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Non-Invasive Blood Glucose Meter

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Abstract: *The glucose concentration in the range from 111-330 mg/dl represents a diabetic patient. it causes physical impairment of vital organs. presently, non-invasive blood glucose monitoring device that uses the blood dielectric and impedance properties is becoming popular for diabetes detection. a realistic reusable low-cost non-invasive glucose meter is developed using wi-fi module. it measures glucose level based on the permittivity changes in human blood with sub-carriers. each sub-carrier is spaced with 312.5 khz bandwidth, generating 64 amplitudes and phases is used for channel estimation. a hampel filter is used to suppress abrupt amplitude variations occurring due to the environment effects. the system is trained using ml.net fast forest quantile regression method. the accuracy obtained is around 90%.*

Keyword: *WiFi ; ML.Ne ; ML*

I. Introduction

Blood glucose monitors are critical to diabetes management. Presently, there is no permanent medicine to cure diabetes. Patient with diabetic symptoms are kept within the range by controlling levels of blood glucose. Various techniques are available to measure and monitor regulation of glucose.

Presently, blood meters use glucose oxidase and platinum coated strips for glucose measurement. Here, initially blood is pecked from the patient's finger and placed on enzyme strips. Further, amperometry analysis is carried on yield hydrogen peroxide engendered from the chemical reactions of glucose and oxygen.

In an Invasive Glucometer one needs a blood sample extracted by pecking needle into patient fingers This is a painful process. This results in formation of copious calluses on the finger-tips and causes more pain to lure blood again and again for repetitive measurements.

Non-invasive glucose monitoring techniques have been heavily researched over the past several decades. They have been divided into the following categories: Interstitial fluid chemical analysis, Breath chemical analysis, Infrared spectroscopy, Optical coherence tomography, Temperature-modulated localized reflectance, Raman spectroscopy, Polarity changes, Ultrasound, Fluorescence, Thermal spectroscopy, Ocular spectroscopy, and Impedance spectroscopy.

A Non-Invasive Glucometer is designed and implemented with the help of Machine learning techniques

II. Litrature Survey

A. Diabetes Mellitus

A condition where the body is unable to regulate the amount of glucose in the blood due to lack of insulin or the body's inability to produce insulin. A condition where there is too much glucose in the blood. Obesity in persons with diabetes is associated with poorer control of blood glucose levels, blood pressure, and cholesterol, placing persons with diabetes at higher risk for both cardiovascular and microvascular disease. The prevalence of obesity among adults with diagnosed diabetes remained high, at 45.7% during 1988--1994 and 54.8% during 1999--2002.

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B. **Glucose Monitoring**

In the absence of a cure for diabetes, home blood glucose monitoring will undoubtedly need to continue and the current commercial dominance of mediated electrochemical biosensors will not be easily displaced. The readings obtained led to recommendations for adjustment of the diabetes regimen. It’s a painful process & proper care has to be taken by patients for home use.

C. **Non-Invasive Glucose Monitoring**

Non-invasive glucose monitoring techniques have been heavily researched over the past several decades. They have been divided into the following categories: Interstitial fluid chemical analysis, Breath chemical analysis, Infrared spectroscopy, Optical coherence tomography, Temperature-modulated localized reflectance, Raman spectroscopy, Polarity changes, Ultrasound, Fluorescence, Thermal spectroscopy, Ocular spectroscopy, Impedance spectroscopy.

D. **Machine Learning**

ML-based studies are mostly restricted to data with high signal-to-noise ratios. We modify the long-established Random Forest (RF) algorithm to take into account uncertainties in measurements (i.e., features) as well as in assigned classes (i.e., labels). To do so, the Probabilistic Random Forest (PRF) algorithm treats the features and labels as probability distribution functions, rather than deterministic quantities. A fast forest quantile regression (FFQR) is an ensemble machine learning model that combines several regression trees to improve speed prediction accuracy.

E. **WiFi Channel State Information**

The Wi-ESP CSI tool has considerable advantages over existing CSI tools and is suitable for practical implementations. The amplitude and phase received from CSI values in Wi-ESP are not random since data are from all 64 subcarriers. The hardware and software dependency of the Wi-ESP CSI tool is much less than other CSI tools. The Wi-ESP CSI tool is flexible, low cost, and easy to deploy as an edge device in large implementations such as IoT. Furthermore, different training fields available in Wi-ESP allow it to receive CSI values for specific applications like breath-rate monitoring and localization with precision. DFWS framework relies on Wi-ESP as a tool for CSI measurement and processing.

III. Proposed Methodology

Imagine diabetics who no longer have to suffer the frequent pain of drawing blood to measure their blood sugar levels. Where monitoring is performed more frequently to gain better disease management, less suffering, fewer medical complications and lowered health care costs. In day to day life, an embarrassment approach by pricking blood from the human body is used to measure and record glucose levels of diabetic patient. This process is carried either in the clinic or at home. However, obtained glucose levels in the blood is at that specific time only. Hence there is a need to monitor and measure unobserved glycemic changes in blood for several times in a day to avoid complications. Therefore, to design painless and low-cost non-invasive meter for continuous glucose measurement is always been areas of interest. Such personal device is found better for glucose control and to take necessary preventive actions at right time to save life.

Figure No 1 : Block Diagram

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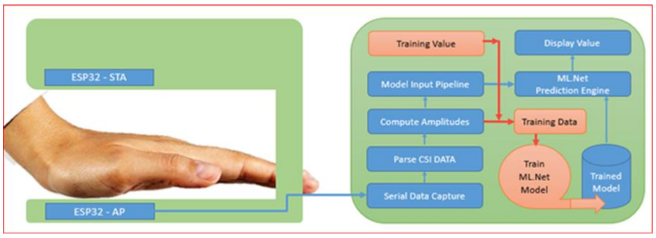


A. **Specifications**

Application: To determine blood glucose in whole blood by Non-Invasive method

Operating Conditions: Temperature: 4 C to 45 C;

Humidity: <98%

Operating Altitude: 0 to 3094 meters.

Display: Large Display with 3.5 inch LCD

Measuring range: 40 mg/dl to 400 mg/dl

Measuring time: less than 3 seconds

Memory Capacity: 2000 Blood Glucose Test Results with Time, Date and daily as well as weekly Avg report for Random or Before or After Meal.

Connectivity: USB Interface

B. **CSI Estimation**

Define the received signal by the antenna RX in complex form as $A_{r2}.e^{j\Theta r2}$, where A_{r2} and Θ_{r2} are the amplitude and phase of signal. Since the received signal is the superposition of multipath components, it can be expressed as follows:

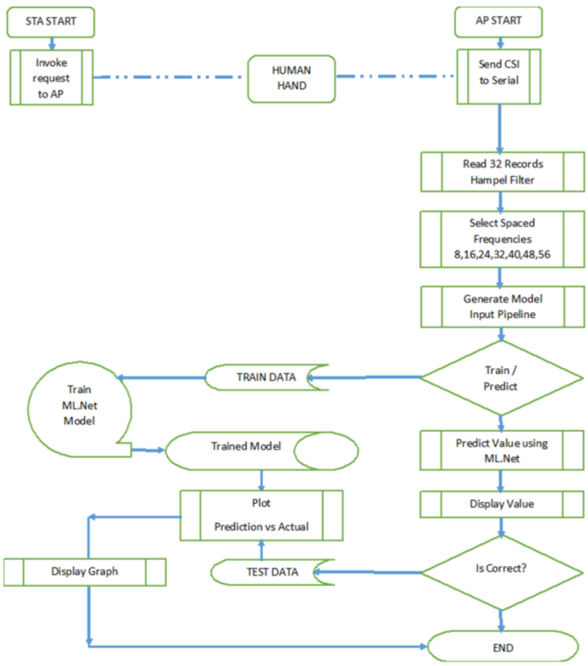
$A_{r2}.e^{j\Theta r2} = A_{LOS}.e^{j\Theta LOS} + A_m.e^{j\Theta m}$

where A_{LOS} and Θ_{LOS} are the amplitude and phase of signal transmitted on LOS where the material exists. While $A_m.e^{j\Theta m}$ represents the total effect of other multipath signals. When the microwave propagates in a dissipative medium, the amplitude is attenuated relative to the dielectric constant and conductivity of the medium. Combining the real and imaginary parts of each subcarrier, we can determine the amplitude ($A^{(i)}$) and phase ($\varphi^{(i)}$) for subcarrier i by the following equations.

$$A^{(i)} = \sqrt{(h_{im}^{(i)})^2 + (h_r^{(i)})^2}$$

$$\phi^{(i)} = atan2(h_{im}^{(i)}, h_r^{(i)})$$

C. *Flow Chart*



IV. Machine Learning

Arthur Samuel, a pioneer in the field of artificial intelligence and computer gaming, coined the term **"Machine Learning".** He defined machine learning as – **"Field of study that gives computers the capability to learn without being explicitly programmed".**

In layman's words, Machine Learning(ML) can be explained as finding result by comparing historical data that is stored using an algorithm (Model). The process begins with collecting data, labelling or marking of data, training data to generate a Model and consuming the Model to Predict result. Evaluation of the Model is done by comparing the measured vs predicted results.

A. *ML.Net*

ML.NET follows the same basic steps for nearly every scenario; it combines data loading, transformations, and model training to make it easy for you to create machine learning models. MLContext is the starting point for all ML.NET operations. The MLContext is used for all aspects of creating and consuming an ML.NET model.

Once you have an instance of an MLContext, you can load and transform data, choose the best algorithm for your machine learning task, train your model. Once trained, you can test your model for accuracy, save it to disk, and use it to make predictions. Machine learning uses known data (for example, training data) to find patterns in order to make predictions on new, unknown data.

The inputs for machine learning are called Features, which are the attributes used to make predictions. The output of machine learning is called the Label, which is the actual prediction.

B. *Fast Forest Regression*

The Fast Forest Regression module in ML.Net Machine Learning is an implementation of random forest quantile regression using decision trees. Random forests can be helpful to avoid overfitting that can occur with decision trees.

A decision tree is a binary tree-like flow chart, where at every interior node, one decides which of the two child nodes to continue to, based on the value of one of the features of the input.

Fast Forest Quantile regression is useful if you want to understand more about the distribution of the predicted value, rather than get a single mean prediction value. This method has many applications, including:

- Predicting prices

- Estimating student performance or applying growth charts to assess child development
- Discovering predictive relationships in cases where there is only a weak relationship between variables

This regression algorithm is a supervised learning method, which means it requires a tagged dataset that includes a label column. Because it is a regression algorithm, the label column must contain only numerical values.

V. Results

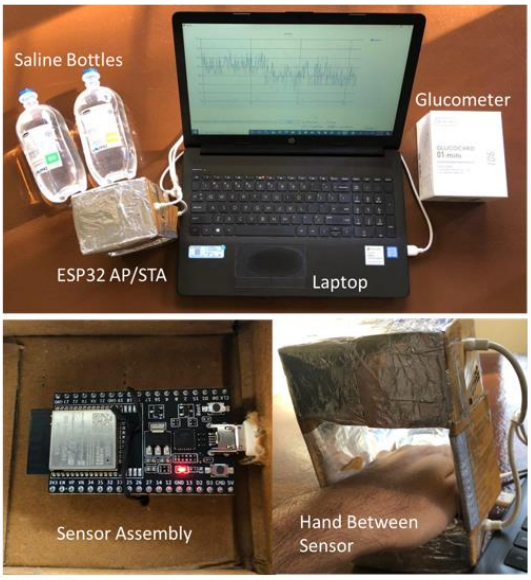


Fig 1. Physical System Setup

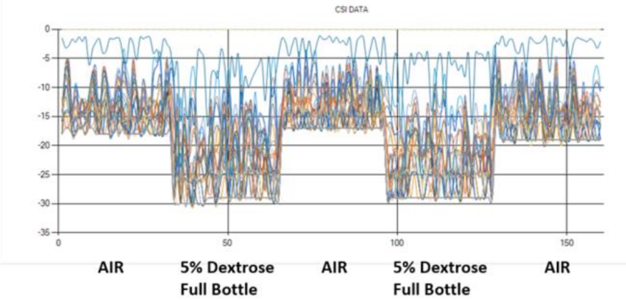


Fig 2. Captured amplitude timeseries

The Amplitude is significantly attenuated when a 5% Glucose solution is placed between AP & STA. The amplitude of the real subcarrier has high variations compared to the modelled amplitude. This is caused by variation of the attenuated reflection of the reflected path due to movements in environment. This attenuation is assumed constant over time.

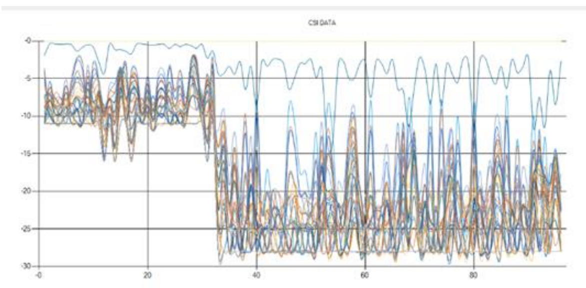


Fig 3. Graph for Blood Glucose Measured 90 mg/dL before lunch.

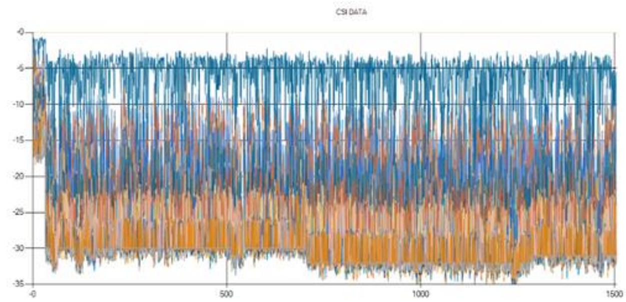


Fig 4. Graph for Blood Glucose Measured 162 mg/dL one hour after lunch

A. *Device Accuracy*

Simulation Parameters

CSI Data of 64 sub-carriers : 20 MHz 802.11n/ac channel consists of 64 subcarriers

No of Samples collected : 32

Operating Frequency : Min 2412 MHz , Max 2484 MHz

The sub-carriers chosen for data extraction :

Channels : 8,16,24,32,40,48,56

Corresponding Freq : 2424,2432,2440,2448,2456,2464,2464 MHz

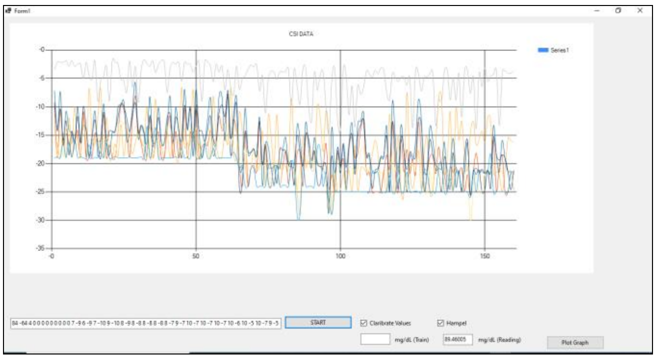


Fig 5. Predicted Blood Glucose Measured 89.4 mg/dL & by Arkray Glucocard 01 Meter 90 mg/dL

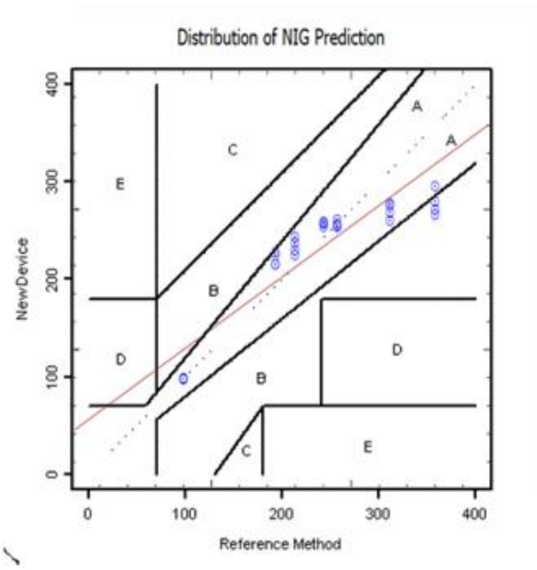


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Fig 7. Clarke Error Grid & Distribution of Prediction

The **Clarke Error Grid** Analysis (EGA) was developed in 1987 to quantify clinical accuracy of patient estimates of their current blood glucose as compared to the blood glucose value obtained in their meter. It was then used to quantify the clinical accuracy of blood glucose estimates generated by meters as compared to a reference value. A description of the EGA appeared in Diabetes Care in 1987. Eventually, the EGA became accepted as one of the "gold standards" for determining the accuracy of blood glucose meters.

VI. Conclusion

A realistic reusable low-cost non-invasive glucose meter is implemented using 802.11a Wi-Fi module. A variation in amplitudes as well as phases of received packets helps to measure blood glucose levels. Further, Fast-Tree Regression algorithm trains the model for different glucose concentration for accurate prediction and detection of diabetes. The accuracy obtained is 95% and can be further increased by considering factors such as skin pigment, blood flow, epidermis and bone density.

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