ORIGINAL ARTICLE

Intelligent and Online Evaluation of Diabetes using Wireless Sensor Networks and Support Vector Machines Algorithm

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Abstract

Objective: International Diabetes Organization estimates that there are 285 million people worldwide who suffer from diabetes, and this figure is expected to increase to 450 million in next 20 years. According to statistics issued by the World Health Organization, diabetes is considered among ten leading causes of death in world and its prevalence in the population is growing.This paper deals with designing and building an Expert System for Diabetes Mellitus diagnosis.

Materials and Methods: We randomly select 78 knowingly volunteered patients as non-intervention from approximately 17 families in Tovhid town in Sabzevar city to test system hardware. The output of these information and ADA database was used to test the performance of software part of the proposed system. In this system, at first citizen information through a wireless sensor network (WSN) is received and these data is transmitted to the central data processing system (CDPS). In the CDPS, intelligent software uses SVM technique based on 8 features to classify data and warns diabetes person due statistical changes.

Results: Acceptable level of accuracy of the proposed system with 95.02%±1.245%, sensitivity 98.30±0.85% and specificity of 97.52±1.06% and Kappa coefficient equal to 0.95 is optimal performance

Conclusion: Accuracy and high speed in data classification make the exact output of the software which is available online information so specialist will be able to alert suspect patients or identity diabetes patients without referring them to therapeutic centers.

Keywords: Diabetes, Support vector machine, Online diabetic data (ODD), Wireless sensor network, Central Data processing system.

Introduction

Diabetes is a disease which is caused by insulin production problems (1). International Diabetes Organization estimates that there are 285 million people worldwide who suffer from diabetes, and this figure is expected to increase to 450 million in next 20 years (2). These patients have high blood sugar which is called Hyperglycemia. This disease is growing rapidly and influences the younger and obese population; it is going to sound the alarm. At the international level, the percent of Gross Domestic Product (GDP) spent on health services is extremely unbalanced and often varies between 5 to 15 percent in different country. Epidemic diseases pose economic and social development to a formidable problem and can reduce the work force from 100 to 30 percent. Thus, public health and socio-economic development of countries require investment in the health system (4). The analysis of diabetes data is one way to increase the safety of determining the efficient method for collecting diabetes-related data (5). Evaluation of healthcare system means to measure or detect a health information system that could help to make required decisions on a particular subject. Information systems have numerous benefits such as increased quality of health care, reduction of costs and medical errors (6), efficient nurses care and patients safety (7-9). Health information system, support health care services and management systems at various levels (10-12). Sometimes we can't accurately detect the diabetes and its subtypes based on symptoms. In other words we need expert system which is able to recognize diabetes based on criteria. According to the National Institutes of Health about 26 million Americans are diabetics (19 million diagnosed and 7 million undiagnosed). National Institutes of Health estimations show that by 2050 between 1 in 3 and 1 in 5 Americans will have the disease. This rising trend is due to, the population aging, increasing risk factors of type 2 diabetes and people with diabetes who are survived longer (13). Diabetes prevalence by age group is shown in Fig. 1 (14).

The results of a survey conducted among physicians about the ability of using computer-based profile system showed that more attention should be paid to the capacity of using such systems if they are going to be adopted extensively. Some techniques draw on intelligent hardware and software technologies among wireless sensor network (WSN) is a key system in detecting the environmental condition (15). Recently, wireless intertwined networks (WMN) have introduced a powerful technology for establishing communication in various networks and remote control (16-17).

The modern alarming systems are a combination of integrated sensor networks, data transmission devices and data processing software. When a sensor network uses a set of biosensor to monitor body changes, it can bridge the gap between the physician and patient with a slight error in the data transmission. So, wearable sensory cloths are used to send information of people with diabetes (18).

In this technique, glucose sensor and biosensors are utilized to transmit vital information of the diabetes patients, and considering the epidemic of this diabetes in old ages, wearing heavy cloths could be a difficult. Also, sometimes the patients forget to wear it at all. In 2012, Thayananthan and Alzahrani (19) used physical sensors which were common in e-Health applications as monitoring and supervising of risk prediction. It was based on Radio-frequency identification (RFID) in addition to diabetes symptoms, could transmit symptoms of other disease to

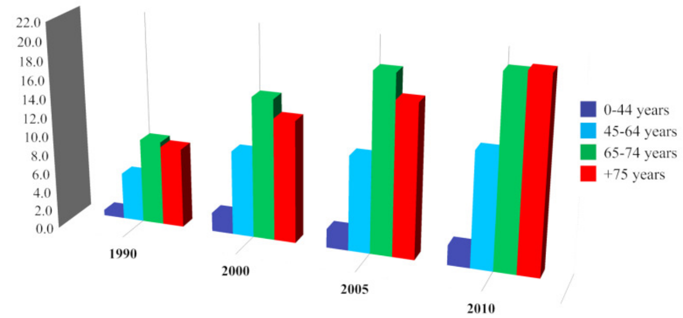

Figure 1. Diabetes prevalence in recent decades based on World Health Organization statistics

the physicians as well. Moreover, Yang et al. (20) used this technique at a broader scale in biosensor networks. It was a semi-automatic method which required wearing special clothes in order to transmit information to the physicians. A thorough study of type 2 diabetes and glucose monitoring was carried out by Allen et al. (21) to investigate the risk and identify inappropriate diet plans and activities which could deteriorate the situation of diabetes patients.

As software, several techniques for segmentation and classification of diabetes patients have been proposed. Data analysis and machine learning can be used as a means of distinguishing diabetes patients from healthy people. Such systems are known as Computer-aided design (CAD) and can help physician in decision-making (22). A proper classifier in this field is Support Vector Machine (SVM) which is widely used in medical diagnosis, machine learning and data analysis (23). This method is highly accurate in separating patient's data and can be perfectly used for classifying linear data. The system proposed of this paper to analyze data of diabetes patients by making use of a combination of biosensor wireless network, intelligent software and vector machine. In this system, with the slightest error in hardware section, data are transmitted to the data segmentation center and the software section separates potential patients from healthy people with precision, sending an alarm to them if necessary. Observing the data relating to the patient, the physician makes the final decision which would supplement the performance of the proposed system.

Materials and Methods

Seventy eight patients were randomly selected from a total of 17 volunteered families in Sabzevar city to participate in the hardware section of the system. The numbers of family members rank from 1 to10 people with the average of 4.58 people in each house. This population was chosen to test the hardware section and send correct information of the candidates to the main processor. There were totally 6 packs used for sending information to the citizens. Designed in Laboratory of Electronics in Hakim University of Sabzvari, each pack was given to families for a daylong period.

The families were randomly selected and the population included78 women with an average age of 42.6±10.1 and 114 men with an average age of 36.5±8.7. Biosensor transmitted the physical condition at specific times. To test the software section of system, the information and ADA database (23) were used, which out of total 768 subjects, 326 with an average age of 56.5±8.3 had diabetes and the rest with an average age of 48.7±9.6 were healthy people. To select the proper input for the central processing, 8 unique features were used which showed whether the person had the diabetes or not. The tests were based on the final reception at Electronics Laboratory of the University and two physicians verified the accuracy of the system in detection of diabetes based on the existing features.

The proposed system (ODD), which includes two separate sections, namely wireless sensor network (WSN) and Central data processing system (CDPS), provides the most detailed online information about the diabetes condition for experts. The WSN section is used inpatients' homes to collect data and display the latest condition of family diabetes, including glucose, cholesterol and blood pressure, and send such data to the pertinent center in the hospital. One of the most popular biosensors in the market is glucose biosensors which measure the blood glucose levels in diabetic patients. The basis of a biosensor is converting biological response into a message. Biosensors are made up of three parts:

1) bio-receptor or bio acceptor
2) Detector
3) Convertor

The second section or CDPS is installed in health care facilities. This section receives, process and monitor information from WSN, and if is necessary (when diabetic state of a person does not comply with the defined standards of the system) will alarm the operator.

Home Installed WSN

ODD is installed in each study participant house. Then, each person can send his/her blood glucose levels through a wireless sensor network at any time to figure out the changes occurred in their physical state compared to the previous test. WSN reports the results to the user after receiving the parameters and analyzing them in a few minutes. At the same time, a detailed report of the tests is sent to the nearest health care center and data are forwarded to the software section. The first step to measure glucose in the blood is to convert the glucose concentration into a voltage or current signal. This is possible with special sensor strips for amperometry. The sensor is used as a blood glucose meter based on a glucose oxide electrode. The glucose oxides are immobilized in a platinized activated carbon electrode. The enzyme electrode is used for amperometry determination by using an electrochemical detection of enzymically produced hydrogen peroxide. Fig. 2 presents the examples of chemical sensors and path design which are employed for detecting the glucose level of blood along the sensory network.

Central data processing system (CDPS)

The second part of ODD, namely CDPS, is installed in the health care center. CDPS is, in fact, the system for receiving the data from different areas of the city. After receiving data and the symptoms of diabetes in the software section using Support Vector Machine (SVM) algorithm, it provide final results to the physicians and help them to determine the possibility of developing the diabetes in citizens with great reliability and precision. Eight confirmed characteristics of people based on the definition of the World Health Organization are as follows:

1- Age

2- The personal history of diabetes (The history of patient)

3- Body mass index (kg/m2)

4- two-hours serum insulin (mu U / ml)

5- Brachial triceps skin thickness (mm)

6- Blood pressure (mm hg)

7- The two hours plasma glucose concentration

8- Number of pregnancies (for female patients)

Software Section: SVM Classifier Training

After normalizing data in the range (0-1), classification and clustering methods are applied. Scaling is defined by a linear transformation according to Eq. (1) where D is the original data, $D_{normalized}$ is the normalized data, D_{max} and D_{Min} are the maximum and minimum values of D. At this min step, all numeric features are constructed and normalized to the interval ($Lower_{bound}$, $Upper_{bound}$).

$$(1)\ D_{Normalized} = \frac{D - D_{\min}}{D_{\max} - D_{\min}}$$

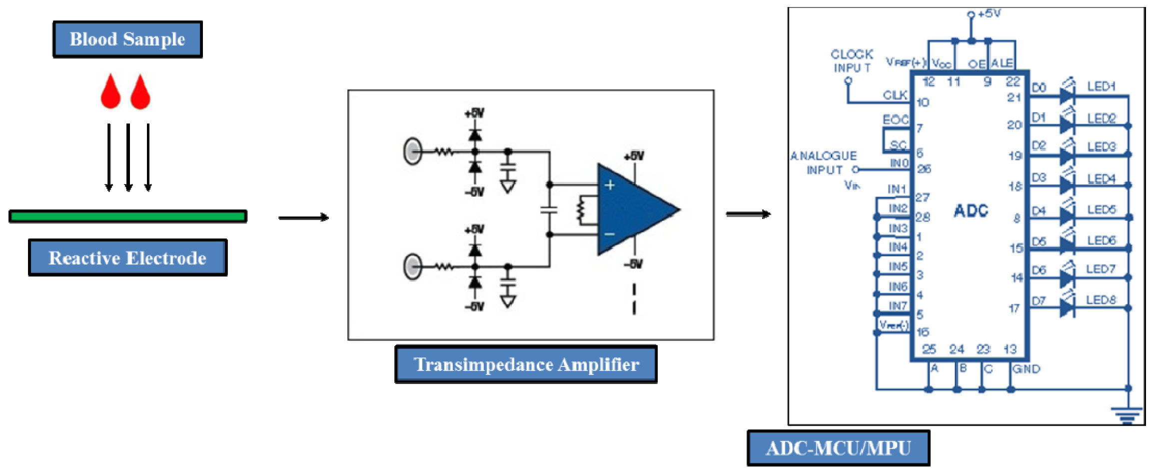

Figure 2. The biosensor and path design which used to measure glucose

Support Vector Machine (SVM) is a classification and regression device, which can help maximizing the accuracy of prediction using learning theory machine. This technique is a supervised learning algorithm that has a variety of functions, including segmentation and classification (24). In two-dimensional mode, this system can be used with a separator line. A Support Vector Machine (SVM) is a discriminative classifier formally defined by a separating Hyper-plane (25). A SVM algorithm is one of the pattern recognition algorithms, which is used when the pattern recognition and object classification in particular classes are needed. Matrix model and kernel function are required for implantation of this method. By selecting kernel function parameters and C value, the α-i values of learning algorithm using nonlinear Programming Solver (PS) were used. The new data can be classified using α-i values and support vectors. Fig. 3 displays an accurate picture of the formation of super surface by SVM. In this figure, the circleis drawn around the points of class -1 and class +1. Line P shows the nearest distance between two circles. First, a circle around the points of each class is assumed. Moreover, h is both super surface separator and the around the points of each class is assumed. Moreover, h is both super surface separator and the perpendicular line that cuts P in half. Also b is width from the origin of super surface with the maximum separation boundary. If b is ignored, the answers will only include super surface that pass through the origin.

The vertical distance of super surface from the origin is achieved by dividing the absolute value of the parameter b by w. The main idea is to select a suitable separator, which has the maximum distance from the neighboring points in both classes.

Another important point is that if the training data is in form of linearly resolution, the two border super surfaces can be chosen by no data between them. Then, it maximizes the distance between these two parallel super surfaces. By applying geometry theorems, the distance between these two super surfaces is equal to |w|/2. Thus, the |w| should be minimized. Moreover, data points should not be situated on inner boundary area. For this, a mathematical limit was added to the formal definition. There are multiple lines providing a solution for the problem in Fig. 4. A line would be unsuitable if passes too close to the points, because it will be noise sensitive and will not generalize correctly.

Therefore, our aim should be to discover the line passing as far as possible from all the points. Hence, the function of the SVM algorithm is based on discovering the hyper plane that gives the largest minimum distance to the training cases of diabetes and non-diabetes. The SVM's theory is formed based on this distance. We can maximize the margin of the training data of diabetes and non-diabetes by optimal separating of hyper plane. For two classes of data such as diabetes, which are shown in Fig. 5, we use SVM algorithm,

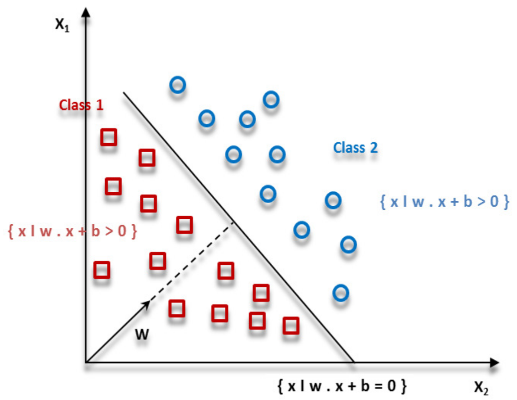

Figure 3. The formation of super surface separating two data classes in two-dimensional space

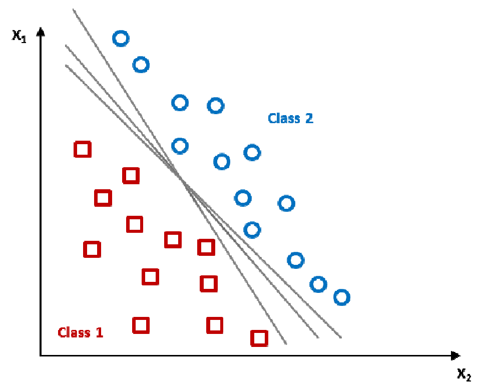

Figure 4. multiple lines which offering a solution for the problem

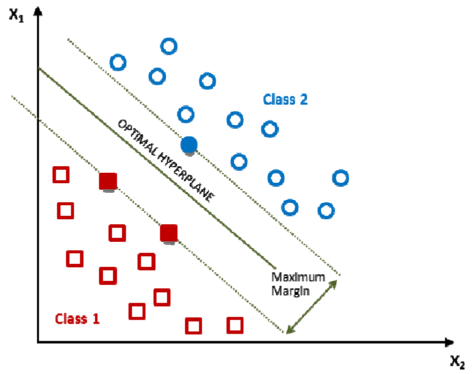

Figure 5. Applying SVM technique to two classes of data (diabetes and non- diabetes)

and consequently, the optimal hyper plane will be detected such as in Fig. 4. The optimal hyper plane is introduced based on the equation in (2), which is used to define formally a hyper plane (26):

(2) $f(x) = \eta_0 - \eta^T x$

In this equation, η is known as the weight vector, η_0 as the bias and x predicates the training cases closest to the hyper plane. The optimal hyper plane can be represented in an infinite number of different procedures by scaling of η and η_0. One best way faced with the constraint is defined as (3):

(3) $|\eta_0 - \eta^T x| = 1$

In general, the training cases closest to the hyper plane are called support vectors and this form. This is known as the canonical hyper plane. We use the result of geometry that gives the distance between a point x and a hyper plane (η, η_0):

(4) $Dis = |\eta_0 - \eta^T x| \times \|\eta\|^{-1}$

For the canonical hyper plane form, the numerator is equal to one, and the distance to the support vectors is as $Dis_{Support\ Vector} = |\eta - \eta_0| \times \|\eta\|^{-1} = 1 \times \|\eta\|^{-1}$. The margin denoted as M, is twice the distance to the closest cases equal to $M = 2 \times \|\eta\|^{-1}$. Finally, the problem of maximizing M is equivalent to the problem of minimizing a function $L(\eta)$ subject to some constraints. The constraints model is a requirement for the hyper plane to classify correctly all the training cases x_i. Formally:

(5) $\min_{\eta,\eta_0} L(\eta) = \frac{1}{2}\|\eta\|^2 \ subject\ to\ y_i(\eta_0 + \eta^T x_i) \geq 1 \forall i$

In which, y_i indicates each of the labels of the training cases. As a special feature, the SVMs simultaneously minimize the empirical classification error and maximize the geometric margin. The effectiveness of SVM depends on the selection of kernel, the kernel's parameters, and soft margin parameter C. The Gaussian kernel is a common choice, which has a single parameter γ. The best combination of C and γ is often selected by a grid search with exponentially growing sequences of C and γ, for example, $C \in \{2^{-5}, 2^{-3}, \ldots, 2^{13}, 2^{15}\}$ and $\gamma \in \{2^{-15}, 2^{-13}, \ldots, 2^{1}, 2^{3}\}$.

The final model used for testing and classifying new data, is trained on the whole training set using the selected parameters to find diabetes and non-diabetes cases (26). To simulate SVM in this study, MATLAB software Version 7.14 was used. The classification is done for two classes, that is diabetes and healthy subjects, all data were put in a two-dimensional array. After determining the data related to the individual patients, these data are again positioned in a two-dimensional array.

Hardware Section: Implementation

One hundred and ninety two patients were randomly selected from a total of 50 volunteered families in Sabzevar city to participate in the hardware section of the system. The numbers of family members rank from 1 to10 people with the average of 4.55 people in each house. This population was chosen to test the hardware section and to send correct information of the candidates to the main processor. There were totally 9packsused for sending information to the participants designed in Laboratory of Electronics in Hakim University of Sabzvari. Each pack was given to families for a daylong period. The families were randomly selected and the population included78 women with an average age of 42.6± 10.1 and 114 men with an average age of 36.5 ±8.7. Biosensor transmitted the physical condition at specific times. To test the software section of system, the above information and ADA database (23) were used. Out of total 768 subjects, 326 with an average age of 56.5 ±8.3 had diabetes and the rest with an average age of 48.7±9.6 were healthy people. To select the proper input for the central processing, 8 unique features were used which showed whether the person had the diabetes or not. The tests were based on the final reception at Electronics Laboratory of the University and two physicians verified the accuracy of the system in detection of diabetes based on the existing features. This data is decoded in a separated board by a computer which contains essential information indicating the level of blood glucose. Such data are then given to the software in form of unique features that separate people having the symptoms of the diabetes, those with severe cases of diabetes and healthy people according to the SVM classification equations

Performance Evaluation

Accuracy (AC), specificity (SP) and sensitivity (SE) which were used to measure the accuracy in detecting the performance of a system. Kappa coefficient represents the reliability degree of a system.

Three factors of accuracy (AC), specificity (SP) and sensitivity (SE), which were presented to measure the accuracy in detecting the performance of a system, were calculated according to equations (8) - (10):

(8) $$Senestivity = \left(\frac{N_{TP}}{N_{TP} + N_{FN}} \right)$$

(9) $$Specificity = \left(\frac{N_{TN}}{N_{TN} + N_{FP}} \right)$$

(10) $$Accuracy = \left(\frac{N_{TP} + N_{TN}}{N_{TP} + N_{FN} + N_{TN} + N_{FP}} \right)$$

N_{TP}: the number of subjects with diabetes who were correctly diagnosed by the software.

N_{FN}: the number of subjects with diabetes who were wrongly detected as healthy by the software.

N_{TN}: the number of subjects without diabetic who were diagnosed as healthy by software.

N_{FP}: the number of subjects without diabetic who were wrongly diagnosed as diabetes by software.

Kappa coefficient represents the reliability degree of a system which has been introduced in equation (11):

(11)

$$K = \left(\frac{2(N_{TP}N_{TN} + N_{FN}N_{FP})}{(N_{TP} + N_{FN})(N_{TN} + N_{FN}) + (N_{TN} + N_{FP})(N_{TP} + N_{FP})} \right)$$

Results

The data received from ADA database and information concerning the residents of Tovhid Town was treated as the output of WSN. Accordingly, the accuracy of each part was estimated according to environmental noise and the performance of intelligence software. First, data were normalized in (0,1) scale and given to Support Vector Machine algorithm as the starting points. According to physician’s diagnosis, out of 768 cases, 326 subjects with an average age of 56.5±8.3 had diabetes and the rest with an average age 48.7±9.6 were healthy. Consistent with the performance of the proposed system and the diagnosis of the physician, the degrees of negative and positive errors were separated at the end. The hardware error of the system, however, was composed of three typed of error:

- The error in wireless transmission of data (from WSN to CDPS), which was equal to 1%.
- The error in sending data from processor to radio sections (an internal WSN error); if the speed of data transmission reaches 9600 bit / sec, then 1.8% of data will be lost.
- Total error of biosensors and chemical sensors which according to the data sheet equals to ± 1.7 (This error is due to environmental noise and factors that change the accuracy of the sensor).

The total error of all three hardware sections was2.8 ± 1.7. In software section, after classifying all data of 768 subjects into three groups, namely diabetes patients, subjects suspicious of diabetes and healthy subjects, the system misidentified 13 cases out of 326 diabetes patients and 31 cases out of 442 healthy subjects.

The value of Kappaco efficient was Kappa = 95.41% which is considered suitable for the system performance. The low PPV and high NPV of the system (reliability coefficients for the clinician and patient) ensure that both clinician and the patient can rely on software and its output.We show clustering results on ADA and Tovhid town datasets in Fig. 6 and Fig. 7 respectively. Also in Fig. 8 the SVM operation for two databases is shown.

In the software section, after calculating these parameters, 98.30% sensitivity, 97.52% specificity and 95.02± 1.245% accuracy were achieved. The calculations have been shown in Table 1.

Compared to such methods as shown in Table 2 as Smart Underwear (17) and Continuous Glucose Monitoring (20), in the proposed method, the sensitivity and other proper features were calculated at a shorter time. Compared to such methods as shown in Table 2 as Smart Underwear (17) and Continuous Glucose Monitoring (20), in the proposed method, the sensitivity and other proper features were calculated at a shorter time.

A detection error tradeoff (DET) graph is a graphical plot of error rates for binary classification systems, plotting false reject rate vs. false accept rate (27) and this concept is shown in Figure 9. The x- and y-axes are scaled non-linearly by their standard normal deviates (or just by logarithmic transformation), yielding tradeoff curves that are more linear than ROC curves, and use image area to highlight the differences of importance in the critical operating region.

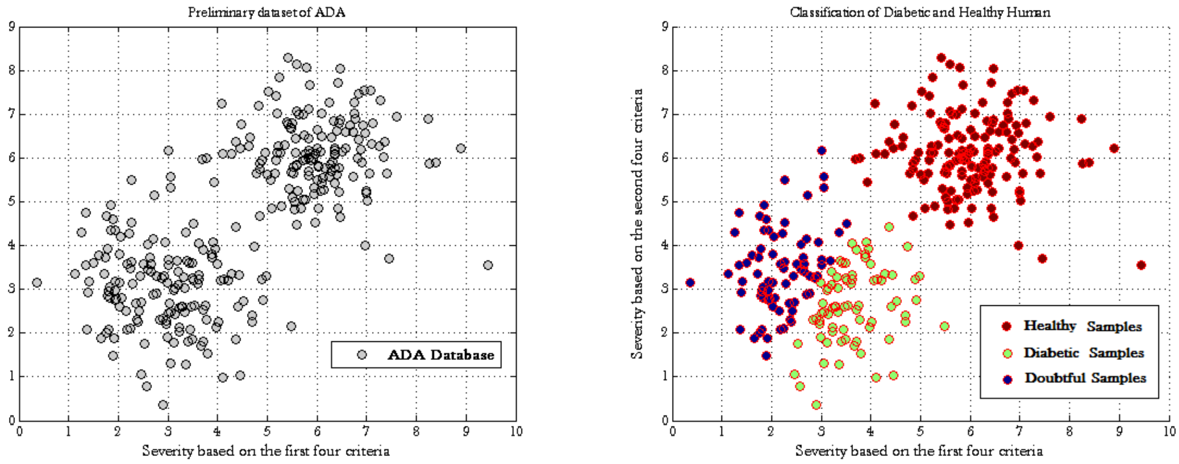

Figure 6. ADA dataset in classification and clustering the Diabetic and non-Diabetic samples (left: preliminary ADA dataset and right: clustering by proposed software section)

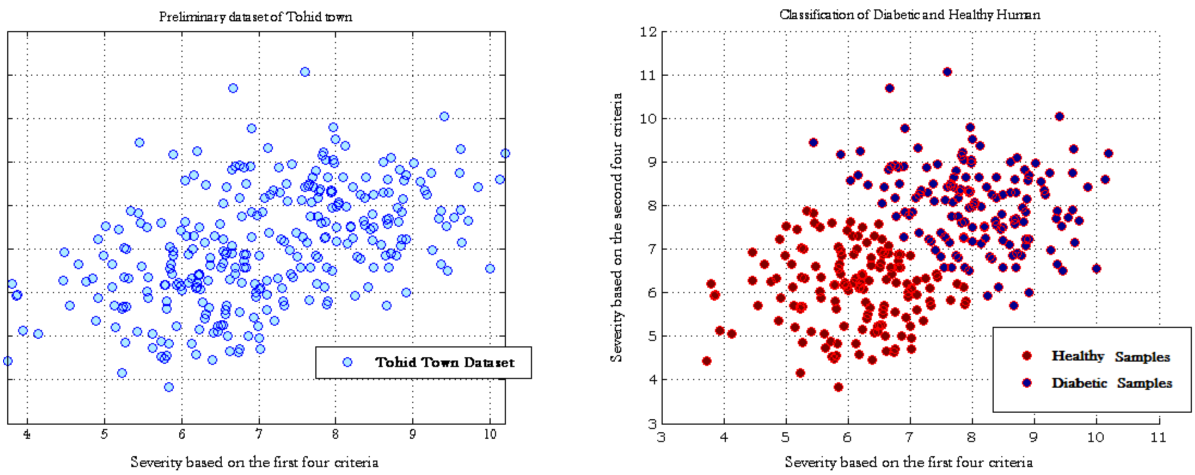

Figure 7. Tovhid city dataset in classification and clustering the Diabetic and non-Diabetic samples (left: preliminary Tovhid city dataset and right: clustering by proposed software section)

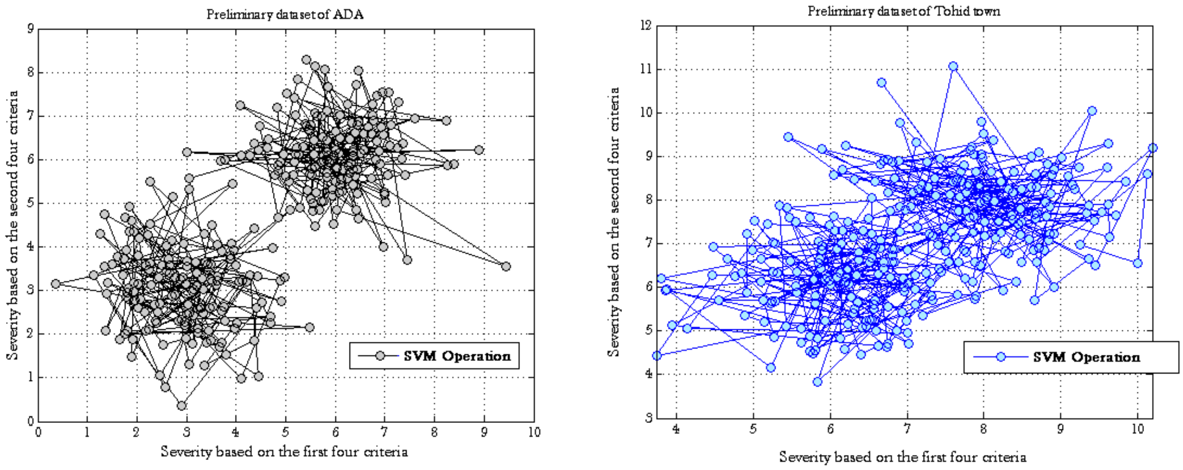

Figure 8. The SVM operation is shown for two datasets

An alternative to the ROC curve is the detection error tradeoff (DET) graph, which plots the false negative rate (missed detections) vs. the false positive rate (false alarms) on non-linearly transformed x- and y-axes. The transformation function is the quintile function of the normal distribution, i.e., the inverse of the cumulative normal distribution.The two curves are located above the bisector of the second quadrant for a set of random data which suggests the proper functioning of the system in accurate diagnosis of diabetes.

Discussion

In this study, the results showed that the system was capable to implement at a broader scale, and the employment of modern technology would considerably increase the sensitivity and accuracy of the performance. This method introduces a new technique which has been compared to other methods used for detection of diabetes in terms of performance. These methods have drawn on relatively different databases, but the method proposed in this paper has been applied to more databases. In terms of accuracy, the techniques proposed by Lim and Yang are respectively at medium and moderate levels. Yang's method, nevertheless, takes longer time to give warning signs of diabetes, which is a major error. The same limitation is also obvious in Allen's technique (20). The major advantage of Allen's method is the simultaneous detection of other symptoms, such as blood pressure. Unlike three common methods used for detection of diabetes, the proposed method provides the results in a shorter time (~0.85sec) and besides higher sensitivity (98%), has greater specificity too (97%). Under some circumstances discussed in the previous methods, the intelligent aspect

Table 1. Calculation of 3 factors to evaluate of system performance

Databases		No. samples	Diabetic human		Uncertain		Software accuracy	Hardware error	Sensitivity	Specificity
			N_{TP}	N_{FN}	N_{TN}	N_{FP}				
ADA	Age>40	472	214	3	250	5	98.30%	2.8 ± 1.1%	98.61%	98.03%
	Age<40	296	107	2	184	3	98. 31%	2.8 ± 0.9%	98.16%	98.39%
Tovhid town	Age>40	58	11	0	44	3	94.82%	2.8 ± 1.65%	100%	93.61%
	Age<40	134	17	1	112	4	96.26%	2.8 ± 1.33%	94.44%	96.55%
Average	-	960	349	6	590	15	97.82%	2.8 ± 1.245%	98.30%	97.52%

Table 2. Comparison with similar methods

Techniques	Author	Accuracy (%)	Time (Sec)
The systems based on board contain send and receive package	Lim (17)	90	3
	Yang (19)	95.5	4.5
	Allen (20)	92.65	2.5
	Our finding	95	0.85

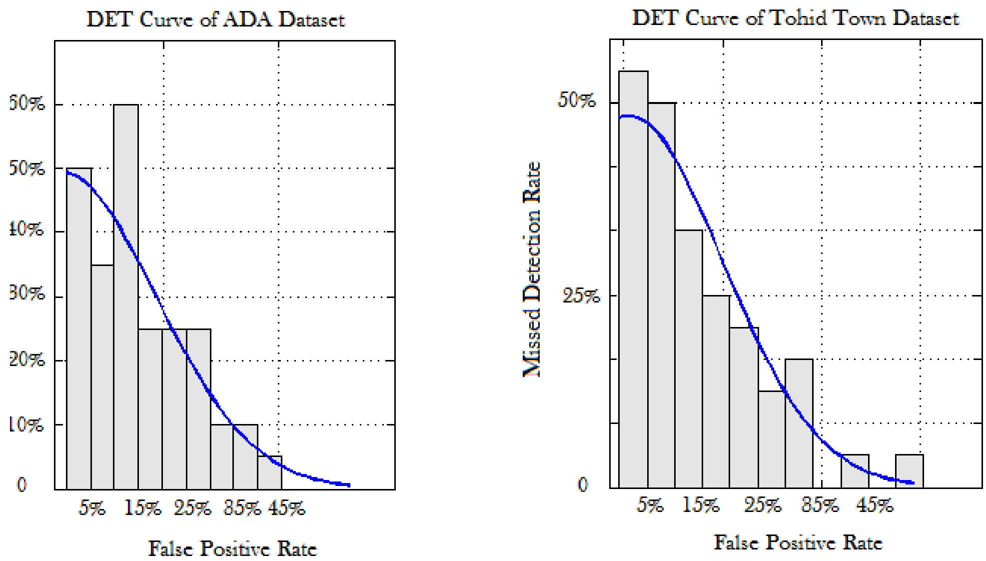

Figure 9. Detection error tradeoff (DET) graph in software section of proposed system for two datasets

of the method is not emphasized, while all three methods draw on hardware techniques and the data need to be reviewed by a physician.

Another problem associated with these systems is the use of wearable sensors that people may either forget to wear or refuse to use them due to their heavy weight. As to the software section, the proposed algorithm reveals higher accuracy in separation and classification of data which reduces the task of the physician to mere confirmation of the diagnosis. The hardware section also allows the data to be transmitted to the data processing enter through the wireless network with the lowest error.

Conclusion

This paper proposed a new system with high potential in general detection of diabetes. This system consisted of hardware sections (WSN and CDPS) as well as software section (intelligent classifier system SVM). The data were first collected from families by WSN. WSN system is based on biosensors which measure the vital factors of diabetes. With the installation of the diabetes data transmission system in a house, all the member of the family can check their health status (blood sugar) on a daily basis. With the transmission of all data related to each person to the Central Data Processing System (CDPS) and classification of SVM algorithm, the physician can propose the possible treatment, thus indicating the blood glucose levels to each person. In general, the system shows an accuracy of 95.02±1.7% and a sensitivity 98.30±0.85%. The Kappa coefficient, which indicates the reliability of a system's performance, was ideally about 95.41±0.26%. The application of this system can minimize human errors and provide new methods for timely treatment of diabetes.

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