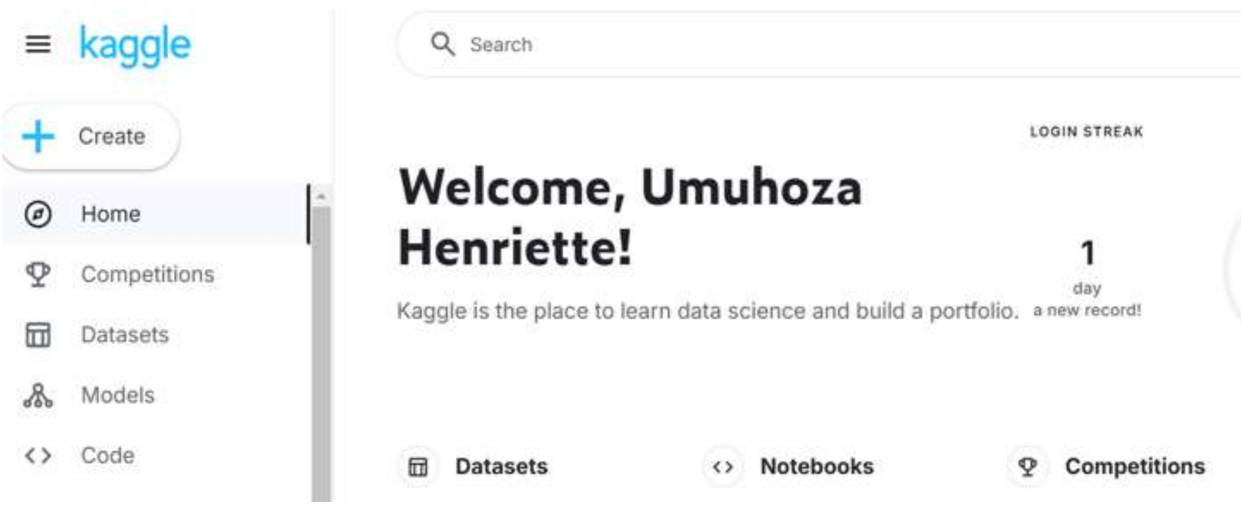


Figure 1: Kaggle online platform

Table 2: Data set downloaded and used to train ML Model

	A	B	C	D	E	F	G	H	I	J	K
1	User_ID	Age	BMI	Heart_Rat	Fitness_Le	Exercise_T	Duration (	Intensity	Suggested	Suitable_Environment	
2	1	47	32.1	90	Intermedi	HIIT	47	Moderate	3 times/w	Indoor/Gym	
3	2	23	32.1	92	Beginner	HIIT	35	Low	4 times/w	Indoor/Outdoor	
4	3	40	39.9	64	Advanced	Yoga	27	High	5 times/w	Gym	
5	4	18	36.6	97	Intermedi	HIIT	16	High	3 times/w	Outdoor	
6	5	25	23.2	65	Advanced	Resistance	44	Moderate	Daily	Indoor	
7	6	23	28.6	89	Beginner	Walking	52	Moderate	4 times/w	Gym	
8	7	50	22.3	77	Advanced	Jump Rop	27	High	4 times/w	Outdoor	
9	8	34	27.3	74	Intermedi	Jump Rop	36	High	4 times/w	Gym	
10	9	60	30.1	64	Advanced	Jump Rop	40	High	3 times/w	Indoor	
11	10	24	39.4	92	Beginner	Cycling	28	High	5 times/w	Outdoor	
12	11	26	37.1	64	Beginner	Yoga	58	Low	Daily	Indoor/Outdoor	
13	12	39	32.2	94	Intermedi	Plyometric	41	High	3 times/w	Outdoor	
14	13	58	27.9	99	Advanced	Yoga	32	Moderate	4 times/w	Outdoor	
15	14	31	21.2	82	Advanced	Jump Rop	58	High	5 times/w	Indoor/Outdoor	
16	15	20	30.2	64	Intermedi	Weightlifti	48	High	3 times/w	Outdoor	
17	16	59	25.3	72	Intermedi	Walking	39	Low	4 times/w	Gym	
18	17	33	29.2	76	Intermedi	Swimming	15	Moderate	4 times/w	Indoor/Gym	
19	18	54	26.6	67	Intermedi	Yoga	48	High	3 times/w	Indoor	
20	19	23	33.1	80	Intermedi	Swimming	18	Low	5 times/w	Outdoor	
21	20	59	26.8	65	Beginner	Running	28	Moderate	3 times/w	Gym	
22	21	62	28.4	69	Advanced	Swimming	52	Low	5 times/w	Pool	
23	22	30	28.5	82	Intermedi	Walking	27	High	4 times/w	Gym	
24	23	49	36	71	Beginner	Resistance	26	High	5 times/w	Indoor/Gym	
25	24	18	38.7	75	Intermedi	Yoga	49	Low	Daily	Outdoor	
26	25	57	35.6	65	Beginner	Cycling	34	Moderate	4 times/w	Indoor/Gym	

3.2.2 Data Analysis

Data analysis is performed using machine learning models integrated into the system. The models process real-time fitness data stored in the cloud to generate personalized workout recommendations based on the user's metrics (heart rate, BMI, etc.). These recommendations help users achieve their fitness goals while ensuring safe workout practices. Monthly fitness reports are generated and shared with gym trainers, providing a comprehensive overview of each user’s progress and fitness level. Additionally, predictive analytics is applied to analyze long-term trends in users’ health and fitness patterns, enhancing the user experience and assisting trainers in refining workout plans for optimal results.

3.3. Machine Learning Process

The Machine Learning Process for the IoT-Based Smart Fitness Monitoring System begins with using **data from Kaggle** to train the machine learning algorithms. This data includes key fitness metrics such as heart rate, weight, and height, which are then transmitted to the cloud for storage and processing. In the cloud, the data is preprocessed to handle any missing or noisy values, ensuring accuracy.

After preprocessing, the data is fed into machine learning models. These models are trained to analyze fitness patterns and generate personalized workout recommendations based on user-specific health metrics like BMI and heart rate. The models are fine-tuned through cross-validation, improving prediction accuracy and ensuring tailored workout plans.

Predictive analytics is applied to forecast users' future health trends, helping users and gym trainers optimize workouts. The system continuously improves as it learns from new data, enhancing recommendations over time.

3.3.1. Random forest algorithm Definition

Random Forest is a powerful machine learning algorithm that uses an ensemble of decision trees to make predictions[29] . Each tree is trained on a random subset of the data and features, which helps reduce overfitting and improve generalization. The final prediction is made by averaging the predictions (for regression) or by majority voting (for classification) of all individual trees. Random Forest is highly accurate, robust to noise, and can handle both numerical and categorical data. It is particularly effective for complex tasks involving large datasets and multiple variables, making it a popular choice for applications such as classification, regression, and predictive modeling.

3.3.2. Application of Random Forest in IoT-Based Fitness Monitoring System

In this research, ML model analyzes fitness data to provide personalized workout recommendations, improving the overall fitness experience for users. Among the various ML algorithms, we chose Random Forest model for its high accuracy, making it ideal for tasks requiring processing and predicting multiple fitness parameters like heart rate, weight, and height. This accuracy ensures reliable fitness recommendations and health monitoring in your system. Additionally, Random Forest is highly scalable, and capable of handling large datasets as your IoT fitness system expands, accommodating more users and data points over time. It also supports real-time processing, enabling immediate predictions and feedback as the system collects user data. This allows for timely health alerts and personalized workout suggestions based on current metrics, enhancing the user experience.

CHAPTER 4. SYSTEM DESIGN AND DEVELOPMENT

4.1. Introduction

In this section, the proposed system architecture for the IoT-Based Smart Fitness Monitoring System is described. The architecture is designed to integrate key fitness monitoring and workout recommendation services for gym users. Upon entering the gym, user identification is automatically carried out through RFID technology, linking each user's fitness profile. In addition to identification, various sensors are implemented to capture essential fitness metrics such as heart rate, weight, and height. These parameters are processed in real-time and analyzed to provide personalized workout recommendations, enhancing the user's fitness experience and overall health management.

4.2. System architecture

4.2.1. Block diagram of the system

Figure 2 Shows the block diagram of the proposed system, how all sensors will be connected to the microcontroller and actuators. The 5V dc will be used to power the system and then after powering the system will start working.

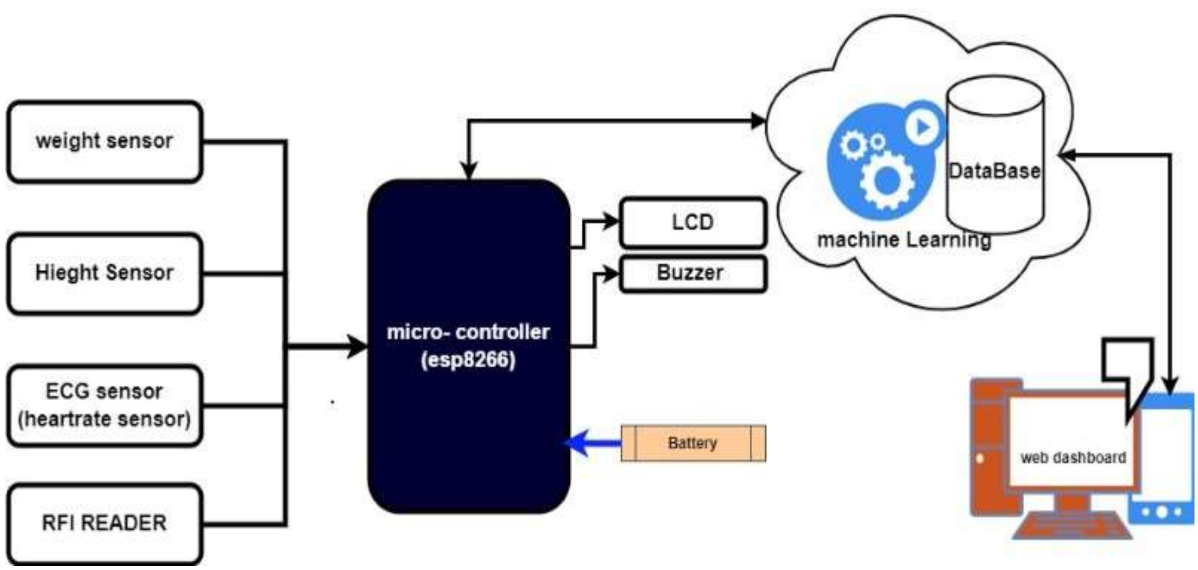


Figure 2: Block diagram of the system

4.2.2. Flow Chart diagram of the system

This flowchart outlines the workflow of an advanced IoT-based fitness monitoring system designed to provide personalized and data-driven fitness management for users. Upon entering the gym, the user is identified via RFID, ensuring that the data collected is accurately linked to their profile. The system then collects essential biometric data through sensors, including height, weight, and heart rate, which are used to calculate the Body Mass Index (BMI). This information is displayed in real-time on an LCD screen, allowing the user to immediately see their health metrics. The system then checks for any abnormal readings such as an unusually high heart rate or concerning BMI and triggers an alert if necessary, ensuring the user's safety. All collected data is transmitted to a cloud platform for further analysis using machine learning algorithms. These algorithms identify suitable fitness styles and generate personalized workout plans, providing tailored recommendations that align with the user's fitness goals and health needs.

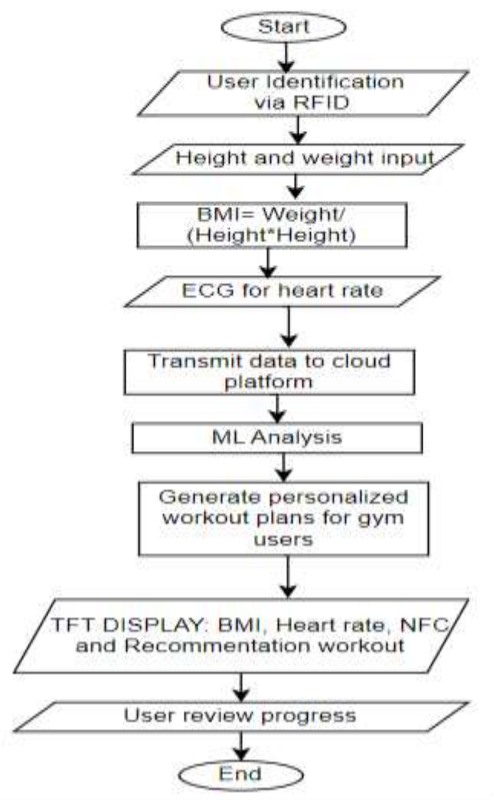


Figure 3: Flow chart of the system

4.3. Tools and component used

4.3.1. Components used and their functions

Table 3:Hardware requirements details and specifications

		Hardware Description and specifications	
S/N	**EQUIPMENT**	**DESCRIPTION**	**SPECIFICATION**
1	Microcontroller	The central unit that processes data from various sensors and manages communication with other components.	**-Processor:** 32-bit Tensilica L106, clock frequency 80 MHz to 160 MHz **-Memory:** 4MB Flash, 128 KB RAM **-Connectivity:** Wi-Fi - **GPIO Pins:** Multiple (depends on the specific board) **-Key Features:** RTOS support, low-power deep sleep mode, ideal for IoT applications
2	Weight Sensor	Measures the weight of the user and sends data to the microcontroller.	-Type: Load Cell - Capacity: 200 kg - Output: Analog signal - Accuracy: ±0.02 kg
3	Height Sensor	Measures the height of the user and sends data to the microcontroller.	- Type: Ultrasonic Sensor - Range: 2 m - Output: Digital signal - Accuracy: ±0.1 cm
4	ECG Sensor	Measures the heart rate of the user and sends data to the microcontroller.	- Type: Electrocardiogram (ECG) Sensor - Output: Analog signal - Accuracy: ±1 BPM
5	RFID Reader	Identifies users and retrieves their data.	- Type: RFID Module - Frequency: 13.56 MHz

			- Range: Up to 10 cm - Output: Serial communication
6	LCD Screen	Displays real-time BMI and heart rate data and workout recommendation.	- Type: TFT Display - Interface: I2C - Voltage: 5V - Backlight: LED -Resolution: Common resolutions include 320×480 pixels
7	RFID Reader Module 13.56Mhz	a **wireless** radio frequency identification device operating at **high frequency (HF)** for reading and writing RFID tags, commonly used in **access control**.	- Type: RFID Reader Module 13.56Mhz - Voltage: 3.3V to 5V - Read Range: Up to 10 cm

HC-SR04 Ultrasonic Sensor

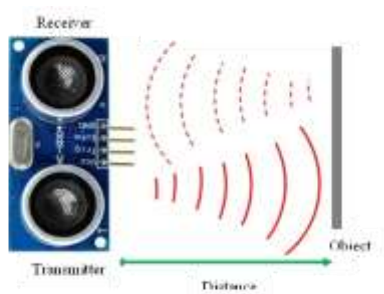


Figure 4:The HC-SR04 ultrasonic sensor

An ultrasonic sensor is an electrical device that periodically emits sound waves at a high frequency of 40 KHz. Sound waves are emitted by the transmitter of an ultrasonic sensor, and the reflected sound waves are picked up by the receiver. The sensor uses the formula D = ½*T*S to compute the distance of an object by measuring the interval between the sound waves' emission and reception. This project uses the HC-SR04 ultrasonic sensor since it has a 3mm accuracy range for measuring distances between 2 and 450 cm[35].

Load cell Sensor and HX711 Load cell Amplifier

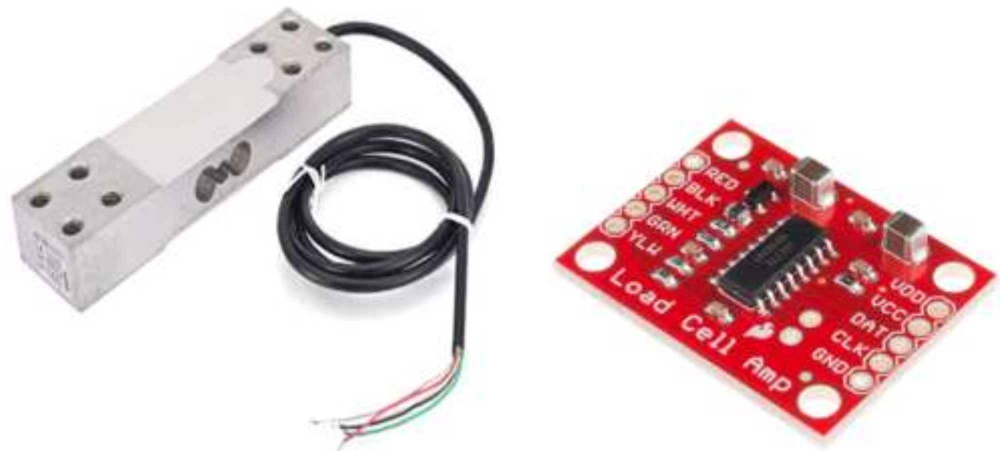


Figure 5:200kg Load cell and Load cell amp

A load cell is a force transducer that produces electricity from pressure, tension, or stress. The electrical output is directly proportional to the applied force. A Wheatstone bridge arrangement is used for the strain gauge load cells. The load cell generates signals in millivolts (mV). The HX711 is a 24-bit Analog-to-Digital Converter (ADC) that converts the load cell's tiny electrical signal into 24-bit voltage fluctuations (0-5V)[36]. Strain gauge load cells are essential for precise axial force measurement, especially in test bench applications requiring high accuracy. They function by converting mechanical deformation into electrical signals via strain gauges on a deformable structure. Optimizing their design and shape enhances sensitivity, load distribution, and performance, influenced by factors like material selection and geometric configuration. Studies using finite element analysis (FEA) have improved their accuracy and durability, making them suitable for high-capacity applications such as 200 kg load measurement. Different types, including bending beam, shear beam, and compression load cells, cater to various industrial and laboratory needs, enhancing reliability in force measurement[37][38].

Figure 6:ECG sensor module

The image shows **an ECG (Electrocardiogram) sensor module**, typically used for **heart rate monitoring** and **biomedical signal acquisition**. This sensor system includes **electrode pads, lead wires, and an analog front-end circuit board**[39] designed to detect and amplify bioelectrical signals from the heart. The electrodes are placed on the skin to capture electrical activity, which is then processed by the sensor module to provide ECG waveforms. These modules are commonly used in wearable health monitoring systems, fitness tracking, and medical diagnostics[40][41].

NodeMCU (ESP8266)

It's an inexpensive development board made for Internet of Things uses. The ESP8266 Wi-Fi SoC powers the firmware, while the ESP12E module serves as the foundation for the hardware. Real time operating systems (RTOS) that run at a clock frequency of 80 MHz to 160 MHz are supported by the processor. 4MB of Flash memory and 128 KB of RAM are available for storing data and programs. Because of its powerful processing capacity and deep sleep operating capability, it is ideal for Internet of Things applications[42].

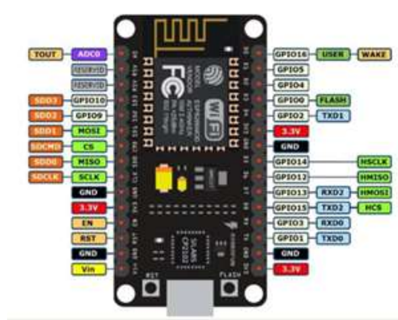


Figure 7: ESP8266 NodeMCU *Figure 8: ESP8266 NodeMCU pin out*

Thin-Film Transistor (TFT) Display

Figure 9: A TFT Display

A **Thin-Film Transistor (TFT) Display** is a type of liquid crystal display (LCD) that uses thin-film transistor technology to improve image quality. TFT displays provide high contrast, fast response times, and better color reproduction compared to standard LCDs. They are commonly used in smartphones, tablets, embedded systems, and IoT projects due to their compact size and efficient power consumption[43][44][45].

RFID Reader Module 13.56Mhz

Figure 10: RFID Reader module

The RFID Reader Module (13.56 MHz) is a wireless radio frequency identification device operating at high frequency (HF) for reading and writing RFID tags, commonly used in access control, payment systems, and inventory tracking. It supports multiple communication interfaces, including SPI, I2C, and UART, and adheres to protocols like ISO 14443A/B and ISO 15693, making it compatible with NFC in some models. With an operating voltage of 3.3V - 5V and a read range of up to 10 cm, its efficiency depends on the tag type and antenna size[46][47][48][49].

Power supply

A regulated DC power supply is used in this project as it provides a more sustainable and reliable alternative to battery power. a regulated power supply ensures consistent voltage, enhancing system stability and long-term efficiency.

Other hardware that was used included wires, bolts and nuts, wooden piece etc.

4.3.2. Hardware Design

Hardware Design in IoT refers to the process of planning, developing, and integrating the physical components that enable devices to connect, communicate, and interact within an IoT ecosystem. This design encompasses a variety of elements, including sensors, actuators, microcontrollers, communication modules, power management systems, and interfaces, all of which work together to collect data, process it, and transmit it to other devices or cloud platforms [50].

Therefore, the proposed system will have three main parts, which are sensing unit, processing unit and actuating unit as shown on hardware design figure

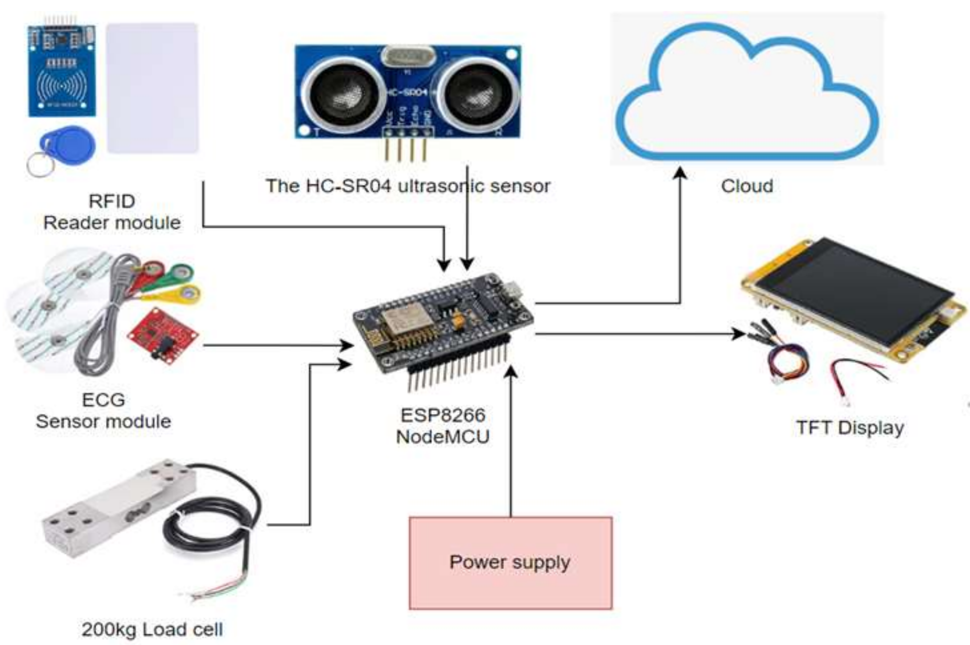


Figure 11: Hardware architectural design

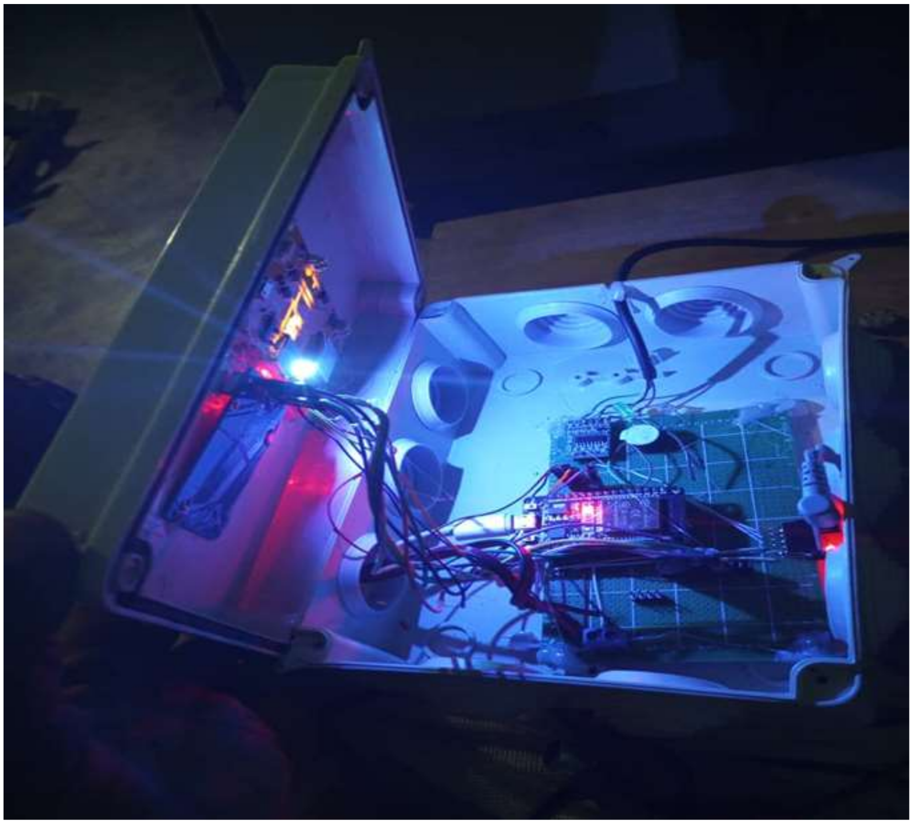


Figure 12: System testbed

4.3.2. Software used and their roles

Table 4: Software used and their roles

Software/ Tool	Role
1. Arduino IDE (C++)	For programming the ESP8266 and fitness sensors
2. ESP8266 Libraries	Connectivity and communication with IoT devices
3. Machine Learning (Python)	Analyze fitness data and generate recommendations
4. MySQL	Database to store user fitness data
5. Web Development Tools	For creating user interface and data visualization (HTML, CSS, JavaScript)

4.4. Design of BMI Structure

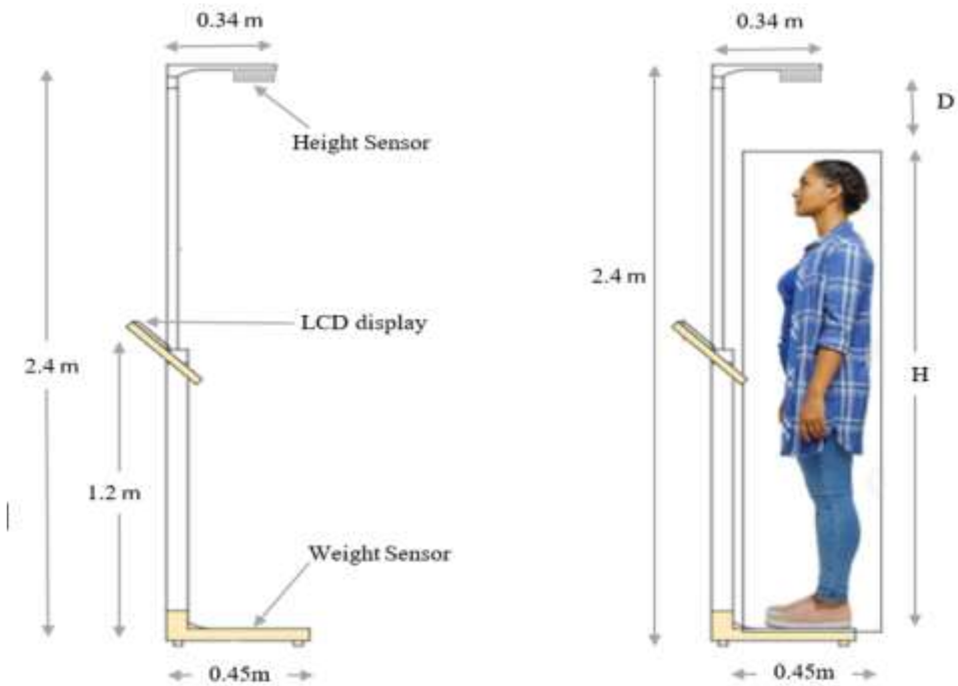


***Figure 13: BMI Structure Design*[30]**

An ultrasonic sensor measures distance by emitting high-frequency sound waves and detecting the time it takes for the echo to return after reflecting off the top of a person's head. In this project, the sensor is mounted at the top of a 2.4-meter stick, facing downward. When a person stands beneath the sensor, it transmits an ultrasonic pulse that travels downward, hits the person's head, and bounces back to the sensor. The sensor calculates the distance (D) between itself and the person's head using the time delay of the returning echo. The height of the person (H) is then determined by subtracting the measured distance from the total height of the stick using the formula:

$$H=2.4m-D$$

Equation 2: Height of the person formula

This simple and cost-effective method is based on the same working principle described in [31], where an ultrasonic-based digital height meter is developed using the HC-SR04 sensor and microcontroller.

To measure the person's weight, a 200 kg load cell sensor is used. The load cell is connected to an HX711 amplifier module, which converts the analog signal from the load cell into a digital value readable by the microcontroller. When a person stands on the load cell platform, their body weight is captured and processed.

After both height and weight are measured, the system computes the Body Mass Index (BMI) using the formula:

$$\text{BMI} = \frac{\text{Weight (kg)}}{\text{Height (m)}^2}$$

Equation 3: BMI formula

This method has been demonstrated in similar studies involving BMI systems using ultrasonic sensors and load cell modules [32] [33].

CHAPTER 5: SYSTEM RESULTS AND ANALYSIS

5.1. Introduction

This chapter presents the results obtained from the implementation and testing of the IoT-Based Smart Fitness Monitoring System. It provides an in-depth analysis of system performance, accuracy, and efficiency in monitoring fitness metrics and generating personalized workout recommendations.

5.2. Prototype Implementation

Figure 14: Prototype of the IoT-Based Smart Fitness Monitoring System

The prototype was tested, and results demonstrated the feasibility and effectiveness of the system in providing real-time fitness monitoring and personalized recommendations. 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.

Figure15: IoT-Based Smart Fitness Monitoring System Display

5.3. User Interface Performance

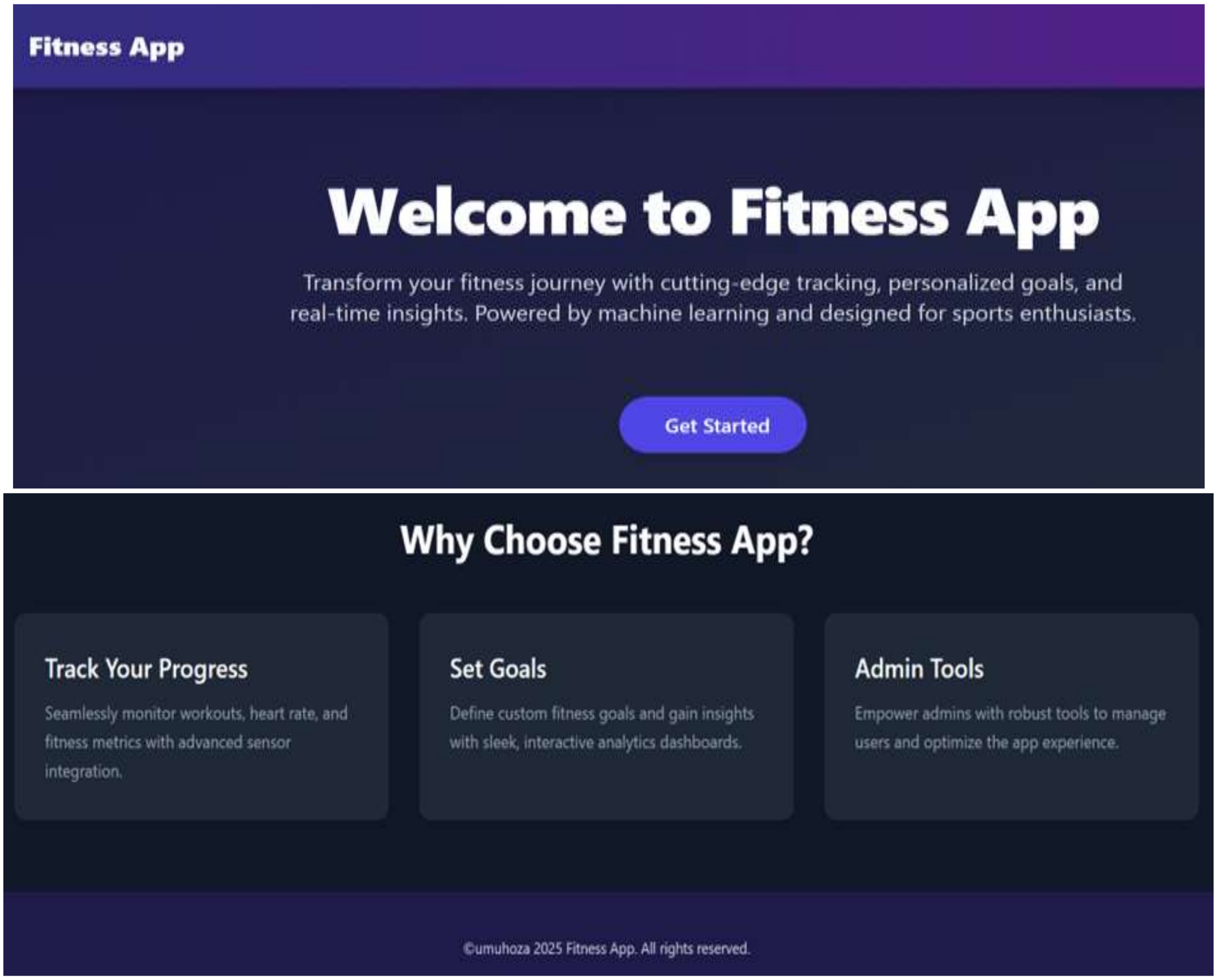
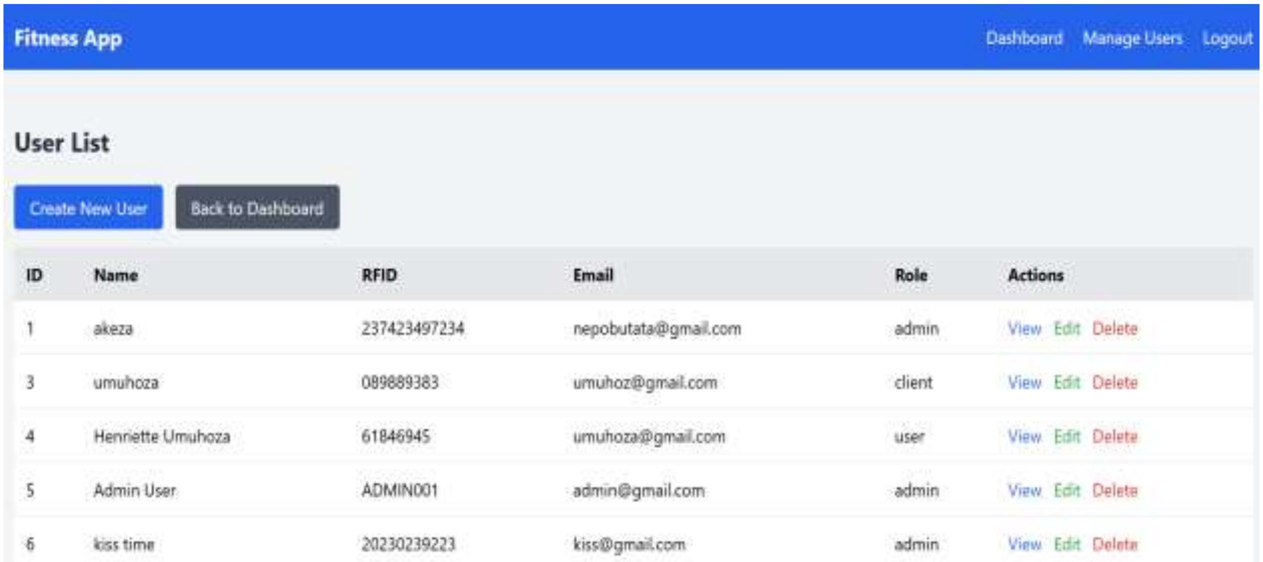


Figure 16:Home page of the system Web App

Admin tasks: The admin can register new gym users, manage user profiles, and oversee fitness data records.



ID	Name	RFID	Email	Role	Actions
1	akeza	237423497234	nepobutata@gmail.com	admin	View Edit Delete
3	umuhoza	089889383	umuhoz@gmail.com	client	View Edit Delete
4	Henriette Umuhoza	61846945	umuhoza@gmail.com	user	View Edit Delete
5	Admin User	ADMIN001	admin@gmail.com	admin	View Edit Delete
6	kiss time	20230239223	kiss@gmail.com	admin	View Edit Delete

Figure 17: Admin records

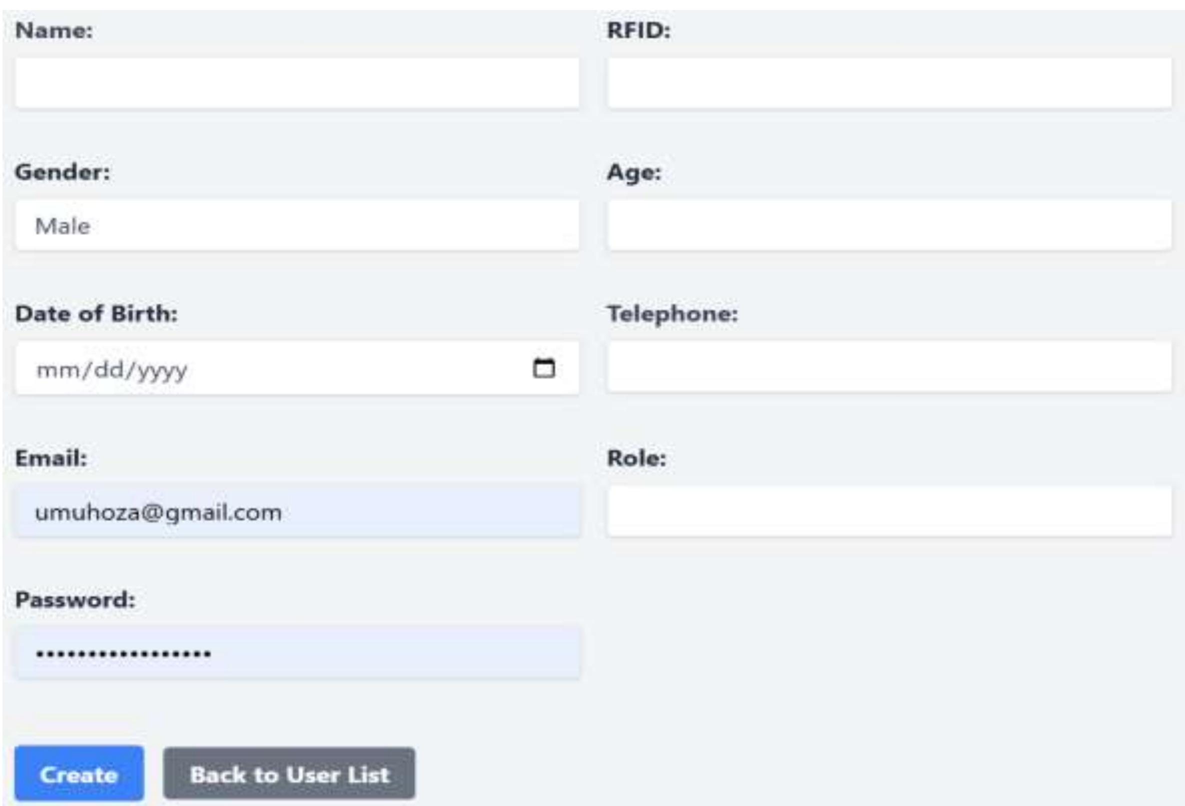


Figure 18: Admin creates new gym user

5.4. Machine Learning Results and Evaluation

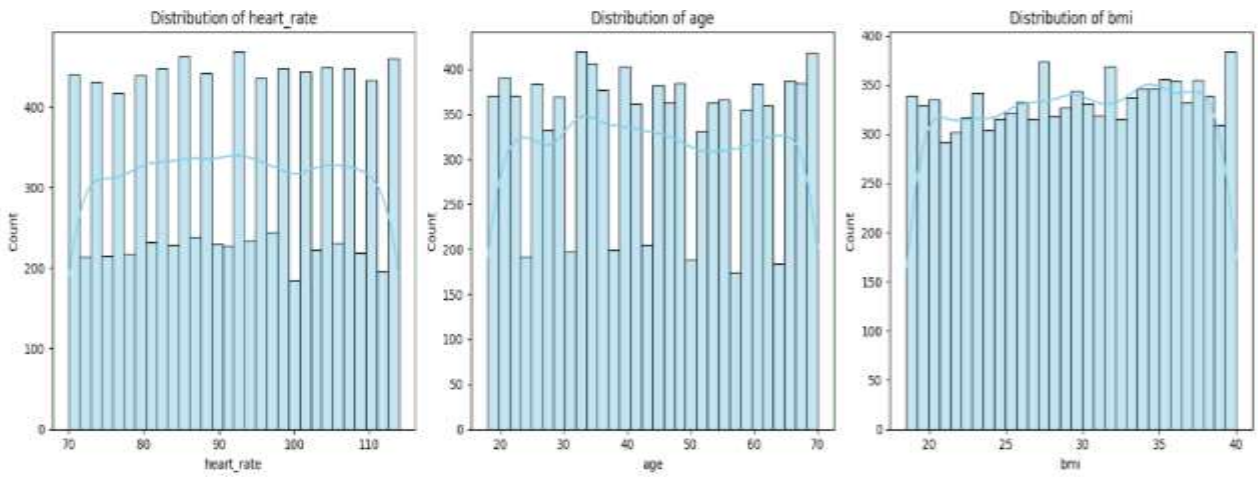


Figure 19: Distribution of the key inputs features (Heart Rate, Age, BMI)

This figure illustrates the distribution of the three key input features used in the fitness recommendation model. Each subplot shows the frequency of values within the dataset:

- **Heart Rate Distribution (70-115 BPM):** Shows consistent data collection across participants, demonstrating the effectiveness of your ECG-based heart rate monitoring component.
- **Age Distribution (20-70 years):** The center graph shows the "Distribution of age" among participants, spanning from roughly 20 to 70 years.
- **BMI Distribution (20-40):** Displays comprehensive coverage across all BMI categories, validating your height and weight measurement sensors.

These distributions ensure the model has sufficient variance for effective training and generalization.

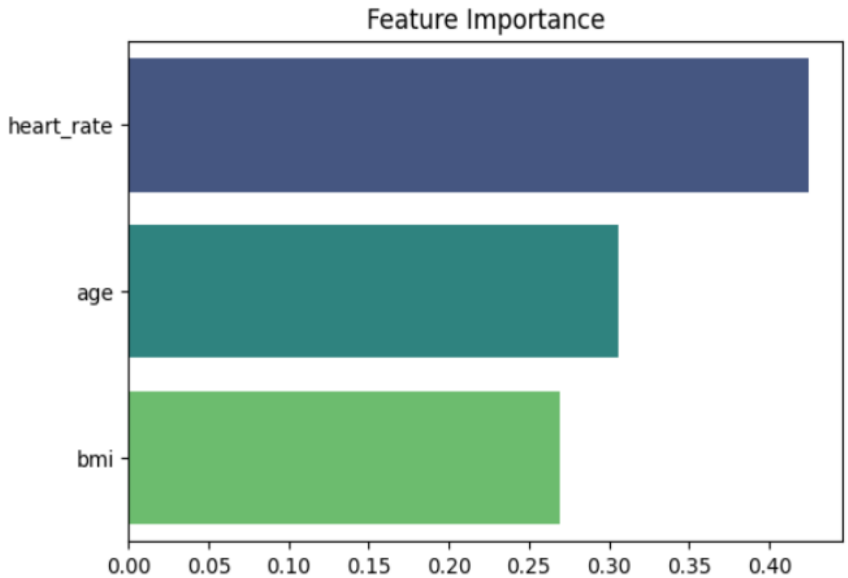


Figure 20:Relative Importance Feature Bar Chart

According to analysis, the ML model's largest metric (40%) is heart rate, which is followed by age (30%) and BMI (26%). This hierarchy confirms the system prioritizes physiological signals and demographic factors when generating personalized workout recommendations, aligning with established exercise science principles.

Table 5: Personalized Fitness Recommendations Based on Biometric Parameters

The data was synthetically generated and used as a simulation to evaluate the system's functionality.

	Age	Gender	Height	Weight	RestingHR	WorkoutHR	FitnessGoal	PreferredExercise	SuggestedSport	BMI
0	21	Male	172	62	64	147	Weight Loss	HIIT	Rowing	20.957274
1	47	Female	157	64	83	155	Weight Loss	Running	Running	25.964542
2	29	Male	182	52	76	132	Weight Loss	Rock Climbing	HIIT	15.698587
3	27	Female	166	67	78	161	Flexibility	Mixed	Stretching	24.314124
4	57	Male	161	56	71	150	Improved Sleep	Cardio	Light cardio	21.604105

Table 4 presents the output of the machine learning model, which was trained to map biometric parameters including age, gender, height, weight, resting heart rate, and workout heart rate to specific fitness recommendations. Each participant's biometric profile was processed as a feature vector, and the model applied classification algorithms to predict the most suitable exercise category based on learned patterns. The diversity of biometric inputs demonstrates the model’s ability to generalize across a wide range of physiological characteristics, providing individualized recommendations that align with established fitness goals. This confirms the system’s capability to utilize supervised learning methods to accurately associate input features with optimal workout prescriptions.

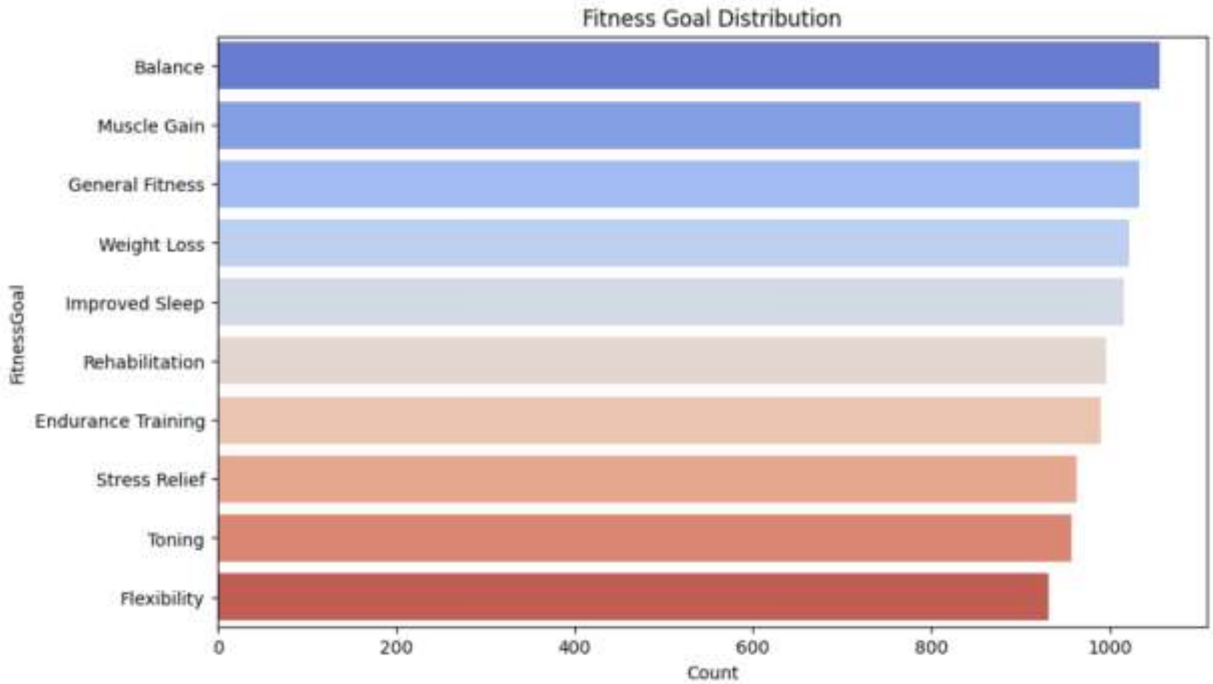


Figure 21: Fitness Goal Distribution Among System Users

The distribution of fitness goals among the user group is shown graphically in this chart. According to the research, users have a diverse range of fitness objectives, with a reasonably balanced distribution across areas like flexibility, muscle gain, balance, and others. This diversity of goals emphasizes how crucial the system is for meeting the requirements of each individual.

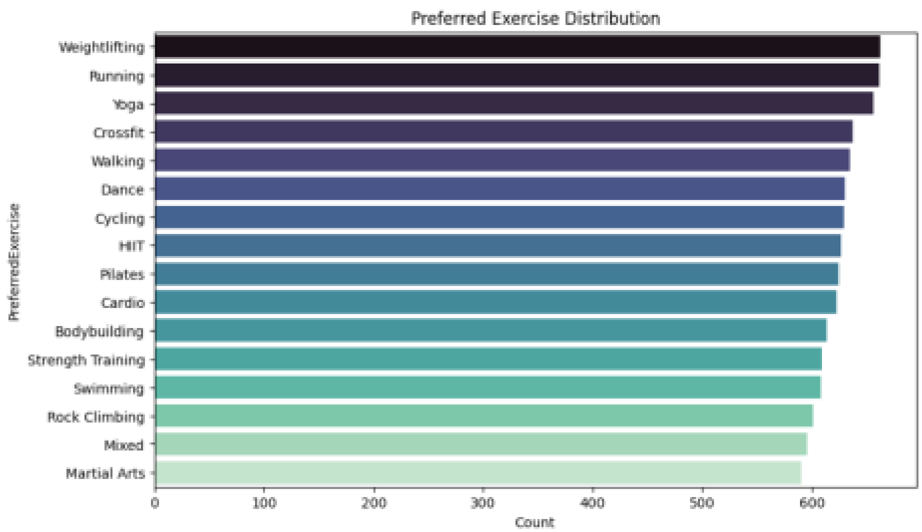


Figure 22: Preferred Exercise Distribution

User Preferences for Exercise displays the distribution of preferred exercises among users. The chart indicates that Weightlifting and Running are the most frequently preferred, while Martial Arts and Mixed are the least. This distribution provides insight into user inclinations for personalized workout recommendations**.**

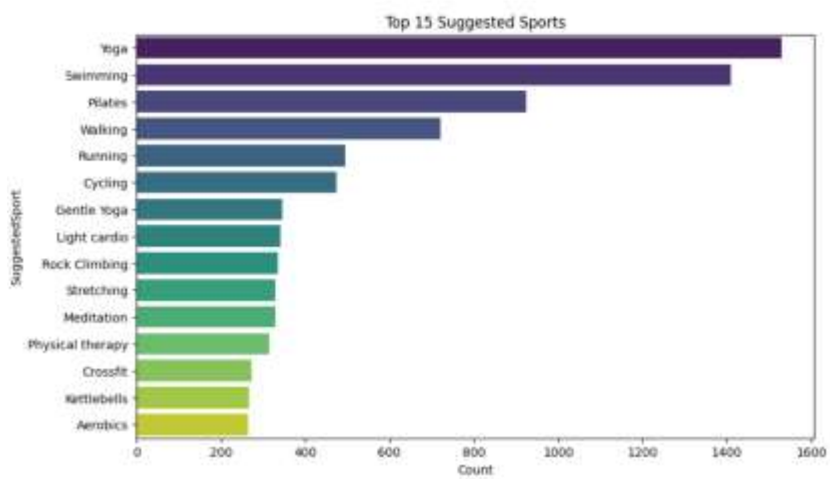


Figure 23: Top 15 Workout Recommendations

This horizontal bar chart displays the top 15 most frequently suggested sports by your IoT-based smart fitness monitoring system. Each bar represents a specific sport, and the length of the bar indicates how many times that sport was recommended to users.

5.5. Model Evaluation Metrics with Simulated Noise

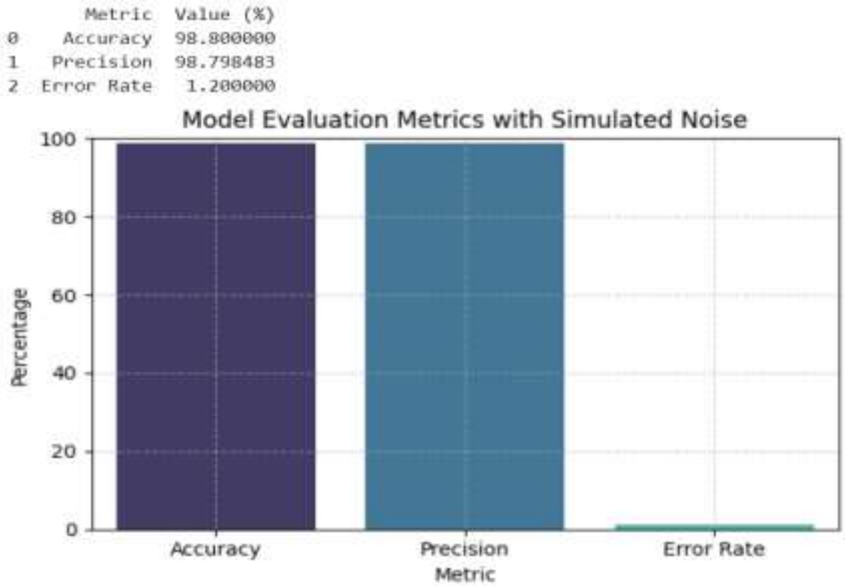


Figure 24: Model accuracy, precision, and error output

Model Evaluation Metrics with Figure21. The performance of the recommendation model when tested with simulated noise is shown in Simulated Noise. Precision (98.80%) shows the proportion of accurately predicted positive situations, Accuracy (98.80%) shows the percentage of correct predictions, and Error Rate (1.20%) shows the percentage of incorrect projections. Considering the noise, the excellent accuracy and precision show how useful the model is.

5.6. Comparative Analysis

To assess the effectiveness of the developed system, a comparison was made with existing fitness monitoring solutions. Key findings include:

1. **Fitness Tracking Accuracy**
   - ✓ **Developed System:** Higher accuracy in fitness tracking due to real-time sensor integration. The system provides immediate data feedback, reducing the delay between activity and result reporting.
   - ✓ **Existing Systems:** Traditional fitness monitoring solutions often rely on less real-time or less precise data, leading to potential inaccuracies in tracking fitness progress.

2. **Personalized Recommendations**

- ✓ **Developed System:** Offers personalized workout recommendations by leveraging machine learning algorithms such as Random Forest, providing tailored fitness plans based on user data and progress.
- ✓ **Existing Systems:** Typically offer generic fitness plans based on limited user information, which might not optimize for individual progress or goals, especially for unique fitness needs.

3. **Cost-Effectiveness**

- ✓ **Developed System:** The system is cost-effective due to its use of affordable IoT hardware and open-source software, making it a practical solution for gym-goers or fitness enthusiasts on a budget.
- ✓ **Existing Systems:** Commercial smart fitness devices often come at a higher price point due to proprietary technology and advanced features, which may not be accessible for everyone.

5.7. Limitations

Certain limitations impact the usability and accessibility of the IoT-Based Smart Fitness Monitoring System. The load cell sensor used to measure weight can only measure up to 200 kg, so it is not appropriate for people who weigh more than that. Taller users may find the ultrasonic sensor inaccurate because it can only assess heights up to two meters for our project. Furthermore, the system is not designed for pregnant women or people with limb disabilities.

CHAPTER 6: CONCLUSION AND RECOMMENDATION FOR FUTURE WORK

6.1. Conclusion

The system successfully achieved its objectives, providing accurate, real-time fitness tracking and personalized workout recommendations. The combination of IoT and machine learning enhanced the overall user experience and effectiveness of fitness management in gyms.

The IoT-Based Smart Fitness Monitoring System enhances fitness tracking by integrating advanced sensors, machine learning, and cloud-based analytics to provide personalized workout recommendations. Utilizing RFID for seamless user identification, ECG for accurate heart rate monitoring, and real-time BMI calculations, the system improves health tracking and user engagement. The incorporation of machine learning ensures data-driven recommendations, allowing gym users to optimize their workouts while enabling trainers to create tailored fitness plans. The trained machine learning model achieved a high accuracy of 98.8% with a low error rate of 1.2%, confirming its reliability in delivering precise and personalized fitness recommendations. By providing real-time feedback through an LCD display and cloud storage, the system facilitates continuous progress monitoring. This innovation revolutionizes gym fitness management by enhancing accuracy, efficiency, and accessibility, ultimately promoting healthier lifestyles and data-driven decision-making in personal fitness and professional training environments.

6.2. Recommendation for future work

Future research should focus on collecting and utilizing extensive real-world datasets from the deployed IoT-based fitness monitoring system to enhance machine learning model training, improving the accuracy of personalized workout recommendations and predictive health insights. Despite advancements in IoT-based fitness monitoring, challenges remain in effectively integrating machine learning with wearable healthcare devices. Research highlights issues such as sensor reliability, energy efficiency, and real-time data processing constraints that impact system performance[34]. Addressing these challenges through optimized data collection methods and model efficiency improvements will enhance the reliability of smart fitness monitoring solutions.

Additionally, expanding the system by integrating advanced biometric sensors, such as oxygen saturation (SpO2) and stress level monitors, would provide a more comprehensive assessment of gym users' health, further refining personalized recommendations and ensuring more precise fitness tracking.

REFERENCES

[1] A. Farrokhi, R. Farahbakhsh, J. Rezazadeh, and R. Minerva, “Application of Internet of Things and Artificial Intelligence for Smart Fitness: A Survey,” 2021.

[2] A. Farrokhi, J. Rezazadeh, R. Farahbakhsh, and J. Ayoade, “A Decision Tree-Based Smart Fitness Framework in IoT,” *SN Comput. Sci.*, vol. 3, no. 1, Jan. 2022, doi: 10.1007/s42979-021-00940-x.

[3] H. Wackerhage and B. J. Schoenfeld, “Personalized, Evidence-Informed Training Plans and Exercise Prescriptions for Performance, Fitness and Health,” *Sport. Med.*, vol. 51, no. 9, pp. 1805–1813, Sep. 2021, doi: 10.1007/s40279-021-01495-w.

[4] B. R. Byrd, R. E. Barnhouse, A. M. Dalleck, and L. C. Dalleck, “Personalized exercise programming enhances both cardiorespiratory and muscular fitness training responsiveness: a double-blind randomized controlled trial,” 2022.

[5] C. E. Garber *et al.*, “Quantity and quality of exercise for developing and maintaining cardiorespiratory, musculoskeletal, and neuromotor fitness in apparently healthy adults: Guidance for prescribing exercise,” *Med. Sci. Sports Exerc.*, vol. 43, no. 7, pp. 1334–1359, Jul. 2011, doi: 10.1249/MSS.0b013e318213fefb.

[6] M. H. P. Chaudhari, “Virtual Fitness Trainer Using AI: A Research Paper,” *Int. J. Res. Appl. Sci. Eng. Technol.*, vol. 12, no. 5, pp. 4082–4089, May 2024, doi: 10.22214/ijraset.2024.62505.

[7] S. K. Jagatheesaperumal *et al.*, “An IoT-Based Framework for Personalized Health Assessment and Recommendations Using Machine Learning,” *Mathematics*, vol. 11, no. 12, Jun. 2023, doi: 10.3390/math11122758.

[8] A. H. Hussein, “Internet of Things (IOT): Research Challenges and Future Applications,” 2019. [Online]. Available: www.ijacsa.thesai.org

[9] P. Ponnampalam *et al.*, “RFID based Smart Healthcare System: A Survey Analysis”, [Online]. Available: https://www.researchgate.net/publication/347994472

[10] Y. Yao, L. Song, and J. Ye, "Motion-to-bmi: Using motion sensors to predict the body mass index of smartphone users," *Sensors (Switzerland)*, vol. 20, no. 4, Feb. 2020, doi: 10.3390/s20041134.

[11] S. Zhang *et al.*, "Deep Learning in Human Activity Recognition with Wearable Sensors: A Review on Advances," Oct. 2021, [Online]. Available: http://arxiv.org/abs/2111.00418

[12] S. Ajami and A. Rajabzadeh, "Radio Frequency Identification (RFID) technology and patient safety," 2013.

[13] Q. Wu, P. Tang, and M. Yang, "Data processing platform design and algorithm research of wearable sports physiological parameters detection based on medical internet of things," *Meas. J. Int. Meas. Confed.*, vol. 165, Dec. 2020, doi: 10.1016/j.measurement.2020.108172.

[14] H. Wackerhage and B. J. Schoenfeld, "Personalized , Evidence - Informed Training Plans and Exercise Prescriptions for Performance , Fitness and Health," *Sport. Med.*, vol. 51, no. 9, pp. 1805–1813, 2021, doi: 10.1007/s40279-021-01495-w.

[15] N. N. Thilakarathne, M. K. Kagita, and D. T. R. Gadekallu, "The Role of the Internet of Things in Health Care: A Systematic and Comprehensive Study," *Int. J. Eng. Manag. Res.*, vol. 10, no. 4, pp. 145–159, Aug. 2020, doi: 10.31033/ijemr.10.4.22.

[16] B. A. Franklin *et al.*, "Exercise-Related Acute Cardiovascular Events and Potential Deleterious Adaptations Following Long-Term Exercise Training: Placing the Risks into Perspective-An Update: A Scientific Statement from the American Heart Association," *Circulation*, vol. 141, no. 13. Lippincott Williams and Wilkins, pp. E705–E736, Mar. 31, 2020. doi: 10.1161/CIR.0000000000000749.

[17] A. Brezulianu *et al.*, "IoT based heart activity monitoring using inductive sensors," *Sensors (Switzerland)*, vol. 19, no. 15, Aug. 2019, doi: 10.3390/s19153284.

[18] B. M. Mahmmod *et al.*, "Patient Monitoring System Based on Internet of Things: A Review and Related Challenges with Open Research Issues," *IEEE Access*. Institute of Electrical and Electronics Engineers Inc., 2024. doi: 10.1109/ACCESS.2024.3455900.

[19] X. Liu *et al.*, "Privacy-Preserving Personalized Fitness Recommender System (P3FitRec): A Multi-level Deep Learning Approach," Mar. 2022, [Online]. Available: http://arxiv.org/abs/2203.12200

[20] A. Verma, G. Agarwal, A. K. Gupta, V. Kumar, and S. Singh, "An adaptive secure internet of things and cloud based disease classification strategy for smart healthcare industry," *Wirel. Networks*, Jan. 2024, doi: 10.1007/s11276-024-03783-5.

[21] Q. Chen and S. Lee, "A machine learning approach to predict customer usage of a home workout platform," *Appl. Sci.*, vol. 11, no. 21, Nov. 2021, doi: 10.3390/app11219927.

[22] S. Vairavasundaram *et al.*, "Dynamic Physical Activity Recommendation Delivered through a Mobile Fitness App: A Deep Learning Approach," *Axioms*, vol. 11, no. 7, Jul. 2022, doi: 10.3390/axioms11070346.

[23] U. Bhimavarapu, M. Sreedevi, N. Chintalapudi, and G. Battineni, "Physical Activity Recommendation System Based on Deep Learning to Prevent Respiratory Diseases," *Computers*, vol. 11, no. 10, Oct. 2022, doi: 10.3390/computers11100150.

[24] A. Hoelzemann and K. Van Laerhoven, "A Matter of Annotation: An Empirical Study on In Situ and Self-Recall Activity Annotations from Wearable Sensors," May 2023, doi: 10.3389/fcomp.2024.1379788.

[25] Z. Zheng and Y. Liu, "Design of Cloud Storage-Oriented Sports Physical Fitness Monitoring System," *Comput. Intell. Neurosci.*, vol. 2022, 2022, doi: 10.1155/2022/1889381.

[26] A. Ç. Seçkin, B. Ateş, and M. Seçkin, "Review on Wearable Technology in Sports: Concepts, Challenges and Opportunities," *Applied Sciences (Switzerland)*, vol. 13, no. 18. Multidisciplinary Digital Publishing Institute (MDPI), Sep. 01, 2023. doi: 10.3390/app131810399.

[27] J. Fang, V. C. S. Lee, H. Ji, and H. Wang, "Enhancing digital health services: A machine learning approach to personalized exercise goal setting," *Digit. Heal.*, vol. 10, Jan. 2024, doi: 10.1177/20552076241233247.

[28] S. Goundar, “Chapter 3-Research Methodology and Research Method.” [Online]. Available: https://www.researchgate.net/publication/333015026

[29] L. Breiman, “Random Forests,” 2001.

[30] “African Center of Excellence in Internet of Things (ACEIoT) MASTER OF SCIENCE IN INTERNET OF THINGS (IoT)-EMBEDDED COMPUTING SYSTEMS (ECS) Design of an IoT-Based Body Mass Index (BMI) Prediction Model.”

[31] O. Olalekan, L. M. Adesina, D. A. Ajala, and I. Yusuf, “Development of an Ultrasonic-based Digital Height Measurement System,” *J. Eng. Res. Innov. Sci. Dev.*, vol. 1, no. 2, pp. 49–54, Oct. 2023, doi: 10.61448/jerisd12237.

[32] M. Premalatha, N. Srinivas, S. Julakanti, B. Meghana, and C. Manju, “Automatic BMI Calculator Using Load Cell & Height Sensing,” 2025. [Online]. Available: www.ijrpr.com

[33] M. El Qibthiyah, “Design Of Monitoring System of Height, Weight and Body Mass Index Using Android-Based Nodemcu ESP8266,” vol. 12, no. 1, pp. 20–25, 2022.

[34] H. S. Saad, J. F. W. Zaki, and M. M. Abdelsalam, “Employing of machine learning and wearable devices in healthcare system: tasks and challenges,” *Neural Computing and Applications*. Springer Science and Business Media Deutschland GmbH, Oct. 01, 2024. doi: 10.1007/s00521-024-10197-z.

[35] Components101, “HC-SR04 Ultrasonic Sensor: Working, Pin Diagram, Description & Datasheet,” *Accessed date*, Feb. 27, 2025.

[36] “AVIA SEMICONDUCTOR 24-Bit Analog-to-Digital Converter (ADC) for Weigh Scales DESCRIPTION.”

[37] O. S. Al-Dahiree *et al.*, “Design and Shape Optimization of Strain Gauge Load Cell for Axial Force Measurement for Test Benches,” *Sensors*, vol. 22, no. 19, Oct. 2022, doi: 10.3390/s22197508.

[38] V. A. Kamble, V. D. Shinde, J. K. Kittur, and R. Scholar, “Overview of Load Cells,” *J. Mech. Mech. Eng.*, no. 6, [Online]. Available: www.matjournals.com

[39] Components101, “AD8232 ECG Module Pinout, Features & Datasheet,” *Accessed date*, Feb. 27, 2025.

[40] N. VAN Helleputte, C. Mora-Lopez, and C. VAN Hoof, “Design of CMOS Circuits for Electrophysiology,” *IEICE Trans. Electron.*, vol. E106.C, no. 10, pp. 506–515, Oct. 2023, doi: 10.1587/transele.2022CTI0003.

[41] K. Alfarhan, M. Yusoff Mashor, K. A. Alfarhan, and A. Rahman Mohd Saad, “A REVIEW OF WIRELESS ECG MONITORING SYSTEMS DESIGN,” 2016. [Online]. Available: http://www.iaemr.com

[42] “About This Guide.” [Online]. Available: https://www.espressif.com/en/subscribe.

[43] J. Kim, W. R. Lee, H. J. Chung, and S. W. Lee, “A low-power memory-in-pixel circuit for liquid crystal displays comprising low-temperature poly-silicon and oxide thin-film transistors,” *Electron.*, vol. 9, no. 11, pp. 1–10, Nov. 2020, doi: 10.3390/electronics9111958.

[44] F. M. Tzu, J. S. Chen, and S. H. Hsu, “Detection of electrical circuit in a thin-film-transistor liquid-crystal display using a hybrid optoelectronic apparatus: An array tester and automatic optical inspection,” *Micromachines*, vol. 12, no. 8, Aug. 2021, doi: 10.3390/mi12080964.

[45] H. Chen *et al.*, “Research of Liquid-Crystal Materials for a High-Performance FFS-TFT Display,” *Molecules*, vol. 28, no. 2, Jan. 2023, doi: 10.3390/molecules28020754.

[46] J. G. Hu, W. Z. Mei, J. Wu, J. W. Li, and D. M. Wang, “A Fully Integrated RFID Reader SoC,” *Micromachines*, vol. 14, no. 9, Sep. 2023, doi: 10.3390/mi14091691.

[47] W. Ji, L. Li, and W. Zhou, “Design and implementation of a RFID Reader/Router in RFID-WSN hybrid system,” *Futur. Internet*, vol. 10, no. 11, Nov. 2018, doi: 10.3390/fi10110106.

[48] E. Cantatore, T. C. T. Geuns, A. F. A. Gruijthuijsen, G. H. Gelinck, S. Drews, and D. M. De Leeuw, “A 13.56MHz RFID system based on organic transponders,” in *Digest of Technical Papers - IEEE International Solid-State Circuits Conference*, 2006. doi: 10.1109/isscc.2006.1696147.

[49] P. Zradziński, J. Karpowicz, and K. Gryz, "Electromagnetic energy absorption in a head approaching a radiofrequency identification (RFID) reader operating at 13.56 MHz in users of hearing implants versus non-users," *Sensors (Switzerland)*, vol. 19, no. 17, Sep. 2019, doi: 10.3390/s19173724.

[50] D. Singh, A. Thakur, A. Sandhu, and N. Priyank, "An Overview of IoT Hardware Development Platforms," *Int. J. Emerg. Technol.*, vol. 11, no. 5, pp. 155–163, 2020, [Online]. Available: www.researchtrend.net

APPENDIX

1. **System expenditure**

S/N	ITEMS	QUANTITY	UNIT COST (USD)	TOTAL COST (USD)
1	ESP 8266	1	15	15
2	Weight Sensor	1	17	17
3	Height Sensor	1	4	4
4	ECG Sensor	1	6	6
5	RFID Reader	1	19	19
6	LCD	1	12	12
7	Buzzer	1	1	1
8	Rechargeable Battery	1	13	13
9	Bread Board	3	7	21
10	enclosure	1	20	20
	Total			128

2. Codes for Machine learning

```python
main.py > ...


import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
import joblib

class SportRecommendationModel:
    def __init__(self):
        # Generate training data
        self.generate_dataset()
        self.prepare_model()

    def generate_dataset(self):
        # Generate 10,000 random data points
        np.random.seed(42)
        heart_rates = np.random.randint(70, 115, size=10000)
        ages = np.random.randint(18, 71, size=10000)
        bmis = np.round(np.random.uniform(18.5, 40.0, size=10000), 1)

        # Assign sport recommendations based on fitness factors
        sports = []
        for i in range(10000):
            hr, age, bmi = heart_rates[i], ages[i], bmis[i]
            if hr <= 80 and age <= 35 and bmi <= 25:
                sports.append('Swimming')
            elif hr <= 90 and age <= 45 and bmi <= 30:
                sports.append('Cycling')
```

```python
            elif hr <= 100 and age <= 55 and bmi <= 35:
                sports.append('Jogging')
            elif hr <= 105 and age <= 65 and bmi <= 40:
                sports.append('Brisk Walking')
            else:
                sports.append('Low-Impact Aerobics')

        # Create the DataFrame
        self.data = pd.DataFrame({
            'heart_rate': heart_rates,
            'age': ages,
            'bmi': bmis,
            'sport': sports
        })

    def prepare_model(self):
        # Separate features and target
        X = self.data[['heart_rate', 'age', 'bmi']]
        y = self.data['sport']

        # Split the data
        X_train, X_test, y_train, y_test = train_test_split(
            X, y, test_size=0.2, random_state=42, stratify=y
        )

        # Scale features
        self.scaler = StandardScaler()
```

```python
        X_train_scaled = self.scaler.fit_transform(X_train)

        # Train the model
        self.model = RandomForestClassifier(
            n_estimators=100,
            random_state=42,
            class_weight='balanced'
        )
        self.model.fit(X_train_scaled, y_train)

    def recommend_sport(self, heart_rate, age, bmi):
        """
        Recommend a sport based on user input

        Parameters:
        - heart_rate (int): User's heart rate
        - age (int): User's age
        - bmi (float): User's Body Mass Index

        Returns:
        - str: Recommended sport
        """
        # Prepare input data
        input_data = np.array([[heart_rate, age, bmi]])

        # Scale the input
        input_scaled = self.scaler.transform(input_data)
```

```python

        # Predict sport
        prediction = self.model.predict(input_scaled)

        return prediction[0]

    def save_model(self, model_filename='sport_recommendation_model.joblib', scaler_filename='scaler.joblib'):
        """
        Save the trained model and scaler to disk.
        """
        joblib.dump(self.model, model_filename)
        joblib.dump(self.scaler, scaler_filename)

    def interactive_test(self):
        """
        Interactive user interface for sport recommendation
        """
        print("\n=== Sport Recommendation Model ===")
        print("Please enter your fitness details:")

        while True:
            try:
                # Get user input
                heart_rate = int(input("Heart Rate (70-115 bpm): "))
                age = int(input("Age (18-70 years): "))
                bmi = float(input("BMI (18.5-40.0): "))

                # Validate inputs
```

```python
                    if not (70 <= heart_rate <= 115):
                        print("Heart rate must be between 70 and 115 bpm.")
                        continue

                    if not (18 <= age <= 70):
                        print("Age must be between 18 and 70 years.")
                        continue

                    if not (18.5 <= bmi <= 40.0):
                        print("BMI must be between 18.5 and 40.0.")
                        continue

                    # Get recommendation
                    recommendation = self.recommend_sport(heart_rate, age, bmi)

                    print(f"\n🏆 Recommended Sport: {recommendation}")

                    # Provide additional context
                    print("\nRecommendation Insights:")
                    print(f"- Heart Rate: {heart_rate} bpm")
                    print(f"- Age: {age} years")
                    print(f"- BMI: {bmi}")

                    # Ask if user wants to continue
                    another = input("\nWould you like to try another recommendation? (yes/no): ").lower()
                    if another != 'yes':
                        break
```

```python

                except ValueError:
                    print("Invalid input. Please enter numeric values.")

            print("\nThank you for using the Sport Recommendation Model!")

# Main execution
if __name__ == "__main__":
    # Create and run the model
    sport_model = SportRecommendationModel()
    sport_model.save_model()  # Save the model after creation
    sport_model.interactive_test()
```