Effective Diagnosis and Monitoring of Heart Disease

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Abstract

Wearable sensor mobile technologies and machine learning techniques are considered as two of the key research areas in the computer science and healthcare application industries. Our main aim is to build a simple yet accurate mobile application that is capable of real-time diagnosis and monitoring of patients with Coronary Artery Disease (CAD) or heart disease which is a major cause of death worldwide. Most available mobile healthcare systems focus on the data acquisition and monitoring component with little attention paid to real-time diagnosis. In this work, we build an intelligent classifier that is capable of predicting a heart disease problem based on clinical data entered by the user or the doctor and by using machine learning algorithms. This diagnosis component is integrated in the mobile application with a real-time monitoring component that continuously monitors the patient and raises an alarm whenever an emergency occurs. Our results show that the proposed diagnosis component has proved successful with a classification performance accuracy of more than 85% with the cross-validation test. Moreover, the monitoring algorithm provided a 100% detection rate.

Keywords: Heart disease diagnosis, heart disease monitoring, wearable sensors, machine learning algorithms, feature selection

1. Introduction and Related Work

With the increasing number of population across the world and with recent changes of humans' life styles, there is increasingly higher numbers of individuals with complex medical conditions. This has led to higher numbers of people visiting hospitals and put stress on the Medicare health systems. Thus, there is an increasingly need for remote health care systems that can assist with these challenges. Recently, there has been growing attention to the advances in the areas of electronic and biomedical engineering and the great applications that these technologies can offer mainly for health diagnosis and monitoring. Smart phones and wearable sensors are now accessible for many people worldwide with affordable prices. These devices in conjunction with artificial intelligence techniques can be effective for monitoring and diagnosis of people with heart diseases reducing the number of visits to hospitals and improving people's lives [18].

According to the American Heart Association (AHA), heart disease, also referred to as coronary artery disease (CAD) is a term used to describe a variety of problems related to plaque buildup in the walls of arteries making it gradually narrow and in consequence it becomes difficult for blood to flow increasing the risk of heart attack and stroke [4]. In 2010, CAD was a major cause of death worldwide and was responsible for one in every nine deaths in the United States [4]. In some cases, people with heart disease may have symptoms like chest pain and fatigue. However, in many cases, there are no symptoms until a heart attack occurs [20]. This was the major motive for us to build a smart system that can continuously monitor the person's heart and raise attention whenever there is any

heart related problem. In addition, the proposed system can efficiently diagnose the presence of a heart disease problem based on the use of intelligent machine learning algorithms.

There are many benefits associated with the medical application of wearable systems and in specific for people with CAD. A main advantage of these systems is the remote monitoring of CAD patients. With this advantage, the patients can have a more independent and easy life. In addition, these systems can provide real-time identification of heart instability and thus, a quick action can be triggered which is crucial as few minutes can save lives for people with heart disease [7].

In addition, with many patients living in rural areas and with a reduced access to health providers, the development of such systems can help with continuous remote monitoring for these people with a reduced number of visits to hospitals. Add to that, the smart diagnostic property of the system that can help in the initial analysis and identification of heart disease.

Moreover, the cost of remote health diagnosis and monitoring systems is affordable to a wide range of people because of the recent advances in consumer electronics and mobile devices which have reduced the production costs and have made it possible to ordinary users to afford inexpensive sensors and mobile phones [7].

At the core of monitoring systems is the use of wearable sensors which would allow people to be constantly monitored. Wearable sensors can be defined as electronic devices that can be unremarkably embedded in the user's outfit as part of the clothing or an accessory. They range from micro-sensors to computerized watches and belt-worn PCs with a head mounted display [23]. Wearable sensors have diagnostic as well as monitoring applications. Their applications include physiological, biochemical, and motion sensing [22].

Sensors are deployed for patients with heart problems for continuous monitoring. For example, in the work of [8], a ring sensor worn on the base of the finger is implemented for the purpose of continuous monitoring for people with congestive heart failure problems. Another example is presented in the work of [12] where an energy efficient ear worn PPG sensor is introduced for the purpose of heart monitoring. The comfortable placement of the sensor makes it suitable for long term monitoring, often referred to this feature as *mobility*. Two major advantages of the abovementioned examples is the small size of the sensors and the low power consumption which are very important issues to be considered in any monitoring problem.

Recently, the authors in [18] proposed an Android-based system for heart monitoring using data collected from a strap worn around the chest named Zephyr Heart Rate Monitor. It measures heart rate and other measurements and uses Bluetooth to send the information to an Android phone device. The measurements are used to identify a number of heart related problems. The system proved useful and the authors achieved good performance results.

It is important to note that health monitoring applications of wearable systems often employ multiple sensors that are integrated together to form a body sensor network. An example of these applications is MyHeart [11], where a number of on-body sensors are used to collect physiological data that are sent wirelessly to a PDA. The information is analyzed and health recommendations are given to the user based on this analysis. Other examples of these applications include LifeGuard [6], AMON [23], HealthGear [17], WANDA [15] and LiveNet [16].
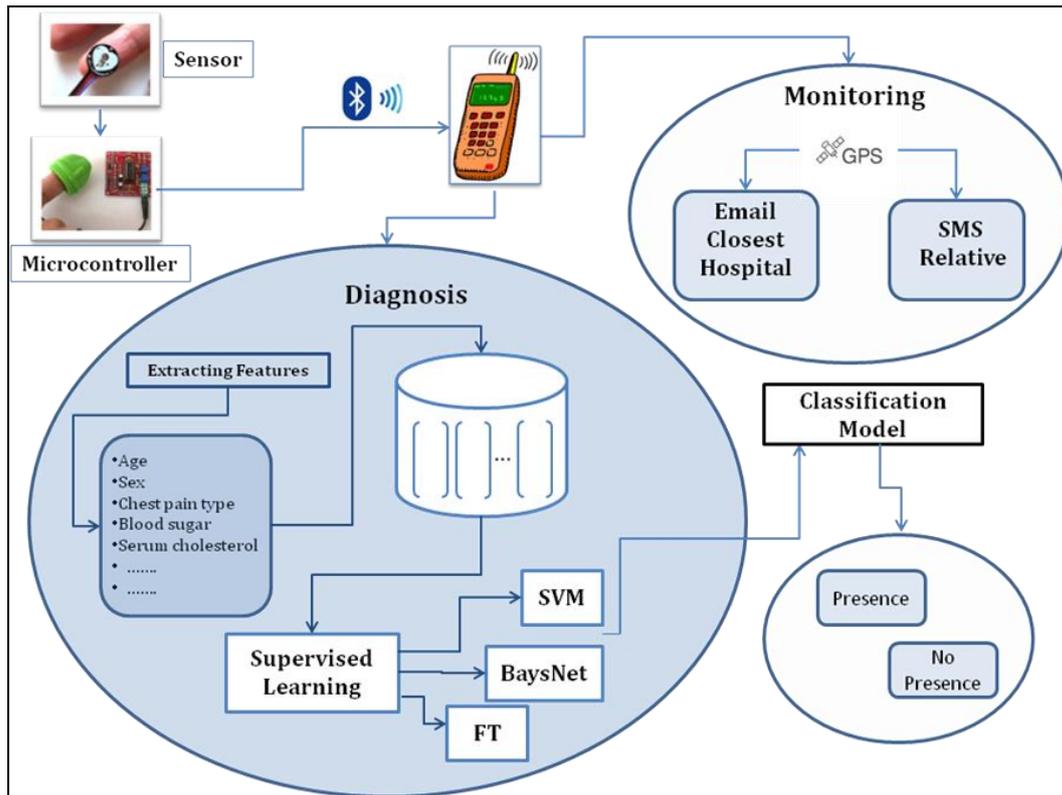
Figure 1. A Conceptual Representation of the Proposed System

Once data is collected, wireless communication is then relied upon to transmit patients' data to a mobile phone or an access point and relay the information to a remote center via the internet. Emergency situations are detected via data processing implemented throughout the system and an alarm message is sent to an emergency service center to provide direct assistance to patients [22].

Recent advances in the artificial intelligence research have led to advanced algorithms that proved successful for many recognition problems. A widely implemented type of these algorithms is machine learning (ML) algorithms which can be very useful for building diagnostic components in the mobile health care applications. ML algorithms are concerned with automatic discovery of regularities or patterns in data through the use of computer algorithms and with the use of those patterns to take actions such as classifying data into different categories [2]. Thus, ML algorithms can be very beneficial in exploring hidden patterns in medical data sets and can be utilized for clinical diagnosis [13]. For example, in the work of [20], a modified neural networks algorithm based on ensemble learning is proposed and is implemented for the purpose of heart disease diagnosis. The authors achieved good results based on a number of features that are directly related to the heart disease problem.

In the work of [21], an enhanced artificial immune system that uses attribute weighting is proposed. Attribute weighting aims to evaluate the importance of attributes and gives weighting based on the contribution of these features. The proposed algorithm has been tested on the Stalog heart disease dataset [1], and a performance accuracy of 87.47% is reported. In a recent study, a comparison between a number of classification algorithms for the purpose of
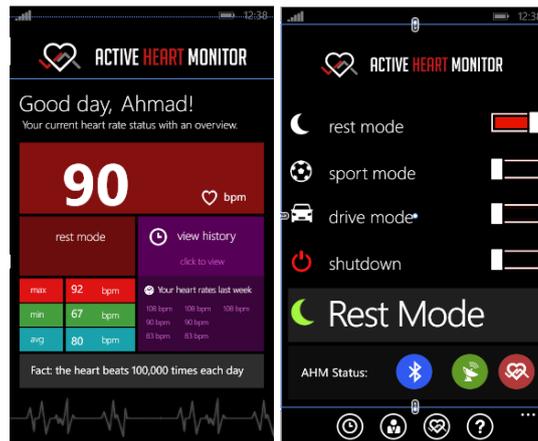
Figure 2. Interfaces from the Proposed Mobile Application

predicting the presence of heart disease is presented [13]. The classification algorithms include K-NN, Naïve Bayes and Decision Trees. This comparison is evaluated on 909 records from the heart database which seem to be collected from four different data sets. Decision trees outperformed the other classifiers with 89% performance accuracy using the hold-out validation test.

Different from previous works on heart disease applications, we propose an integrated system for both heart disease diagnosis and monitoring. The proposed system can continuously monitor the user and raise an alarm for any emergency caused by the detection of a heart problem. In addition, a diagnostic component is incorporated to the application which provides clear and immediate diagnosis results to medical personnel and users. It smartly predicts if the user have any related heart problems. Our proposed system consists of three main parts: 1) the data collection using a sensor, 2) the communication hardware and software to relay data to a remote center, and 3) data analysis and understanding to extract clinically relevant information.

The rest of this paper is organized as follows: In Section 2, we explain in detail the components of the system. Section 3 presents the experimental results of the proposed application. Finally, Section 4 concludes the paper and suggests future work.

2. System Design

Although there are many commercially available healthcare systems, they usually share a common prototype [7]. For heart monitoring systems, this prototype usually consists of a sensor carried by the patient that is connected to a backbone network via a gateway node. The patient and doctors can monitor and diagnose heart rate information by a graphical user interface (GUI). In the case of an emergency situation, an alert is sent to a laptop or a personal computer in the closest hospital.

Our proposed application consists of three main components: i) the sensor, ii) a gateway to the wide area networks (WANs), and iii) the end user health care application. In this section we will discuss each component in details (see Figure 1 for a conceptual representation of the proposed system).

2.1. The Sensor

To detect the heart rate, we implement a commercially available sensor named, the Pulse Sensor AMPED [19]. It combines a simple optical heart rate sensor with amplification and noise cancellation circuitry making it fast and easy for getting reliable heart pulse readings.

This specific sensor was chosen because of its reliability, high usability and good performance. Moreover, it is of a small size and a modest price. The sensor can be simply worn by clipping it to the finger tip and connecting it to a microcontroller.

An important issue to consider when implementing sensors is power consumption. The implemented sensor is energy efficient with a power consumption of only ~4mA at 5V with voltage ranging from 3V to 5V. Moreover, the low output transmission power of the sensor is important for keeping its effects minimal on the patient's health.

2.2. Gateway to WANs

This component is responsible for connecting the sensing component to the infrastructure based WANs. In other words, data collected from the sensor should be transmitted through a gateway, which is usually a mobile phone or a personal computer, to a remote site such as a hospital.

In our application, this connection is carried out by firstly connecting the sensor to an arduino microcontroller and then the sensing data is wirelessly transmitted through a Bluetooth technology to a mobile phone. The Bluetooth module that is integrated in the arduino microcontroller is HC-06 module which uses the UART (Universal asynchronous receiver/transmitter) protocol. UART makes it easy and reliable to send and receive data wirelessly.

In case of an emergency situation which is identified based on the data analysis on the mobile device, an emergency alert is relayed to the closest hospital through the Internet. The location of the closest hospital is identified using GPS technology which is integrated with the majority of mobile phones currently available with people worldwide.

As the information is relayed to the hospital through a network system, the Internet, it is crucial to have reliable communication protocols for wide area networks. A universal broadband connectivity is very important to achieve such reliability. Broadband technologies are currently available in the majority of the developed countries and across many developing countries [22].

2.3. The End User Healthcare Application

The end user application is a central part of the system where the collected data are analyzed and actions are triggered [7], (see Figure 2 for two screens of the application interface). In our mobile application, there are two main components: diagnosis and monitoring.

2.3.1. The Diagnosis Component: The diagnosis component is capable of smartly identifying the presence of a heart disease based on a number of inputs entered by the patient or the doctor. This intelligent component is built using clinical data from the Cleveland heart

Figure 3. Input Data for the Diagnosis Component

disease data set which is available from the UCI machine learning repository [1]. Based on this data set and by using machine learning algorithms, classification is attained and a system is built that can predict the presence or absence of a heart problem for a new patient.

In this work, we experiment with three widely known classifiers: BayesNet, Support Vector Machines (SVM), and Functional Trees (FT):

• BayesNet: enables the use of a Bayesian Network learning using various search algorithms and quality measures. It provides data structures such as network structure, conditional probability distributions, and others [9].

• Support Vector Machines: maps pattern vectors to a higher dimensional feature space where a maximal separating hyperplane is constructed. For a two class problem, two parallel hyperplanes (canonical) are constructed on each side of the separating hyperplane that separates the data. The points that lie on the separating hyperplane are called support vectors. The distance between canonical hyperplanes and the separating hyperplan is called margin. The main idea is to maximize the margin between the classes by selecting a minimum number of support vectors [2, 5]. In this work, we implement a variant of the SVM, which is sequential minimal optimization. It breaks optimization problem into a series of smallest possible sub-problems, which are then solved analytically [9].

• Functional Trees: are classification trees that could have logistic regression functions at the inner nodes and/or leaves [9].

The performance of the classifier is evaluated in terms of classification accuracy and average false positive rate. Classification accuracy is calculated as the proportion of the number of correctly classified instances against the total number of tested instances. On the other hand, false positive rate (FPR) is calculated as the proportion of all instances predicted wrongly against the sum of the true negatives (TN) and the false positives (FP).

2.3.2. The Monitoring Component: The monitoring component performs reasoning with computational algorithms to continuously monitor the patient's heart rate and save all the readings of the heart rates (Beats Per Minute (BPM)) to a log file. This saved data can be reviewed when needed, *e.g.*, when the patient visits his/her health clinic.

Once an emergency situation occurs, the algorithm detects it and automatically generates an email that contains the patient's information from name, mobile phone, age, and the exact location based on the GPS coordinates. An emergency SMS is also generated. The email is sent to the closest hospital to the patient's location. The closest hospital is identified using the GPS technology. The location of the user is updated every 1 minute. Moreover, the emergency SMS alert is sent to the patient's relative together with the exact location of the patient.

According to the American Heart Association, most people have a resting heart rate of 60 to 100 beats per minute. For people playing sports, this heart rate may increase while playing to reach values of up 150 BPM. We adopted this criterion in our system, and our algorithm raises an alarm whenever the heart rate deviates from the aforementioned rates.

The proposed monitoring component implements two modes: the rest mode and the sport mode which are set by the user. If the person is in the rest mode and the heart rate deviates from its specified thresholds, the system waits for window interval of 5 minutes and during this time, if the heart rate remains unstable, the system notifies the user whether he/she is playing sport or not. If the user is playing sports, then the system changes to the sport mode and if not, it sends an emergency alert. Similarly, in the sport mode, if the monitoring system detects an emergency status that remains for a window interval of 5 minutes, it sends a notification email and an SMS alert to the closest hospital and the patient's relative, respectively. The window interval is inspired by works like [18] and based on consultations with a number of medical experts. In addition, a driving mode can be also be set for a continuous display of BPM on the vehicles windshield making it easier for the driver to monitor his/her heart rate.

3. Experimental Results and Analysis

Experiments are conducted in order to evaluate the performance of the proposed system. We carried out two major experiments for the two components of the system: diagnosis and monitoring. We carried out these experiments using Nokia lumia 520 mobile phone. It is equipped with a Duel-core 1 GHz qualcomm snapdragon S4 processor, an internal 8 GB storage and it includes a Bluetooth v 4.0 interface. An Initial experiment was run in [3] and it showed us encouraging results.

3.1. Diagnosis Experiment

Our main aim is to build an intelligent classifier that is capable of recognizing a new patient and assigning it to one of two classes: no presence or presence of heart disease. For this purpose, we experiment with well-known machine learning algorithms to train the classifier and use it for classification.

3.1.1. The Dataset: We select the Cleveland heart data set from the UCI Machine Learning Repository [1] as it is widely used by the pattern recognition community (*e.g.*, [14] and [20]). The data set consists of 303 individuals' clinical records of which 164 did not have the disease. There are six samples that have missing feature values and we have replaced these missing values with the average of all values for that specific feature across all samples. The data set is represented with 76 features; however, only 13 features have been implemented in previous research works on this data set. Thus, we use these 13 features in our experiments which are the following:

- Age,

- Sex,

- Chest pain type,

- Resting blood pressure,

- Serum cholesterol in mg/dl,

- Fasting blood sugar

- Resting electrocardiographic results,

- Maximum heart rate achieved,

- Exercise induced angina

- Old peak, ST depression induced by exercise relative to rest,

- The slope of the peak exercise ST segment,

- Number of major vessels colored by flourosopy,

- Thal: 3 = normal; 6= fixed defect and 7 = reversible defect.

Figure 3 shows the GUI interface for entering the abovementioned data in the proposed application.

3.1.2. Hold-out and Cross Validation Tests: We carried out two experiments to validate the proposed feature set with the selected algorithms. The first validation method is the hold-out test and the second method is the cross-validation test. In the hold-out experiment, we partitioned the 303 samples into two independent data sets. Almost 2/3 of the data is used to train the classifier and build the classification model using different classification algorithms. After that, the testing data are tested by the model and the predicted instances are compared with the original ones and accuracy and false positive rates are calculated.

Figure 4 shows the number of correctly and incorrectly classified instances across different classifiers. Moreover, Figure 5 shows the accuracy and false positive rates of the proposed feature set using the aforementioned classification algorithms. It is clear from this figure that the highest accuracy is achieved with SVM classifier with an accuracy rate of 88.3% and a low false positive rate of 1.2%. These results are promising given the problem in stake.

To further examine the strength of the feature set, we experimented the different algorithms with a 10-fold cross validation test. In this test, all the 303 instances of the dataset are used and divided into ten disjoint groups where nine of them are used for training and the rest group is used for testing. The algorithm runs for ten times and the average accuracy across all the folds is calculated. Figure 6 shows the number of correctly and incorrectly classified instances across different classifiers. Moreover, Figure 7 shows the accuracy and false positive rates of this validation method across the different classifiers. It is clear from this figure that the BaysNet and SVM provide the highest accuracy results with an accuracy performance of 83.8% and a low false alarm rates of 1.6% and 1.7% for BaysNet and SVM, respectively. It is encouraging results considering the size of the testing set which is bigger than the one used in the first experiment. Usually, with the cross-validation test the results decrease from the ones with the hold-out test as the algorithm runs over ten testing data sets rather than one testing data set. However, in our experiments, the results remain
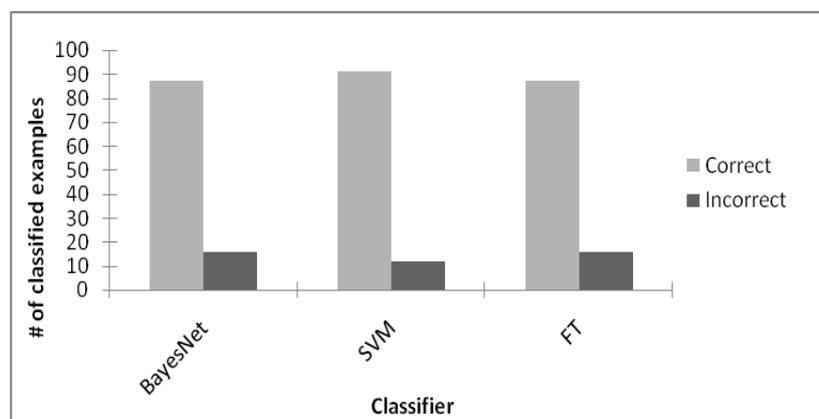

Figure 4. Number of Correctly and Incorrectly Classified Instances Across the Different Classifiers with the Hold-Out Test
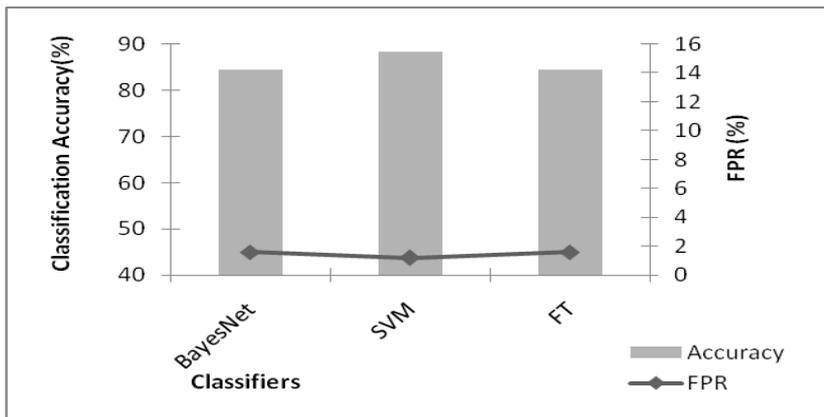
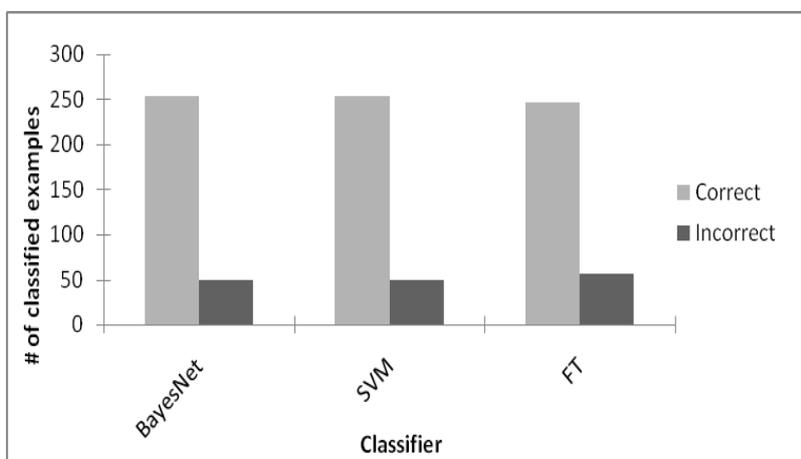**Figure 5. Accuracy Results and False Positive Rates Across Different Classifiers with the Hold-Out Test**

Figure 6. Number of Correctly and Incorrectly Classified Instances Across the Different Classifiers with the Cross Validation Test
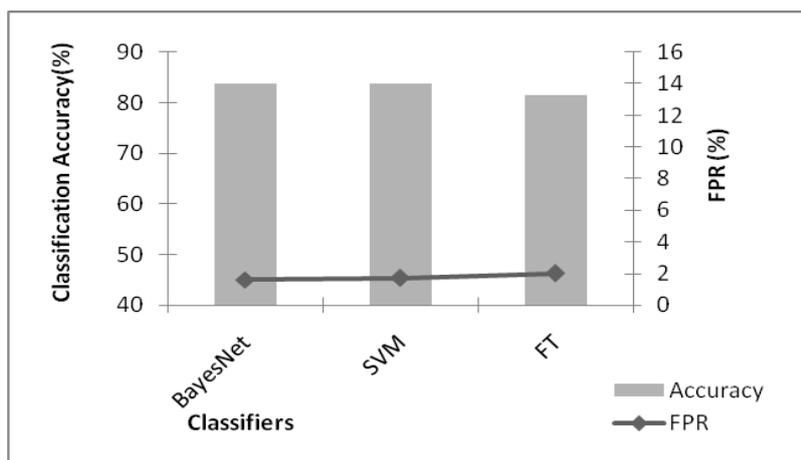

Figure 7. Accuracy Results and False Positive Rates Across Different Classifiers with the Cross Validation Test
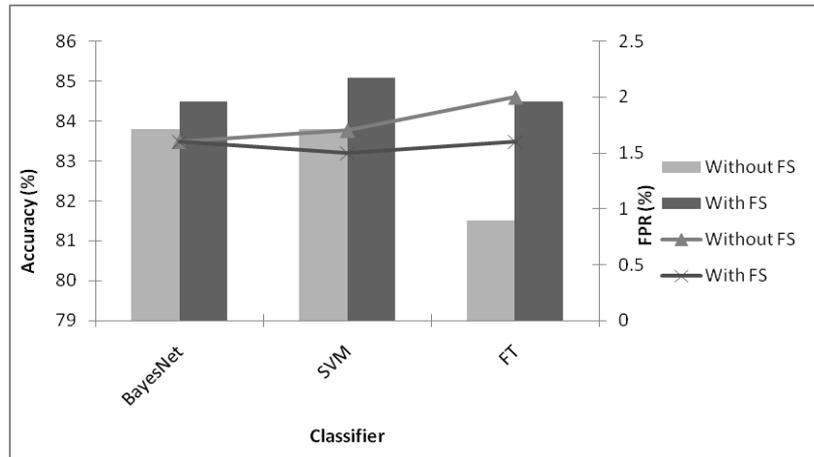
Figure 8. Performance Results Before and After Applying Feature Selection (FS)

Table 1. Performance Results Before and After Applying Feature Selection

Classification Algorithm	Accuracy %		FPR %	
	Without FS	with FS	Without FS	with FS
BayesNet	83.8	84.5	1.6	1.6
SVM	83.8	85.1	1.7	1.5
FT	81.5	84.5	2.0	1.6

Table 2. Monitoring Results

Test Case	# of samples	detection results
Healthy / Rest mode	15	100%
Healthy / Sport mode	5	100%
Patients / Rest mode (simulated)	10	100%
Patients / Sport mode (simulated)	10	100%

stable with slight decreases and there are no dramatic changes between the two validation tests.

3.1.3. A Comparison of Performance Evaluation Before and After Feature Selection:
Feature selection is the process of selecting a subset of relevant features to be used in building a classifier. It improves the prediction performance and provides a faster classifier [10]. Because of these benefits, we ran a third experiment to compare the classification performance using all the 13 features with that of the 7 best features selected by the Best First selection algorithm [9]. We chose 10-fold cross validation for results validation. Figure 8 shows a comparison of classification performance with the complete feature set and with that of the selected features.

It is clear from this figure that the feature selection process has improved the classification performance results across the different classifiers with accuracy improvements of up to 3% with the FT classifier. In addition, FPR has decreased with the inclusion of these features (see Table 1 for the accuracy and FPR percentages). These are interesting findings and show the effectiveness of the feature selection algorithm in enhancing the classification performance.

3.2. Monitoring Experiment

To evaluate the performance of the monitoring component, we carried out trial experiments involving 20 healthy individuals where 5 of them were asked to play sport while carrying the monitoring device. As all the selected personnel were healthy, there were no deviations from the specified thresholds and thus no alerts generated. The first two rows in Table 2 show the results of the heart monitoring test with the selected sample.

It is clear from this table that the algorithm is 100% accurate in the monitoring component for both modes and with no generated false alarms. Moreover, the BPM detected values are comparable to real values. These are interesting results and prove the usefulness of the proposed monitoring system.

To further test the performance of the proposed system for heart disease patients, we used offline implementation that simulates real time device operation for 20 unhealthy cases where both the rest mode and sport mode were tested. Deviations from normal rates for both modes were simulated with different values that are more and less than the specified thresholds. The monitoring system accurately detected these deviations and emergency alerts and SMSs were generated in all the tested cases. Moreover, GPS locations were accurately detected across all cases. Again a 100% detection accuracy of spotting deviations from normal rates was achieved and it is illustrated in Table 2.

Privacy and reliability are two important issues to be considered in any health care application. An end-to-end privacy mechanism is applied, where the patient's data and BPM readings are only accessible by the patient or by the doctor upon approval of the patient. Reliability is also ensured throughout the system where the BPM data is reliably transmitted through a dependable connection between the sensor and the arduino device. In addition, we implement a reliable Bluetooth module for accurate transmission of data from the microcontroller to the mobile device and it has proved to be effective across the tested cases. Furthermore, Broadband technologies which are currently available in the majority of the developed countries ensure a reliable communication medium between the mobile device and WANs.

4. Conclusions and Future Work

In this paper, we presented a real-time diagnosis and monitoring system appropriate for users with coronary artery disease. Different from many existing healthcare systems, the proposed system is an integrated system for both diagnosis and monitoring.

The diagnosis component of the system is capable of diagnosing heart disease problems in a fully automated manner using ML algorithms and based on instances from the heart disease dataset. On the other hand, the monitoring component is based on a simple and inexpensive wearable sensor that detects heart rate and sends it wirelessly to a mobile device via an arduino microcontroller. A monitoring algorithm is applied on the mobile phone for checking variances from normal heart rates and raising an alarm to the closest hospital and the patients' relatives.

To prove the effectiveness of the proposed system, we ran experiments for both components: diagnosis and monitoring. For the diagnosis component, we ran two experiments with three popular classification algorithms: BayesNet, SVM, and FT. The first experiment was carried out with the hold-out test and an accuracy of 88.3% was achieved with the SVM method proving the strength of implemented classifier. To further

prove the robustness of the proposed classifier, we ran a 10-fold cross validation test and the proposed classifier retained, to a certain degree, its accuracy results. In addition, we carried out a third experiment and showed the effectiveness of the feature selection algorithm in improving the classification performance with up to 3% accuracy improvements.

For the monitoring component, we carried out two experiments. In the first experiment, the system was tested on 20 healthy individuals for both rest and sport modes. In the second experiment, a simulation for 20 cases of patients with heart problems was conducted. In both experiments, the monitoring component provided a 100% detection accuracy. For the first experiment, no false alarms were generated and for the second experiment, the deviations from normal rates were detected and alarms were generated.

In the future, we plan to make the application cross-platform to be applicable on other platforms such as Android and IOS.

Acknowledgements

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