A NOVEL LOW-COST SYSTEM FOR REMOTE HEALTH MONITORING USING SMARTWATCHES

Thanh-Nghi Doan[1,2]
[1]Faculty of Information Technology, An Giang University, An Giang, Vietnam
[2]Vietnam National University Ho Chi Minh City, Vietnam
dtnghi@agu.edu.vn

Abstract

The healthcare industry is advancing rapidly in both technology and services. One recent development is remote health monitoring, which has become increasingly important in a world where the aging population is facing more health complications. Initially, this technology was limited to monitoring patients within hospital rooms. However, advancements in communication and sensor technologies have made it possible to monitor patients while they go about their daily activities at home. One popular device being used for this purpose is the smartwatch, due to its efficiency and ease of use in transmitting health data quickly and conveniently via smartphones. This study proposes an end-to-end remote monitoring framework for predicting and managing health risks using different types of personal health devices, smartphones, and smartwatches. Several machine learning methods were applied to a collected dataset, which underwent feature scaling, imputation, selection, and augmentation to predict health risks. The tenfold stratified cross-validation method achieved an accuracy of 99.5%, a recall of 99.5%, and an F1 of 99.5%, which is competitive with existing methods. Patients can utilize various personal health devices, such as smartphones and smartwatches, to monitor vital signs and manage the development of their health metrics, all while staying connected with medical experts. The proposed framework allows medical professionals to make informed decisions based on the latest health risk predictions and lifestyle insights while maintaining unobtrusiveness, reducing cost, and ensuring vendor interoperability. The cost of entire system is 328 USD.

Keywords: Deep convolutional neural networks; large-scale insect detection; large-scale insect datasets.

1. Introduction

The healthcare sector is quickly advancing in both technology and services. One recent advancement with numerous benefits is the remote monitoring of patients [1], [2], [3], [4], [5], [6], [7], [8], [9]. Through modern communication and sensor technologies, patients can be monitored while participating in their usual daily activities. There are a variety of sensors available today that can monitor several vital signs such as body temperature, pulse rate, respiration rate, blood pressure, heart rate, blood glucose levels, temperature, abnormal activity, and neural system activity. This remote health monitoring can be particularly useful for individuals with chronic illnesses, the elderly, premature infants, and accident victims. There are different technologies available for monitoring patients, such as sensors attached to the body, sensors attached to the environment, and innovative contactless monitoring techniques. Currently, remote health monitoring with smartwatches is a cutting-edge technology that enables

individuals to monitor their health status in real-time and without visiting a medical facility [10], [11], [12]. Smartwatches come with several sensors that can keep track of essential indicators like heart rate, blood pressure, and oxygen saturation levels. These sensors continuously collect data and transmit it to a mobile application that can be accessed by both the user and healthcare professionals. Remote health monitoring with smartwatches has many advantages, especially during a pandemic where remote healthcare is highly encouraged. This technology allows healthcare professionals to monitor patients' health status remotely and detect any health abnormalities promptly. This can prevent hospitalization, reduce the risk of complications, and improve patients' quality of life. Moreover, remote health monitoring with smartwatches is highly convenient for patients, as they can monitor their health status in real time without leaving their homes. This can also reduce the burden on medical facilities and prevent overcrowding. Overall, remote health monitoring with smartwatches is a promising technology that can revolutionize the healthcare industry, especially for individuals who require constant health monitoring, such as those with chronic diseases or elderly patients. In [10], a real-time online activity and mobility monitoring (ROAMM) framework was proposed by the authors, which includes a smartwatch application for data collection, a server for data storage and retrieval, as well as online monitoring and administrative tasks. The framework was evaluated for collecting actigraphy data on the wrist and used for feature detection and classification of different

tasks of daily living conducted by participants. This study opened up many future studies to develop health monitoring frameworks for remote patients using smartwatch devices [13], [14].

Smartwatches can be useful for general health monitoring as they offer a range of features that can track basic health metrics like heart rate, steps taken, and calories burned. They can also track sleep patterns, and stress levels, and provide reminders to stand up and move around. Compared to medical monitoring devices, smartwatches are more convenient to wear and use. They are lightweight, easy to use, and can be worn throughout the day without discomfort. They also offer wireless connectivity to smartphones and other devices, which can help users keep track of their health data and monitor their progress over time. However, it's important to note that while smartwatches can provide valuable information about a person's general health status, they are not as accurate or reli- able as medical monitoring devices when it comes to tracking specific health conditions or vital signs. Medical monitoring devices are specifically designed for monitoring specific health conditions and provide more accurate and detailed information. Therefore, smartwatches are a useful tool for general health monitoring. In this study, the smartwatch was chosen to build a remote health monitoring system because of its low cost, ease of installation, and practical use. The system is compatible with various types of smartwatches currently on the market, using the Google Fit platform, and can run on ordinary mobile devices with Android or iOS operating systems. Fig. 1 depicts the overview of our proposed system.
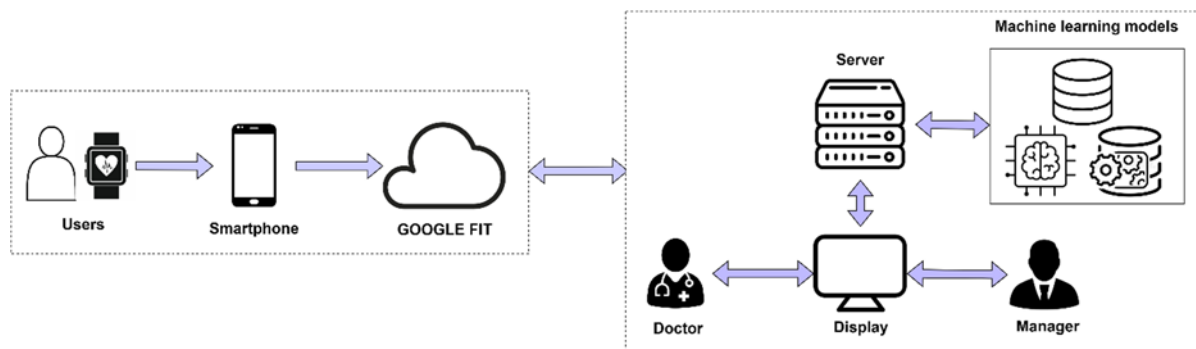

Fig. 1: The overview of our proposed system.

2. Related work

The authors in [3] provided a review of the latest de- velopments in remote healthcare and monitoring using both with-contact and contactless techniques was presented by the authors. The paper discussed various issues that are common in most systems and also provides some suggestions for future research. A smartwatch-based framework was developed by the authors in [13]. The proposed framework consists of a smartwatch application and a server. The smartwatch application is responsible for collecting and preprocessing data, while the server is used for data storage, retrieval, remote monitoring, and administrative purposes. By combining sensor-based and user-reported data collection, the ROAMM framework enables real-time data visualization and summary statistics. In [14], the authors proposed an end-to-end remote monitoring framework for automated diabetes risk prediction and management, which utilizes personal health devices, smart wearables, and smartphones. They developed a support vector machine for diabetes risk prediction using the Pima Indian Diabetes Database, incorporating feature scaling, imputation, selection, and augmentation. This approach achieved compet- itive performance metrics, including accuracy, sensitivity, and specificity scores of 83.20%, 87.20%, and 79%, respectively, via the tenfold stratified cross-validation method. Patients can leverage various healthcare devices, smartphones, and smartwatches to monitor vital parameters, manage diabetes progression, and maintain communication with medical professionals. The proposed framework empowers healthcare providers to make informed decisions based on the latest diabetes risk predictions and lifestyle insights while ensuring unobtrusiveness, reduced costs, and vendor interoperability. In [15], the authors presented a smart home health monitoring system that analyzes a patient's blood pressure and glucose readings at home and sends notifications to healthcare providers in the event of any detected abnormalities. The system employs a combination of conditional decision-making and machine learning techniques to predict hypertension and diabetes status using the patient's glucose and blood pressure readings. A supervised machine learning classification algorithm was trained to predict the patient's diabetes and hypertension status, with the support vector machine classification algorithm identified as the most accurate and used for model training. The proposed work includes a user-friendly graphical user interface for a home health monitoring application that diagnoses blood pressure and diabetes status and sends categorized alerts and real-time notifications to the patient's registered physician or clinic, all from the comfort of their home. The authors in [16] introduced a novel healthcare monitoring framework that utilizes a cloud environment and a big data analytics engine to accurately store and analyze healthcare data, improving classification accuracy. The big data analytics engine is based on data mining techniques, ontologies, and bidirectional long shortterm memory (Bi-LSTM). Data mining techniques preprocess healthcare data efficiently

and reduce data dimensionality. Ontologies provide semantic knowledge about entities and aspects and their relations in the domains of diabetes and blood pressure (BP). Bi-LSTM classifies healthcare data accurately to predict drug side effects and abnormal conditions in patients. The proposed system also classifies patients' health conditions using healthcare data related to diabetes, BP, mental health, and drug reviews. The framework is developed using the Protégé Web Ontology Language tool with Java. Results indicate that the proposed model handles heterogeneous data accurately and improves health condition classification and drug side effect prediction accuracy. In [17], the authors presented a smart healthcare system for heart disease prediction using ensemble deep learning and feature fusion approaches. The feature fusion method combines extracted features from both sensor data and electronic medical records to generate valuable healthcare data. The information gain technique eliminates irrelevant and redundant features, selecting only important ones to decrease the computational burden and enhance system performance. The conditional probability approach computes a specific feature weight for each class, further improving system performance. Finally, the ensemble deep learning model is trained for heart disease prediction. The proposed system is evaluated with heart disease data and compared with traditional classifiers based on feature fusion, feature selection, and weighting techniques. The proposed system achieves an accuracy of 98.5%, which is higher than existing systems. These results demonstrate that the proposed system is more effective for heart disease prediction compared to other state-of-the-art methods. The authors in [18] have proposed a SmartCare solution that leverages a smartwatch for the real-time detection of heart failure and diabetes. By using health data provided by the user in combination with data collected through the smartwatch, the proposed system can predict heart failure, severity levels of heart failure, diabetes disease, and types of diabetes. To develop these prediction models, Random Forest and Logistic Regression algorithms are employed. The system is evaluated on patients' data collected from local hospitals and achieves an F1 score of 0.72, 0.7, 0.72, and 0.86, respectively, for heart failure detection, severity levels of heart failure, diabetes disease, and types of diabetes, demonstrating its effectiveness in disease detection. The authors of [19] have developed and validated an AI-based smartwatch electrocardiogram (ECG) to identify heart failure with reduced ejection fraction (HFrEF). The study included 137,673 patients with 458,745 ECGs and 38,643 patients with 88,900 ECGs from hospital A for developing the ECGT2T and HFrEF detection models, respectively. Using smartwatch ECG, the AI achieved an area under the receiver operating characteristic curve of 0.934 (95% confidence interval 0.913-0.955) in detecting HFrEF, with 755 patients from hospital B. The sensitivity, specificity, positive predictive value, and negative predictive value of AI were 0.897, 0.860, 0.258, and 0.994, respectively. The study concludes that an AI-powered smartwatch 2-lead ECG can detect HFrEF with reasonable performance. The proposed solution in [20] involves a smart wearable interfaced with a vehicle that can continuously monitor the wearer's heart rate, SPO2 levels, and temperature, and detect the occurrence of epilepsy. In case of abnormal conditions, the device sends an immediate signal to the Arduino UNO, which operates the relay and stops the vehicle to prevent accidents. Additionally, the device sends the user's current location through Global System for Mobile Communication (GSM), potentially saving the driver's life. In their study [21], the authors concentrated on the precise categorization of squat movements and proposed a wearable system using a smartwatch that could identify subtle variations in motion. To gather data, they requested 52 participants to execute one correct squat and five incorrect squats with three distinct arm postures (straight arm, crossed arm, and handson waist). They employed deep neural network models and a conventional machine learning technique (random forest) as a benchmark. According to experimental findings, the bidirectional GRU/LSTMs with an attention mechanism and the arm posture of hands on the waist achieved the highest test accuracy (F1-score) of 0.854 (0.856). High-dimensional embeddings in the latent space learned by attention-based models demonstrated more closely packed distributions than those learned by other DNN models, indicating that attention-based models learned features from the complicated multivariate time-series motion signals more effectively. To comprehend the machine-learning system's decision-making process, they investigated the attention-based RNN model's outcomes. The bidirectional GRU/LSTMs exhibited a consistent attention pattern for the defined squat classes, but these models assigned different weights to the attention given to various kinematic events of the squat motion (such as descending and ascending). Prior systems were expensive, did not work with a wide range of smartwatch devices, necessitated high configurations, were challenging to set up, and lacked the integration of machine learning techniques to forecast unusual health states in users. Consequently, we conducted research and developed a system that integrates machine learning techniques to observe users' health in a more efficient manner, while also being cost-effective, simple to install, and easy to deploy in practical situations. The main contributions of this paper are mentioned as follows:

- Develop an automated remote monitoring system that integrates patient vital information from diverse per- sonal health devices, smartphones, and smartwatches provided by multiple vendors, in order to improve diagnostic decision-making.
- Integrate machine learning models into the framework and leverage a subset of the collected data to delive real-time risk predictions for health issues.
- The system can be easily installed and deployed in practice, with costs that are suitable for the economic conditions of many patients (cost 328 in USD).

3. Materials and Methods

3.1. *The important indicators for monitoring health*

Heart rate refers to the number of times a person's heart beats per minute. It is an important indicator of cardiovascular health and can be influenced by various factors such as physical activity, emotions, and medical conditions. The normal range of heart rate for adults is typically between 60 to 100 beats per minute, although this may vary depending on factors such as age, fitness level, and health status. A resting heart rate that is consistently outside of this range may be a sign of an underlying health issue and should be evaluated by a medical professional. The heart rate indices for each age group are presented in Table 1.

Age	Standard heart rate (beats/minute)
Infant	120 - 160
Children from 1-12 months	80 – 140
Children 1 - 2 years old	80 – 130
Children from 2 to 6 years old	75 - 120
Children from 7 to 12 years old	75 -110
Adults 18 years and older	60 – 100
Athletes	40 – 60

Table 1: The heart rate indices for each age group.

SpO2 stands for peripheral capillary oxygen saturation, which is a measure of the amount of oxygen in a person's blood. It is typically measured using a pulse oximeter, which is a non-invasive device that clips onto a person's finger or earlobe and uses light to determine the oxygen saturation level in the blood. SpO2 is expressed as a percentage, with a normal range for healthy individuals typically being between 95% to 100%. A reading below 90% may indicate a problem with oxygen delivery to the body's tissues and organs and should be evaluated by a medical professional.

Blood pressure refers to the force that blood exerts on the walls of arteries as it is pumped by the heart throughout the body. It is measured using two numbers: systolic pressure, which is the pressure in the arteries when the heart beats, and diastolic pressure, which is the pressure in the arteries when the heart is at rest between beats. Blood pressure is typically expressed in millimeters of mercury (mmHg), and a healthy blood pressure reading for adults is typically considered to be less than 120/80 mmHg. High blood pressure, also known as hypertension, is a common condition that can increase the risk of serious health problems such as heart disease, stroke, and kidney disease if left untreated.

3.2. *Smartwatch*

Smartwatches can be used to monitor and track a variety of health metrics, such as heart rate, steps taken, calories burned, blood glucose levels, and sleep quality. This can be particularly helpful for people who are trying to establish healthy habits or manage chronic conditions. Some smartwatches even have advanced features such as ECG monitoring and blood oxygen level tracking. Smartwatches can provide feedback on health metrics in real time, allowing users to make adjustments to their behavior or activity levels. Additionally, some smartwatches can be synced with health apps on smartphones to provide a more comprehensive view of overall health and fitness progress. However, it's important to note that smartwatches should not be used as a substitute for professional medical advice or treatment. If you have a health condition or concerns about your health, it's important to consult with a healthcare professional. Smartwatches on the market are currently being improved, with an emphasis on measuring health parameters. The benefits of smartwatches include their portability, compactness, low-cost, and ease of use. Users do not need to visit medical facilities to monitor their health status at any time or from any location. Furthermore, with intelligent features, the smartwatch will be a helpful assistant to help improve users' health on a daily basis, and the reasonable price is appropriate for all types of users. In this study, the smartwatches Mi Smart Band 5 and HUAWEI Band 7 were used to collect health monitoring data. The specifications of these smartwatches are detailed in Table 2. The images of HUAWEI Band 7 and Mi Smart Band 5 are shown in Fig. 2.

Fig. 2: The images of HUAWEI Band 7 and Mi Smart Band 5.

Data synchronization between a smartwatch and a smartphone involves transferring data wirelessly, usually over Bluetooth or Wi-Fi (3G, 4G, 5G). The types of data that can be synchronized vary but typically include notifications, music playback, and fitness tracking. Pairing the devices is necessary before data can be synchronized, and the process may involve automatic or manual synchronization. Fig. 3 presents data synchronization between smartwatch and smartphone.

Specifications	HUAWEI Band 7	Mi Smart Band 5
Body	43.35 x 26 x 9.99 mm, 16gm (without strap)	46.95 × 18.15 × 12.45 mm
Strap	Removable silicone straps	TPU
Display	1.47" AMOLED panel, 2.5D curved glass	1.1" AMOLED display
Resolution	194 x 368 pixels resolution, 283 PPI	126 x 294 pixels resolution
Control	Touch, swipe, side button	Touch, swipe, side button
Connection	Bluetooth 5.0 (BLE)	Bluetooth 5.0 (BLE)
Compatible with	Android 6.0 and above, iOS 9.0 and above	Android 5.0, or iOS 10.0 and above
IP Rating	5 ATM water-resistance (up to 50m)	IP68 Waterproof
Sensors	Acceleration, Gyroscope, Optical heart rate	3-axis accelerometer and 3-axis gyroscopePPG heart ratesensor
Sports Mode	96	11 professional sports modes
Health	Track 24/7 heart rate, SpO2, blood pressure, monitor sleep, count steps, calculate calorie consumption, and track activities such as swimming, run- ning, walking, and cycling	Track 24/7 heart rate, SpO2, and blood pressure, moni-tor sleep, count steps, calcu- late calorie consumption, and track physical activities such as swimming, running, walk- ing, and cycling
Companion App	Huawei Health (Android - iOS)	Mi Fitness
Battery	Up to 14 days of endurance	14-day extra-long battery life with a magnetic charger
Charger	Proprietary Magnetic charger	Proprietary Magnetic charger

Table 2: Product details of HUAWEI Band 7, Mi Smart Band 5.
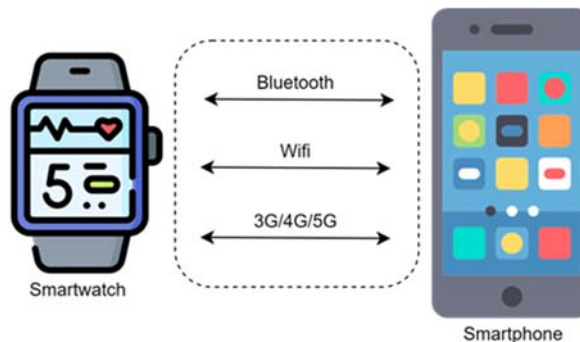

Fig. 3: Data synchronization between smartwatch and smart- phone.

3.3. *Machine learning methods*

Integrating machine learning (ML) algorithms into the system is extremely important and brings many benefits, such as detecting anomalies in heart rate, blood pressure, and SpO2 data, helping users to detect their health issues early. Based on these user data, machine learning can provide suggestions for healthcare, including lifestyle, and nutrition, and send alerts to doctors and hospitals for timely emergency response when there are serious health issues. The process of integrating machine learning models is presented in Fig. 4. The ML algorithms implemented for binary prediction of the two outcomes of normal and abnormal health of the users are the K-nearest neighbors, Gaussian Naive-Bayes, Support Vector Machines, Artificial Neural Networks, and Gradient Boosting.
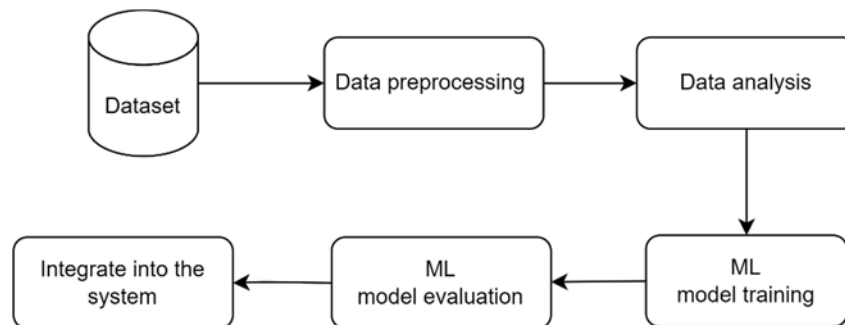

Fig. 4: Process of integrating machine learning into the system.

a) K-nearest neighbours: K-nearest neighbors (k-NN) [22] is a machine learning algorithm used for classification and regression analysis. It works by finding the K nearest data points in the training dataset to a given query point and using their labels or values to predict the label or value of the query point. k-NN is a non-parametric and lazy learner and can handle both classification and regression tasks. It is known for its simplicity and interpretability but can be sensitive to the choice of K and the distance metric used. k-NN is commonly used in applications such as image recognition, recommend systems, and anomaly detection. Numerous articles have already studied the application of the k-NN model for predicting and classifying health issues, as evidenced by [14], [23], [24].

b) Gaussian Naive-Bayes: Gaussian Naive-Bayes (GNB) [25] is a machine-learning algorithm used for classification tasks. It assumes that the input features are independent of each other and have a normal (Gaussian) distribution, and calculates the probability of a data point belonging to a particular class based on the probability of the features given that class. GNB is a fast and simple algorithm that works well for high- dimensional datasets, requires only a small amount of training data, and can handle missing data. However, it may not always be accurate if the assumptions of independence and normal distribution do not hold for the dataset. Many articles have studied the application of the Naive Bayes model for disease prediction and classification [14], [26], [27].

c) Support vector machines: Support Vector Machines (SVM) [28] is a supervised machine learning algorithm used for classification and regression analysis. It finds a hyperplane that separates data points of different classes in a way that maximizes the margin between the two classes. SVM can handle both linearly separable and non-linearly separable data by using kernel functions to map the data into a higher-dimensional space, where it can be linearly separable. SVM is effective even in high-dimensional spaces, less prone to overfitting, but can be computationally expensive for large datasets. There have been many articles that have studied the application of SVM models in predicting and classifying health-related issues [29], [14], [30].

d) Artificial Neural Network: Artificial Neural Network (ANN) [31] is a machine learning algorithm inspired by biological neural networks in the human brain. It consists of interconnected nodes called neurons, arranged in layers. ANNs can be used for both classification and regression tasks and can handle non-linear relationships between inputs and outputs. They have many applications in image recognition, speech recognition, natural language processing, and financial analysis. ANNs have some limitations like the need for large amounts of data for training and the possibility of overfitting, but have been successful in many applications and have led to the development of more advanced neural network architectures. Many articles have investigated the application of the ANNs model in predicting and classifying health issues, as evidenced by [14], [32], and [33].

e) Gradient Boosting: Gradient Boosting [34] Gradient Boosting is a machine learning technique that combines several weak learners, typically decision trees, to create a stronger learner by iteratively training weak models on the residual errors of the previous model. It can be used for both classification and regression problems and is known for its high accuracy, robustness to outliers, and ability to handle complex relationships between features. However, it can be prone to overfitting, computationally expensive, and difficult to interpret the final model. Many research studies have been conducted on the use of the Gradient Boosting model for predicting and classifying health-related problems, as evidenced by several publications [35], [36], [37].

The proposed pipeline for the implementation of machine learning models in the prediction node is depicted in Fig. 5. First, imputation is performed to account for missing data, and this is followed by feature scaling to standardize the range of the dataset values. Feature selection methods are applied to remove redundant features that do not contribute highly to the prediction outcome during training and enhance overall model fidelity. To rectify class imbalances, an oversampling method is used to synthesize strongly similar samples of the minority class in the data augmentation step. Finally, the binary classifiers are fit with the data during the k-fold cross-validation step, where all samples are used for training, validation, and testing, thereby producing a more robust classifier.
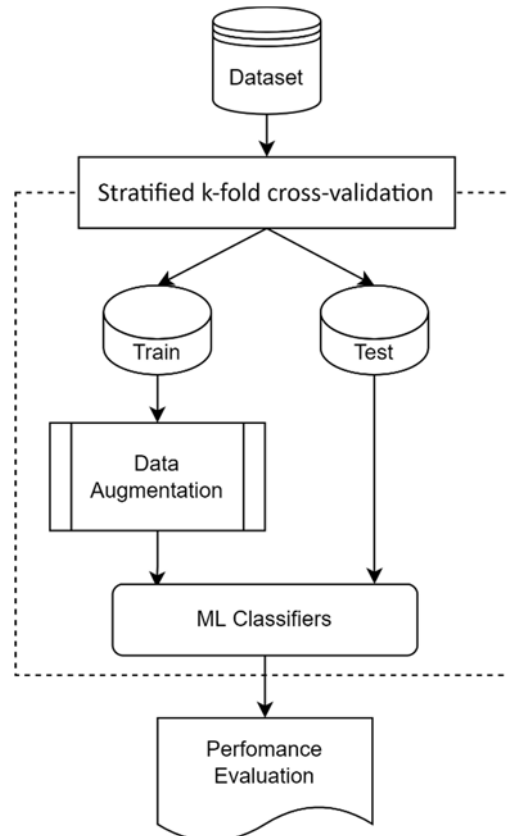

Fig. 5: Framework of the machine learning pipeline.

4. Experimental Results And Discussion

4.1. *Experimental setup*

The remote health monitoring system is installed and developed on a computer running Windows 11 operating system,with an Intel Core i7-1165G7 2.80 GHz CPU and 8GB RAM. Visual Studio Code [38] is utilized for coding and application development. The web application is built on the NodeJS platform, a runtime environment that provides all the necessarycomponents for executing a program written in JavaScript.MySQL [39] is used for storing and managing user data and health monitoring metrics. MySQL is an open-source database management system that operates on a client-server model.The system is tested with HUAWEI Band 7 [40], Mi Smart Band 5 [41], Samsung Note 8 smartphone [42], and the free health-tracking platform Google Fit [43]. The cost of the entiresystem is presented in detail in Table 3.

Devices	Cost in USD
Smartwatch HUAWEI band 7	85.12
Normal Smartphone Samsung	200.00
Web hosting in a year	42.56
Total	**327.68**

Table 3: Cost of the entire system.

4.2. *Data Collection*

Our proposed system was tested as a "proof of concept" by collecting free-living data from 20 participants over the course of approximately one week. During this time, participants were asked to wear the smartwatch on their left wrist from 8 am to 8 pm and were prompted at four random times with a minimum three-hour gap

between two consecutive prompts. They were also instructed to charge the watches every night. In total, we collected 200 samples of data, consisting of 168 hours of sensor and patient-reported outcome data. Almost all the data being collected was readily available on the server for visualization, with only a few exceptions. Table 3 summarizes representative results for each participant over the one-week wear period. The health monitoring indicators collected include gender, age, weight (WT), heart rate (HR), blood oxygen saturation level (SpO2), systolic blood pressure (SBP), diastolic blood pressure (DBP), and warnings when any of these conditions show abnormal signs. Specifically, if heart rate data is within the range of 60-100 (beats per minute), it is considered normal, and if the data exceeds > 100 (beats per minute) or is < 60 (beats per minute), it is considered abnormal and triggers a warning. If SpO2 data is within the range of 95-100%, it is considered normal, and if the data exceeds > 100% or is < 95%, it is considered abnormal and triggers a warning. If systolic blood pressure data is within the range of 90-120 (mmHg), it is considered normal, and if the data exceeds > 120 (mmHg) or is < 90 (mmHg), it is considered abnormal, and triggers a warning. If diastolic blood pressure data is within the range of 60-80 (mmHg), it is considered normal, and if the data exceeds > 80 (mmHg) or is < 60 (mmHg), it is considered abnormal, and triggers a warning. Some representative samples collected from users in a week are presented in Table 4.

ID	User code	Sex	Age	Weight	Heart rate	SpO2	SBP	DBP	Warning
1	BN001	Female	40	50	67	95	67	97	Normal
2	BN001	Female	40	50	90	98	78	100	Normal
11	BN002	Male	55	60	95	95	70	100	Normal
12	BN002	Male	55	60	90	95	75	100	Normal
29	BN003	Male	70	69	80	99	41	88	Abnormal
30	BN003	Male	70	69	81	97	49	111	Abnormal
...	…	…	…	…	…	…	…	…	…
199	BN020	Female	74	61	99	99	71	111	Normal
200	BN020	Female	74	61	100	99	70	110	Normal

Table 4: Some representative samples collected from users in a week.

4.3. *Sensor node*

The devices within this node are responsible for collecting user data. Initially, the user provides their static profile information. The smartwatch and smartphone enable data collectionby automatically tracking the user's steps, caloric expenditure,and activity type and duration. Specifically, devices with the Android operating system utilize available sensors to collect and aggregate activity data. This information is then presented to the user via the Google Fit web portal or mobile application,which leverages sensors such as the gyroscope, accelerometer, and heart rate monitor on both smartphones and smartwatches.By tracking movements, activities, heart rates, blood pressure, respiratory rate, oxygen saturation, and estimated calories burned and step counts, the Google vendor API provides comprehensive health data. Fig. 6 presents the data collectedby the Google Fit application for the subject in this work.The proposed framework's server can retrieve all patient data from Google every hour by connecting to the respective vendorcloud through RESTful principles. This process requires a one-time credential authentication, but no further user intervention. Authentication using the OAuth protocol [44] is necessaryto connect the system to the Google Fit API, which is the industry standard for authorization in web, desktop, and mobileapplications. Google Fit, a part of the Google Play Services package, allows for the tracking of user health data. The user'sdata can be retrieved based on their needs, such as daily or monthly. Additionally, all user data is stored online and is secure and trustworthy. The use of Google Fit makes it easyto develop a health-tracking system. The Google Fit REST APIenables the storage and reading of health data within Google Fit. The REST API provides resources and methods to: 1) create, retrieve, list, and modify data sources, which representa single sensor data source, where all health data is linked to a specific data source; 2) create, retrieve, aggregate, and delete data sets, which represent a collection of data points from a specific data source; 3) list data points and add them to a data set, where a data point represents a sample from a specific datasource; 4) create, retrieve, and delete sessions, where a sessionrepresents a time interval with metadata associated with it (APIREST — Google Fit — Google Developers, n.d.).
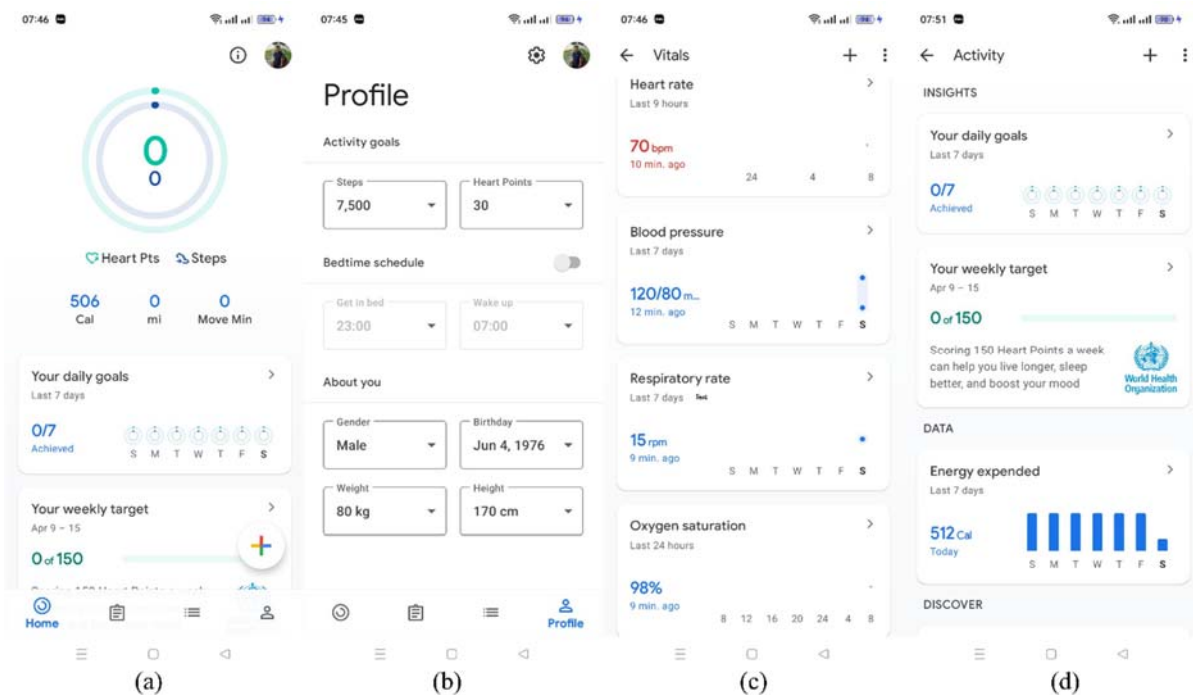
Fig. 6: Patient data collected from smartphone/smartwatch by Google Fit as shown on the respective application.

4.4. *Evaluation metrics*

Our performance metrics are precision, recall, and F1-score. Before defining the metrics, we define True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) terms. TP is the number of correctly classified samples by the algorithm. TN is the number of correctly missed samples. FP is the number of wrongly detected samples. FN is the number of wrongly missed samples. The TNis not used in calculating our performance metrics.

Precision was the one factor that was used for the main comparison, as it is a good indicator of how reliable a method works on a specific data set. It mainly focuses onthe identification of data as true positive or false positive and calculates how accurately a method can predict a falling event of the crutch. It is calculated with Equation 1.

The recall metric measures the number of wrongly missed samples by the algorithm. Its value decreases as the number of false negatives increases. The recall is an important evaluation criterion in the applications that necessitate no misses in the classification task. It is computed as the ratio of correctly detected objects to the total number of samples (both correctly classified and missed), the formula of recall is in Equation 2.

As the number of classified samples increases, the probability of correctly classified samples (TP), as well as the probability of falsely classified samples (FP), will increase. Thus, the precision will decrease. On the other hand, increasing the number of classified samples decreases the probability of wrongly missed samples (FN), hence, the recall increases. This implies that the precision and recall are inversely proportional. The F1-score combines the precision and recall with equal weights in a single score as in Equation 3.

Confusion matrices are a type of table used to evaluate the performance of a machine-learning model. They display. They display the number of true positive, false positive, true negative, and false negative predictions made by the model. The rows of the matrix represent the actual class labels of the data, while the columns represent the predicted class labels. Thus, the cells of the matrix show the number of instances that were correctly or incorrectly classified by the model. By analyzing the values in the confusion matrix, we can calculate various metrics such as accuracy, precision, recall, and F1-score, which provide insights into the model's performance and identify areas for improvement.

$$Precision\ (P) = \frac{TP}{TP + FP} \tag{1}$$

$$Recall\ (R) = \frac{TP}{TP + FN} \tag{2}$$

$$F = \frac{2.\,Precision.\,Recall}{Precision + Recall} \tag{3}$$

4.5. *Applying the machine learning method*

To analyze web hosting data, a classification problem must first be solved to accurately label the received data as "normal health" or "abnormal health". The most suitable machine learning method for the specific problem needs to be determined through cross-validation. The collected data is split into training and testing data, with most of the data used for algorithm training and the rest used to test its reliability. This process is repeated for each method to find the best one to use. In this case, the training data comprised 80% of the collected data, and the remaining 20% was used for testing. A 5-fold cross-validation method was used, and the process was repeated ten times for each method. K-Nearest Neighbors, Gaussian Naive Bayes, Support Vector Machine, Neural Network, and Gradient Boosting were evaluated using the data in Table 4.

The intricate patterns exhibited by each class, particularly in relation to health status, pose a challenge for the system, leading to reduced performance. To evaluate the classifiers' performance visually and identify the classes and features that receive greater emphasis from the machine learning models, we present several confusion matrices from Fig. 7 to Fig. 11. This analysis enables us to determine the inter-class confusion and devise strategies for future procedures aimed at preventing them.

In Fig. 7, the k-NN algorithm is configured with a number of neighbors set to 5, the distance metric as Euclidean, and uniform weight. It achieves an accuracy of 98.8% for predicting the "Normal" label, and 96.5% for predicting the "Abnormal" label, but misclassifies "Abnormal" as "Normal" with an error rate of 3.5%, and misclassifies "Normal" as "Abnormal" with an error rate of 1.2%.

The use of the Naive Bayes machine learning method in Fig. 8 demonstrates a 100% accuracy rate in predicting the label "Abnormal," a 96.5% accuracy rate in predicting the label "Nnormal," and a 3.5% misclassification rate of "Nnormal" within the "Abnormal" label. This exhibits absolute accuracy in predicting the "Abnormal" label.

Using a Cost (C) configuration of 1.00, a Regression loss epsilon (ϵ) of 0.10, a Kernel RBF, a numerical tolerance of 0.0010, and an iteration limit of 100, the SVM machine learning method shown in Fig. 9 demonstrates a 98.3% accuracy rate for predicting the "Abnormal" label, a 98.8% accuracy rate for predicting the "Normal" label, a 1.2% misclassification rate for predicting "Normal" when the true label is "Abnormal," and a 1.7% misclassification rate for predicting "Abnormal" when the true label is "Normal."

Using the Neural Network machine learning method with a configuration of 100 neurons in the hidden layer, ReLu activation function, Adam optimization solver, regularization of 0.0001, and a maximum number of iterations of 200, Fig. 10 demonstrates a 100% accuracy rate in predicting the "Normal" label, a 99.1% accuracy rate in predicting the "Abnormal" label, and a 0.9% misclassification rate in predicting the "Abnormal" label as "Normal". This indicates an absolute accuracy in predicting the "Normal" label.

Using the Gradient Boosting machine learning with a configuration of 100 trees, a learning rate of 0.1, a maximum depth limit of 3 for individual trees, a minimum subset size for the splitting of 2, and using a fraction of 1.00 of the training instances, Fig. 11 demonstrates a 98.8% accuracy in predicting the "Normal" label, a 99.1% accuracy in predicting the "Abnormal" label, a 0.9% misclassification rate for the "Abnormal" label within the "Normal", and a 1.2% misclassification rate for the "Normal" label within the "Abnormal" label.

	Predicted		
	Abnormal	**Normal**	Σ
Abnormal	96.5 %	3.5 %	115
Normal	1.2 %	98.8 %	85
Σ	112	88	200

Fig. 7: Confusion matrix using k-NN classifier.

	Predicted		
	Abnormal	**Normal**	Σ
Abnormal	100.0 %	0.0 %	115
Normal	3.5 %	96.5 %	85
Σ	118	82	200

Fig. 8: Confusion matrix using Naive Bayes classifier.

Fig. 9: Confusion matrix using SVM classifier.

Fig. 10: Confusion matrix using Neural Network classifier.

Fig. 11: Confusion matrix using Gradient Boosting classifier.

4.6. *Numerical results and discussion*

In order to decide, which machine learning method was suited the best for this data set, the confusion matrices were taken into consideration and a ROC analysis was conducted. Considering the graphs of the ROC analysis of ML methods featuring "Abnormal" and "Abnormal" shown in Fig. 12 and Fig. 13, it can be seen, that all machine learning methods performed very well. The default threshold for the ROC analysis was set to a typical 0.5. It shows the rate between True Positives (TP), meaning correctly identified cases of the wanted attribute, and False Positives (FP), falsely classified data as the wanted attribute. As only very few data sets were falsely classified, the graph is drawn very close to one.

Table 5 presents a comparison of different methods based on various parameters, including AUC (Area under the curve), CA (Classification accuracy), F1, Precision, and Recall. AUC is determined by comparing the curves from the ROC analysis and identifying the curve with the largest area underneath. CA measures the percentage of correctly classified examples. Precision calculates the proportion of true positives out of all instances classified as positive, while recall measures the proportion of true positives out of all positives in the data. F1 is a weighted harmonic mean of precision and recall.

ML Model	AUC	CA	F1	Precision	Recall
kNN	99.9	97.5	97.5	97.5	97.5
SVM	99.9	98.5	98.5	98.5	98.5
Neural Network	99.9	99.5	99.5	99.5	99.5
Gaussian Naive Bayes	99.9	98.5	98.5	98.5	98.5
Gradient Boosting	99.9	99.0	99.0	99.0	99.0

Table 5: Overall performance (%) of different ML methods.

Looking at the performance of the methods using precision as the last indicator, it is clear that Neural Network displays the most promising results when it comes to diagnosing medical issues with a precision of 99.5%. With 98.5%, Nave Bayes and SVM had the poorest results. Overall, the Neural Network fared the best across all metrics.

Our system remotely monitors users' health with a smartwatch, providing basic functions such as real-time tracking of users' health indicators, managing user information, and assigning doctors to supervise patients. The interface is simple and intuitive, allowing users to easily track their information. In case of emergencies, the system can send alerts to doctors.
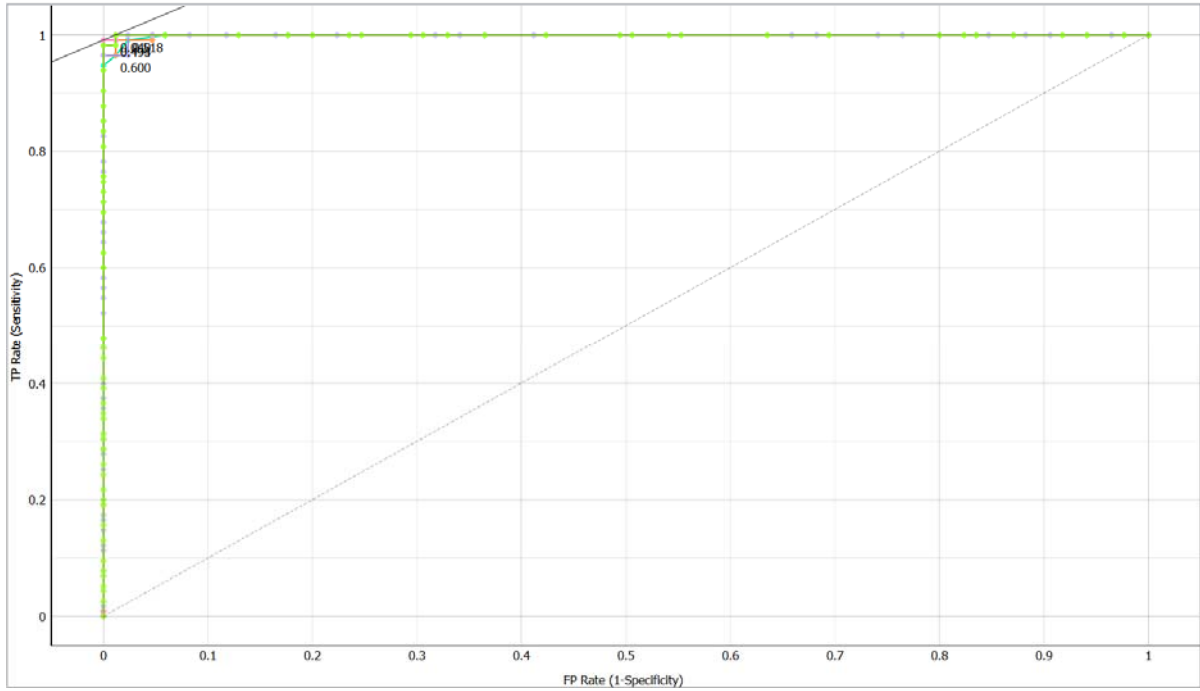
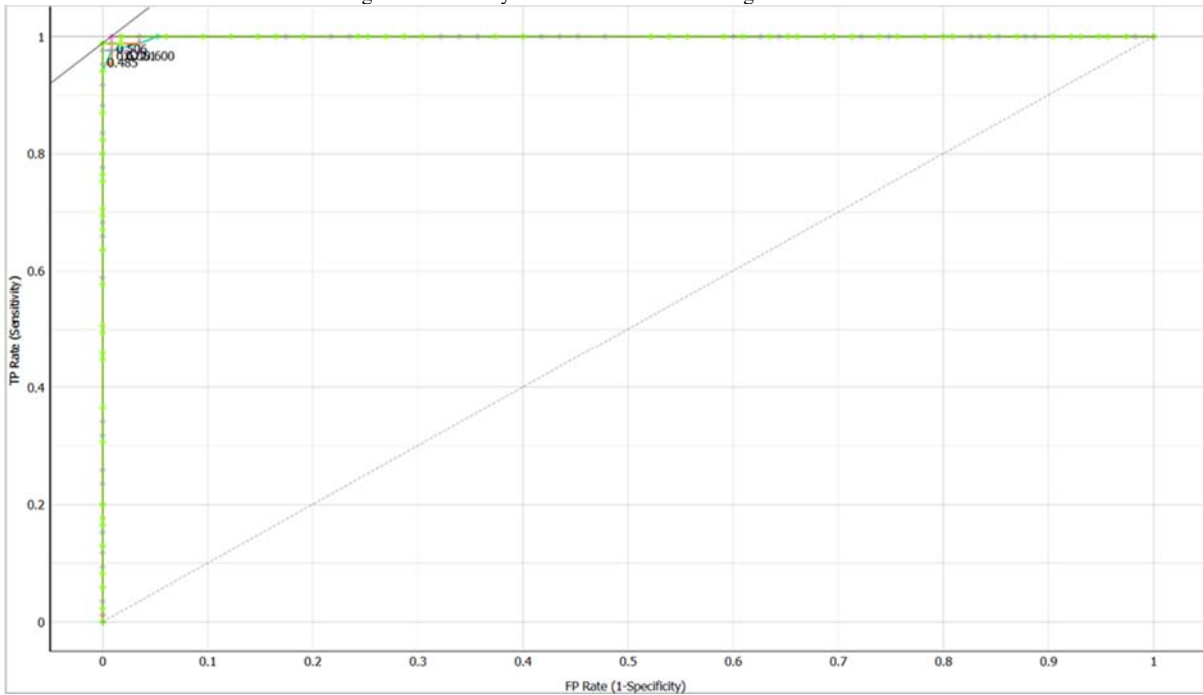Fig. 12: ROC analysis of ML methods featuring "Abnormal".

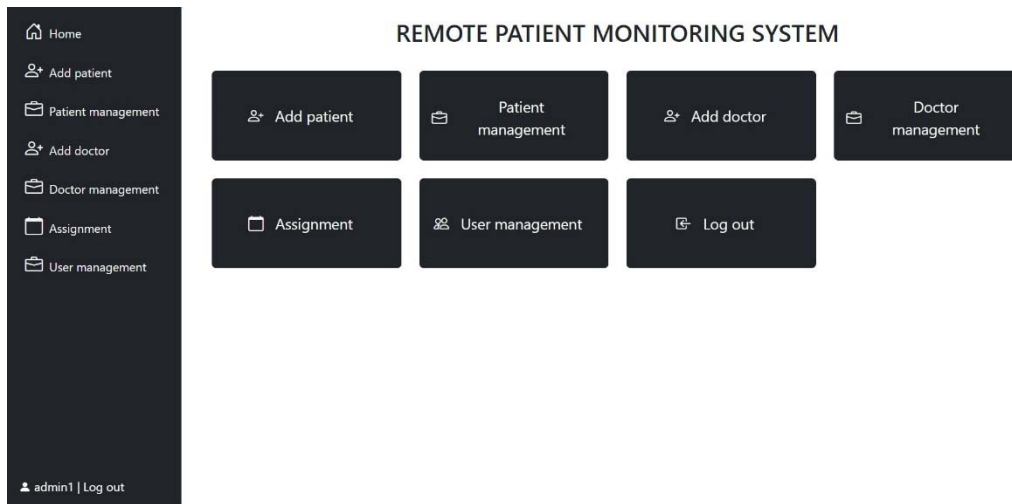Fig. 13: ROC analysis of ML methods featuring "Normal".

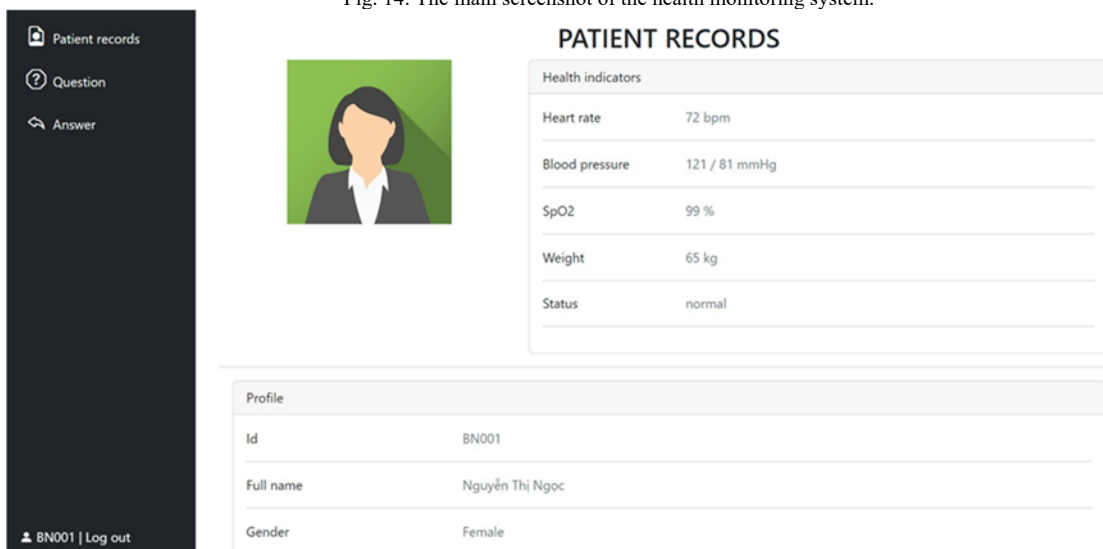Fig. 14: The main screenshot of the health monitoring system.

Fig. 15: The screenshot of health monitoring of the users.

5. Conclusion And Future Research Work

In this study, a novel low-cost system was proposed to automate the detection of health issues and alert medical professionals for timely intervention. The system integrated various smartwatch devices through cloud principles and provided the collected data to medical professionals to improve diagnostic decision-making. The system utilized five supervised ML algorithms, and the best-performing algorithm, artificial neural networks, was deployed with an accuracy of 99.5%, a recall of 99.5%, and an F1 of 99.5%. The major contribution of this study is the implementation of a health prediction model into a modular, multi-faceted framework that requires minimal patient interaction. The system is vendor-independent and interoperable, allowing for the integration of new prediction models and personal healthcare devices to enhance patient outcomes. The cost of the whole system is about 328 in USD. Future research will involve conducting a longitudinal study with a larger patient cohort and integrating additional devices and patient information for testing the system.

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Authors Profile

Thanh-Nghi Doan received his doctorate degree in computer science from University of Rennes 1, France, in 2013. He has worked as a Ph.D. candidate in TEXMEX Research Team, IRISA, France. He is currently working at An Giang University, Vietnam National University Ho Chi Minh City, Vietnam. His research is mainly focused on machine learning, data mining and high-performance computing in computer vision, agricultural applications including insect pest image classification systems, prediction of the damage of rice diseases. Especially he made a major contribution to 2D and 3D image understanding systems in agriculture in Mekong Delta.