IoT ML Driven Holistic Health Monitoring and Fitness Assessment Empowering Proactive Wellbeing Management

Sachin Mishra
Dept. of Computer Science and Engineering
Government Engineering College, Raipur
Raipur, Chhattisgarh, India
007mishrasachinmishra@gmail.com

Anurag Singh
Dept. of Electronics & Communication Engineering
International Institute of Information Technology
Naya Raipur, Chhattisgarh, India
anurag@iiitnr.edu.in

Abstract— **In recent years, significant advancements in the area of non-invasive and wearable technology have paved the way for widespread applications of personalized and remote health monitoring. Health monitoring enables proactive management of one's well-being, and enhances overall health outcomes. With the advent of such technologies there are lots of platforms developed. But such platforms are not successful in providing the followings: 1) the ability to monitor all major health vitals in one unified application, & 2) the provision of a holistic health score derived from these non-invasive vitals for fitness measurement. In response, this paper presents a novel solution featuring: 1) An IoT-ML enabled platform for self-monitoring of important health vitals, and 2) A fitness assessment score derived through ML algorithm using the health vitals of a person. By integrating data on various health parameters including heart rate, blood oxygen levels, and sleep patterns, advanced machine learning models are developed to analyze this data and predict the fitness score that accurately reflects an individual's overall health and fitness level. The performance of the proposed estimation model is evaluated using R^2 and mean square error (MSE) and the best value is achieved using the XGBoost regressor of values 0.967 and 0.0033. This solution empowers individuals to take control of their well-being and improve their overall quality of life. Overall, the integration of non-invasive methods and IoT sensors for health vitals monitoring and fitness assessment presents a novel approach with significant potential to revolutionize health care. By empowering individuals with real-time insights and a comprehensive fitness score, this solution facilitates informed decision-making and enables individuals to proactively manage their health and well-being, ultimately enhancing their overall quality of life.**

Keywords— IoT, ML, health monitoring, fitness assessment, wearable technology, remote monitoring, proactive wellbeing, personalized health, non-invasive, XGBoost regressor.

I. INTRODUCTION

The convergence of IoT sensors and advanced health monitoring technologies has ushered in a new era of remote health assessment and fitness tracking by using some means of portable health monitoring system which is low-cost as well as easy to use [1]. The smart devices have capabilities to monitor the vital signs of a person on the go. By integrating different healthcare sensors on an IoT platform, individuals can have access to non-invasive vital signs that can be used to derive a comprehensive fitness score of the person on the developed mobile application. However, these platforms fail to monitor major health vitals comprehensively.

PPG-based IoT sensors provide real-time insights into various health metrics, including heart rate, blood oxygen levels, sleep patterns, and stress levels. These sensors leverage light-based technology to track clinical variables, such as temperature, pressure, pulse, glucose, and respiratory issues including changes in blood volume [2] offering a non-intrusive and convenient means of monitoring vital signs. It empowers individuals with the ability to monitor their as well as their loved one's health remotely. Such a health monitoring system also shows patients' body temperature, heartbeat, and other health vitals tracked live with timestamps over the Internet [3].

This work aims to develop an innovative solution that utilizes non-invasive methods by using IoT sensors to collect diverse health vitals in one place and monitor the health for early detection and intervention for potential health issues. Furthermore, it also aims to derive a comprehensive fitness score using a machine learning algorithm. The proposed solution gathers data on various health metrics including heart rate, blood oxygen levels, physical movement, and sleeping patterns. Advanced machine learning models are developed to analyze the collected data and derive a fitness score that accurately reflects an individual's overall health and fitness level. The efficiency of the proposed monitoring system is evaluated and compared to the previous traditional health monitoring systems. The rest of the paper is organized as follows. Section II outlines the literature review. Section III shows the Material and the discussion of the proposed Method and Section IV gives the results and discussion and V gives conclusion.

II. RELATED WORK

Das et al. [4] proposed a health monitoring device which monitors body temperature, Heartbeat, Oxygen level, acceleration and real-time electrocardiography (ECG) signal. They have used LM35 temperature sensor, ADXL345 and MAX30102 sensor integrated in Raspberry Pi and Thing speak server. (2021) koulouris et al. [5] they proposed an IoT and AR-enabled platform for healthcare; it combines augmented reality and IoT on mobile devices to promote physical activity through serious games, monitoring users' health, and cognitive status.

Nookhao et al. [6] discussed about a method that uses an Arduino board to connect the temperature sensor and pulse (Easy pulse V 1.1) sensor which shows the output on LCD display and at the same time sends them to thing Speak IoT platform in real-time via Wi-Fi. The proposed system

2024 IEEE Students Conference on Engineering and Systems (SCES) | 979-8-3503-7471-1/24/$31.00 ©2024 IEEE | DOI: 10.1109/SCES61914.2024.10652387

monitors two vital signs, the body temperature and the heartbeat.(2020)

Tirkey et al. [7] proposed a model that measures the level of glucose in the body using the transmission of light. Li-Fi technology is used and as it is faster and efficient than the traditional Wi-Fi systems. (2020)

Miah et al. [8] had proposed an offline system by using Arduino-UNO connected with a heartbeat sensor TCRT5000 and body temperature sensor LM35. The proposed model monitor's the continuous Heartrate and Body temperature of a person using Arduino-Uno and android devices. (2015)

Reddy et al. [9] proposed an IOT based health monitor system which only measures body temperature and heartbeat. They have used DS18B20 sensor and SEN-11574 sensor with Raspberry Pi. They have developed an android application to show the data with the facility of emergency call and text message for given numbers. (2017)

Kumar et al. [10] proposed a method which monitors body temperature, respiratory rate, heart beats and acceleration by using IOT sensors in Raspberry pi which is connected to the internet and hosted on a website. It can be monitored on a computer screen from anywhere. (2016)

Swathi at al. [11] proposed a health care device that monitors glucose, pulse rate and BMI of a patient using a spectral sensor that measures IR and transmits it to a photo-diode. They have used pulse sensors to monitor pulse rate in a mobile app.

III. MATERIALS AND METHODS

The proposed approach involves two phases: the data acquisition phase and the ML model creation phase for fitness tracking/estimation. Machine Learning models are then trained which are then validated and tested using the recorded data to produce a fitness score. Amalgamation of Internet of Things and Machine Learning for Smart Healthcare Applications are the future advancement in medical technology [14]. A brief description of the required hardware components is given below and their hardware implementation is discussed for data collection using Arduino.

A. Data acquisition

The following components were used for data acquisition:

- Heart Rate and Oxi-meter sensor: Max30100 is a sensor for measuring heart rate and blood oxygen levels. It gives SpO2 in percentage and pulse rate in numerical integer value. It measures the heart rate of an individual after every 1 minute.

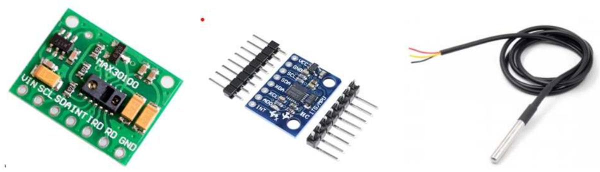

Fig. 1. Hardware Components (i) Max30100 oximeter sensor (ii) Accelerometer sensor (iii) Temperature Sensor

- Accelerometer sensor: MPU6050 is a three-axis accelerometer sensor used for measuring acceleration and Physical movement in X, Y, and Z directions as shown in Fig.1 Hardware Components.
- Temperature sensor: DS18B20 is a digital temperature sensor with a unique 1-Wire interface which provides accurate temperature readings.

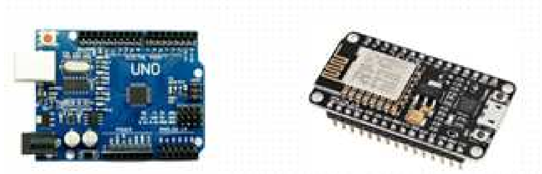

Fig. 2. Arduino-Uno and Node MCU

- Arduino board: An Arduino board consists of a micro-controller and a software development environment used for writing, compiling, and uploading code to the microcontroller.
- Node MCU: It consists of a micro-controller with built-in Wi-Fi functionality.

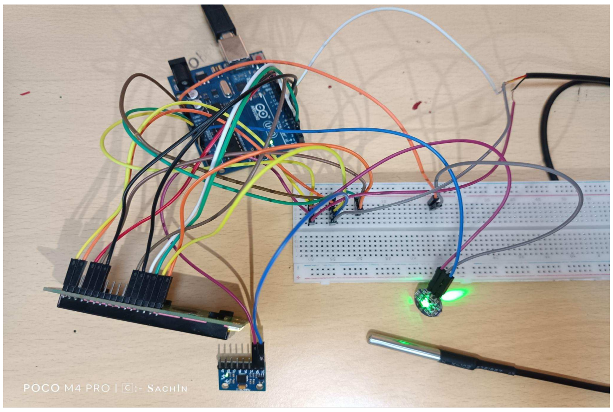

Fig. 3. Amalgamated hardware IoT Sensors

- Arduino IDE: The coding part of Arduino boards are programmed in a software application that is a development work-space referred to as Arduino IDE (Integrated Development Environment).

The hardware components are integrated into an Arduino-uno board using a breadboard and jumper wires as shown in Fig.3 Amalgamated Hardware sensors. The physiological data from the Heartbeat sensor, Oxi-meter, Accelerometer, and temperature sensor is displayed on an LCD (Liquid crystal display) screen and stored on the server/computer by interfacing the Arduino ports.

B. Proposed Methodology

This work aims to present a methodology for developing an IoT-enabled health monitoring platform using non-invasive technology and machine learning algorithms. In the previous section, we demonstrated the data acquisition process, for testing the ML model in real-time data. We have trained the ML models on a similar existing database, called the SaYoPillow database, and tested/validated it on our recorded database. In this way, we are trying to properly train the ML models with the SaYoPillow dataset and then testing on the practically recorded data. ML for taking intelligent decisions and depends on the cloud-type infrastructure for remote storage and computing [15] for which firebase is incorporated. These ML algorithms extract relevant features and are trained using different regression models to predict the fitness score. The trained model is deployed for proactive health monitoring of individuals through a mobile application.

Layer 1: Collection of Health vitals.

- IoT-based sensors measuring Heart rate, Oxygen level, and Acceleration.
- Temperature: A method for measuring body temperature using thermal sensors.

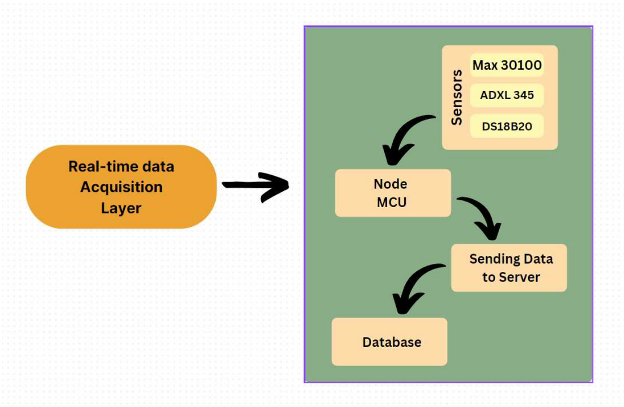

Fig. 4. Data Acquisition

We have considered the IoT-based sensors for recording and storing the physiological data. The real-time data is collected from the aforementioned various IoT sensors. The approach has amalgamated the MAX30100, MPU6050, and DS18B20 to an Arduino-Uno to record the heart rate, Oxygen level, and state of the body either rest or in motion (accelerating) to check the limb movement and body temperature. This data is sent to a database server using Node MCU. The developed setup enabled remote recording of the physiological data stored in the Database. This would also fetch the data for further analysis in machine learning algorithms.

Layer 2: Data processing with Machine learning model.

The model is derived from the forward propagation of data in the machine learning model, the data used in training the model is SaYoPillow which has major health vitals that converge into a comprehensive fitness assessment score.

2.1 Dataset Description

The dataset for this research paper focuses on assessing physiological fitness using key health indicators. In the SaYoPillow database, various crucial health parameters are interconnected. These include breathing rate, body temperature, limb movement, sleep hours, blood oxygen level, and stress levels. Stress levels are categorized on a scale from 0 (normal/low) to 4 (high), providing a comprehensive overview [13].

As the stress level is considered as the target feature for stress detection and from Fig.7 Co-relation Matrix. The correlation matrix has strongly positive or strongly negative correlations with the health vitals present in the data set. As per the general intuition, we have considered stress level inversely proportional to the target feature which is the fitness score in the data set. The fitness score is represented in the range of percentages.

$$\textit{Fitness Score} \propto 1/\textit{stress} \qquad (1)$$

The feature matrix used for training the ML models is of dimension [7 X 630]. Since the original dataset has 6 matrices and the 7[th] feature is derived by using the above fitness score (1).

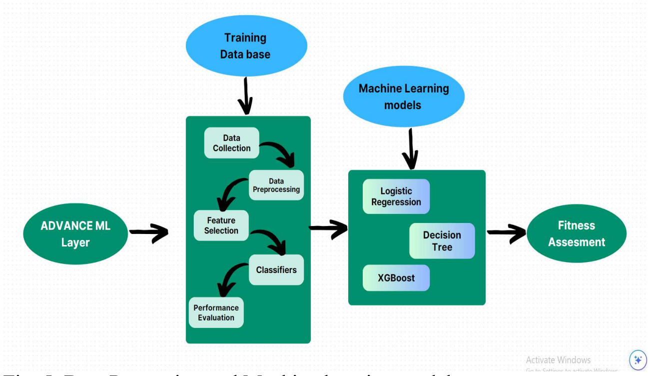

Fig. 5. Data Processing and Machine learning models

2.2 Training process

The Data is pre-processed including feature scaling and feature selection (extracting of major features) as shown in the Fig. 5 Data Processing and ML models. Then the classified features are scaled and a target feature (fitness score) is selected from data. The data is divided into X-train, X-test, y-train, and y-test to perform feature scaling in the data and used in different machine learning models layer by layer.

2.2.1 Feature Selection

Correlation Matrix: The correlation matrix of SaYoPillow represents correlation among different health vitals to extract the important vitals as shown in Fig.6 Correlation Matrix. In this approach the fitness assessment score is comprehensively generated considering all the health vitals as correlated in the matrix, using a machine learning algorithm.

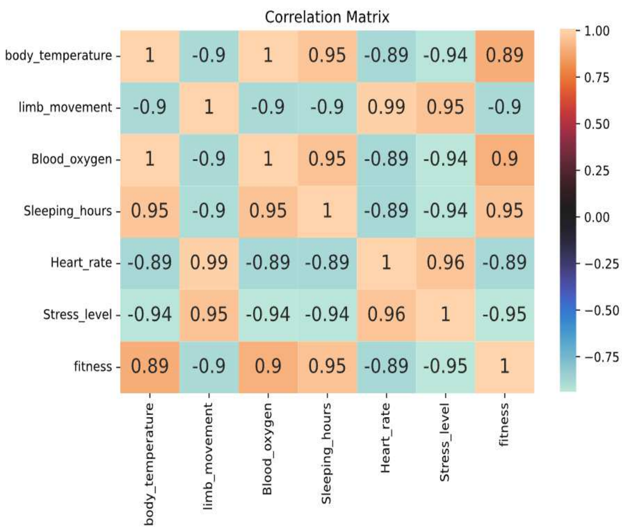

Fig. 6. *Co-relation Matrix*

2.3 Testing Dataset

The approach utilizes our collected data for testing purposes. This data is acquired from 10 people using the developed hardware, which gathers information on heart rate, blood oxygen levels, limb movement, and body temperature as given in TABLE I. Additionally, two additional features, sleep hours and stress levels, are provided through the developed mobile application. Here, P1 to P10 are people, and SpO2 is oxygen saturation levels.

TABLE I. CLINICALLY COLLECTED DATA OF 10 PEOPLE

S. No	*Body temperature*	*Limb movement*	*Sp O2*	*Heart rate*	*Sleep hours*
P1	91.84	16.6	89.84	74.2	4
P2	91.552	15.88	89.552	72.76	5
P3	96	10	95	60	9
P4	90.768	13.92	88.768	68.84	3
P5	97.872	6.496	96.248	53.12	9
P6	95.376	9.376	94.064	58.44	7
P7	97.2	5.6	95.8	52	8
P8	99	8	97	55	10
P9	96.168	4.224	95.112	50.28	7
P10	95.104	9.104	93.656	57.76	7

2.4 Machine learning model

This paper aims to use the most appropriate machine learning models after feature scaling, the following section includes the machine learning regression models used to predict the Fitness score derived from selected health vitals with very little error. The models are as follows.

Linear Regression: It is used in predicting a target value because there is a linear relationship between the input features (predictor variables) and the target variable. The linear regression model as shown in Fig.7 assumes a linear relationship between the variables.

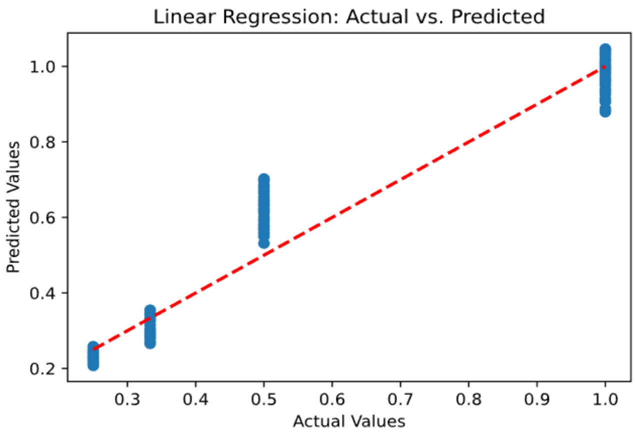

Fig. 7. Scatter plot with regression line

XGBoost regressor: It is an ensemble learning method that combines multiple weak learners (usually decision trees) to create a more powerful predictive model. Increases the robustness and feature importance then the decision tree. XGBoost improves the learning rate of models, which has lesser mean square error in training and testing.

Decision tree regressor: Decision tree captures the non-linear relationships between the health vitals and the target variable as shown in Fig. 8. The Decision trees (DT) are robust to outliers and can handle them better than Linear Regression. Also, the important features, helping to identify the most relevant predictors for the target variable.

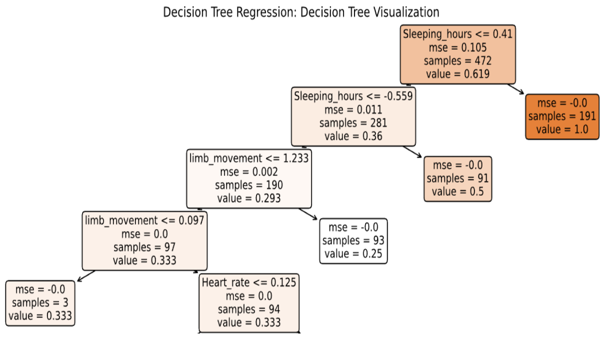

Fig. 8. Decision tree visualization

Layer 3: Integration of model with FITNESS CHECK App

The developed model is to be integrated with an android app. It lies in the service layer for the user which has integrated the developed advanced machine learning model, designed to monitor the health vitals and fitness score of users as shown in Fig. 9.

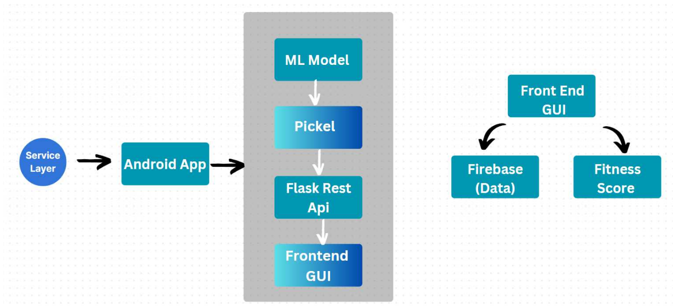

Fig. 9. Integration of Model with App

The developed model is integrated with mobile applications by using the Flask API (Application Programing Interface). The Machine learning model is pickled by using Python code referred to as the pickling process. The process of Pickling is a serialization technique in Python that allows conversion of a Python object, such as a trained machine learning model, into a byte stream that can be saved to a file or sent over a network using pipe-lining. This step is very important to use the machine learning model from ML model weighted file to use in an application. The model is then implemented into a mobile application as a API call and served in the backend of the application which takes a NumPy array of data and derives a fitness score from the ML model.

This work stands with all major health vitals integrated unified in an application and the comparison of existing works is shown in TABLE II.

TABLE II. COMPARISION TABLE OF EXISTING STUDIES WITH HEALTH VITALS VS PROPOSED SOLUTION.

Reference No.	Dataset	Heart rate	Sp O2	Body Temp	Sleep hours	Limb	Accuracy
Ref 5	Private	✔		✔		✔	Nan
Ref 6	Private	✔		✔			Nan
Ref 7	Private	✔		✔			Nan
Ref 8	Private	✔					Nan
Ref 9	Private	✔		✔			Nan
Ref 10	Private	✔	✔	✔		✔	Nan
Proposed solution	SaYo Pillow	✔	✔	✔	✔	✔	96.7 %

IV. RESULT AND DISCUSSION

In this research, three distinct machine learning - regression models are used to estimate the stress level and subsequent fitness score of individuals as shown in TABLE III. The comparison was conducted among three types of regression models: Linear regression, Decision tree Regressor, and XGBoost Regressor.

TABLE III. COMPARISION BETWEEN ML MODEL'S R^2 AND MSE

S. No	***Machine Learning Model***	**R^2 *Score***	***MSE***
1	Linear regression	0.9481	0.0053
2	Decision tree Regressor	0.9574	0.0426
3	XGBoost Regressor	0.9674	0.0033

The vital signs such as heart rate, blood oxygen level, body temperature, and physical movement were made visible through the designated buttons in the application interface. These vital signs were obtained from hardware integration utilizing IoT sensors. The user places fingers on the sensors, and the integrated hardware measured and stored the vitals in a database (used cloud-based storage), which functioned as a cloud for the ML model data

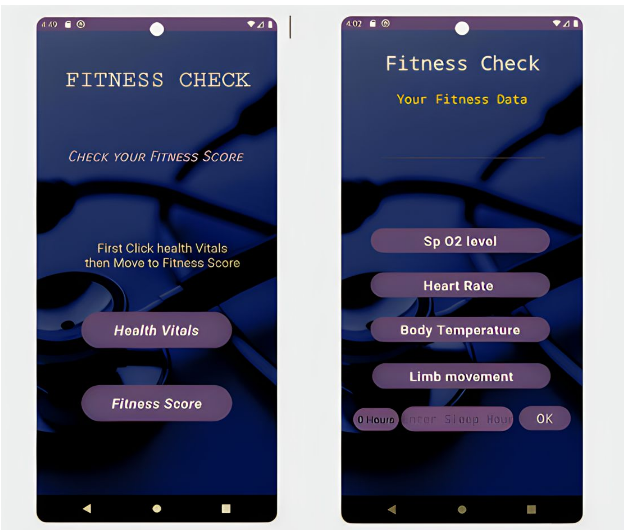

Fig. 10. Health Monitoring App user Interface

retrieval.

The user manually entered their sleep hours into the application. The application interface includes a dedicated Fitness score button accessible only after the hardware input, shown above in the Fig. 10. This data was then fed into the developed machine learning model to derive the fitness score of the user. The fitness score was represented within a percentage range, illustrating varying degrees of fitness: The Fitness is represented in the range of percentages showing (0%- Very Unfit with high-risk health issues, 25% - moderately unfit with health issues, 50% - moderately fit, 75% - Fit, 100%- Very Fit). The fitness score derived comprehensively processing the health vitals is shown below in Fig. 11.

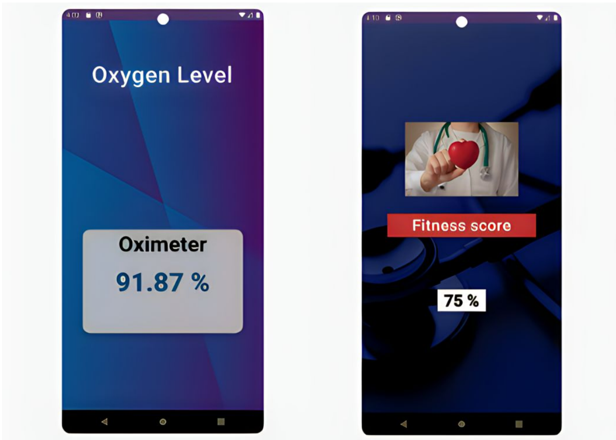

Fig. 11. Fitness score assessment with health vitals

V. CONCLUSION

A new era of remote health evaluation and fitness tracking has begun as a result of the convergence of IoT-enabled devices for health monitoring. This study offers a novel way for gathering non-invasive health data from Internet of Things devices and generating a full fitness score. The suggested method tries to correctly portray a person's overall health and fitness level by analyzing data on numerous health parameters. People who have access to real-time insights can proactively manage their health and choose their exercise regimens with knowledge. The possibility for early health issue diagnosis and the incentive to adopt healthy habits demonstrate the transformative impact of technology-driven healthcare, which promises a healthier and more knowledgeable future for all.

The future scope of this research extends to the incorporation of additional health metrics into the existing IoT-enabled system. The proactive wellness management features have to be incorporated to provide different aspects of statistical notification regarding the changes in an individual's health vitals. The development of a multi-modal approach catering to different age groups, such as infants, youth, and athletes, will further enhance the system's versatility. Personalized recommendations based on individual health data will be implemented to guide users towards better fitness routines. Long-term progress tracking will enable users to monitor their health journey over time. These advancements will revolutionize remote health monitoring, fostering a more proactive and personalized approach to overall well-being.

ACKNOWLEDGMENT

The author would like to thank supervisor, Associate Professor Dr. Anurag Singh for his insightful ideas, invaluable discussions, and encouragement in finishing this project. The author would also like to thank all the people that worked along with him in IIIT, Naya-Raipur with their patience and openness they created an enjoyable working environment.

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