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# Software module development for non-invasive blood glucose measurement using an ultra-wide band and machine learning

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**Abstract.** Diabetes is a chronic disease and in uprising trend worldwide. There is no remedy, hence, blood glucose management is essential by screening blood glucose concentration levels (BGCL) regularly to maintain a healthy life. However, the present way of measuring BGCL is invasive by using a glucometer and drawing a blood sample directly from the human body. To overcome this discomfort-problem, a non-invasive device to measure BGCL is in demand. This paper presents an autonomous software module with a user-friendly graphical user interface (GUI) based on digital signal processing (DSP) and artificial neural network (ANN) to process, classify and recognize the BGL signature from captured ultra-wideband (UWB) signal through human blood medium. To capture the signal, a pair of UWB bio-antenna is placed in between the human earlobe. Received signals are captured and processed through GUI and undergo signal processing, ANN training, testing, and validation. An interface is developed to integrate the hardware (UWB transceiver, bio-antenna, etc.) and the developed software module to make a system. The initial system showed a consistent result with reliability and demonstrated 90.6% accuracy to detect the BGCL. The detection accuracy is 9.6% improved compared to existing work. Besides, this proposed system is cost-effective, user-friendly and suitable to be used by both doctors and home users.

## 1. Introduction

Diabetes is a health concern when a human body does not produce enough insulin. Insulin is a kind of hormone produced by pancreas which is used to regulate blood glucose. Diabetes has no remedy, hence, regular blood glucose concentration level (BGCL) monitoring and to maintain a healthy lifestyle is the only way to be healthy. Unmanaged BGCL can cause serious diseases such as kidney failure, heart attack, stroke, blindness and lower limb amputation [1]. According to the research of Colin Mathers and D Loncar, the incidence of diabetes among the people with 18 years old and above was 8.5% in 2014, which was double compared to cases in 1980 (4.7%) [2]. Based on the statistics and trends, it was predicted that in year 2030, diabetes can be the seventh leading cause of death compared to eleventh in 2002 [2]. The traditional way to measure and monitor their BGCL is invasive, which includes laboratory blood tests in a hospital or using a glucometer in their own house. The blood sample is usually drawn directly from the body by pricking the fingertip or arm. The process is painful



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and intimidating besides cost (though not much), especially for children (or those with Type-A diabetes). Hence, only diagnosed patients follow the process as per necessity, while healthy (or undiagnosed) people do not examine their blood (health condition) regularly. Resulting, many undiagnosed cases exist because of this painful measurement procedure. Therefore, a non-invasive blood glucose monitoring technique is highly in-demand. Over the decades, many researches have been conducted for the development of non-invasive blood glucose monitoring devices with various technologies. However, the so far developed devices are costly, along with inconsistent reliability [3-14]. Vashist [3] and Benjamin Freer [4] analysed most of the non-invasive technologies along with their advantages, disadvantages and future challenges. Some of recent proposed technologies are near-infrared spectroscopy [5], raman spectroscopy [6], breath chemical analysis [7], thermal emission spectroscopy [8], ocular spectroscopy [9], impedance spectroscopy [10], ultrasound [11], fluorescence [12], optical coherence tomography (OCT) [13], and temperature-modulated localized reflectance [14] which showed initial success. However, they have limitations in terms of accuracy, reliability, and cost, so they need further improvements for practical use.

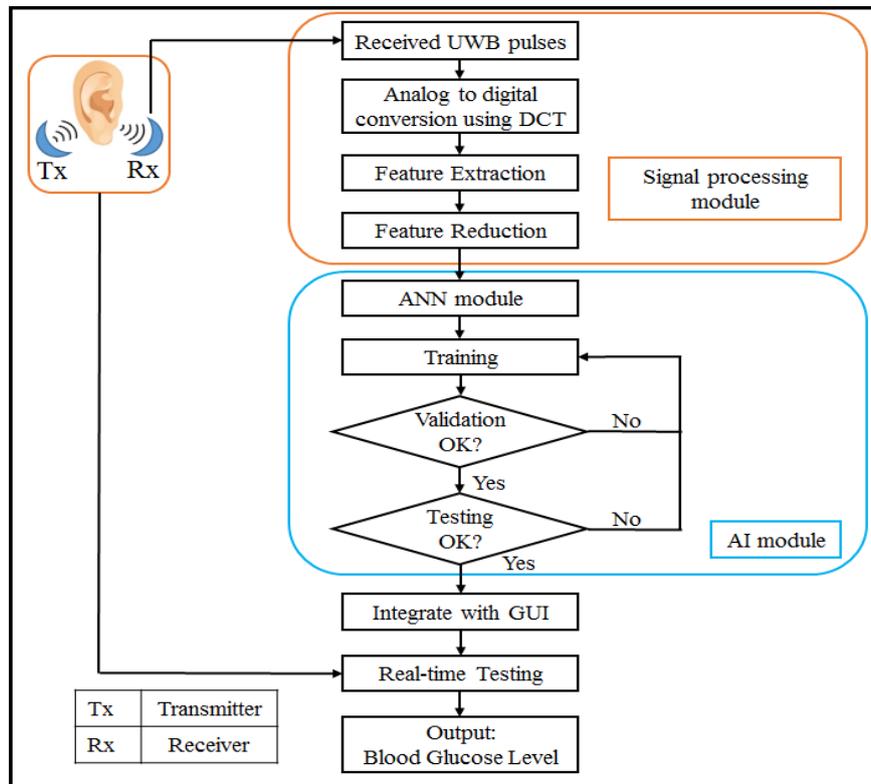
To explore the feasibility and potential of non-invasive blood glucose monitoring techniques, one alternative way can be the ultra-wideband (UWB) imaging technique. In February 2002, the Federal Communication Commission (FCC) has allocated an unlicensed bandwidth from 3.1 GHz to 10.6 GHz for UWB applications [15]. UWB technique can be used in medical applications due to it has significant advantages such as high data rate, lower transmit power and has frequency spectrum below noise level which bring no harm to the human body [16]. Topsakal et al., [17] found that the dielectric properties decrease when the glucose concentration increases, and the difference is more apparent at the high-frequency range. This proved that the performance of the UWB system depends on the various blood dielectric properties as a function of frequency. Xia Xiao et al., [18] and Shawkat et al., [19-20] has been done investigation on non-invasive blood glucose detection at human earlobe and arms using a UWB imaging technique. Besides, Shawkat also successfully investigated and developed an automatic blood glucose detection system using Artificial Neural Network (ANN). However, the system is still not convenient for the normal user as it does not have a proper platform for the user to operate the system.

This paper presents a non-invasive blood glucose monitoring system using the UWB and ANN with a Graphical User Interface (GUI) for users convenient. The remaining of this paper is organized as follows: Section II presents the steps to develop the software module and integration with a hardware system, followed by the results and discussions in Section III, and the conclusion at the end.

## 2. Software module development and system integration

### 2.1. System workflow

The system consists of a pair of UWB transceiver, two antennas (transmitting antenna (TX) and receiving antenna (RX)), and a software module (for signal processing and classification using ANN) along with a GUI. The human earlobe can be placed in between the TX and RX antennas connected with two transceivers. Then, the UWB signal with the centre frequency of 4.3GHz is transmitted by the TX antenna and received by the RX antenna through the human earlobe. The received signal is processed, classified and measure the BGCL through software module. The BGCL results can be saved, manipulate and observed through GUI. The theoretical system model is shown in Figure 1.



**Figure 1.** Theoretical system model.

*2.2. Development software module with graphical user interface (GUI)*

Graphical User Interface (GUI) was developed using MATLAB 2017a software. The purpose of developing a GUI is to ease the user to operate the system without requiring any specific knowledge and skills. Here, the GUI is separated into two parts for two different types of users: hospital and home users. For hospital users (doctors or staffs), they can set password (as per need to protect patients records to prevent them from being accessed by unauthorized people), register patients, maintain patients accounts and records to check their health conditions. Similarly, home users also can set the password to maintain their records in a family. The user can import a Comma-Separated Values (.csv) file which produced by the software module into the GUI to analyze and obtain the blood glucose level. All the data will be stored in an offline database called SQLite. The preliminary design of the GUI is shown in Figure 2.

**Patient :**

**LET'S CHECK!!!**

Blood Glucose Level (mmol/L)  
 Temperature (°C)  
 Blood Pressure (mm Hg)  
 Pulse Rate (bpm)

\*Note: Please double check. The process cannot be reversed.

**Results**

Categories	Readings		Status
Blood Glucose Level (mmol/L)			
Temperature (°C)			-
Blood Pressure (mm Hg)	Systolic	Diastolic	
Pulse Rate (bpm)			-

**Standard Range References :**

**Figure 2.** Preliminary design of GUI.

CSV file can be imported using the ‘load’ button from GUI, then by executing the ‘check’ button, the BGCL (along with three optional features, such as temperature, blood pressure and pulse rate) results can be observed with ‘readings’ and ‘status’. Here, ‘readings’ means the measured value; whereas the ‘status’ shows the health concern. For example, for a BGCL reading ‘5.1mmol/l’, status should be ‘healthy’, and so on. Details information and previous records can be seen by clicking ‘open’ and ‘check record’ button respectively. The ‘change patient’ button pops-up the registration page for new entry.

### 2.3. Hardware and system set-up

A pair of UWB microstrip patch antenna was connected with transceivers (P400 RCM) using SMA connectors of 0.5 meters long. The antenna has the bandwidth, gain and directivity of 8.77GHz (3.23GHz to 12 GHz), 6.09dB and 8.15dBi respectively. Then the transceivers were connected to a computer (PC) through ethernet cable in order to transmit and receive the signal as shown in Figure 3. The signal transmission, reception, saving, processing and analysis was done through the PC using software interface. A preliminary design of the prototype and experimental system setup is shown in Figures 4 and 5 respectively.

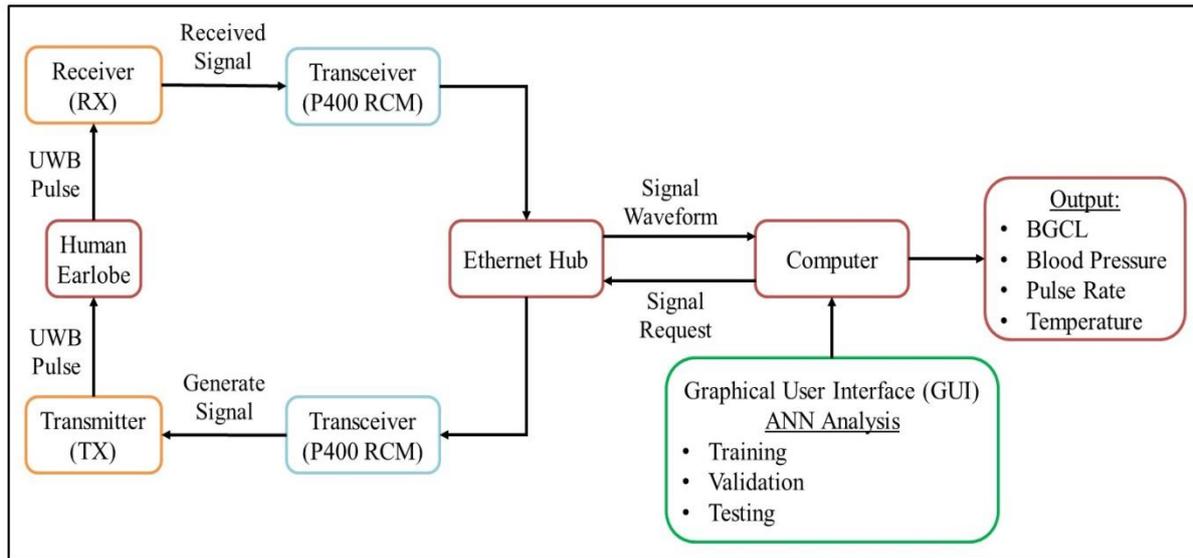


Figure 3. System block diagram.

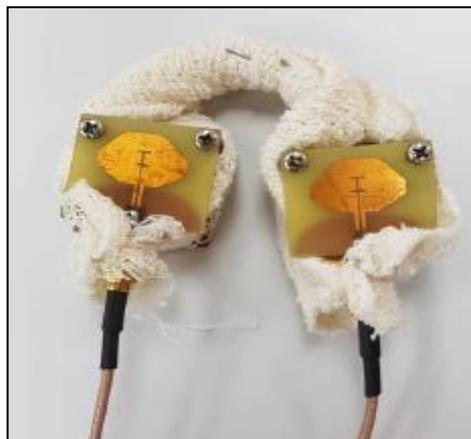


Figure 4. A Prototype of the UWB antenna.

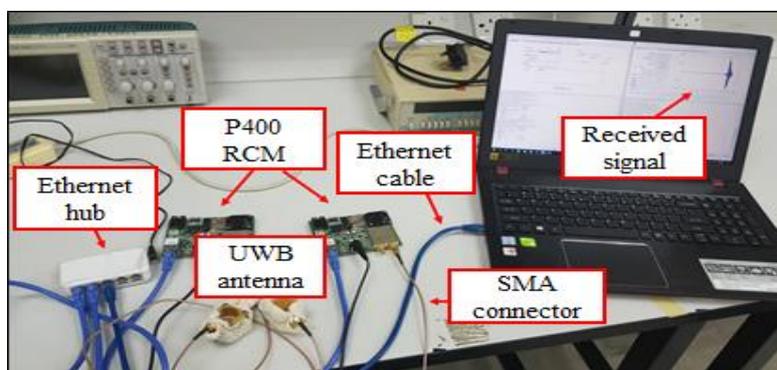


Figure 5. Experimental system setup.

2.4. Signal acquisition

The human earlobe was chosen to acquire signal. Because, it contains a very small amount of fat, no bone and saturated blood vessels with relaxed blood flow. Hence, the earlobe is suitable for monitoring blood glucose levels. The UWB signals were collected through the earlobe and used and used for training, validation, and testing the ANN. The received scattered signal was converted from analogue to discrete value and then processed further for classification and BGCL signature / pattern recognition.

A total 225 data (UWB signals and actual BGCL) were collected from students and staff of Universiti Malaysia Pahang as well as some local volunteers. The data collection was carried out at UMP Health Centre in presence of medical doctors and nurses. The volunteers signed the consent form prior to collect data. UWB signals were collected through the left earlobe after checking their actual BGCL by doctors. Along with BGCL, systolic blood pressure (SBP), diastolic blood pressure (DBP), pulse rate (PR) and temperature (Temp) were also recorded from all volunteers. The experimental setup for the UWB signal data collection is shown in Figure 6.

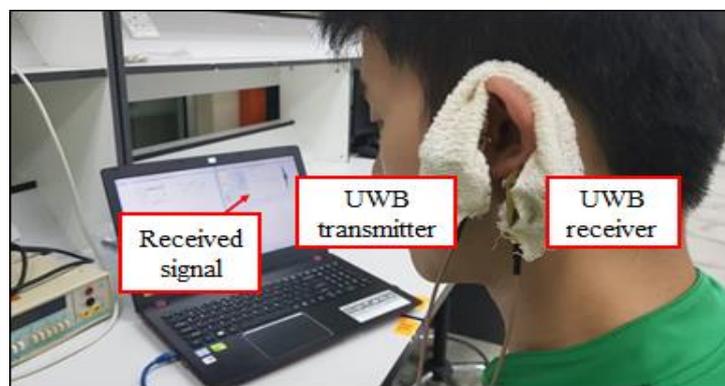
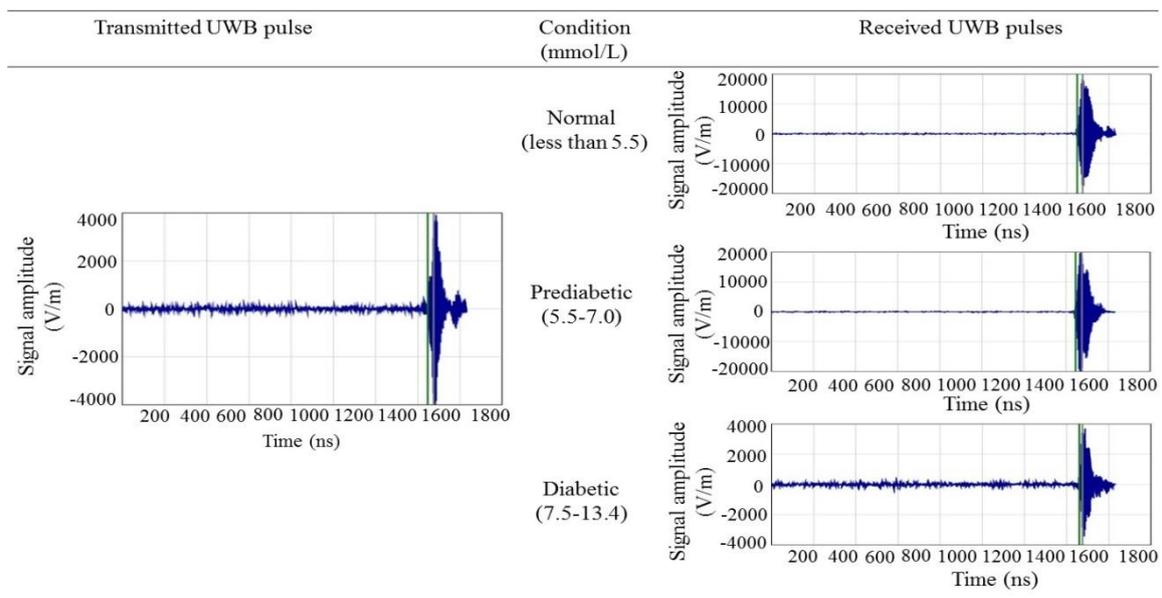


Figure 3. Collection of UWB signal data through the left earlobe.

The transmitted UWB signal and the corresponding received signal depending on BGCL is shown in Figure 7.



**Figure 4.** Transmitted and received the UWB signal through the left earlobe.

### 2.5. Signal processing through software module

Discrete Cosine Transform (DCT) is used to convert the received analogue signal to digital form, as a result, 1632 discrete data points were extracted. These data points were reduced into four prominent feature values, which are skewness, kurtosis, variance and mean absolute deviation (MAD). The calculation of these features values are shown in Equations 1 to 4. This can improve training performance and increase processing speed.

$$\text{Skewness (skew)} = \frac{1}{N} \sum_{i=1}^N \left[ \frac{(X_i - \bar{X})}{\sigma} \right]^3 \quad (1)$$

$$\text{Kurtosis (kurt)} = \frac{1}{N} \sum_{i=1}^N \left[ \frac{(X_i - \bar{X})}{\sigma} \right]^4 \quad (2)$$

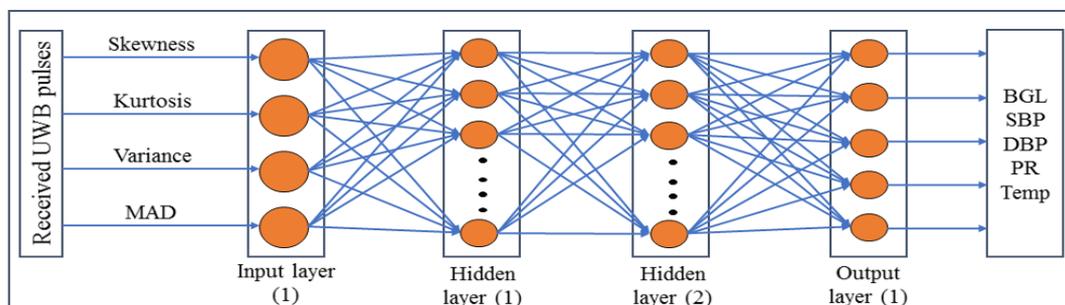
$$\text{Variance } (\sigma^2) = \frac{\sum_{i=1}^N (X_i - \bar{X})^2}{N} \quad (3)$$

$$\text{MAD} = \frac{\sum_{i=1}^N |X_i - \bar{X}|}{N} \quad (4)$$

Where N is the number of data points, X is the matrix of the UWB pulse.

### 2.6. Feature classification through the software module

Reduced feature values were used as input to ANN to classify and detect. Here, feedforward back-propagation artificial neural network (FFNN) is used as ANN. FFNN is considered due to its simplicity to make the proposed system lightweight with tolerable accuracy level. This ANN consists of a single input layer with four neurons, two hidden layers with eight neurons each and a single output layer with five neurons. The architecture of the ANN model is shown in Figure 8.



**Figure 8.** The architecture of the ANN module.

Four input neurons refer to skewness, kurtosis, variance, and MAD, while the output neurons refer to BGCL, SBP, DBP, PR and Temp. The used activation functions for hidden and output layers were

tan-sigmoid and linear transfer functions respectively. Due to optimum performance, 'trainlm' function is used to optimize the whole training process. Equation 5 was used for ANN regression.

$$y = \sum_{t=1}^n w_n x_n + w_0 x_0 \quad (5)$$

Where,  $y$ ,  $w$ ,  $x$  represent output value, weight vector and input data respectively. Based on the theory of the back-propagation algorithm, the value of the weight vector,  $w$  is adjusted and updated backward from output to input according to the error at the output level in each training iteration. This process is continued until the desired output is achieved.

The 225 data samples were divided into three categories as follows to measure and analyse the performance of the system:

- Training: 157 samples (70%)
- Validation: 34 samples (15%)
- Testing: 34 samples (15%)

Equation 6,7 and 8 were used to calculate the accuracy of the ANN system.

$$Error = \frac{|Actual Value - System Output|}{Actual Value} \times 100\% \quad (6)$$

$$System Accuracy, A = 100\% - Error \quad (7)$$

$$Average System Accuracy = \frac{1}{N} \sum_{n=1}^N A_{nn} \quad (8)$$

where  $N$  is the total number of samples.  $A_{nn}$  is the diagonal elements.

Equations 9 and 10 were used to calculate true positive rate (TPR) and false negative rate (FNR).

$$TPR = \frac{TP}{TP + FN} \quad (9)$$

$$FNR = \frac{FN}{FN + TP} \quad (10)$$

### 3. Results and discussions

Figure 9 shows the best validation performance of the network in terms of mean square error (MSE) value is 0.73979 at the fourth epoch (iteration). The error and accuracy of each sample were calculated using Equations 6, 7 and 8 respectively. The average system accuracy (using Equation 8) is around 90.6% as shown in Table 1.

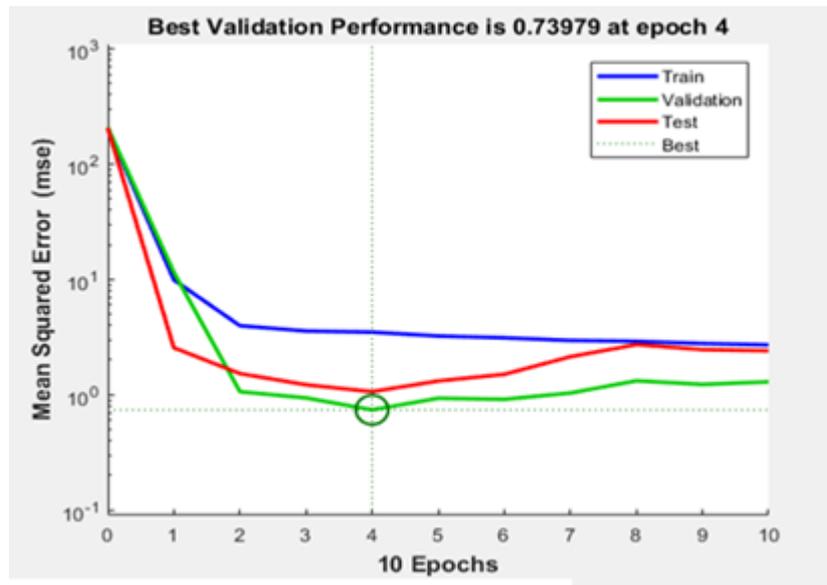


Figure 9. Best Validation Performance.

It also shows the TPR and FNR. TPR and FNR are calculated using Equations 9 and 10 respectively. The performance comparison with proposed system and existing work is shown in Table 2, which show the average accuracy was 81% [19] and for proposed system average accuracy is 90.6%. The detection accuracy is improved 9.6%.

Table 1. Accuracy rates of proposed ANN.

		Predicted output			TPR	FNR
		Normal	Prediabetic	Diabetic		
Actual input	Normal	90.6%	6.7%	2.7%	90.6%	9.4%
	Prediabetic	5.4%	94.6%	0%	94.6%	5.4%
	Diabetic	2.7%	10.7%	86.6%	86.6%	13.4%

Table 2. Comparison with existing work.

	Relative average accuracy	Improvement
Reference [19]	81%	9.6%
Proposed system	90.6%	

The measurement of BGCL, SBP, DBP, PR, and Temp (for one specific case) through GUI along with the health status is shown in Figure 10. The ‘readings’ show BGCL = 9.0814 mmol/L with ‘status’ diabetic; SBP = 124.783mmHg, DBP = 73.0175mmHg, resulting ‘status’ pre-high; PR = 83.5393bpm, and Temp = 36.5712°C with ‘status’ normal by indicating ‘-’.

**Patient :** ABCD

**LET'S CHECK!!!**

Blood Glucose Level (mmol/L)  
 Temperature (°C)  
 Blood Pressure (mm Hg)  
 Pulse Rate (bpm)

C:\Users\USER\Desktop\blood\_glucose\bg\_data\bg.csv

Random

\*Note: Please double check. The process cannot be reversed.

**Results**

Categories	Readings		Status
Blood Glucose Level (mmol/L)	9.0814		Diabetic
Temperature (°C)	36.5712		-
Blood Pressure (mm Hg)	Systolic	Diastolic	Pre-High
	124.783	73.0175	
Pulse Rate (bpm)	83.5393		-

**Standard Range References :**

**Figure 10.** One specific measurement is shown through the GUI.

#### 4. Conclusion

In this paper, a non-invasive blood glucose level measurement system with software module development has been presented. UWB technology, bio-antenna and ANN is used to develop the system. The system works with 90.6% accuracy by showing its suitability for practical use. The system is suitable to be used by any user due to its user-friendly software module with GUI. Besides, this system is non-invasive, low-cost, as well as suitable to be used by doctors in hospitals or end-users at home for regular blood glucose monitoring. It can measure the BGCL, SBP, DBP, PR, and Temp simultaneously in one go with health status. Increased sample size and reduced signal-to-noise ratio during data collection can further improve the system accuracy.

#### Acknowledgments

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