Exploring EEG Signals for Noninvasive Blood Glucose Monitoring in Prediabetes Diagnosis

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***Abstract*— Prediabetes, characterized by elevated blood glucose (BG) levels without reaching the threshold for diabetes, necessitates early detection to avert complications. Unfortunately, traditional BG monitoring methods involve painful finger pricking. Hence, exploring noninvasive alternatives for BG estimation and continuous monitoring is imperative. This paper investigates electroencephalogram (EEG) frequency parameters, an underexplored aspect of prediabetes diagnosis. Our investigation involved 25 participants (17 healthy and 8 prediabetes) subjected to an oral glucose tolerance test. Continuous EEG signals were collected from three positions: frontal (F), occipital (O), and parietal (P). The analysis employed boxplots to elucidate signal patterns in three phases at 40-minute equal time segments; start phase, middle phase, and end phase. The outcomes revealed compelling results: the left hemisphere's occipital (O) recorded an impressive 90.3% and the right hemisphere's parietal (P) exhibited a notable 90.5% change at the end phase analysis. These findings underscore the significance of EEG signal analysis for BG estimation, especially in O and P positions, where parameters like alpha and beta mean power showcase promise (P-value<0.05). Combining these EEG frequency parameters in a wearable device holds potential for healthcare and clinical solutions, facilitating noninvasive BG status estimation and prediabetes diagnosis.**

***Index Terms*— EEG Signal, Blood Glucose, OGTT, Physiological Signal, Prediabetes, Frontal, Occipital, Parental**

I. Introduction

The global prevalence of diabetes mellitus (DM) is on the rise, posing significant health challenges worldwide. Projections suggest that by 2040, the number of individuals affected by DM could reach 642 million [1-2]. In the United States, 30.3 million people already have diabetes, with an additional 97.6 million adults in the precariously intermediate stage known as prediabetes [2]. Prediabetes is characterized by elevated blood glucose (BG) levels that have not yet reached the diabetes threshold but still pose serious health risks. According to the American Diabetes Association (ADA) guideline, prediabetes is diagnosed if BG exceeds 7.8mmol/dL (140mg/dL) after a two-hour oral glucose tolerance test [2]. Prolonged prediabetes can progress to diabetes, potentially causing irreversible damage to vital organs, the cardiovascular and nervous systems, the retina, and in severe cases, leading to mortality [3].

Regrettably, there is currently no cure for diabetes. However, early diagnosis and diligent monitoring of BG levels can significantly mitigate the health complications associated with this condition. Traditional methods for BG detection and monitoring involve the painful and inconvenient practice of pricking a finger to obtain a small blood sample. This approach, while effective, is far from ideal and can deter individuals from regular monitoring due to the pain and discomfort. The pursuit of an alternative, noninvasive method for continuous BG monitoring has led to the exploration of various techniques, including microwave sensors [4-5], Raman spectroscopy [6], refraction of visible laser light [7], contact lenses for tear film glucose concentration monitoring [8], and bioimpedance [9]. Although these methodologies exhibit potential for BG monitoring, they frequently pose challenges that necessitate further investigation to enhance their adaptability for wearable device integration. As ongoing research endeavors aim to address these challenges, an alternative and promising avenue for continuous BG monitoring is through the utilization of physiological signals, specifically electroencephalogram (EEG) signals. This passive source of data presents an alternative for advancing the field of continuous BG monitoring.

It is widely acknowledged that glucose serves as the primary source of energy for the human brain, as supported by extensive research [10-11]. Emerging evidence suggests that changes in BG levels can impact brain activity, making EEG signals a potentially valuable resource for continuous noninvasive BG estimation [12]. EEG signals record the electrical activity of the brain's cortex from its surface, making

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them a prime candidate for investigation in the context of BG-related changes. Various quantitative studies have delved into the impact of glucose on different brain regions. One such investigation, conducted by An et al. in 2015[13], aimed to explore the effects of glucose on brain activity. In this study, 24 healthy fasting volunteers engaged in an eight-hour resting-state EEG analysis. The experiment involved two attention exercises, one during a fasting state and another after the ingestion of a glucose solution. The findings revealed an improvement in participants' performance on the attention test following glucose intake. Furthermore, there was a significant increase in low alpha (8-10Hz) and theta (4-8Hz) power observed in the parieto-occipital and frontal regions of the brain.

In an experimenter-blind crossover study conducted by Walker et al., 2021 [14], the impact of glucose metabolism on adult brain excitability and network activity was investigated. Participants received either a 75g glucose solution or an equivalent volume of water on two separate visits. Analysis of the EEG frequency spectrum showed significant modulations in alpha frequency peak and aperiodic signal components, indicating increased excitation. Interestingly, peak alpha power exhibited a negative correlation with changes in BG levels, highlighting the influence of BG on neurological functions related to alertness and attention. Additionally, Wang and Dykman (2004) [15] elucidated the connection between BG and cognitive functioning and memory through a double-blinded study. Participants received either a carbohydrate supplement or placebo in alternating weeks. EEG data recorded from frontal, parietal, and occipital regions showed enhanced power in theta, alpha, and beta wave frequencies during the carbohydrate supplement phase, not observed in the placebo group. However, while these studies provide valuable insights into the relationship between BG and brain activity, their findings are not specific to prediabetes and may not directly apply to prediabetes diagnosis.

Previous studies have investigated the relationship between EEG signals and glycemic changes, primarily in type 1 or type 2 diabetes management. Hyllienmark et al. (2005) [16] studied 35 type 1 diabetes patients and 45 healthy subjects, observing increased slow activities in delta and theta bands, and reduced alpha peak frequency in the frontal region of diabetic patients. Additionally, Rubega et al. (2020) [17] demonstrated the utility of EEG signals in detecting hypoglycemia in type 1 diabetes patients, achieving a 90% accuracy rate in predicting euglycemia and hypoglycemia using neural network analysis. However, these studies have not explored the use of EEG signals in prediabetes diagnosis, which could aid in early detection and implementation of preventive measures to mitigate diabetes onset.

Early diagnosis of prediabetes is crucial for effective intervention in preventing progression to type 2 diabetes. Treatment modalities for prediabetes include weight loss, pharmacotherapies, and sustaining beta-cell function [18-19]. The ADA recommends four diagnostic methods for diabetes, which are equally applicable for pre-diabetes screening: Fasting Plasma Glucose Test (FPG), Oral Glucose Tolerance Test (OGTT), A1C (Glycated hemoglobin) levels, and Random Plasma Glucose test, particularly for patients exhibiting symptoms of hyperglycemia or hyperglycemic crisis. These methods are integral for the timely and accurate identification of individuals at risk [20-21]. This paper aims to fill this knowledge gap by investigating changes in EEG signals at specific locations in the rain—parental, frontal, and occipital positions—across different frequencies during an OGTT in healthy and prediabetes participants. The objective is to identify EEG frequency parameters at different stages of the OGTT experiment that correlate with BG variations and ascertain the hemisphere of the brain that is primarily affected by glucose. It is worth mentioning that this is an extension of our previous research in identifying features in EEG signals for prediabetes diagnosis [22].

There are previous investigations that have considered EEG signals for noninvasive BG monitoring. Research on diabetes patients reveals the association of low-frequency bands in the EEG signal with glycemic changes such as hypoglycemia [23], detecting nocturnal hypoglycemia using electroencephalography signals with an optimization-based neural network [24-25]. The number of EEG frequencies considered in these studies was limited to alpha and theta, and the location was not investigated. Also, another investigation explored the possible difference in the EEG pattern between normal and hypoglycemia patients [26]. However, EEG frequency features and parameters have been scarcely investigated for application in prediabetes. The brain signals from the right and left hemispheres, according to the 10-20 system, provide the required structural location for capturing EEG signals [27]. Therefore, these positions should be studied to provide the appropriate location and frequency signal parameters to achieve the possibility of noninvasive BG status monitoring. This knowledge can also be integrated into a ‘smart helmet’ device that can measure EEG signals suitable for healthcare intervention and patient monitoring [28-29].

The subsequent sections of this paper are structured as follows: Section 2 provides a detailed description of the research methodology, while Section 3 presents the findings and engages in a comprehensive discussion. Discussion and conclusion are presented in Sections 4 and 5, respectively.

II. METHOD

In this section, we discuss the OGTT experiment conducted to acquire BG readings and EEG signals. Figure 1 illustrates the block diagram of the experimental procedure.

A. EEG Frequency

The EEG signals encompass five distinct frequency bands, each with their unique characteristics and operational frequencies. These bands include alpha (8-13Hz), beta (14-30Hz), delta (0.5-3Hz), theta (4-8Hz), and gamma (>30Hz). A representative section of these frequency signals, captured during the experiment utilizing BIOPAC AcqKnowledge software, is visualized in Figure 2.

B. Experiment

To explore the impact of varying BG levels on different brain regions, we conducted an OGTT involving twenty-five participants. Of the participants, nineteen were male, and six were female, all of whom were thoroughly briefed on the experimental procedures and provided informed consent. An illustration of a participant during the experiment is depicted in Figure 3. The participants' demographic characteristics include an average age of 24 ± 1.5 years, a body weight of 69.8 ± 9.2 kg, a height of 1.71 ± 0.11 meters, and normal body temperature. The selection process for participants was guided by the need to capture a diverse representation of individuals across several age groups that will include those with and without prediabetes. Participants with prediabetes were identified based on established diagnostic criteria, and they are prominent between the ages of 18 and 44 years, which are usually undiagnosed [1].

To ensure that the collected EEG signals are strongly related to glucose level variation, before the study, participants received detailed instructions outlining specific activities to avoid before and during the experimental sessions. This included refraining from consuming caffeinated beverages, taking any form of meals, engaging in intense physical exercise, or participating in mentally demanding tasks. The experimental sessions took place in a quiet room with minimal distractions to reduce the likelihood of extraneous variables affecting the EEG signals. Following the experimental sessions, participants were debriefed to inquire about any activities or factors that may have influenced their mental or physical state during the data collection.

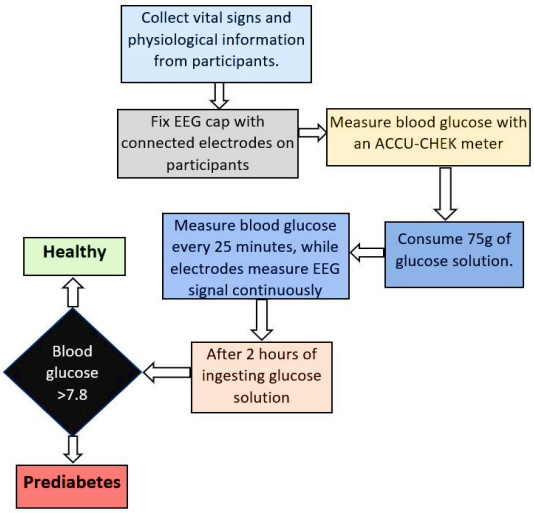

Fig. 1. A systematic description of the method for acquiring EEG signal and blood glucose during the two-hour oral glucose tolerance test.

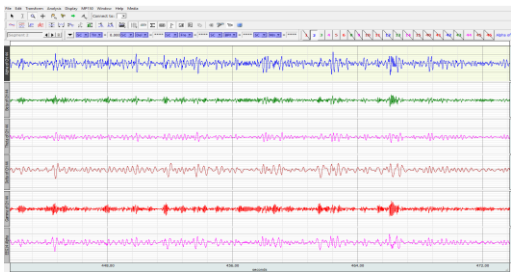

Fig. 2. An example of EEG frequency band obtained from the occipital electrode position during the experiment from BIOPAC and AcqKnowledge software.

Fig. 3. An example of a male participant during the experiment, taking glucose solution while EEG signals are recorded continuously.

Each participant underwent the experiment over two consecutive days. On the first day, they consumed a 75g anhydrous glucose solution (glucose experiment), while on the second day, they refrained from glucose intake, serving as the control. The experiment commenced in the morning before 9:00 a.m. and spanned two and a half hours. Thirty minutes into the experiment, participants ingested the 75g anhydrous glucose solution for the first day. Throughout the investigation, continuous EEG signals were recorded. At 25-minute intervals, BG values were measured through finger pricking, and BG levels were determined using a strip device known as the ACCU CHEK meter.

EEG signals were continuously captured using a Biopac device system (model number: MP150) in conjunction with AcqKnowledge software. This device facilitated the continuous acquisition of physiological signals. The BIOPAC (MP150) is a versatile and expandable data acquisition system that functions as an on-screen chart recorder, oscilloscope, and X/Y plotter. It enables users to record, view, save, and print data, making it an invaluable tool in life science laboratories for recording data from various sources such as human bodies, animals, or tissue preparations. The MP150 data acquisition and analysis systems, coupled with the AcqKnowledge software, provide a flexible platform for life science research. These systems are compatible with any Ethernet-ready computer. With variable sample rates of up to 400 kHz (aggregate), multiple data can be recorded efficiently through different channels. The AcqKnowledge software is an interactive and intuitive program that allows data to be instantly viewed, measured, transformed, replayed, and analyzed. It provides a user-friendly interface with simple pull-down menus and dialogs, eliminating the need to learn a programming language or new protocol. Whether performing complex data acquisition, stimulation, triggering, or analysis tasks, the BIOPAC (MP150) system and AcqKnowledge software offer a seamless and efficient solution for research [30].

Participants wore an EEG cap, equipped with dry electrodes positioned according to the international 10-20 system. The electrodes in the cap were strategically located at F3, F4, O1, O2, P3, and P4. Here, F, O, and P represent the frontal, occipital, and parietal lobes (or locations) of the brain, respectively, signifying different brain regions. The selection of these six locations aligns with prior studies examining EEG power and glucose fluctuations in young adults with type 1 diabetes [21,25] and the connection between glucose metabolism, brain activities, and cognitive function [13-15]. Notably, odd, and even numbers assigned to the locations, such as O, P, and T indicate electrodes positioned on the left and right hemispheres, respectively.

C. Analysis

EEG frequency bands were extracted from EEG signals obtained during the experiments at the six designated locations using AcqKnowledge software. The software's filtering process effectively eliminated noise and artifacts, enhancing the suitability of the data for subsequent analysis.

For the comparative changes analysis in both experiments, the following parameters were derived from each frequency band at 5-second epoch intervals: mean power, median frequency, mean frequency, spectral edge, and peak frequency. The selection of a 5-second epoch interval aligns with its utilization in analyzing EEG signals in the context of type 1 diabetes [21] and serves to approximate the frequency values recorded within an average minimum duration. The two-hour duration of the OGTT procedure was divided into three equal segments of 40 minutes, representing the start, middle, and end phases of the experiment. The start phase indicates a period before and just when the ingested glucose solution is observed in the measured BG, and the middle phase represents the period when maximum glucose concentration is observed in the measured BG, while the end phase depicts the period of decline in the measured BG due automatic BG regulation by the body.

A boxplot analysis was performed to visualize the alterations in EEG frequency across each brain location in these segments for all participants. The boxplot representation includes key statistical values such as the maximum value, third quartile (75th percentile), median, lower quartile (25th percentile), and minimum value, providing a comprehensive overview of the data distribution. These statistical values are used to describe the changes between the different categories of participants. Furthermore, an assessment of changes in the interquartile range within the boxplot (denoted as P) was conducted to ascertain variations in the parameters.

$$\Delta P_g = P_{g75} - P_{g25} \quad (1)$$

$$\Delta P_c = P_{c75} - P_{c25} \quad (2)$$

Where P_{g75} and P_{g25} are the value of the 75th percentile and 25th percentile, respectively, for the glucose experiment. While P_{c75} and P_{c25} are the corresponding 75th percentile and 25th percentile, respectively for the control experiment. Therefore, ΔP_g and ΔP_c represents the size of the interquartile range for glucose and control experiments, respectively. Furthermore, the parameter from EEG frequency bands that show consistent change is further investigated to determine which hemisphere is most sensitive to BG.

$$\Delta P_2 = \Delta P_{2g} - \Delta P_{2c} \quad (3)$$

$$\Delta P_1 = \Delta P_{1g} - \Delta P_{1c} \quad (4)$$

$$P_h = \Delta P_2 - \Delta P_1 \quad (5)$$

Where ΔP_1 and ΔP_2 are the sizes of the interquartile range for the left and right hemispheres respectively and where P_h refer to the direction of change which can either be 1, 0 or -1 when $\Delta P_2 > \Delta P_1$, $\Delta P_2 = \Delta P_1$ or $\Delta P_2 < \Delta P_1$ respectively. Table I shows the pattern description for the different conditions of EEG frequency due to changes in BG and the value of P_h. The change ratio is described as:

$$S_2 = \frac{\sum(P_h=1)}{\sum(P_h)} \times 100\% \quad (6)$$

$$S_1 = \frac{\sum(P_h=-1)}{\sum(P_h)} \times 100\% \quad (7)$$

Where S_1 and S_2 are the percentage change of the left and the right hemispheres, respectively. The percentage change describes the region of the brain where changes are observed during the change in the measured BG. The higher the value of S_1, the lower the value of S_2, Similarly, the higher the value of S_2, the lower the value of S_1.

III. RESULT

At the end of the OGTT experiment, eight participants were diagnosed with prediabetes because their BG ≥ 7.8mmol/L, while seventeen participants were identified as healthy because their BG < 7.8mmol/L. Table II presents an overview of the BG values recorded from all participants throughout the glucose experiments in the three phases. Specifically, the table provides mean values accompanied by their respective standard deviations for both the healthy and prediabetes participants. In both participants, the start and end phases recorded the lowest BG values compared to the middle phase where the peak BG values were recorded. The lowest BG values are observed in the start phase before the ingestion of glucose. Generally, within the prediabetes group, the values of BG in each phase are higher than the healthy participants. Both the healthy and prediabetes groups have approximately the same mean BG value with no statistically significant difference (P-value>0.05).

Figure 4 displays boxplots illustrating alpha mean power for parietal, frontal, and occipital electrodes. While the frontal electrode exhibits no discernible change across the three phases, noticeable alterations are observed in the patterns of the parietal and occipital electrodes. Figures 5-7 compare EEG parameters between the middle and end phases, focusing on those with ≥50% changes and P-value<0.05. The start phase was excluded due to parameter changes <50% and P-value >0.05. Three

TABLE I
DESCRIPTION OF EEG FREQUENCY CONDITIONS

Influence of Glucose	Hemisphere Difference	Change pattern
$\Delta P_g > \Delta P_c$	$\Delta P_2 > \Delta P_1$	Increase
$\Delta P_g < \Delta P_c$	$\Delta P_2 < \Delta P_1$	Decrease
$\Delta P_g = \Delta P_c$	$\Delta P_2 = \Delta P_1$	Equality

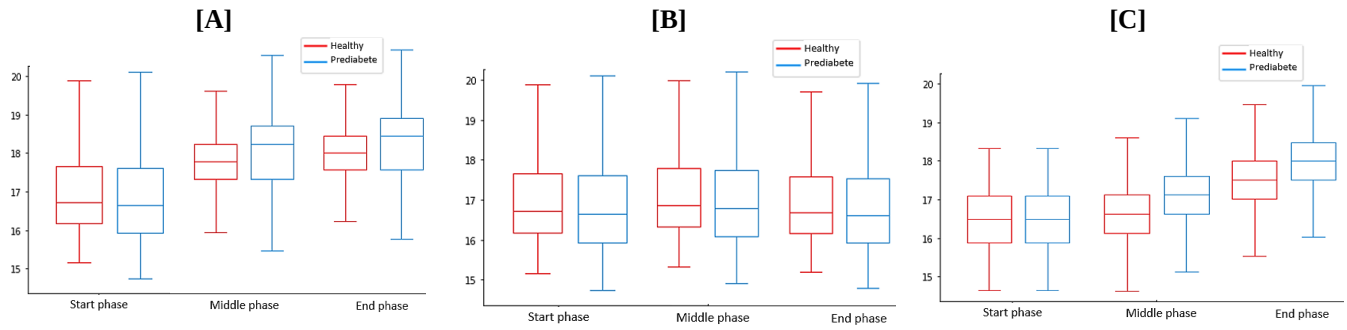

Fig 4. An example of a boxplot for alpha mean frequency at the start, middle, and end phase from [A] P2 electrode [B] F2 electrode [C] O2 electrode

TABLE II
DESCRIPTION OF BLOOD GLUCOSE AMONG THE PARTICIPANTS

Prediabetes(mmol/dL)			**Healthy(mmol/dL)**		
Start phase	Middle phase	End phase	Start phase	Middle phase	End phase
5.4±0.6	13.8±1.3	8.4±0.9	4.9±0.5	10.4±0.7	5.8±0.6

parameters exhibit significant differences between healthy and prediabetes groups in the middle and end phases within the F electrodes (Fig. 5). Notably, there is a >50% decrease pattern in alpha mean frequency (AMNF), gamma mean frequency (GMNF), and gamma peak frequency (GPF). Moreover, in the end phase, the percentage decrease pattern for AMNF, GMNF, and GPF intensifies, while the increase and equality percentage changes diminish.

Comparing the middle and end phases, noticeable differences were observed between healthy and prediabetes experiments in the O and P electrodes (Fig. 6 and Fig. 7). The P electrode exhibited a consistent increase in alpha mean power (AMNP), beta mean power (BMNP), theta mean power (TMNP), delta mean power (DMNP), and gamma mean power (GMNP). Additionally, there was a difference in alpha median frequency (AMDF) in the O electrode. However, the P electrode gamma spectral edge (GSE) and gamma peak frequency (GPF) showed an equality pattern >50% in the middle phase. Percentage changes in the O electrode were found in AMNP, alpha median frequency (AMDF), BMNP, DMNP, and GMNP, while changes in the P electrode were identified in AMNP, BMNP, DMNP, TMNP, and GMNP. Generally, there was a decreased percentage change pattern in the O electrode and an increased percentage pattern with the P electrode.

The results in Tables III, IV, and V outline the proportion of changes between the left and right hemispheres across different phases of the experiment. During the start phase, differences between hemispheres are minimal, with no percentages exceeding 50%. The maximum percentage change is 10.3% in the right hemisphere of the F electrode, while the minimum is 7.0% in the right hemisphere of the P electrode. Similarly, in the middle phase, changes do not exceed 50%, with a maximum change of 30% observed in the O electrode's right hemisphere and a minimum of 10.3% in the right hemisphere of the F electrode. However, significant changes are evident in the end phase, with a percentage change of 90.5% in the right hemisphere of the P electrode and 90.3% in the left hemisphere of the O electrode.

Table 6 shows a comprehensive comparison regarding the merits and limitations of some technologies for non-invasive BG measurement. In our study, the accuracy of prediabetes identification was based on post-OGTT BG values as defined in [20-21]. It is pertinent to note that our model, as presented in this paper, abstained from the classification or identification of individuals as normal or prediabetic using EEG signals, eliminating the possibility of errors in this context. However, potential sources of variability emerged in the measurement of EEG signals, warranting attention. Individual variability, inherent in the diverse nature of EEG signals among individuals, and external interference, stemming from environmental factors or external noise during data collection, were identified as key contributors to potential inaccuracies. Additionally, challenges in preprocessing EEG data, leading to signal processing artifacts, and the inherent heterogeneity in prediabetes presentation further underscored the need for meticulous consideration of these factors in the pursuit of accurate physiological signal-based prediabetes diagnostics.

IV. DISCUSSION

Exploring EEG signals in prediabetes offers insights into correlating EEG features with metabolic dysregulation. Prediabetes, marked by elevated BG, affects various physiological and neurological functions. We examine EEG patterns in the parietal (P), occipital (O), and frontal (F) brain regions and their relation to BG changes. Studies indicate that BG fluctuations can alter EEG amplitude and frequency, shedding light on neural mechanisms driving cognitive fluctuations in prediabetes.

Utilizing EEG as a diagnostic tool in prediabetes may aid in early detection and risk assessment. Identifying specific EEG patterns associated with prediabetes could potentially serve as a noninvasive biomarker for early diagnosis. This early identification might allow for timely interventions to prevent the progression of diabetes occurrence.

The parietal region of the brain plays a crucial role in sensory processing, spatial awareness, and various cognitive functions. In our analysis, with a threshold of 50%, both the right and left hemispheres of the P region of the brain do not show a major change that indicates that the P region is suitable for prediabetes diagnosis. Although there were three parameters (AMNF, GMNF, GPF) from the regions that show changes in the end phase of the analysis.

Fig 5. Percentage change in frontal electrode parameters at the [A] middle phase [B]end phase

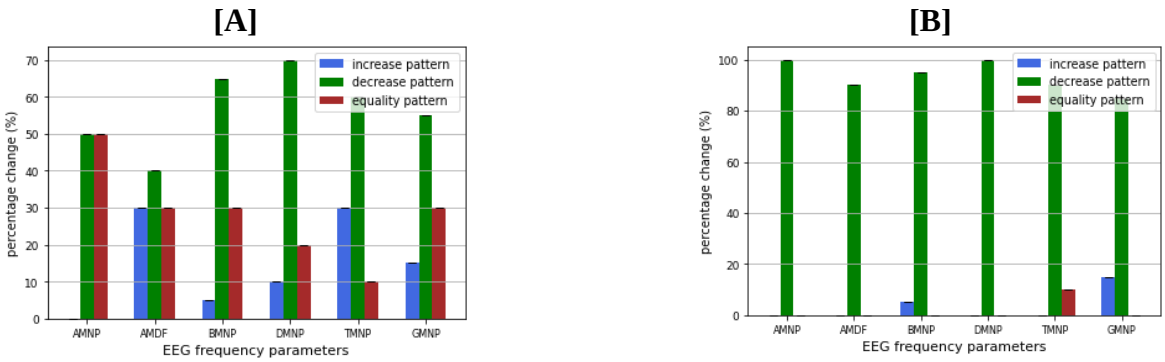

Fig. 6 Percentage change in occipital electrode parameters at the [A] middle phase [B]end phase

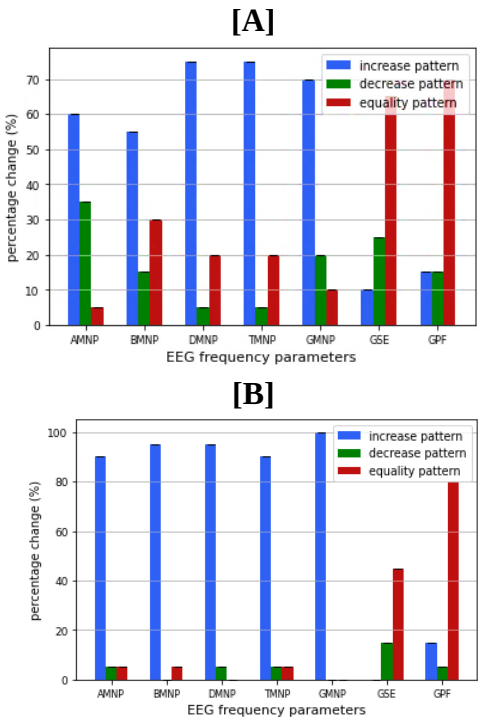

Fig. 7 Percentage change in parental electrode parameters at the [A] middle phase [B]end phase

The occipital brain region, vital for visual processing, was explored for potential links with prediabetes, offering insights into how metabolic dysregulation might affect it and its diagnostic implications. A significant 90% change in the left hemisphere during the end phase suggests its relevance for prediabetes diagnosis. However, a 30% change in the right hemisphere during the middle phase may not be sufficient for diagnosis. Additionally, the parietal region, implicated in sensory and cognitive functions, was investigated for its association with prediabetes, highlighting the potential impacts of metabolic changes on neural processing. Notably, the right hemisphere of the P electrode shows an 80% change compared to the left hemisphere's 10% during the end phase, indicating its diagnostic potential for diabetes.

In general, the middle phase exhibits greater differences between glucose and control experiments compared to the start and end phases, while the end phase shows more differences between healthy and prediabetes states compared to the start and middle phases. Parameters like AMNP, BMNP, DMNP, TMNP, and GMNP in the P and O electrodes are important considerations for prediabetes diagnosis.

Noninvasive blood sugar monitoring methods, including those using infrared light, have gained significant interest and research focus [31]. They show promising accuracy compared to standard laboratory systems. However, infrared-based methods have distinct advantages and limitations. While they allow direct glucose measurement through spectroscopic analysis without invasive procedures, like finger pricking, they face challenges related to tissue penetration depth and skin variability. In contrast, EEG signals provide insights into neural activity but require advanced processing. Both methods aim for noninvasive glucose monitoring, but each has unique strengths and considerations that merit exploration for comprehensive prediabetes diagnosis. Table VII presents a comparison of infrared light and EEG-based methods.

One limitation of EEG-based BG monitoring is the indirect relationship between EEG signals and glucose levels, which may introduce variability and complexity in data interpretation.

TABLE III
CHANGES BETWEEN HEMISPHERES AT THE START PHASE

ECG electrode	Right Hemisphere	Left Hemisphere
Frontal	10.1%	10.3%
Occipital	8.9%	9.3%
Parental	7.0%	7.4%

TABLE IV
CHANGES BETWEEN HEMISPHERES AT THE MIDDLE PHASE

ECG electrode	Right Hemisphere	Left Hemisphere
Frontal	10.3%	10.5%
Occipital	30%	22.3%
Parental	10.5%	13.7%

TABLE V
CHANGES BETWEEN HEMISPHERES AT THE END PHASE

ECG electrode	Right Hemisphere	Left Hemisphere
Frontal	35.8%	50.3%
Occipital	6.6%	90.3%
Parental	90.5%	5.4%

TABLE VI
COMPARISON OF NON-INVASIVE METHODS FOR BLOOD GLUCOSE MEASUREMENT

Aspect	EEG	Microwave sensors	Raman Spectroscopy	Contact Lens
Invasiveness	Non-invasive	Non-invasive	Non-invasive	Non-invasive
Cost-Effectiveness	Generally, more cost-effective	Cost may vary depending on system complexity	Cost may vary depending on equipment complexity	Cost may vary depending on equipment complexity
Accessibility for Special Populations	Feasible for various populations	Accessibility may vary for certain populations	Accessibility may vary for certain populations	Accessibility may vary for certain populations
Accuracy and Precision	Influenced by factors like electrode placement, skin conditions, and external interference	Affected by environmental factors and tissue properties	High accuracy, but technical challenges	Accuracy can be affected by lens fitting
User Comfort and Practicality	Maybe less comfortable for extended periods	May vary depending on the specific design	May pose challenges due to equipment setup	Generally comfortable, but user dependent
Continuous Monitoring Potential	Suitable for continuous monitoring, but may have practical limitations	Potential for continuous monitoring, but technical challenges	Limited to intermittent measurements	Suitable for continuous monitoring
Portability	Can be designed to be portable	Portability depends on the system design	Portability may vary	Portability may vary
Adaptability to Wearable Devices	Suited for wearables but may pose challenges due to the helmet design	Potential for integration into wearable devices	Limited adaptability for wearables	Well-suited for wearables

TABLE VII
COMPARISON OF INFRARED LIGHT AND EEG-BASED METHODS

	Infrared Light Method	EEG-Based Method
Sensitivity	Sensitivity can vary depending on factors such as tissue depth and composition	Sensitivity may vary based on the specific EEG parameters analyzed
Accuracy	Accuracy can be influenced by factors such as calibration, tissue properties, and environmental conditions	Accuracy may depend on the specific EEG parameters used and the extent of correlation with glucose levels
Selectivity	May face challenges in distinguishing glucose signals from other tissue components or interfering substances. Selectivity can be influenced by the specificity of the analytical techniques employed	May offer selectivity based on the neural correlates of glucose metabolism. However, selectivity may vary depending on factors such as signal processing algorithms and the influence of confounding variables.
Prediabetes Forcasting	May provide insights into glucose dynamics but may not specifically target prediabetes indicators	Have the potential to identify neural correlates associated with prediabetes states. Patterns in EEG signals may offer insights into metabolic dysregulation and predisposition to diabetes, potentially enabling prediabetes forecasting

Additionally, EEG signals can be influenced by various physiological and environmental factors, potentially confounding the analysis and interpretation of results. Furthermore, the need for specialized equipment and expertise for EEG signal acquisition and processing may pose practical challenges in clinical settings. We will explore potential strategies to address and mitigate these limitations in our future research to further enhance the robustness and applicability of EEG-based BG monitoring methods.

V. CONCLUSION

In this study, we conducted an Oral Glucose Tolerance Test (OGTT) experiment to explore changes in EEG frequency parameters. Twenty-five participants wore EEG caps with electrodes. We analyzed EEG signals from the frontal, occipital, and parietal regions of both hemispheres during three periods (start, middle, and end).

To build upon our promising findings, future research will involve a larger participant pool to validate our conclusions. We plan to expand our investigation by analyzing EEG frequencies across different phases (start, middle, and end) in both healthy and prediabetes groups to predict prediabetes status. Although previous studies have examined ECG data for this purpose [32-34], our research aims to compare ECG and EEG models.

To enhance our analysis, we aim to employ cutting-edge machine learning and deep learning techniques for prediabetes prediction [35-36]. Our goal is to develop an adaptive deep-learning model for noninvasive prediabetes diagnosis via wearable devices. This research represents a significant advancement in harnessing wearable technology for healthcare and early prediabetes detection.

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