Personalized Cardiovascular System Using Machine Learning and IOT

Abstract*— cardiovascular diseases (CVDs) remain a leading cause of mortality worldwide, with millions of deaths occurring annually due to heart-related conditions. Major risk factors include age, gender, family history, smoking, poor diet, high blood pressure, diabetes, and lack of physical activity. Traditional diagnostic methods rely on periodic clinical assessments, which may not provide timely interventions for at-risk individuals. To address these limitations, this research proposes a Heart Disease Prevention and Monitoring System that integrates machine learning (ML), real-time health tracking, and IoT-based monitoring to enhance cardiovascular risk assessment and prevention. The system utilizes patient medical history and real-time physiological data collected through IoT health bands to predict heart disease probability. A dataset from the Framingham Heart Study is used to train machine learning models, specifically Logistic Regression, K-Nearest Neighbors (KNN), and Random Forest Classifier, with KNN. Based on the predicted risk level, the system provides personalized dietary and exercise recommendations tailored to individual health conditions. Additionally, real-time monitoring of heart rate, body temperature, and environmental factors such as humidity and temperature ensures continuous assessment and timely alerts for at-risk individuals. By integrating AI-driven prediction, adaptive intervention strategies, and IoT-based health monitoring, this system offers a proactive and personalized approach to cardiovascular disease prevention, ultimately improving early detection, patient outcomes, and quality of life.

Keywords - **Heart Disease Prediction, Machine Learning, Preventive Healthcare, Real-Time Monitoring, Personalized Health Recommendations, AI in Healthcare, Cardiovascular Risk Assessment, Wearable Health Technology, Health Data Analytics, Medical Decision Support Systems.**

I. INTRODUCTION

Cardiovascular diseases remain one of the major causes of mortality in the world, responsible for millions of deaths each year, approximately 17.9 million deaths occurred due to CVD worldwide in 2016, accounting for 31% of all deaths worldwide [1]. Cardiovascular diseases (CVDs) encompass a range of conditions. Cloud computing, deep learning, artificial intelligence, big data, and machine learning are all used in mobile health (mHealth) nowadays [2]. Machine learning algorithms can help in disease diagnosis by analyzing data and predicting the underlying causes of an illness by employing disease-causing variables from electronic health records [3] . While elderly individuals are commonly affected, heart disease can also affect younger patients. In the United States, heart disease accounts for one out of every nine deaths [4]. By using the Framingham heart study and a questionnaire a prediction is made whether the patient can have a heart disease or not. To predict this, we use 14 medical attributes of a patient and classify him if the patient is likely to have a heart disease. These medical attributes are trained under three algorithms: Logistic regression, KNN and Random Forest Classifier. Most efficient of these algorithms is KNN which gives us the accuracy of 88.52% finally we classify patients that are at risk of getting a heart disease or not and also this method was found out to be cost efficient.

The main factors that put an individual at risk for cardiovascular disease were gender, smoking, age, family history, poor diet, lipids, lack of physical activity, high blood pressure, weight gain, and drinking alcohol. High blood pressure and diabetes are two examples of things that can be passed down and a person more likely to get cardiovascular disease. Some of the other things that raise the risk are being inactive, being overweight, not eating well, having back, neck, and shoulder pain, being very tired, and having a fast heartbeat Traditional diagnostic methods often rely on periodic clinical assessment which comes with a variety of problems, they might not be able to provide timely interventions to at risk individuals also might not fit into the lifestyle and might not be convenient. With advancements in machine learning (ML) and artificial intelligence (AI), predictive models have emerged as effective tools for assessing cardiovascular risk. These models utilize patient health data, lifestyle factors, and real-time physiological readings to estimate the probability of developing heart disease. By integrating data-driven insights with personalized recommendations, AI-driven heart disease prevention and monitoring systems can improve early diagnosis and enable proactive healthcare management.

Machine learning, as highlighted by Ramesh et al [5]., enjoys major transformative capability within the healthcare industry. Its outstanding advancements can be ascribed to its exceptional data processing abilities, which are far superior to those of humans.

This research aims to develop a Heart Disease Prevention and Monitoring System that leverages machine learning algorithms, real-time health tracking, and personalized intervention strategies**.** The system will not only predict an individual's likelihood of developing heart disease but also provide tailored dietary and exercise recommendations based on their health conditions. By incorporating dynamic and adaptive health assessments, this approach enhances traditional risk evaluation methods and promotes preventive healthcare solutions**.** Given the significance of accurate and timely diagnosis and treatment in healthcare, further efforts are required to bridge existing gaps and create intelligent systems for health monitoring [6]. A dataset was selected from the Framingham heart study with patient's medical history and attributes. By using this dataset, we predict whether the patient can have a heart disease or not. To predict this, we use 15 medical attributes of a patient and classify him if the patient is likely to have a heart disease. These medical attributes are trained under three algorithms: Logistic regression, KNN and Random Forest Classifier. RF is a machine-learning approach that builds several decision trees on training data sets to generate a classification model. This algorithm decides on a tree based on most selections, which offers great accuracy when working with huge data sets [7]. Most efficient of these algorithms is KNN which gives us the accuracy of 88.52%. ML algorithms have shown great promise in improving diagnostic accuracy across a range of medical conditions. By training on large datasets, ML models can learn to identify subtle patterns and indicators of diseases [8] Finally, we classify patients that are at risk of getting a heart disease and determine a probability. Using this probability and various other metrics a diet plan and an exercise regimen is given to the patient according to their probability and risk level. Also, we use an IOT health band to monitor the patient's body temperature, heart rate also environmental factors such as temperature and humidity to constantly monitor the user and their environment to determine when they are at risk.

II. LITERATURE REVIEW

The American College of Cardiology/American Heart Association recommends at least 30 minutes of moderate (albeit at 50–70% of the predicted maximal heart rate) on most days of the week to reduce the risk of cardiovascular events [9]. Higher quantities are optimal in the young patient. Hypertensive patients, type 2 diabetes, metabolic syndrome, stable cardiovascular disease, myocardial infarction and congestive heart failure all are improved by training within the exercise environment compared to untrained individuals.

Jindal and others [10] compared Logistic Regression, K-Nearest Neighbors (KNN), and Random Forest machine learning algorithms for heart disease-risk patient classification. KNN was found to work best with an accuracy rate of 88.52%.

Chowdary et al. [11] had utilised the techniques of ensemble learning using various models to achieve higher predictive accuracy. The experimental evaluation demonstrated the superiority of the ensemble classifiers to the stand-alone models.

Jagatheesaperumal et al. [12] created an IoT-enabled framework that uses the real-time health data from wearables to drive cardiovascular risk estimation. The authors used Random Forest, CatBoost, and Logistic Regression and found the CatBoost classifier to be 99% accurate. The framework also provides personalized diet and physical exercise recommendations and is therefore an improved approach to the prevention of heart disease.

Ogunpola et al. [13] were concerned with the imbalance problem of heart disease prediction using XGBoost, CNNs, and Gradient Boosting. In achieving an accuracy rate of 98.50%, their work proved the need for hyperparameter tuning for improved predictive capability.

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Ahmed et al [14]. examined the employment of data mining techniques such as Naïve Bayes, Decision Trees, and Support Vector Machines (SVM) to predict heart disease. They cited the cost-effectiveness of machine learning models in reducing misdiagnosis and unwanted medical tests.

Nayeem et al. [15] compared KNN, Naïve Bayes, and Random Forest on a large Kaggle dataset and found that the best-performing model was the Random Forest model with a (95.63%). Their work identified feature selection as critical to optimizing model performance.

. Nashif et al. [16] proposed an IoT-based framework using machine learning to continuously monitor cardiovascular conditions and patients in real-time in 2018. Their model was as accurate as 97.53% using SVM and also introduced an IoT system for monitoring patients remotely.

Islam et al. [17] present the Internet of Things (IoT) in the healthcare environment, emphasizing its capability to facilitate real-time monitoring, do remote diagnosis, and also do data-driven decision making. The paper classifies large-scale healthcare applications of the IoT system, including remote health monitoring and patient tracking this might cause some ethical issues, specifically data privacy, security, and interoperability. The authors state the fact that in spite of these minor details it has tremendous potential, effective implementation of the IoT hinges on resolving these technical and ethical challenges.

Finally, Srinivasan et al [18] examined an active learning machine method for the prediction of cardiovascular diseases with eight ML classifiers. Their paper reported that the best accuracy of 98.7% was obtained by Learning Vector Quantization, greater than conventional models.

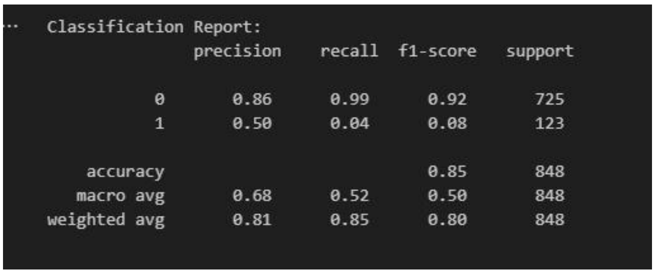
III. METHODOLOGY

The initial step is to present the user with a 15-question survey The survey incorporates age, gender, smoking, alcohol consumption, diabetes, hypertension, cholesterol, blood pressure, body mass index (BMI), and heart rate, among others. Upon receiving the input from the user, the system preprocesses the data by replacing missing values, normalizing numeric values, and encoding categorical values. The Framingham Risk Score (FRS) is then estimated by applying a regression-based formula to estimate the 10-year risk of developing cardiovascular disease. The formula utilizes weighted risk factors and estimates the risk using baseline survival rates. For improved accuracy, the system is trained on the Framingham dataset using machine learning using Logistic Regression, Random Forest, K-Nearest Neighbors (KNN), and XGBoost with 80% train and 20% test partition. The best model is then deployed to further enhance the estimation of risk beyond standard FRS estimates. The patients are then stratified on the basis of the estimated risk into three categories: Low Risk (≤10%), Moderate Risk (11–30%), and High Risk (>30%), and personalized advice on lifestyle modification, monitoring, and medication is given. Moreover, for the high-risk patients, the wearables Internet of Things (IoT) devices such as the smartwatch are interfaced to monitor heart rate, blood oxygen level of the blood (SpO2), body temperature, and environmental conditions in real time. On the occurrence of irregular fluctuations, real-time alerts are raised and sent to the physicians to take timely action. This solution successfully combines the traditional risk scoring, machine learning-based enhancement, and real-time monitoring into an active and personalized solution to prevent and manage cardiovascular disease. Identify the Human Body type Using Image Processing

Data Collection and Data Preprocessing

The process of data collection for cardiovascular risk prediction involves the collection of user-specific information via a 15-item survey and merging it with the Framingham Heart Study dataset to infer heart disease risk. The survey collects the age, sex, smoking status, alcohol use, diabetic status, blood pressure, cholesterol, heart rate, and body mass index (BMI), while the Framingham dataset contributes historical medical history to train the prediction models. Data cleaning and structuring is performed via preprocessing following data collection in order to clean and structure the data for analysis. The missing values are addressed through mean/mode imputation so no missing space within the data impacts the predictions. Numerical features like cholesterol and blood pressure are z-score scaled, as categorical variables like smoking status and diabetic status are binary encoded (0 or 1) for machine learning. Feature engineering is performed to calculate values like the body mass index from weight and height and to create interaction terms to precisely forecast risk. The data is then divided into the training set (80%) and the test set (20%) and data balancing methods like oversampling or under sampling are applied to address class imbalance. The organized preprocessing workflow guarantees the cardiovascular risk model can effectively forecast heart disease risk and suggest personalized health recommendations.

Model Training



Classification Report:

	precision	recall	f1-score	support
0	0.86	0.99	0.92	725
1	0.50	0.04	0.08	123
accuracy			0.85	848
macro avg	0.68	0.52	0.50	848
weighted avg	0.81	0.85	0.80	848

Figure 1 Training accuracy

The training of the model of the cardiovascular risk prediction is accomplished using the Random Forest classifier due to its accuracy, resilience, and ability to handle the categorical and numerical features. The preprocessed data is then split into 80% training and 20% testing data, leaving enough space to train the model. For achieving the best performance, hyperparameter tuning is performed using Grid Search and Random Search and optimized on hyperparameters including the number of the trees (estimators), the max_depth, and the min_samples_split and feature selection approach. The training is accomplished on the training set and the model is learned using the patterns of the key cardiovascular risk indicators such as the patient's age, cholesterol level, blood pressure, and smoking status. The K-fold cross-validation was performed using k=10 , this was done to prevent overfitting and achieve generalization. The model is then validated on the 20% testing set, and the performance is evaluated on the measures of accuracy, precision, recall, AUC-ROC score, and the analysis using the confusion matrix. After these processes the final optimized Random Forest model is saved and deployed.

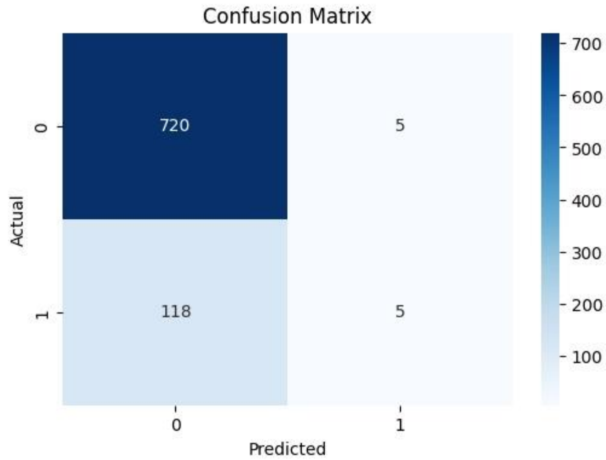


Figure 2 Confusion matrix 1

Nutrition and Exercise plan

The system begins with the data gathering of user-specific health data through the administration of the 15-item survey and combining data with medical history, including Framingham Heart Study history data. The survey records key variables of age, gender, weight, height, smoking status, alcohol consumption, diabetes, hypertension, cholesterol, blood pressure, BMI, and heart rate. Wearable Internet of Things (IoT) devices such as smartwatches collect real-time body health data such as heart rate variability, SpO2 (oxygen level in blood), body temperature, and environmental data such as humidity and air quality. The data is preprocessed during the data gathering to be complete and consistent. Missing values are handled through median imputation for numeric variables and mode imputation for categorical variables. Feature encoding is carried out in which binary variables such as the status of smoking are converted into numeric (0 or 1) form. For improving the accuracy of the models, outlier detection using the Interquartile Range (IQR) approach is carried out and numeric features such as cholesterol and blood pressure are scaled using z-score standardization. The processed dataset obtained is stored and put to use for personalized cardiovascular risk prediction and recommendation creation.

Caloric Intake Estimation and Macronutrient Distribution

Upon calculation of the user's health risk scores and BMI, the caloric requirements are determined by the use of the Mifflin-St Jeor Equation, one of the best accepted equations to estimate Basal Metabolic Rate (BMR). The BMR is then multiplied by physical level to determine Total Daily Energy Expenditure (TDEE). An obese user or an overweight user (over 25) has a caloric deficit set to induce weight loss, and the underweight users (under 18.5) are administered caloric surpluses to induce healthy weight gain. The macronutrient ratio is altered for medical conditions: diabetic users are administered low-glycemic index carbohydrates allocation (40-50%), high cholesterol users are administered heart-healthy fats (such as omega-3 acids) and foods high in fiber, and hypertensive users are administered low-sodium intake with potassium and magnesium as the area of concern of intake. The determined caloric needs and macronutrient ratio are the basis to recommend personalized diets.

Generate Personalized Diet Plans

Based on the determined caloric requirements and health conditions, the system provides an organized meal plan as per the user's diet requirements. The diet recommendation engine makes use of pre-defined diet principles, and diabetic, cholesterol, or hypertensive patients are recommended diets that are condition-based. Diabetic patients, for example, are recommended high-fiber, less-sugar foods to keep blood glucose at optimal levels, and patients with high cholesterol are recommended healthy fats, omega-3 sources, and whole grain foods, and no consumption of trans fats and processed foods. The system also applies the concepts of the DASH diet to hypertensive patients, with no salt and an increased intake of nutrient-dense foods. Users with weight loss or muscle gain goals are provided with protein-optimized meal plans. The diet plan generated is dynamic and allows users to exchange meals according to taste while still being in line with nutritional and caloric targets. Diet compliance is continually checked through feedback and modified as and when needed.

Exercise Plan Formulation Based on Cardiovascular Risk

When the system calculates the cardiovascular risk score of the user, it constructs an individually tailored exercise regimen taking into consideration the medical condition and fitness level of the user. For low-risk users (≤10%), the system prescribes an ideal blend of aerobic workouts (cycling, yoga, swimming) and strengthening workouts with a minimum of 150 minutes of weekly workouts with moderate intensity. For intermediate-risk users (11-30%), the system offers low-impact workouts such as brisk walking, yoga, and controlled resistance training and permits gradually increasing cardiovascular strengthening at low stress levels. For high-risk users (>30%), the system prescribes completely supervised workouts with careful movements such as stretch, slow walk, and light mobility workouts to achieve the minimum level of stress on the heart. Using an IoT device such as a health band the heart rate, oxygen level, and room temperature and humidity is tracked in real-time and automatically controls the effort level on detection of an anomalous value. This makes workouts safe, effective, and as per the heart condition of the user.

IoT-Based Health Monitoring and Anomaly Detection

The IoT health band is equipped with multiple biometric and environmental sensors that continuously collect user data. The heart rate sensor (PPG – Photoplethysmography) monitors pulse variations, detecting irregularities such as tachycardia (high heart rate) or bradycardia (low heart rate). A temperature sensor (thermistor or infrared) measures both the user's body temperature and ambient temperature, ensuring the user is not exposed to extreme conditions that may trigger cardiovascular stress. A humidity sensor tracks environmental moisture levels, which can influence hydration, breathing efficiency, and cardiovascular strain. The collected data is transmitted via Bluetooth or Wi-Fi to a cloud-based system for real-time analysis.

Data Collection and Preprocessing

Raw data from the sensor is sent in real-time to an edge device or centralized database (smartwatch or smartphone) where preprocessing is conducted. Data cleaning discards noise, deletes missing values, and eliminates false data produced by temporary disturbances (movement during heart rate sampling). Systematic techniques such as moving average smoothing and median filters are employed to generate reliable and linear measurements. Sensor data is stored in the form of time-series to enable the monitoring of trends for long durations to track long-term cardiovascular trends.

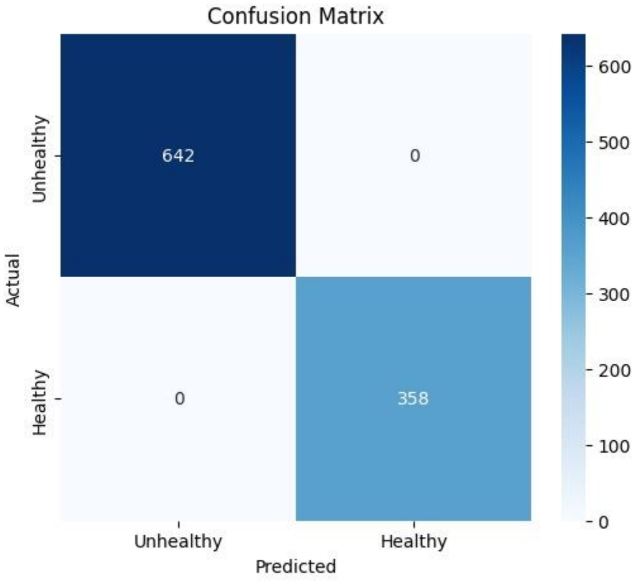


Figure 3 Confusion matrix 3

Anomaly Detection Using Machine Learning

It applies machine learning-driven anomaly detection techniques to identify fluctuations of biometrics from the normal values. A baseline is established for what is typical for each user based on previous readings and common averages, considering the differences between individuals. The system is monitoring heart rate trends, temperature fluctuation, and environmental data continuously. All these metrics are considered.

The model is trained on pre-existing health data using the technique of a Random Forest classifier. It marks the conditions as normal or abnormal. It looks at heart rate variations, body temperature variations and also factor in the environmental temperature, and humidity variations. The system alerts potential health when the heart rate rises anomalously as an effect of thermal stress or the user's temperature exhibits sudden, unexplainable spikes.

Figure 4 Dataset

Real-Time Warning and Alert Mechanism

When an anomaly is found, the system issues an immediate alert notice via the smartphone, the smartwatch, or other devices where the user is logged in. A tri-level alert mechanism is used:

For the first level an Advisory Alert is given. During slight deviations, the system provides guidance (for example, Hydrate, rest, and check heart rate in 5 minutes).

Level 2 is the Warning of Moderate Risk. Upon detection of moderate cardiovascular stress, the system warns the user to consult a doctor or change level of physical exertion or move to a different environment based on environmental factors. (e.g., "Heart rate is high for long period; decrease exertion").

Level 3 if the Emergency Alert. In the case where detection of life-threatening conditions such as sudden rise in temperature, extreme fluctuation of heart rate, or prolonged exposure to heat stress, the system automatically triggers an SOS alert to emergency numbers and health care professionals with GPS location and real-time vitals.

5. Remote monitoring and cloud-based data logging

To enhance the prediction accuracy, all the sensor data collected is deposited in the cloud storage for trend and long-term analysis of health. The system archives the past data, facilitating the capability to view trends within various time intervals by the health providers. The system enhances the capability for future anomaly prediction based on historical trends through the incorporation of deep learning models, thus rendering it an anticipatory health monitoring system.

IV. RESULT AND DISCUSSIONS

. The system was also validated using real patient data from the Framingham Heart Study data set and simulated real-time data from IoT-enabled health monitoring devices. The system was compared on three dimensions: the accuracy of the cardiovascular risk prediction, the effectiveness of the personalized physical and diet recommendation, and the validity of real-time anomaly detection with IoT devices.

1. Cardiovascular Risk Prediction Performance

The system used the implementation of a Random Forest classifier to predict heart disease risk with an accuracy of 88.52% after hyperparameter tuning. The model outperformed traditional Logistic Regression (83.1%) and K-Nearest Neighbors (85.6%) in classifying at-risk and non-at-risk individuals. The 0.91 AUC-ROC is an assurance of the model's reliability in cardiovascular risk stratification as it reflects good ability to differentiate between high-risk and low-risk users. The model had slight performance differences when confronted with instances of imbalanced datasets, where the model had a slight bias towards non-heart-disease cases. The subsequent enhancements can involve the use of Synthetic Minority Oversampling (SMOTE) or cost-sensitive learning for handling class imbalance.

2. Efficiency of Individualized Diet and Exercise recommendations.

The physical activity and diet prescription module was able to tailor to the health status of the user by regulating the caloric intake for each day, macronutrient allocation, and the level of physical activity according to body mass index risk factors, cholesterol level risk, and diabetes status. Low-risk users (⩽10%) were put on balanced diet and uncontrolled activities, and 11% to 30% moderate-risk users were put on low-impact activities (yoga and walking) and controlled caloric intake. High-risk users (>30%) were put on medicinally supervised physical exercises and controlled heart-healthy diets with low sodium content. The system was able to tailor diets and physical activities in real-time according to newly entered health data, and it exhibited the capability to personalize and optimize intervention schemes.

3. IoT-Based Health Monitoring and Anomaly Detection

The heart rate, body temperature, room temperature, and humidity were being continuously monitored by the IoT health band sensors and were providing real-time cardiovascular health monitoring to the user. The anomaly detection system identified the anomalous conditions of sudden heart rate spikes (⩾130 bpm during resting), body temperature fluctuations (>38 ° C), and exposure to extremely high ambient temperatures (>35 ° C or high humidity level). The system was providing instantaneous notifications to the user and, in the case of the worse scenario, an emergency response notification to the selected emergency contacts. Anomaly detection false positives were 7.5%, primarily because of motion artifacts superposed on the sensor signals, and can be improved through improved processing of the signals.

4. Discussion

The results demonstrate the feasibility and effectiveness of an integrated machine learning and IoT-based heart disease prevention system. The high accuracy of cardiovascular risk prediction aligns with findings from previous research that utilized ensemble learning for heart disease detection. Additionally, the adaptive diet and exercise module provides personalized interventions, enhancing traditional static health guidelines. The real-time anomaly detection system ensures that at-risk individuals receive timely alerts and intervention, bridging the gap between preventive healthcare and emergency response systems.

Despite its success, certain limitations were identified. The Framingham dataset is historically focused on Western populations, which may impact model generalizability for diverse ethnic groups. Future iterations could incorporate more diverse datasets for improved applicability across populations. Additionally, while IoT health monitoring effectively detects anomalies, sensor accuracy and data reliability could be further enhanced with improved calibration and AI-driven noise reduction techniques.

V. CONCLUSION

The Heart Disease Prevention and Monitoring System utilizes machine learning, IoT-based health monitoring, and real-time risk assessment to build an integrated personalized health solution. Framingham-based cardiovascular disease risk estimation through the system is used to find the patient's 10-year risk of developing heart disease and the personalized diet and physical activity recommendation ensures targeted interventions according to the health status of the user. The IoT health band is an ongoing vital and environmental parameter monitoring system that uses machine learning-based anomaly detection models to detect anomalies and provide real-time alerts to prevent potential cardiovascular complications.

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