A Decision Support System using Classification of the Blood Glucose and HbA1C Level Classes from Palm Perspiration Data

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Abstract:-The invasive measurement techniques which puncture the skin are used for blood data values detection generally. In this paper, artificial neural network structures were used for the classification of the relationship between blood data values and palm perspiration rate as a non-invasive measurement technique. For this purpose, a comparative study was realized by using feed forward multilayer, Elman, probabilistic, radial basis and learning vector quantisation neural network structures. The quartz crystal microbalance type and humidity sensors were used for detection of palm perspiration rate. A data set for 91 volunteers is used for this study. Data of 21 volunteers are used for training the neural networks and the remaining data were used as test data.

Keywords:- HbA1C, blood glucose, palm perspiration, neural networks, classification.

1 Introduction

Diabetes is a major health problem in both industrial and developing countries, and its incidence is rising [1,2]. The people with diabetes must be control the glucose rates. Because glucose very important for them [3]. The long-term excess of glucose (hyperglycemia) can cause many problems for diabetes such as blindness, damaged nerves and kidneys (renal failure), or even increase the heart diseases, strokes and birth defects. On the contrary the long term low glucose rate (hypoglycemia) can cause confusion, coma and even death. Monitoring the glycaemic state of patients is cornerstone of diabetic care [3-5].

Glucose sticks to the haemoglobin to make a haemoglobin A1C (HbA1C). The tests used most widely in monitoring the glycemic status of people with diabetes are blood glucose and HbA1C. Haemoglobin A1C value reflects mean glucose level during the previous 2-3 months' period and is a useful indicator for risk assessment of diabetic complications [5].

The invasive measurement techniques are used for blood data values detection generally. Invasive techniques are widely used for diagnosis and treatment in medicine. During these invasive techniques, some damage and pain could occur in the human body. Therefore, patients suffer during an invasive technique. So, non-invasive measurements at routine time intervals are very attractive for patients. The perspiration contains information about some blood data values. So, classification of blood data values can be determined by measuring the perspiration rate of the palm [3].

Artificial neural network (ANN) structures for classification systems in medical diagnosis are increasing gradually [6-9]. There have been several studies reported focusing on invasive measurement techniques for blood glucose detection using artificial neural network structures [3,10,11].

The feed forward multilayer neural network structure are the most common neural network structure which have been successfully used for the disease diagnosis systems [7-9,12]. The Elman neural network structure commonly is a two-layer network with feedback from the first-layer output to the first-layer input [13]. The Elman neural network structure has been used for the blood glucose detection [3]. The probabilistic neural network (PNN) structures provide a general solution to pattern classification problems by following an approach developed in statistics, called Bayesian classifiers [14]. Because the PNN provides a general solution to pattern classification problems, it is suitable for the disease diagnosis systems [1,7,15]. The radial basis functions greatly reduce the training time and make related analyses much easier [16,17]. The RBF network structure has been successfully used for the disease diagnosis problems [6,18]. The classification of the learning vector quantization (LVQ) neural network structure is based on the similarity of the unknown data and these prototypes. [13,19,20]. The LVQ neural network structures have been successfully used for the disease diagnosis systems also [7,9,15].

In this paper, artificial neural network structures were used for the classification of the relationship between blood data values and palm perspiration rate as a non-invasive measurement technique. For this purpose, a comparative study was realized by using feed forward multilayer, Elman, probabilistic, radial basis and learning vector quantisation neural network structures. The quartz crystal microbalance type and humidity sensors were used for detection of palm perspiration rate. A data set for 91 volunteers is used for this study. Data of 70 volunteers are used for training the neural networks and the remaining data were used as test data.

2 Method

2.1 Measurement system and sample collection

A schematic diagram of the measurement system for detection of glucose concentration in blood from palm perspiration are shown in Figure 1. It has four parts: a sampling tube, quartz crystal microbalance type and humidity sensors placed into the tube, a measurement unit and a PC for data records.

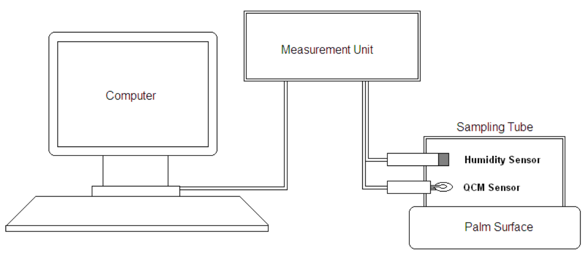

Fig. 1. A schematic diagram of the measurement system

The quartz crystal microbalances (QCM) are useful acoustic sensor devices. The principle of the QCM sensors is based on changes Δf in the fundamental oscillation frequency upon ad/absorption of molecules from the gas phase [21]. The piezoelectric crystals used were AT-Cut, 10MHz quartz crystals (ICM International Crystal Manufacturers Co., Oklahoma, USA) with gold plated electrodes (diameter ∅ = 3 mm) on both sides mounted in a HC6/U holder. The sensitive coating materials of the piezoelectric crystal sensors were octa (13,17-dioxanonacosane-15-sulfanyl) substituted nickel(II) phthalocyanines synthesized by TUBITAK MAM Sensor Technologies Laboratory researchers [22,23]. The humidity sensor is made of a thin film capacitance and has a relative humidity range of 10%–95%. It has a relative humidity resolution of 0.1%.

The data used in this research were taken at room temperature and 91 volunteers were tested. An illustration of left and right palm perspiration for a volunteer is shown in Figure 2 as an example.

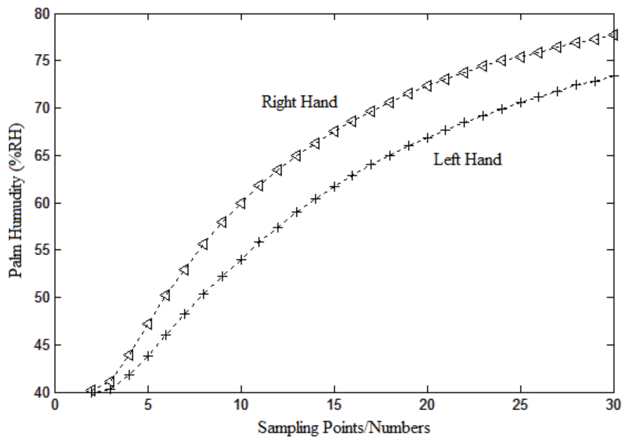

Fig. 2. Left and right palm perspiration for a volunteer

2.2 Data preparation

The quartz crystal microbalance type and humidity sensors were used for detection of palm perspiration rate. Right and left palm perspiration versus blood glucose concentration value was examined for the 91 volunteers. Data for 70 volunteers were used for training the neural network structures and data for the other 21 volunteers were reserved as test set. The palm perspiration data were taken for 1 min in 2 s intervals for each hand.

The response values change very fast at the beginning of the QCM and humidity sensor measurement. That is, the slope of the transient response is bigger at the beginning and decrease with time. A time series is a set of data collected

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sequentially over a period of time at regular intervals. Time series data of the transient response provide additional information about the trend and slope of the sensor response [24]. This information can be used for detection of relationship between blood glucose, HbA1C and palm perspiration rate. That is why, the palm perspiration deviations and means of the palm perspiration differences were used additionally as the input values of the neural network structures. The calculation method for the palm perspiration differences can be shown in Figure 3.

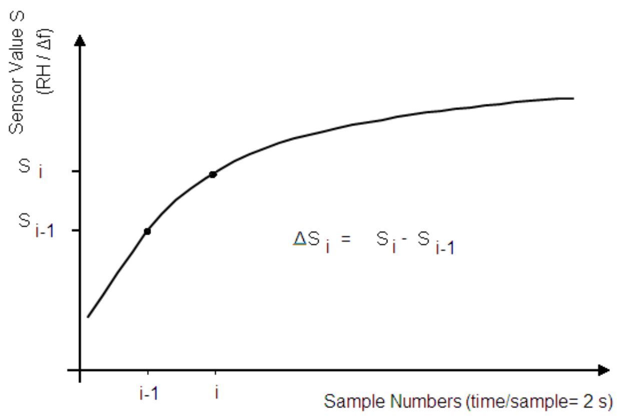

Fig. 3. Calculation of the palm perspiration differences

The palm perspiration deviations were computed according to

$$\Delta S = S_{30} - S_2 \tag{1}$$

where RH_i is humidity value of the sample i. And the mean values of the palm perspiration differences were computed according to

$$mean(\Delta S_i) = \frac{1}{29}\sum_{i=2}^{30} S_i \tag{2}$$

2.3 Blood Glucose and Haemoglobin A1C detection using neural networks

In this study, the feed forward multilayer, Elman, probabilistic, radial basis and learning vector quantisation neural network structures classification of the relationship between blood data values and palm perspiration rate as a non-invasive measurement technique.

Glucose and haemoglobin A1C level classes were used as the neural network outputs. Table 1 shows the classification levels for the glucose and HbA1C.

Table 1. The classification levels for the glucose and HbA1C

Level	Glucose(mg/dl)	HbA1C (%)
Low	<70	<3.5
Normal [x]	70-110	3.5-6.5
High	110<	6.5<

The input values contained the palm perspiration deviations and mean values of the palm perspiration differences (right and left hand, QCM and humidity: 8 inputs).

3 Results and discussion

In this study, a comparative study for the classification of the relationship between blood data values and palm perspiration rate as a non-invasive measurement technique was realized by using feed forward multilayer, Elman, probabilistic, radial basis and learning vector quantisation neural network structures. Table 2 shows the accuracy performances of the neural network structures for the glucose and HbA1C level classes.

Table 2. The E(RAE) performances of the neural network structures for the glucose and HbA1C

Neural Network Structure	Accuracy (%) for glucose	Accuracy (%) for HbA1C
FF multilayer NN	71.43	76.19
Elman NN	57.14	66.66
Probabilistic NN	71.43	80.95
Radial Basis	57.14	61.90
LVQ NN	66.66	71.43

From the Table 2, it can be seen also that the best results for the classification accuracy were obtained from Probabilistic NN in this study. The classification performance of the FF multilayer NN was very close to that of the Probabilistic NN structure. The third good performance was performed by the LVQ neural network in this study. In addition to the above results, the accuracy values of the Elman neural network were a bit better than that of the radial basis neural network.

As the conclusion, the following results can be summarised;

- It was seen that neural network structures could be successfully used to classify the glucose and HbA1C level classes.

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- The best results for the classification accuracy were obtained from the Probabilistic NN structure for the classification of the glucose and HbA1C level classes.
- The classification performance of the FF multilayer NN was very close to the classification performance of the Probabilistic NN structure for the classification of the glucose and HbA1C level classes.
- And, it was obtained that neural network structures could be successfully used to help the classification of the glucose and HbA1C level classes. So, the structures can be helpful as learning based decision support system for contributing to the doctors in their diagnosis decisions.

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