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NON-INVASIVE METHOD OF GLUCOSE LEVEL DETERMINATION

[1]Mrs.D.Nithiya Priya, [2]I.Vignesh, [3]T.Surendaran, [4]S.Rajamanickam

[1]Assistant Professor St-2, [2]B.Tech, [3]B.Tech, [4]B.Tech
[1]Department of Electronics and Communication Engineering,
[1]Rajiv Gandhi College of Engineering and Technology, Puducherry, India.

Abstract : There's worldwide demand for an affordable glucose monitoring solution, which is a particularly critical need in developing countries. The Desktop, which is the most entered device in both rich and resource constrained areas, would be a suitable choice to make this result. This design proposes a noninvasive position dimension processes. Also its compared the variation in data collection spots, memoir signal processing ways, theoretical foundations, photoplethysmography(PPG) signal and features birth process, machine- learning algorithms, and prediction models to calculate glucose level. This analysis was also used to recommend realistic approaches to make a Desktop- grounded point- of- care tool for glucose measurement in a noninvasive manner.

***IndexTerms* - Acetone, Non-invasive, Machine Learning, Feature Extraction.**

1.INTRODUCTION

Diabetes mellitus, a chronic metabolic disorder characterized by elevated blood glucose levels, poses a significant global health challenge. With increasing prevalence, effective management of diabetes has become imperative to mitigate complications and e nhance the quality of life for those affected. Central to diabetes management is the continuous monitoring of blood glucose levels, a process traditionally reliant on intermittent and invasive methods such as finger stick testing. The limitations and drawbacks of these methods have led researchers to explore alternative approaches, with a particular focus on predictive modeling using advanced technologies..

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1.1 Motivation

The motivation behind this extensive exploration lies in the transformative potential of predictive modeling for blood glucose levels. Conventional monitoring methods, while essential, offer only a snapshot of an individual's glucose status at a specific point in time. Predictive modeling, on the other hand, holds the promise of anticipating fluctuations in bloodglucose levels, empowering individuals with diabetes to adopt preemptive measures. The motivation is rooted in the desire to shift from reactive management strategies to proactive interventions, fundamentally altering the dynamics of diabetes care.

iagnosis	**A1c Value %)**	**alue ng/dl**	**alue ng/dl**	**alue ng/dl)**
ormal	5.7	99	139	-
re-diabetic	7-6.4	00-125	40-199	-
iabetic	6.5	126	200	200

Table 1.1 Diagnostic chart for Diabetes

1.2 Non Invasive Methods

Non-invasive methods for glucose monitoring are the most desirable and excellent alternative methods as compared to the conventional invasive methods. Non-invasive methods are found to be more comfortable and relaxed for regular glucose monitoring. Non- invasive glucose monitoring can be broadly classified as optical and non-optical methods. For blood glucose measurement, optical methods are found to be more useful since glucose is an optically active substance.Different locations on the human body where th glucose measurements have been done using the non-invasive method are the finger, ear lobe, cheek, arm and palm. Finger has a higher density of the capillary network. Since the finger is a hair-free site, it is found to be the most convenient place for measurement.

Important techniques employed for the monitoring of blood glucose are Polarimetry, Raman spectroscopy, photoacoustic spectroscopy optical coherence tomography, thermal emission spectroscopy, impedance spectroscopy, and Mid-Infrared Spectroscopy (MIRS), Near-Infrared Spectroscopy (NIRS). The direct interaction of light and glucose molecule is utilized to determine the glucose concentration in Raman spectroscopy, NIRS, MIRS and photoacoustic sensing spectroscopic studies. Indirect measurement of glucose by measuring the signal from the molecules that can reversibly bind to glucose is performed in fluorescence sensing. Change in scattering properties using human tissue as a function of glucose concentration is done in optical coherence tomography.

Raman spectroscopy is a spectroscopic technique in which spectral fingerprints of molecules are determined concerning the vibrational modes of molecules. A shift in photon energy occurs when light is incident on the target because of molecular vibrations. Such inelastically scattered photons give the structural and chemical information of the molecule. This is the principle behind Raman spectroscopy. Since the resulting frequency shift in the Raman spectrum is specific to the vibrational modes of the molecule and is independent of excitation photon frequency, the Raman spectrum for glucose monitoring can be clearly distinguished from the spectrum of other biological compounds. Sharper and less overlapped spectra compared to NIR spectroscopy is obtained in Raman spectroscopy.

Optical rotary dispersion of polarized light occurs in polarimetry in which all waves of light vibrate on the same plane. Polarimetry utilizes visible light. Since scattering depolarizes light, polarimetry is sensitive to the scattering properties of the investigated tissue. Optical Coherence Tomography (OCT) is utilized to perform real-time and precise non-invasive glucose monitoring. To measure the interferometric signal using OCT, a low coherence light source and a photodetector are used. Change in skin temperature of several degrees having significant effects on signals is the main drawback of OCT in measuring glucose. Whether OCT has an advantage over other scattering technique is not yet established.

Acoustic waves produced from the materials by the absorption of infrared light principle are used to measure the glucose concentration in the Photo acoustic Spectroscopy (PAS). PAS combines heat measurements with optical microscopy. The blood glucose concentration can be analyzed by measuring the changes in the peak-to- peak value of laser- induced pressure waves due to change in scattering/absorption. PAS technique is affected by chemical interferences, sensitive to environmental changes like pressure, temperature and humidity, and also it is expensive. The EM (electromagnetic) spectrum ranging from 2,500 to 10,000 nm is the range of the MIRspectrum. The principle employed in NIR spectroscopy is used in the MIR spectrum also. As the MIR region falls in the longer wavelength band, absorption dominates scattering. Hence the penetration of MIR light in human skin is only about 100 µm.

2 EXISTING SYSTEM

Blood glucose monitoring is crucial for individuals with diabetes to manage their condition effectively. Non-invasive methods for predicting blood glucose levels have gained attention inrecent years. Acetone, a ketone body produced during fat metabolism, has been suggested as apotential biomarker with a correlation to blood glucose levels.When the body enters a state of ketosis, which can occur during fasting or low-carbohydrate diets, acetone is produced as a byproduct of fat metabolism. Elevated levels of ketone bodies,including acetone, may be associated with insulin resistance or changes in blood glucose levels. Devices such as breath analyzers can be used to detect and measure acetone levels in the breath. The idea is that by analyzing acetone concentrations, one could infer the state of the body's metabolism and potentially predict blood glucose levels.

2.1 Architecture of Correlation Neural Network

The CORNN architecture is designed by amending the architecture of conventional CNN. To get the best features out of the sensor response signal, we used the correlation operation rather than the convolution. Fig. 1 depicts the con- ceptual layout of the CORNN learning model. The network has layers of correlation and sub-sampling, followed by a layer for classification.The key component of this model is the correlational part. The procedure of feature extractionisused to extract the important features from the input signal. In signal-processing applications, convolution and corre- lation techniques are extensively utilised. The fundamental correlation operation involves applying the filter to the inputsignal and the computing sum of the products of the overlap- ping data . By using the same filter on the whole input signal, this procedure is repeated.

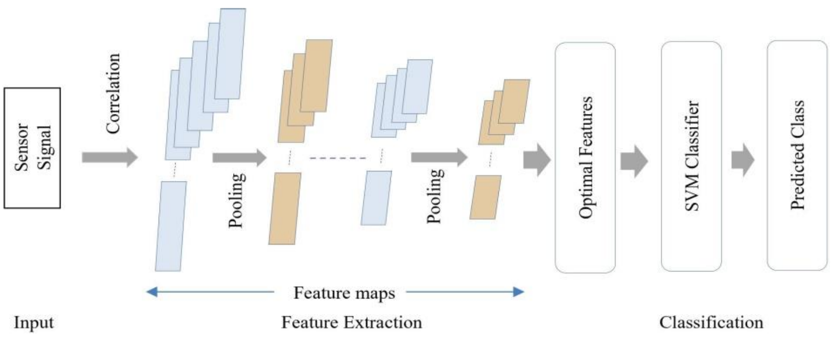

Fig.1 Architecture of CORNN

In a typical convolution procedure, the kernel is flipped prior to convolution between the applied input signal and kernel. Convolution operations are essentially cross-correlation operations in deep learning networks as the kernel flipping is not done here. Kernels are important in the feature extraction process. The kernel's values will be inverted upon flipping, delivering a different result. As a result, neural net- works do not flip the kernels before the convolution process. The correlation and convolution techniques are the same whenapplied to deep learning networks. The correlation network presented in this paper, however, represents a novel strategy that differs from the methods already in use. The cross-correlation procedure is applied to draw the best feature ma2ps in the proposed design. Additionally, we used adaptive kernels to run the network that were derived from the sensor signal itself.

2.3 SYSTEMDESIGN AND TESTING UNIT

A. DESCRIPTION OF SENSOR UNIT

The detection circuit of the TGS1820 acetone sensor is depicted in the above figure. The circuit voltage is applied between the sensor's two ends the load resistor, which connected in series with the network. A circuit voltage of 2.3V is applied, and a load resistor of 10 ohm is connected to the circuit, to maintain the sensing element at the ideal temperature that is suitable for acetone gas detection. A Wheatstone bridge comprised of the sensor, a load resistor, and two resistor pairs is used to measure the sensor output.

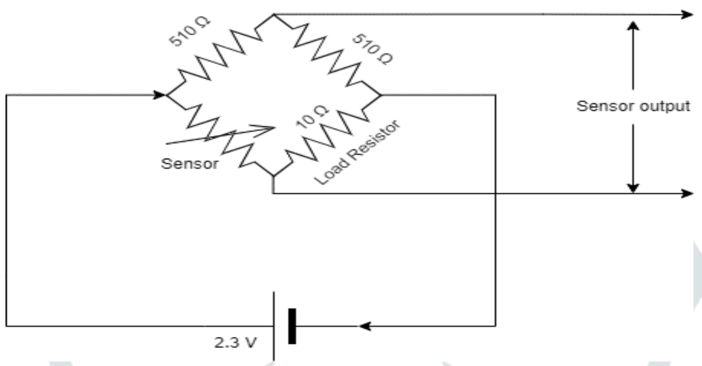

Fig.**2** Detection circuit of the TGS1820 sensor

The acetone sensor provides the voltage and resistance readings. It is important to track the pressure inside the chamber as improper blowing into the test chamber's mouthpiece can impact the acetone readings. The pressure inside the chamber is measured by connecting a BMP180 sensor to the sensor array . A DHT11 sensor is used to measure the humidity and temperature [22]. For carrying out the testing process, we designed a test chamber. Fig. 4 displays the graphic representation of the designed test chamber. An air-blowing mouthpiece is located at the front of the chamber. The three sensors are placed at the back end of the test chamber.

B.DEEPLEARNING MODULE

An advanced deep-learning CORNN model is employed for analyzing the sensor output. For extracting the best features, we used the correlation operation rather than the convolution operation. We used the cross-correlation approach to obtain the ideal features for classifying the samples. Also, we have used adaptive kernels rather than predetermined kernels, which are produced from the sensor pattern itself. The correlation approach will ascertain whether there is a correlation between the input signal and the kernel [23]. A kernel trained from the input data may analyse the signal more successfully because this verifies the similaritybetween the signals. The size of the input signal at each phase determines the kernel size. Sincethe kernels are created from sensor data, they can easily adapt to the input signal and can analyze the behaviour of the input signal in greater depth.

2.4 Result and Discussion

The objective of this study is to build an automated diagnosis system for detecting diabetesfrom exhaled breath. Machine learning and deep learning algorithms are employed in this work to make automated predictions of the tested samples.

3. PROPOSED SYSTEM

The main idea of this proposed system is to predict a Blood Glucose level using machine learning . The device used to give NIR value and Acetone value to predict Blood Glucose level In addition, it can determine Blood Glucose level and displaying the Blood Glucose level on the LCD screen.

3.1 NIR Spectroscopy

NIR spectroscopy is the only noninvasive blood glucose monitoring technology ever reviewed by a public Food and Drug Administration (FDA) panel for marketing blessing. Although a blessing was not granted, the press content of the hail in 1996 reacted to heightened public awareness of the competition to produce a noninvasive blood glucose monitoring system and of NIR spectroscopy as a technology that might make analogous monitoring possible. "Near-infrared light" describes the usage of an external light source that has infrared wavelengths that are close to visible light wavelengths.. A bodily part may reflect or pass through an NIR source. . Blood glucose and other body constituents absorb a small amount of the light at each wavelength. Spectroscopy, an established technology used to measure energy containing multitudinous wavelengths, detects the amount of NIR absorbed with each wavelength by comparing a reference shaft with the discovery shaft that has passed through or been reflected by the body. With spectroscopy, a data processing fashion known as chemo criteria or multivariate analysis simultaneously analyzes the amount of light absorption at named wavelengths for each blood glucose position..

A polynomial formula is generated that converts the sum of the relative contributions of absorption at the named wavelengths to the blood glucose concentration. This technology is used in oximetry to measure the oxygen aromaticity of blood. The need for regular recalibration is the main issue with employing NIR spectroscopy for blood glucose monitoring. NIR spectroscopy does not measure one signal specific for blood glucose, but rather multitudinous signals that are neither specific for blood glucose nor linked to blood glucose situations in a direct fashion. Blood glucose is responsible for<0.1% of NIR absorbed by the body. Water, fat, skin, muscle, and bone account for the vast majority of NIR absorption. Perturbations in the amounts of these substances can alter NIR absorption and thus invalidate the calibration formula for correlating light absorption with Blood Glucose concentrations that was generated during the calibration process.

3.2 Block Diagram:

Data acquisition through sensors is a fundamental process involving the collection of information from the physical environment. Sensors, specialized devices designed to detect and measure physical properties, play a crucial role in this process. They come in various types, including temperature sensors, pressure sensors, motion sensors, and more. When a sensor detects a physical parameter, it converts this information into an electrical signal, which may be analog or digital. To optimize signal quality, amplification, and conditioning circuits may be employed. Analog-to-digital conversion is often necessary for compatibility with digital systems. The acquired data is then processed and, in many cases, transmitted to central processing units or storage systems using wired or wireless communication. This data undergoes further processing, which may include filtering or averaging, and is stored for analysis or retrieval. In some applications, sensor data is integrated into control systems, influencing real-time decision-making and system adjustments. Regular calibration and maintenance are essential to ensuring sensor accuracy over time. The security and privacy of sensor data, particularly in sensitive applications, are critical considerations. Overall, the data acquisition process via sensors is a versatile and integral aspect of various fields, ranging from industrial automation to healthcare and environmental monitoring.

The raw signal obtained from sensors during the data acquisition process is the unprocessed electrical output that directly mirrors the physical parameter under observation. This initial signal is typically analog, representing a continuous spectrum of values and offering a direct reflection of the sensor's sensitivity to environmental changes. The amplitude and frequency of the raw signal vary based on the nature and speed of the measured physical alterations, such as motion, temperature, or pressure. However, the raw signal is susceptible to noise and interference, both from the surrounding environment and the sensor itself. Its dynamic range, or the span between the smallest and largest detectable values, is a critical consideration to ensure comprehensive coverage of potential variations. The units of measurement associated with the raw signal are specific to the sensor type and the parameter it gauges. Calibration is essential to accurately relate the raw signal to the real-world physical quantity, enhancing the precision and reliability of subsequent data analysis or control applications. As a foundational element in the data acquisition chain, the raw signal undergoes further processing, including amplification, filtering, and analog-to-digital conversion, to refine and optimize the acquired data for practical use in diverse applications.

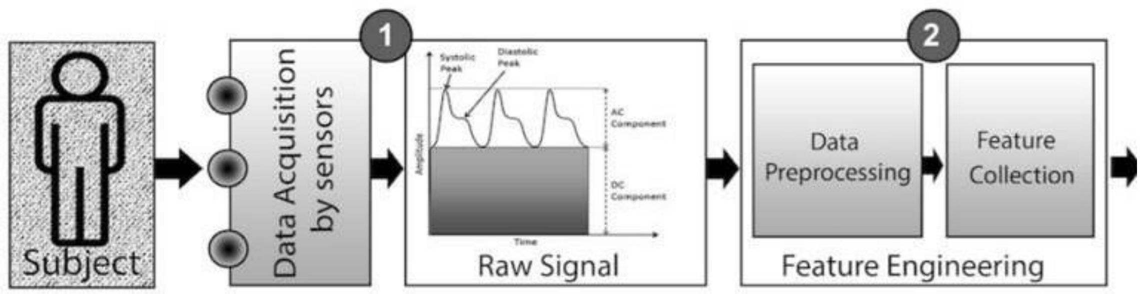

Fig.3 Block Diagram of Proposed System

Data preprocessing from raw signals is an essential step in refining and optimizing the information obtained from sensors for meaningful analysis. Initially, raw signals often contain unwanted noise, interference, or irregularities that can obscure the underlying patterns. To address this, filtering techniques are applied to eliminate noise, and adjustments, such as amplification or attenuation, may be made to ensure the signal falls within an appropriate range. Normalization scales signals to a standard range, promoting uniformity across different sensors or units. Smoothing methods reduce variations, while interpolation fills in missing data points. Detrending removes long-term trends unrelated to the phenomenon of interest. Decimation or upsampling adjusts the signal's sampling rate, and outlier detection ensures extreme values do not distort analysis. Time synchronization aligns timestamps in signals from multiple sensors. Overall, these preprocessing steps enhance data quality, making it more conducive to accurate analysis, modeling, and integration into various applications, ultimately enabling more reliable insights and decision-making.

Feature extraction is a critical stage in data preprocessing that involves selecting and transforming relevant attributes or characteristics, known as features, from the preprocessed data. Once raw signals have undergone filtering, normalization, and other preprocessing steps, the extracted features aim to capture essential information for analysis or modeling. The choice of features depends on the specific goals of the analysis and the nature of the data. Feature collection involves identifying key patterns, trends, or characteristics within the preprocessed data that are most relevant to the desired outcome. This process not only reduces the dimensionality of the dataset but also enhances its interpretability and computational efficiency. Feature extraction methods can include statistical measures, frequency domain analysis, time-domain analysis, or domain-specific techniques tailored to the characteristics of the data. The resulting set of features serves as the input for subsequent stages, such as machine learning algorithms, where the focus is on leveraging the most informative aspects of the data to make accurate predictions or draw meaningful insights. Overall, feature collection plays a pivotal role in transforming preprocessed data into a more manageable and information-rich representation for advanced analysis and modeling applications.

3.4 Future Works

So for we extracted the features from the sensors signal. In future we have train to the model based on the values from the features which got from the sensors.

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