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METHODOLOGIES AND APPLICATION

A new machine learning-based healthcare monitoring model for student's condition diagnosis in Internet of Things environment

Alireza Souri[1] · Marwan Yassin Ghafour[2] · Aram Mahmood Ahmed[3,4] · Fatemeh Safara[1] · Ali Yamini[5] · Mahdi Hoseyninezhad[1]

Abstract

Advancement in sensor technologies has resulted in rapid evolution of Internet of Things (IoT) applications for developing behavioral and physiological monitoring systems such as IoT-based student healthcare monitoring system. Nowadays, a growing number of students living alone scattered over wide geographical areas, and tracking their health function status is necessary. In this paper, an IoT-based student healthcare monitoring model is proposed to continuously check student vital signs and detect biological and behavioral changes via smart healthcare technologies. In this model, vital data are collected via IoT devices and data analysis is carried out through the machine learning methods for detecting the probable risks of student's physiological and behavioral changes. The experimental results reveal that the proposed model meets the efficiency and proper accuracy for detecting the students' condition. After evaluating the proposed model, the support vector machine has achieved the highest accuracy of 99.1% which is a promising result for our purpose. The results outperformed decision tree, random forest, and multilayer perceptron neural network algorithms as well.

Keywords Internet of Things · Health monitoring system · Smart student care · Data mining · Support vector machine

1 Introduction

The Internet of Things (IoT) is an environment where every connected node can communicate with other nodes inside the network in order to transfer essential data for accurate and real-time decision making. This makes IoT a very effective environment in critical situations such as medical purposes.

IoT can effectively provide platform for developing smart healthcare systems. It is able to connect patient to the health services as fast as possible in order to assist students and disabled people especially when they may have some possible imposes to live alone and independently (Henze et al. 2016). Therefore, fast declining health condition of students motivates us to focus on online health monitoring systems for preventing the common threatening diseases such as cancers (Richard et al. 2019). Recent technologies such as wireless sensor networks (WSN) and IoT contribute significantly to develop the smart healthcare monitoring

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systems. These technologies also contributed in development of applications that can transfer health data to provide accurate analytic information for physicians and healthcare centers. This analytical information will be useful in early diagnosis of non-contagious diseases such as cancers and mental illness (Perez et al. 2018; Souri et al. 2019). Medical IoT devices provide remote students' condition monitoring while they are at home, school, in hospital, or being anywhere else. Medical IoT devices attached to the patient transfer continuously vital health data to medical team from anywhere and anytime (Pramanik et al. 2019).

With respect to progress in applying modern sensor technology and IoT (Hussain et al. 2015), many smart healthcare and medical monitoring systems have been provided (Hamim et al. 2019). Most contemporary studies focused on overall wellness and chronic diseases such as heart failures, renal disorders, and diabetes mellitus. However, besides monitoring student's vital signs such as heart's health parameters, diabetes condition, and blood pressure, tracking other physiological parameters comprising activity patterns and behavioral model of the students is also indispensable for on-time care support systems (Fried et al. 2001). Moreover, most of the existing systems still face some important limitations including offline data collection, processing and analyzing, and focusing just on detecting chronic diseases such as cardiovascular disorder and diabetes without prediction approaches. These limitations lead us to provide a student health monitoring model based on the health function status of students in an IoT platform which tracks both biological and behavioral indicators simultaneously. The proposed model comprises the biomedical sensors and health nursing tools to collect and store students' health data. Then machine learning algorithms are applied on the collected information to monitor the student's general health function status. The main involvements of this paper are:

- Presenting a machine learning-based healthcare model in IoT environment.
- Monitoring student's health status through continuously tracking two groups of health condition parameters: behavioral and biological changes parameters.
- Classification of student's health function status using support vector machine (SVM) algorithm to achieve optimal prediction.

Proceeding with this paper, Sect. 2 reviews the related work in this field. Explanations about the proposed model that includes three layers are given in Sect. 3: IoT layer, cloud layer, and students' health monitoring layer. Section 4 shows the experimental outcomes of the suggested model using four existing machine learning methods and comparing their results. Conclusion and the future research guidance in this context are provided in Sect. 5.

2 Related work

A number of research studies have been presented in IoT-based healthcare systems recent years. For instance, Kaur et al. (2019) applied different techniques of machine learning and healthcare datasets stored in the cloud space for improving the interaction between physicians and patients based on IoT infrastructures, which makes remote health monitoring possible. In this paper, prediction systems were evaluated for heart diseases, breast cancer, diabetes, thyroid, liver disorder, and dermatology diseases. Jabeen et al. (2019) presented an efficient recommender system based on IoT for diagnoses a cardiac disease that provides physical and dietary plan recommendations. In the first step, biosensors were collecting data remotely from the patient and the data were transmitted to the server. Then, heart disease prediction model is implemented which is an efficient hybrid recommender system for cardiovascular disease by utilizing wireless sensor networks, and can diagnose eight different classes of cardiovascular disease. Also, Lakshmanaprabu et al. (2019) proposed a cloud-based clinical decision support system (CDSS) framework. They employed a deep neural network (DNN) classifier to predict chronic kidney disease (CKD) and the severity of it. Cai et al. (2018) presented a decision support system to analyze the elderly wellness condition at the Hong Kong community level. This personalized system uses a wearable wellness tracker that helps monitoring elderly vital signs. The health monitoring support system could lead to a reliable and stable data sharing system that offers an effective solution to reduce human error and time cost of data collection. On the other hand, Lee et al. (2017) investigated the relationship between 16 various types of health functional indicators and elderly frailty using univariate analysis, multivariate analysis, and a decision tree. Eventually, they concluded that health functional indicators are independent of the applied algorithm and also the nutritional problem is the most important indicator for the frailty of the student. Lee et al. (2014) presented a prediction approach to identify important factors influencing student healthcare with chronic disease. They introduced monthly income, analysis of chronic illness, despair, discomfort, and health status as the main factors.

Hussain et al. (2015) presented a platform for real-time monitoring of students' health condition and disabled people health condition that provides emergency support service in critical and dangerous situations on mobile device. Mainetti et al. (2016) introduced one of the European Commission programs, IoT-based City 4Age platform. Briefly, this project helps to monitor behaviors of students using digital devices and sensors at home and smart cities. Chavda et al. (2019) analyzed a cardiac-related data to early detection of cardiac diseases through a machine learning-based algorithm. Their proposed system used 8 symbolic features and 6 numeric features such as age, sex, and chest pain type. Eventually, healthy habits, daily exercise and quitting smoking are so important to prevent heart disease. Hamim et al. (2019) presented an android application based on IoT, which consists of sensor of a heart pulse, body temperature sensor, and sensor of galvanic skin response. All the data obtained from the sensors stored and transferred to cloud space to remote health monitoring. In this paper, behavioral and biological parameters of students are gathered through IoT-based healthcare systems proposed. This information is then integrated and mined to propose appropriate medical service.

Overall, many different healthcare systems are designed in order to help fast diagnosis along with close monitoring of patient's health status. In the proposed systems, various technologies have been utilized in order to monitor the patient's health in indoor or even outdoor environments. In our research, we monitor student's health data using sensor and data communication services. Along with real-time data, we also provide historical data to get a complete report on student's health status.

3 System model

In this section, the model proposed in this paper for students' health monitoring is presented in detail. The model is constructed from three layers: IoT layer, cloud layer, and student's health monitoring layer. In addition, machine learning algorithms that are used in the proposed model and for evaluating it, decision tree (DT), random forest (RF), SVM, and multilayer perceptron (MLP) are presented briefly. At the end of this section, evaluation criteria are explained.

The proposed model is explained in Fig. 1. The conceptual model for IoT-based students' intelligent healthcare monitoring system consists of three layers and three consist of three main phases. In the first phase, patient's data are obtained through medical devices and sensors. These devices will send data to the cloud subsystem using an input path or local processing unit (LPU). In the second phase, data mining techniques are performed on patient's data using to make cognitive decisions about students' health. In the third step, parents or caregivers will be given information and warnings about student health if needed. In addition, an alert may be given to the hospital if an emergency situation occurs to call medical emergency services to patient's location. (This is possible if a proper Android app is available.)

The focus of this paper is on the cloud layer of healthcare monitoring model which tries to probe students' probable illnesses by exploring student health data using machine learning methods.

3.1 IoT layer

Inside the IoT layer, we gather two kinds of data from students, historical and real time. Historical data are gathered using data entered by parents. First, the health details of each student which were registered through mobile applications installed on subject's parents' cellphone are entered into the student health monitoring system. An external device such as a smartphone gives us the ability to control and manage the way our data will be received in the cloud layer. Having a direct way as such will help the system to have instant access to subject's health records. Since smart phones are vastly used in the communities, they can be an elegant and easy approach for our purpose. When the historical information gathering from parents is done, we need to keep track of the user's data. Our data are going to be transferred through layers inside our network and be analyzed and stored in the end. A common way of knowing that which data belong to a user is by having a registration number for each student. Having our historical data, we can now proceed to the real-time data. Since this is an online system for tracking subject's health, it's the system's responsibility to gain the most recent information from the client since in the monitoring layer, we need to take appropriate actions at the right time and this requires detailed data on subject's current health status.

For the real-time data gathering, using a wearable device inside the school we can get a complete check on the most important health factors of the student instantly. The information that will be recorded from these sensors will have a direct effect on our future decisions for the subject's health monitoring. It is important to gather data in various ways since the system is capable of performing many analytical tasks in the cloud layer. In addition, together with historical data, real-time student health data are obtained by data gathering system. This enables incorporating smart sensor data and data of medical devices. These sensors are installed inside the body or on the surface of a human body to monitor the functioning of the organs.

Algorithm 1. IoT Layer

Step1: Historical data gathering:
1. Install mobile application on student's parent's device.
2. Enter student's health data.
3. Automatically assign a registration number for each student.

Step2: Real-time data gathering:
1. Place ECG / EEG and blood pressure biosensors inside the subject's body or on the subject's body surface or wearable devices in the school.
2. Collect physiological data in structured and unstructured ways.
3. Synchronize as LPU unit or it's gateway which can be a portable device or a smartphone.

Step3: Data Transmission:
1. Send the collected information to service repository using 5G / 4G / GPRS mobile networks
2. Apply security measurements such as third-party encryption, user authentication and credential mapping.

In our proposed model, body sensors both implanted in the body or installed on the body surface, and the sensors on wearable jackets form a body sensor network. Data are collected from the network, which are stored on a portable device or a smartphone. In addition, there is a gateway that communicates with the service repository using wireless communication technology including 5G/CDMA/GPRS mobile networks. In addition, to secure data transmission, a variety of security protocols are acknowledged, including third-party encryption, user authentication, and credential mapping in order to help us to secure healthcare application on student's parents and sensor connection to the service.

3.2 Students' health monitoring layer

In this layer, the system will keep gathering data from IoT layer in the service repository and keeps track of student's health status and gets the analyzed data output from cloud layer to decide its future actions. It is necessary to send the data to the cloud layer as soon as possible. If subject's health status is critical, subject's life depends on quick detection. So, data need to be transferred instantly to the cloud layer for further actions. Proposed networks in IoT layer are well tested and are commonly used through different devices, so these networks are reliable and can be used to perform real-time data transmission.

After data are transferred to the cloud layer, and when cloud layer is done with processing, it will send final results to the student's health monitoring layer. Now student's health monitoring layer should decide its next action. If the student's health status is "Not Sensitive" condition and is exposed to sickness, in that case system will notify the school physician about student's status and helps to prevent sickness. In a more severe case, if the student's health status has is "Sensitive" condition which is a critical stage, the proposed system will automatically send an alert to the nearest medical center to call emergency service to student's location. In this level, the system actions are totally driven by the results from cloud layer output and this shows the importance of accurate data gathering and analysis.

Algorithm 3. Student Health Monitoring Layer

```
The process follows steps bellow:
1. if (Student's health status == Not Sensitive)
2.         Inform the physician about student's health status
3. else if (student's health status == Sensitive)
4.             Send an alert to the closest medical center about student's health status
5.       else
6.             Insert information to student's health record
```

3.3 Cloud layer

In the cloud layer, students' health information that gathered via IoT devices and kept inside service repository in student's health monitoring layer is stored in the cloud data centers which is an infrastructure as a service (IaaS)

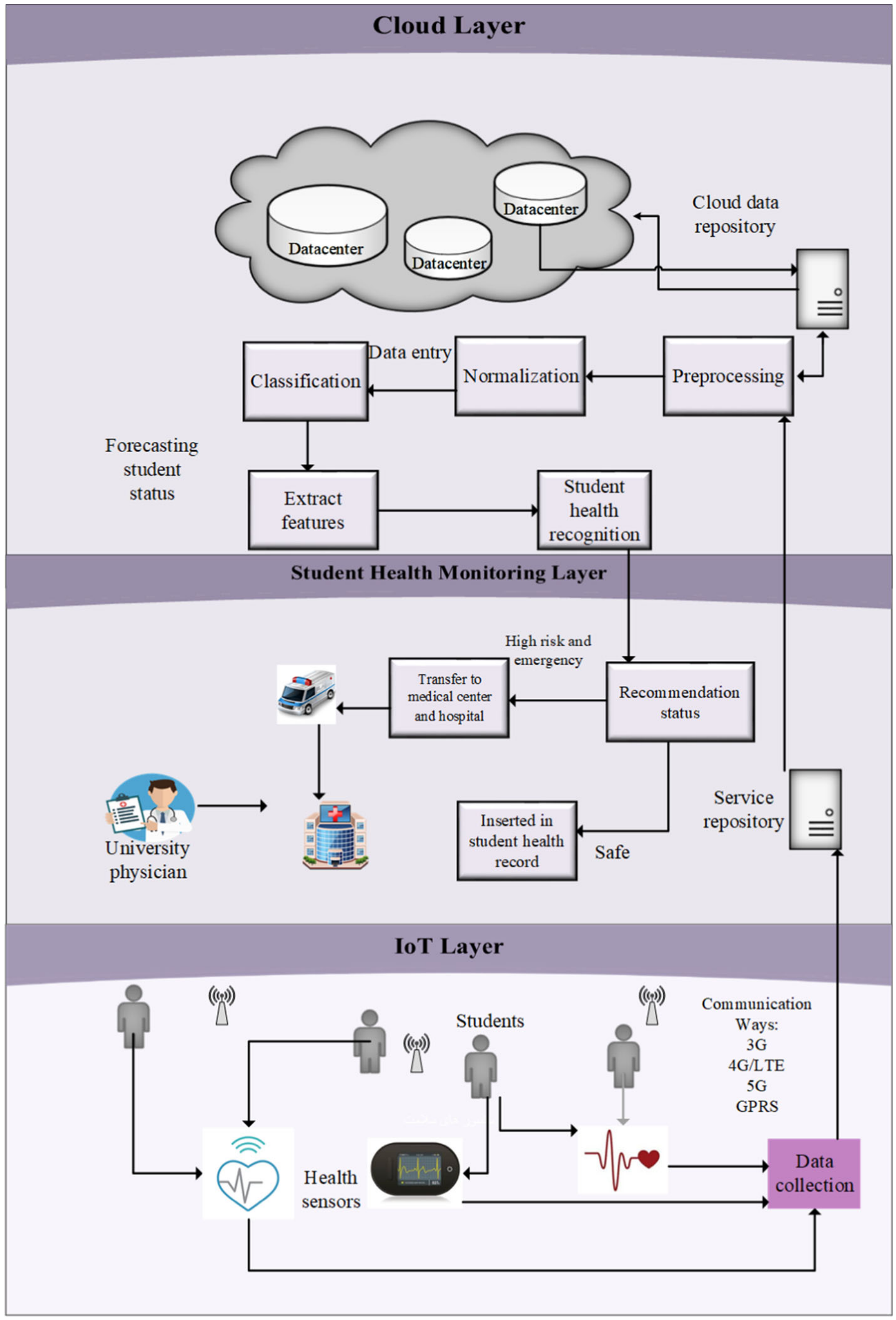

Fig. 1 Student health monitoring model

provider. The information includes historical data and real-time data collected from smart sensors and medical devices, which are equally important for our evaluation of subject's health. The cloud layer's capability of performing preprocessing is giving us a great freedom to gather these data, since it will help us to gather both structured and unstructured data from service users.

A cloud storage repository is designated on the server side for effective cognitive decision making and storage. Health-related measurements are temporarily extracted and sent to the medical detection system where the student health index is processed and the detection mechanism used to establish the severity of a disease. The diagnostic procedure is based on predefined medical words and expressions gathered from medical sources through hands-on medical experience and consultants. In addition, to create the security system, there are two classes of users that can get through the cloud robotic database. The first group includes watcher and licensed physicians that have access to shared and separate data. The second group will include users who may require the information in order to develop new drugs. The student's health monitoring layer will inform the physician if there is a possibility of sickness using common communication services such as 3G, 4G, or even voice mail; otherwise, the student's health information record will be recorded and archived.

In the cloud layer student's health data are stored and data analysis tasks will be executed to get student's health status. The outcomes of this layer will lead our next actions in the monitoring layer. Several tasks will be performed on our data in order to make it ready for our analysis. IaaS service will provide us with the resource needed for computing and storage. There are many IaaS service providers that can serve for our data storage and computing tasks. The importance of a reliable provider is evident, since the whole student's health data are going to be stored on it and be used for later duties. The cloud storage repository is an environment for a data set to be mined for reporting and analysis. A data repository is a large database infrastructure which helps us to collect, manage, and store data sets, in order to perform data analysis tasks. We can choose data warehouses, data lakes, data marts, or even data cubes to use the repository capabilities. This environment has many beneficial effects for our system. The isolation that is being provided using this service allows easier and faster data reporting and data analysis due to the fact that the data are clustered together. Another beneficial thing is the administrator's ease of access to the repository which let them to track problems easier. Before starting our classification job, we need to use a set of techniques to organize the data is stored in our database. Normalization as a systematic approach helps us in decomposing tables in order to eliminate data repetition and anomalies. Insertion and deletion anomalies are very frequent for databases that ignore normalization. After that, our classification process begins. This is the part which gives us the clue for deciding our actions in the next layer.

3.4 Data mining algorithms

In this section, we introduce four data mining algorithms utilized in this paper to compare and evaluate our model. These evaluations will lead to choose the best suited algorithm for our model.

3.4.1 Decision tree

Decision tree (DT) is an algorithm that constructs a tree from the input data. The tree could be used to extract a set of rules which lead to determining a class or value. Decision trees use sequential data to make separate groups and maximize the distance between each group.

In knowledge-based decision tree classification algorithms, the output is presented as a tree from different states of adjective values. The representation of knowledge in the form of a tree has resulted that the DT classifications are perfectly explainable. The superflexibility and comprehensibility are its biggest advantages which is influential in its popularity. DT is a great tool for predicting different categories considering the value of the predicted attributes is. Visualizing the tree is a very informative decision, and its flexibility actually benefits us. When other methods have failed, the DT may be used successfully. DTs can be used as a response; many issues arise from data and information areas. DTs are used as knowledge-based expert systems.

3.4.2 Support vector machine

Support vector machine's goal is to search for a hyperplane in an N-dimensional space. (N is the number of features.) The hyperplane will markedly classify these data points. In order to make different classes from data points, we can choose a variety of hyperplanes. The purpose of the SVM

Algorithm 2. Cloud Layer

Step1: Store retrieved data from service repository on a cloud storage which is the IaaS service provider.

Step2: Transfer data from data center into the cloud storage repository for effective cognitive decision making.

Step3: Apply normalization to set the data into 0 to 1 range.

Step4: Execute classification algorithm, SVM, to assess student's heath status.

Step5: Last layer of the system is dedicated to archive student's health data and taking the necessary measures for improving student's health status or saving data in the cloud storage.

algorithm is to find the best boundary between the data, and it takes the longest possible distance from all categories and is not sensitive to other data points. SVM is a classification algorithm and is recognized as one of the best techniques for categorizing and predicting and detecting off-site data. Unlike clustering algorithms, it is considered a supervised learning category and has two phases of training and testing.

3.4.3 Random forest

Random forest (RF) is an easy-to-use machine learning algorithm that often produces very good results even without adjusting its parameters. Because of its simplicity and usability this algorithm, it is one of the most widely used machine learning algorithms for both classification and regression. In a DT, this guess is refined starting with a basic guess based on one's knowledge of the problem's world and get more information. During this process, and gradually, data are collected to refine our estimate and a decision is made. Instead of searching for the most important features when dividing a node, this algorithm looks for the best features among a random set of features. This results in a lot of variation and ultimately a better model. Therefore, in a RF, only a subset of features is considered by the algorithm to divide a node. With the added use of random thresholds for each feature, trees can be made even more random in search of the best possible threshold.

3.4.4 Multilayer Perceptron

Multilayer perceptron (MLP) artificial neural network (ANN) is an approach that comes from feed-forward artificial neural network class which has three or more layers. An MLP neural network must include three main layers, which are an input layer, a hidden layer, and an output layer. In an MLP neural network, there could be a number of arbitrary hidden layers which are the computational engine of the network. Each node inside one layer will connect to every node in its following layer considering a certain weight. This method is often applied to supervised learning problems. To model the correlation in these networks, MLP should be trained on a set of input–output pairs and begin its learning. The supervised learning process which is done through backpropagation begins by changing weight values in each iteration of data processing. The network then computes the error in each output and compares them to the expected outcomes. MLP helps to stochastically solve problems which brings approximate solutions to problems that can be very complex.

3.5 Evaluation criteria

The knowledge that is produced during the model learning phase should be analyzed in the testing phase. These criteria can be calculated for both the training data set at the learning stage and the test record set at the evaluation stage. We consider the criteria for evaluating the concept of confusion matrix classification algorithms. According to Table 1, this matrix shows how the classification algorithm works with respect to the input dataset.

Each of the elements of the matrix is described (Ghanbari-Adivi and Mosleh 2019):

- The TN is the number of records which their real class is negative and the classification algorithm correctly classifies them negatively.
- The TP is the number of records which their real class belongs to positive and the classification algorithm rightly identifies their class.
- The FN is the number of records which their real class is positive and their classification algorithm is detected as negative.
- The FP is the number of records which their real class is negative and their classification algorithm is detected as positive.

Accuracy is the most popular and common criterion for calculating the efficiency of classification algorithms. The classification accuracy is obtained using Eq. (1) (Ghanbari-Adivi and Mosleh 2019).

$$\mathrm{AC} = \frac{\mathrm{TN} + \mathrm{TP}}{\mathrm{TN} + \mathrm{FN} + \mathrm{TP} + \mathrm{FP}} \tag{1}$$

Equations (2) to (4) are for calculating precision, recall, and F-score of a classification algorithm.

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{2}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{3}$$

$$F\text{ - Score} = \frac{\mathrm{Precision} * \mathrm{Recall} * 2}{\mathrm{Precision} + \mathrm{Recall}} \tag{4}$$

In this section, the proposed approach and proposed architecture are presented using DT, SVM, RF, and MLP algorithms and criteria of accuracy, precision, recall, and F-score were used that was explained in their chapter. In

Table 1 Confusion matrix

Real records		Positive	Negative
	True	TP	FN
	False	FP	TN

the next chapter, we will discuss how to implement this proposed approach and compare the results.

4 Experimental results

At the beginning of this section, we demonstrate the data, environment, and implementation of algorithms. Following that, we execute the proposed approach on student's health data gathered from both student's parent phone as historical data and sensors data as real-time data, and we evaluate and compare the outcomes based on accuracy, precision, recall, and *F*-score metrics.

To this day, the science and research world has published many educational and commercial software packages for data analysis in various fields of data. Each one is focusing on particular algorithms concerning data types that they analyze. Precise and scientific comparison of these tools must be done by considering various and different aspects like input data diversity and format, possible data processing size, implemented algorithms, results from evaluation methods, visualization methods, preprocessing methods, user-friendly interfaces, and compatible platforms for execution, price, and software availability. Among those, we introduce Weka with vast capabilities, comparing different output features, well documentation, capable user interface, and compatibility with other windows application. In addition, it has filters which are the tools that we use for data preprocessing stage.

4.1 Dataset description and experimental setup

We employed a dataset for student health care that was gathered from 1100 instances. Based on the existing dataset, categorization of students' information is presented according to Table 2. The following health information is important attributes to evaluate health level of each student.

We classify dataset into two classes: (1) Sensitive events class and (2) Not Sensitive events class. Sensitive events class are occurrences that can take student's health to critical conditions. For example, some blood pressure levels can be sensitive and some blood pressure levels are not sensitive and even have less effect on student's health compared to an attribute like sleep hours in day. We applied 70% of instances for train the model and 30% for testing model. Tenfold cross-validation is done to evaluate the models.

4.2 Evaluation and data analysis

To assess prediction results, according to dataset with the features presented in Table 2, we evaluate the suggested method with DT, SVM, RF, and MLP classification algorithms. According to Figs. 2, 3, 4, and 5, the SVM is far more efficient compared to other three methods. SVM achieved 99.1% accuracy which is better than those of RF, DT, and MLP with accuracies of 92.4%, 95.1%, and 93%, respectively.

Table 2 The main student's clinical attributes and their definition

Attributes	Possible values	Properties
Age	–	Numerical
Gender	Male/female	Nominal
Weight	Low/medium/high	Numerical
Body temperature	Medium/high	Nominal
Blood pressure	Low/medium/high	Nominal
Heartbeat	Low/medium/High	Numerical
Cigarette consumption	Yes/no	Nominal
Alcohol consumption	Yes/no	Nominal
Sleep hours	Low/normal/high	Numerical
Fasting blood sugar	Normal/borderline/high	Numerical
Cholesterol	Normal/borderline/high	Numerical
HDL	Normal/high	Numerical
LDL	Normal/high	Numerical
Triglyceride	Normal/borderline/high	Numerical
TSH	Low/medium/high	Numerical
T4	Low/medium/high	Numerical
T3	Low/medium/high	Numerical
Health status	Not Sensitive/Sensitive	Nominal

Precision calculates the random error of a method, which is the scatter in the data. Classification precision is acquired with Eq. 2 presented in Sect. 3.5 and presented in Fig. 3.

Recall determines the percentage of total relevant results correctly classified by an algorithm, and F-score implies alert rate according to negative class as shown in Figs. 4 and 5.

Based on the outcomes of our examinations on student's health dataset in experimental results, it can be understood that SVM is much better choice for our model compared to RF, DT and MLP methods, since it has better results in all accuracy, precision, recall, and F-score results.

5 Conclusion and future work

In this paper, an IoT-based student's health monitoring system is proposed to check vital signs and detect biological and behavioral changes of students via smart student care technologies. According to the conceptual model and the modular structure of the proposed system, three levels

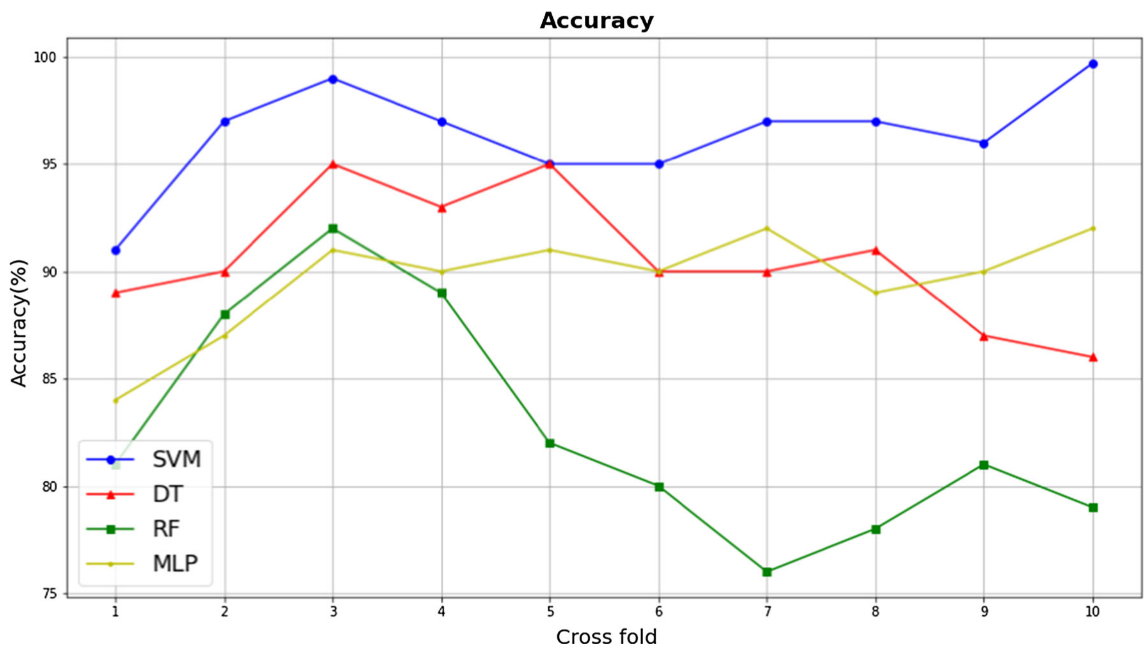

Fig. 2 Comparing accuracy of DT, SVM, RF, and MLP

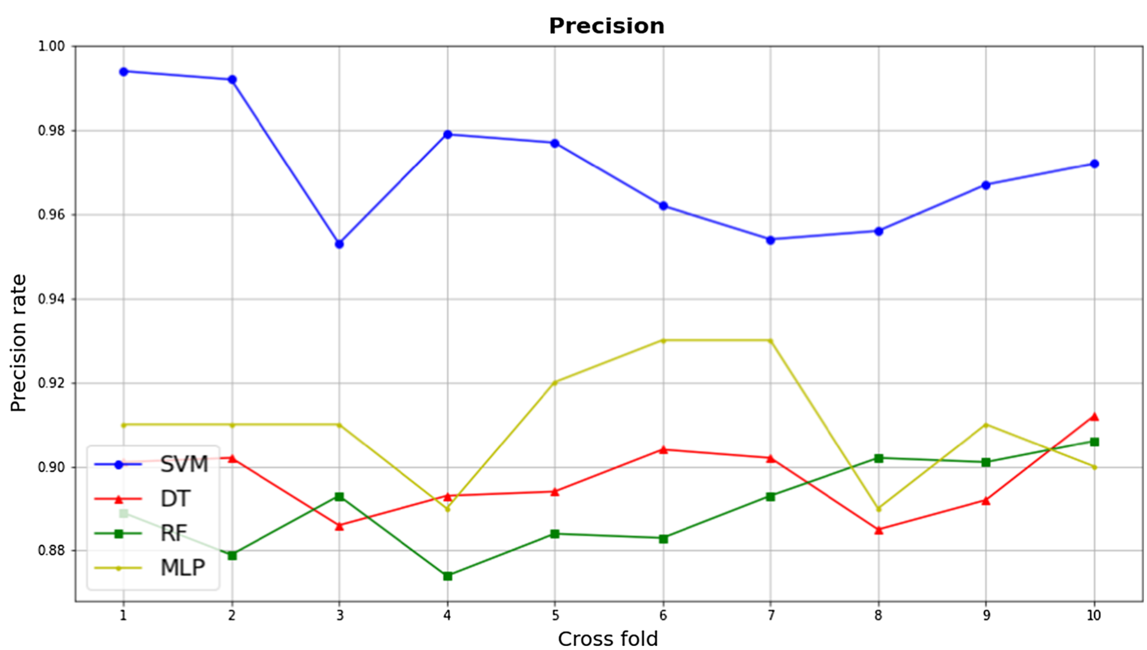

Fig. 3 Comparing precision of DT, SVM, RF, and MLP

have been considered. These levels include determining the required data for student health monitoring system according to the biological and behavioral indicators, data collection via biomedical sensors and smart IoT devices, and data preprocessing. The proposed model was evaluated with different classification methods. The applied classifiers included SVM, DT, RF, and MLP. The experimental results revealed that the classifying algorithms performed well in terms of the precision, recall, accuracy, and F-score. SVM reached the highest performance for diseases predicting in our scenario with 99.1% accuracy, 97.2% precision, 99.5% recall, and 93.2% F-score. High accuracy of SVM in comparison with other applied classifiers is a significant difference that makes it applicable in real-time health function status monitoring for students. The future work of this study is to suggest an edge-based data

Fig. 4 Comparing recall of DT, SVM, RF, and MLP

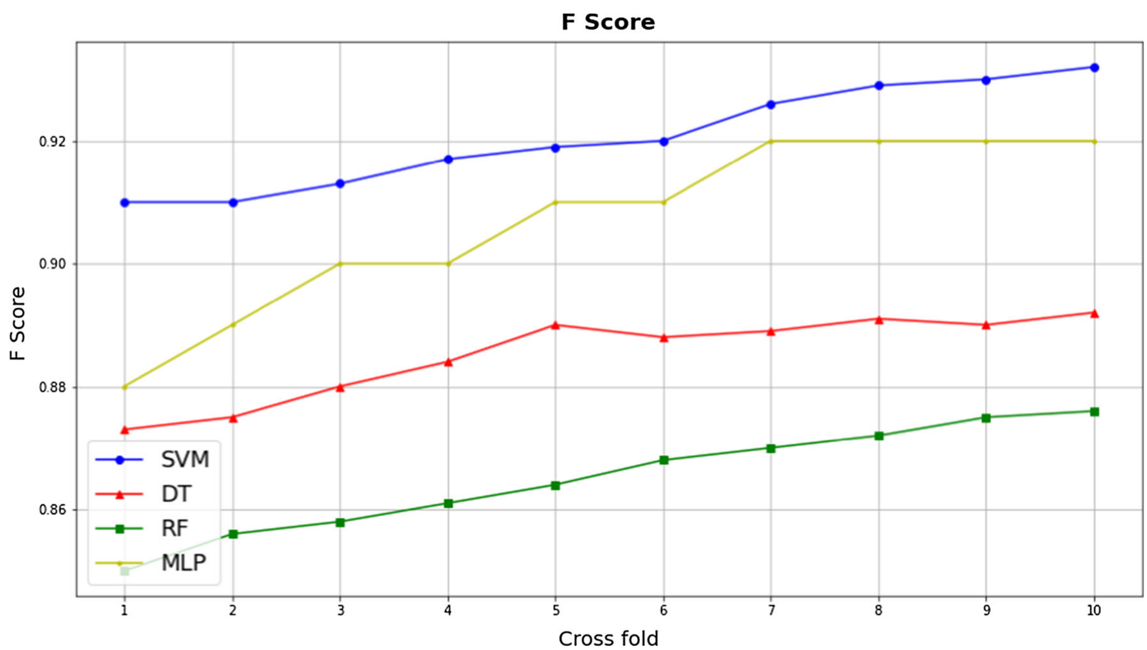

Fig. 5 Comparing F-score of DT, SVM, RF, and MLP

processing system to bring computation and data storage closer to the patient's location to improve emergency services response time and save bandwidth in the system. Developing such a system can result in better health care for students, since our response time can be shorter than the proposed system.

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Compliance with ethical standards

Conflict of interest All authors declare that there is no conflict of interest in this manuscript.

Human and animal rights This article does not contain any studies with human participants performed by any of the authors.

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