Real time Prediction of Blood Sugar level using Sweat through BSl Band

Mr. Sachine Kamble, Aniket Wakle, Atharva Pingle, Dhiraj Patil, Rohan Tawar
Department Of Information Technology, Shri Vile Parle Kelvani Mandal's Institute Of Technology, Dhule, India
s.kamble@svkm.ac.in, aniketwakle55709@gmail.com, atharvapingale2002@gmail.com, dhirajmp2002@gmail.com, rohantawar15243@gmail.com

***Abstract* — We have developed a system which has the capability to provide user feedback through a mobile application by receiving data from the device via Bluetooth. The measurement of proposed physiological parameters was successfully attained with the necessary precision conforming to clinical standards. Diabetic patients have employed glucose monitoring technology for over three decades to monitor their blood glucose levels. This article examines the primary methodologies for detecting blood glucose and implementing intelligent insulin regulation. The most prevalent and extensively used approach involves invasive techniques where users prick their fingers to obtain blood samples. However, recent advancements have introduced numerous innovations for non-invasive blood glucose monitoring, fostering rapid growth in this field. This paper proposes a mobile physical health monitoring system based on the Android smartphone platform. The Android device acquires parameters through Bluetooth communication from each health sensor module and simultaneously presents the monitoring data.**

Keywords— Physical health monitoring system, Bluetooth connectivity, Android app, health sensors, Blood Glucose level, IoT Technology.

I. INTRODUCTION

Advancements in modern technology have facilitated the creation of compact, wireless, and portable health monitoring systems capable of continuous surveillance while remaining power-efficient. These innovations have led to a shift in health monitoring, where wearable body sensors are gaining popularity. Such devices play a vital role in detecting anomalies, unforeseen situations, and even forecasting potential symptoms based on monitoring physiological parameters [1]. Parameters such as heart rate, heart rate variability, and movement data are commonly utilized to gain insights into the physical performance of both professional and amateur athletes [2]. Additionally, the practice of monitoring blood lactate concentration during step ergometer or treadmill tests is prevalent in sports science to gauge the physical capacity of athletes [3].

Diabetes mellitus impacts the body's capacity to regulate blood sugar levels. Individuals managing diabetes routinely track their blood glucose levels (preferably maintaining between 70 to 180 mg/dL, influenced by dietary intake) using medication, exercise, and a balanced diet. Levels below 70 mg/dL suggest potential hypoglycemia, while levels above 180 mg/dL may indicate clinically significant hyperglycemia [1], [3]. Regular monitoring empowers those with diabetes to take necessary actions in adjusting their blood glucose levels, thereby reducing the risks associated with both low and high blood sugar levels. In addition to plasma glucose measurement, finger-prick testing using glucose strips and accompanying meters remains the most dependable method for self-monitoring. A glucose meter consists of a testing strip coated with enzymes (such as glucose oxidase, glucose dehydrogenase, and hexokinase) and a detecting apparatus. When blood is applied to the strip, the enzymes react with the glucose, initiating an electrochemical reaction that produces a current proportional to the concentration of glucose [4]. There are four primary types of diabetes: Type 1, Type 2, pre-diabetes, and gestational diabetes. Type 1 diabetes occurs due to the immune system's destruction of the pancreas's beta cells responsible for producing insulin. Inadequate insulin leads to elevated blood glucose levels, potentially causing dehydration, weight loss, diabetic ketoacidosis, and adverse effects on various body parts, predominantly affecting teenagers and adults. Type 2 diabetes, more common among adults, involves the loss of sugar regulation in the body, impacting organs like the kidneys, heart, eyes, feet, liver, etc. Blood glucose monitoring is crucial to observe glucose levels in the blood, with various causes leading to diabetes such as bacterial infections, toxins in food, autoimmune responses, unhealthy habits, aging, family history, overweight, pancreatic conditions, PCOS, Cushing's syndrome, glucagonoma, steroid-induced diabetes [5]. Monitoring blood glucose levels involves invasive and non-invasive methods. Invasive methods puncture the skin for blood, while non-invasive methods do not. Diabetic patients often need to monitor their glucose levels regularly, as levels fluctuate. However, the necessity of pricking the skin for blood, especially when insulin intake is required, poses a painful task that many patients avoid, leading to inadequate medication adherence [5].

II. METHODS

A. *Existing Method*

Diabetes risk assessment traditionally relies on familial history and certain diabetes indicators. Professionals estimate the likelihood of diabetes based on genetic predisposition, suggesting a 50 percent chance if one parent has diabetes and a 75 percent chance if both parents are affected. Individuals over 30 are recommended to undergo regular testing to determine the likelihood of diabetes [6]. Blood glucose levels are typically monitored using invasive methods, involving glucometers that require a small amount of blood from a finger prick. This method involves checking glucose levels regularly, which can lead to complications and other health issues due to repeated invasive procedures [7].

B. *Subjects*

Forty individuals in good health (35 males and 5 females) willingly took part in this study, which formed part of a sports clinical assessment. To qualify for participation, athletes needed to be of legal age and free from pre-existing cardiovascular conditions. Their fitness levels ranged from recreational athletes (35 individuals) to professional long-distance runners (5). The participants' ages ranged from 18 to

61, with an average age of 39.9 ± 12.5 years. The mean body height was measured at 180.3 ± 7.9 cm, and the mean body weight was 80.9 ± 12.7 kg. Gender was not distinguished in the lactate diagnostics phase. Prior to data collection, all participants were briefed about the study's objectives and procedures, and written consent was obtained from each individual. The study received approval from the local Ethics Commission at the Friedrich-Alexander University Erlangen-Nuremberg [8].

C. Exercise Protocol

Participants arrived at the testing facility well-rested and adequately hydrated. Before commencing the sports clinical assessment, essential metadata such as age, height, weight, and details regarding the participants' fitness levels were documented. They engaged in exercise using an electromagnetically controlled cycle ergometer, gradually increasing the workload until reaching their maximum capacity. Before starting the protocol, participants were equipped with a 12-channel ECG Custo Diagnostic (Custo Med, Ottobrunn, Germany) featuring adhesive electrodes, along with a respiratory gas monitoring system, Cortex Metasoft Studio, which included the Metalyzer 3B-2014 (Cortex, Leipzig, Germany). Continuous measurements of heart rate and respiratory gases were collected during the exercise. Baseline data was collected while participants were at rest. The exercise began with participants cycling at 50 W, and the workload increased by 25 W every two minutes. Participants had the liberty to halt the exercise at any point if they felt they had reached their maximum capacity [9]. The maximum workload achieved by any participant was 375 W. The count of participants reaching each stage of the exercise protocol was recorded.

III. RELATED WORK

A wearable sensor serves to collect various physiological data, such as blood glucose levels, and transmits this information wirelessly to a smartphone. Subsequently, it transfers the data to a cloud server for storage within an Electronic Health Record (EHR) [10]. A reliable data manager oversees incoming calls from different applications, validating them against set criteria. To ensure the reliability of Medical Monitoring Applications (MMAs), Health Device Beta (dev β) tools have been proposed for developer use. Security validation involves spatial-temporal modeling through hybrid automata (STHA). Body Sensor Network (BSN) technology is pivotal in the Internet of Things (IoT) healthcare system, enabling patient monitoring via tiny, lightweight sensor nodes. This modern healthcare system based on BSN meets various requirements including safety, sustainability, and security. Security assurance for any control input from MMAs is attained by verifying it against a hybrid automata-based model. Time-Division Multiplexing (TDM) supported sensors ensure long-term availability with a sustainable design. Data collected by different applications are stored in a secure database accessible only to authorized applications. Physiology-based end-to-end security (PEES) establishes a secure communication channel directly between the sensor and the medical cloud [11]. Wireless Sensor Network (WSN) nodes offer diagnostic capabilities and networks large enough for comprehensive analysis, but they may incur significant deployment costs. Frameworks like UPHIAC (Ubiquitous Personal Health Information Access) and PRISM (Platform for Remote Sensing Using Mobile Devices) ensure health data security through Application Programming Interfaces (APIs) that link smartphone sensors with cloud data storage. The Inevitable Health Management System (IHMS) facilitates dynamic adjustments in user context due to mobility. Hierarchical Power Management (HPM) architecture ensures consistency by integrating ultra-low-power processors. The goal is to streamline the interface between various external sensors and client Android devices. Smartphones can connect to external sensors via wired or wireless channels, simplifying device interaction, which can be complex when a single application needs to integrate with multiple sensors using different communication channels and data formats. A framework aims to streamline this interface between various external sensors and client Android devices, emphasizing usability, simplicity, and ease of deployment [12].Blood glucose measurements utilize electrical conductivity measurement, where the conductivity of a sweat sample indicates its ability to conduct electricity, correlating sodium content from sweat to a voltage measurement. The sugar level correlates with voltage ranges using an interpolation equation. Electrical conductivity between two plate electrodes separated by a fixed distance measures the solution's conductivity. Copper, while offering high tensile strength, is commonly used for electrical contacts and electrodes despite its inferior oxidation resistance. It is alloyed with graphite, tellurium, and tungsten to produce brass and bronze for various applications due to its strength and conductivity.

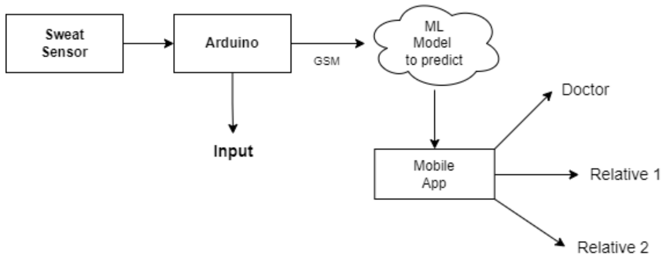

Figure No. 1: Basic Architecture

IV. L ITERATURE SURVEY

N. Sneha and Tarun Gangil (Sneha 2019) explored the fundamental aspects of diabetes, focusing on prevalence rates among different populations. Their study discussed causes, impacts, and various testing methodologies including decision trees, Naïve Bayes, support vector machines, random forests, and k-nearest neighbors. To simplify diabetes complexity and enhance people's lives, they gathered a dataset from the UCI machine repository, divided it for training and testing, applied different algorithms, calculated correlation values, and plotted ROC curves. Their findings showed increased accuracy in various algorithms when correlation values were computed. Specifically, Support Vector Machine (SVM) achieved 77.73% accuracy, while Naïve Bayesian reached 73.48%. However, an improved SVM accuracy of 77% and a Naïve Bayesian accuracy of 82.30% proved most effective in identifying diabetic and non-diabetic patients, with SVM indicating a disease prevalence rate of 45.7%.[19]

Hyunjae Lee and Changyeong Song (Hyunjae 2017) developed a non-invasive glucose monitoring system focusing on sweat collection. Their method involved a multi-layered patch design and sensor miniaturization to enhance sweat collection efficiency and sensing accuracy. They emphasized the relationship between pH, temperature, humidity, and accurate sensing, utilizing a wearable patch-based system for non-invasive sweat glucose monitoring. This system incorporated humidity sensors to monitor sweat collection via impedance change and glucose sensors for sweat analysis. The wearable patch remained reliable across different skin temperatures, absorbing sweat before connecting to hardware for analysis.[12]

K. Nivetha, N. Ramya, and R. Thendral (Ramya 2018) proposed a non-invasive blood glucose monitoring technique using sweat, focusing on the dissolved particles between two copper electrodes. They discussed normal glucose levels for diabetic individuals, comparing the invasive and non-invasive glucose monitoring methods. Their hardware setup included copper electrodes, an Arduino UNO, and an LCD display. By measuring conductivity, they estimated salt levels, considering low salt content's correlation to low glucose levels.[18]

Wira Hidayat bin Mohd Saad and Muhd. Shah Jehan Abd (Shah Jehan) introduced a low-power wearable system for continuous blood glucose level monitoring using a GSR (Galvanic Skin Response) sensor. Their study emphasized the relationship between GSR values and blood glucose levels, employing a circuit with resistors, capacitors, and operational amplifiers. They utilized filters to manage skin resistance variations and noise. Their findings suggested an inverse relationship between GSR and blood glucose levels, where increased calories burned and glucose concentration reduced GSR values.[20]

V. PROPOSED METHODOLOGY

The block diagram of the framework consists of two main sections: the AI component and the continuous monitoring system for glucose, stress, and hydration. In the AI segment, a dataset serves as the input, which undergoes preprocessing to convert strings into integers. This dataset is divided into two parts: training and testing. The training segment allows the machine to recognize patterns in the data, cross-validating to enhance accuracy and efficiency of the algorithms used. The testing section assesses the machine's ability to predict new outcomes based on its training. Various AI algorithms and classification rules are applied, and the accuracy of each classification method is evaluated. The most accurate method is employed for prediction, constituting the primary process in AI. In the continuous monitoring segment, a GSR sensor captures sweat readings, with an Arduino Uno acting as the controller and receiving power supply. The GSR sensor monitors sweat, measuring skin conductance as its output. The sensor output is analog, converted into digital using an Analog-to-Digital Converter (ADC) for ease of processing. Skin conductance inversely correlates with salt content, and this conductance is converted into voltage readings. The GSR sensor's output is inversely proportional to the glucose level. The voltage obtained from the sensor aids in monitoring sugar level, stress, and hydration. Salt level directly corresponds to the sugar level. The voltage readings are converted into sugar levels using a provided formula (Equation 1). The collected results are stored in the cloud [17].

$$((Out-a)/(b-a)) * (c-d) + d \quad (1)$$

Out=Acquire from sensor
a=Minimum voltage b=Maximum
voltage c=Maximum sugar
esteem d=Minimum sugar

The glucose levels obtained from continuous monitoring are utilized in the AI segment for prediction. A Graphical User Interface (GUI) enables input of glucose levels, age, and family history. Following the prediction, a pop-up message displays the likelihood of diabetes based on the existing dataset. Various classification methods' accuracy rates were calculated, and the most accurate method was employed for prediction. Additionally, an ROC curve was plotted to assess the model's performance. Using data from the sweat sensor, glucose levels are estimated. Through the GUI, these values are inputted into the AI segment for predictions. A pop-up message displays the prediction outcome, which is then stored in the cloud [18].

Machine Learning:

The AI component was developed using Python programming language. Python installation was completed, and subsequent to the installation, the core program was developed. Predictions were conducted using both a virtual database and real datasets. In the proposed system, a real database was utilized.

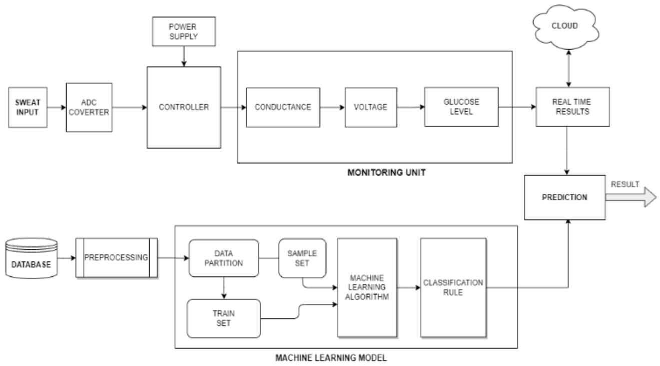

Figure No. 2: Block diagram of proposed system

Virtual database:

The virtual dataset was obtained from the Pima Indians Diabetes Database, containing information such as age, number of pregnancies, glucose levels, blood pressure, skin thickness, insulin, BMI (Body Mass Index), family history of diabetes, and outcomes. This dataset comprises 768 entries across 9 columns. To utilize the entire dataset effectively, it was divided into training and testing subsets.

Real Database:

The real dataset was collected through surveys and collating details from numerous individuals. This database includes information like age, glucose levels, stress levels, sodium intake, weight, height, BMI, family history, and outcomes. The dataset consists of 50 entries spanning 10 columns. To optimize the use of the entire dataset, it was divided into training and testing subsets.

VI. RESULTS AND DISCUSSION

The process begins by detecting and measuring blood glucose levels; initially, a device is responsible for this task and sends the value to a smartphone. The glucose monitoring system connects to the smartphone via Wi-Fi. Following the instructions displayed on the smartphone, a finger is placed inside an NIR sensor equipped with an IR Transmitter and IR Receiver. The sensor detects the pulse rate and determines the blood glucose level, which is then displayed on an LCD and transmitted to the smartphone. Normal human blood glucose levels are typically between 70 mg/dl to 130 mg/dl. The subsequent phase involves administering the required insulin dosage based on the displayed blood glucose value received from the smartphone. The non-invasive measurement estimates the blood glucose level based on the set value from the smartphone. However, it's noted that invasive methods generally offer higher accuracy than non-invasive measurements [19].

This research investigates the presence of ammonium in both blood and sweat during a controlled step ergometer test involving participants with varying fitness levels. This study marks the first attempt, to our knowledge, to directly measure blood and sweat ammonium levels while correlating them with heart rate and blood lactate in a controlled setting, aiming to assess sweat ammonia as an indicator of physical fatigue in wearable devices. Blood lactate concentration rises with physical exertion. As anticipated, professional athletes maintain lower lactate concentrations below the aerobic threshold, indicating a delay in the onset of anaerobic energy pathways compared to untrained individuals. The overall lactate values mirror the subjects' diverse fitness levels, explaining the narrower curves observed in the averaged curve due to earlier exhaustion in subjects with lower fitness levels. Concurrently, blood ammonium concentration also increases with exertion, paralleling the pattern seen in blood lactate. The elevation in blood ammonia during intense exercise is a documented phenomenon linked to the depletion of skeletal muscle ATP during high-intensity workouts. This triggers heightened activity in the Purine-Nucleotide Cycle, leading to increased turnover from AMP to IMP and subsequently higher concentrations of muscle and blood ammonia. Similarly, blood ammonia levels in well-trained subjects rise later and at higher exertion levels compared to untrained individuals, aligning with the patterns observed in lactate concentrations during exhaustive exercise. While lactate, ascertainable only through blood tests, cannot be non-invasively measured in sweat, ammonia, as a weak base, follows the pH gradient from plasma to sweat. The significant loss of ammonia through sweat is a notable pathway. Thus, this study delved into sweat ammonia concentration across different exertion levels as an indicator of physical fatigue.

Although sweat ammonia concentrations display wide variability, an overall decrease in ammonia levels with increased exertion is apparent among most subjects [20]. While the measured values exhibit diversity, the consistent decline in ammonia levels is noticeable. Despite the decrease in sweat ammonia with exertion, there's a notable increase in sweat rate. This increase in sweat rate might augment the overall loss of ammonia through sweat, even amidst declining concentrations. Therefore, a logical step would involve integrating an ammonia sensor with a sweat rate sensor to better understand their relationship.

VII. CONCLUSION

Monitoring blood glucose levels in diabetic patients employs innovative glucose-monitoring technology. A non-invasive approach utilizes NIR sensors based on blood flow rates, eliminating the need for blood draws. These sensors detect glucose levels without invasive measures and transmit the data to a smartphone, enabling control over crucial health devices like infusion pumps. This non-invasive method not only enhances patient compliance but also improves the quality of life and overall health of individuals managing diabetes.

Diabetes, being a chronic condition, lacks a definitive method for prevention or cure. Healthcare professionals rely on family history to predict the likelihood of its occurrence, estimating an average probability rate. Early detection greatly benefits individuals, and the increasing significance of AI plays a pivotal role due to its advantages: reduced reliance on human intervention, increased precision, and efficiency. Our proposed system employs AI algorithms to predict the likelihood of diabetes based on various factors such as age, blood glucose levels, and family history.
Using invasive methods for glucose prediction yields multiple results, prompting the use of non-invasive techniques for monitoring glucose levels. Furthermore, an individual's anxiety and hydration levels can be inferred from sweat. The IoT concept facilitates storing these results in the cloud. As AI and IoT technologies continually advance, these initiatives will garner more attention and support, offering increased value and fostering further development.

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