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Non-Invasive Blood Glucose Monitoring using ECG Signal

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***Abstract*— As a chronic metabolic disease, diabetes mellitus need ongoing blood glucose monitoring. The invasive nature of traditional blood glucose monitoring methods, which require finger pricks might make patients uncomfortable and reduce their compliance. As alternatives, non-invasive technique shave attracted a lot of interest recently, with electrocardiogram (ECG)-based glucose monitoring showing promise. The possibility of estimating blood glucose levels without invasive methods using ECG signals are explored to study. Changes the heart rate variability (HRV) and the shape of the ECG waveform are two examples of how physiological changes brought on by variations in glucose concentration are known to be reflected in ECG signals. Features are taken from the ECG signals and linked to the associated glucose levels using sophisticated signal processing techniques and machine learning algorithms. This method offers a continuous, real-time, and painless monitoring option. The initial findings show a strong relationship between blood glucose levels and ECG-derived characteristics, suggesting that ECG may be used as a stand-in marker for glucose monitoring. The goal of this effort is to improves the development of non-invasive, wearable glucose monitoring device that can help patient control their diabetes and live better lives.**

***Keywords*— Electrocardiogram (ECG), Blood glucose stimation, Heartrate variability (HRV), Machine learning, Glucose prediction, Continuous glucose monitoring (CGM), Signal feature extraction.**

I. Introduction

A chronic metabolic disease characterized by high blood sugar levels, diabetes mellitus continues to be significant global health problem that impacts millions of people around the world. Reliable and efficient blood glucose monitoring is crucial for maintaining diabetes control and for preventing the serious side effects, such as nephropathy, neuropathy, and cardiovascular disorders. Blood glucose monitoring has often relied on invasive methods like finger-prick tests. Continuous glucose monitoring has also depended on these intrusive techniques along with devices that use sensors placed under the skin. At pandemic levels [1], diabetes mellitus has become aa serious threat to world health. In 2019, 463 million people were diagnosed with diabetes, according to International Diabetes Federation (IDF), which indicates the disease
prevalence has increased to around 9.3% of the world population world's population. The IDF predicts that by 2030, this figure may increase to 578 million, highlighting the need for worldwide action to combat this chronic illness. whether blood glucose level are excessively high (hyperglycemia) and low (hypoglycemia), uncontrolled blood glucose levels can cause major health problems.

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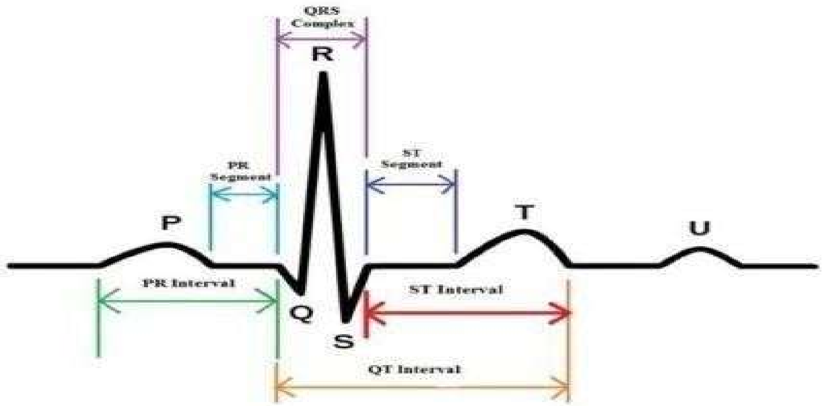

Fig.1 The Normal ECG Waveform

Chronic problems like cardiovascular disease, diabetic uropathy, and diabetic retinopathy are exacerbated by hyperglycemia over time. Traditional methods for the glucose measurement, such as Fingerstick tests, are invasive, uncomfortable, Fig.1 and often discourage frequent monitoring, especially among diabetic patients. Recent research has shown that variations in blood glucose levels can subtly influence by the heart electrical activity is recorded by using electrocardiogram (ECG)signals. The IDF predicts that by 2030, this figure may increase to 578 million, highlighting the need for worldwide action to combat this chronic illness On the other hand, hypoglycemia can result in abrupt and severe symptoms such as disorientation, shaking, high perspiration, unconsciousness, and in severe situations, coma or death. Thus, early identification and strict. Glucose control are essential, especially in the pre diabetics period, when treatment can greatly lower the chance of developing diabetes. Blood glucose monitoring has historically depended on intrusive techniques like finger-prick testing several times a day. Although is approach works well, it is frequently viewed as unpleasant, costly, and inconvenient, particularly for those who need to be checked frequently. Additionally, the lack of continuous data restricts our ability to comprehend how glucose levels change throughout the day. Systems such as Continuous Glucose Monitoring (CGM) have been developed to overcome these constraints. With measurements being taken every five minutes, these devices provide real-time blood glucose monitoring. For many diabetics, CGM have significantly improved glucose control. But they have disadvantages as well. CGM are still considered intrusive because they must be inserted beneath the skin and have a 7–14 day operating lifespan. Given these challenges, there is a growing interest in noninvasive glucose monitoring technologies that can provide continuous, reliable, and user- friendly alternatives to existing methods[2]. This paper focuses on one such approach: the use of electrocardiogram (ECG) signals for estimating blood glucose levels, offering the potential to revolutionize diabetes care with a painless and accessible solution.

TABLE I: ECG WAVEFORM PARAMETERS

Amplitude(mV)	Duration (Seconds)
PWave-0.25mV	PRinterval-0.12sto0.20s
RWave-1.60mV	QTinterval-0.35sto0.44s
QWave-25%ofRWave	STinterval-0.05sto0.15s

The most common types of noise [3] that affect the ECG signal are:

- Base-line wandering
- Power-line interference
- Electromyogram (EMG)
- Contact noise
- Motion artifacts

To extract the P, Q, R, S, and T waves from an ECG signal, it is important to effectively remove noise. Over the years, significant work has been done on automatic ECG beat detection, as shown in Table.1 Several commercial software tools are available for this task. However, their performance is often not satisfactory.

Using MATLAB, some researchers have proposed improvements to existing algorithms by applying wavelet transforms [2]. These enhancements are not only to reduce the complexity of earlier methods but also improve the signal-to-noise ratio (SNR) of the ECG signal.

II. LITERATURE SURVEY

In recent years, there has been growing momentum toward developing non-invasive methods for blood glucose monitoring, motivated by the limitations of traditional invasive techniques. Among the various physiological signals being explored, the electrocardiogram (ECG) has shown promising potential due to its ability to reflect autonomic nervous system responses, which are in fluenced by blood glucose levels[3].This section provides a review of existing research efforts that leverage ECG signals in combination with signal processing and machine learning techniques estimate blood glucose concentrations without non-invasively methods. Blood glucose fluctuations can induce measurable changes in the cardiovascular system, especially in heart rate variability (HRV) and ECG waveform morphology. Studies have established a link between autonomic nervous system activity and glycemic states. Hyperglycemia and hypoglycemia both influence vagal and sympathetic tone, which can be detected through subtle variations in ECG signals. These changes have laid the groundwork for developing ECG- based glucose prediction models. Researchers have focused on extracting relevant features from ECG signals that correlate with glucose levels. These include:

- Time-domain features: RR intervals, heart rate variabile it metrics (SDNN, RMSSD).
- Frequency-domain features: Powers pectraldensityin low- and high-frequency bands.
- Morphological features: Amplitud eandurationofP, QRS, and T waves.

Nuryanietal. (2021)demonstrated that glucose levels could be predicted using features extracted from lead IIECG signals. They used statistical feature extraction methods along with machine learning algorithms like decision trees and support vector machines , achieving significant accuracy under controlled test conditions. Recentadvancesin wearable ECG technology have enabled real-time acquisition of high-quality ECG signals. Studies like Rachi metal .(2020) have explored embedding non-invasive glucose monitoring into we arablepl at form such as smart watches. Their approach involved real-time ECG feature extraction and glucose prediction using an embedded AI model, making continuous monitoring feasible outside clinical environments. Some researchers have explored hybrid model that combine ECG with other noninvasive signals like PPG (photoplethysmography) or skin impedance[4].Liuetal. (2022) demonstrated that combining ECG and PPG improved prediction accuracy compared to single-signal models, due to complementary physiological information captured by the two modalities.

Extracting various features from the ECG signal is an important part of ECG analysis. Identifying the P, Q, R, S, and T waves, which together make up the QRS complex, is an important part of feature extraction. These waves provide important information about the heart's condition and help doctors diagnose various cardiac disorders.One common way to detect the QRS complex is by using non-linear filtering, which is simple and efficient in terms of computation. However, this approach performs poorly when there are variations in the frequency of QRS complex. Noise can also cause the frequency band of the QRS complex overlaps with the noise frequency band, leading to false positives and false negatives in detection.

III. EXISTING METHODS

Several studies have improved disease forecasting by focusing on blood glucose level prediction using various data-mining techniques. Researchers have applied different methods such as decision trees, K-Nearest Neighbours, support vector machines, and neural networks, each differing in terms of accuracy and computational performance.Villena Gonzales et al. examine trends in Minimally invasive and non-invasive glucose monitoring uses electrical, thermal, optical, and nanotechnology-based[5] methods, with the most effective systems combining chemical, electrical, optical, thermal, and acoustic properties, and current wearable devices typically measuring glucose through interstitial fluid, sweat, breath, saliva, or ocular fluid using technologies like wristbands, smart eyeglasses, tooth-mounted sensors, and smart contact lenses.Non-invasive blood glucose monitoring using EC (electrocardiogram) signals is an emerging field where researchers explore the correlation between ECG signal features and blood glucose levels. Existing methods often involve machine learning algorithms that analyze variations in heart rate, QT interval, and other ECG- derived parameters. For example, study by Sanet al. (2020) proposed by the deep learning approach that utilized ECG signals to predict blood glucose levels, showing promising results in capturing glucose-induced autonomic nervous system changes.

These methods typically preprocess ECG data to remove noise, extract features (such as RR intervals and PQRST complex characteristics), and then apply regression models or neural networks for glucose estimation. The motivation behind this approach is the autonomic modulation caused by glucose fluctuations, which subtly alters the ECG morphology. While still in experimental stages, such techniques hold potential for real-time, painless glucose monitoring. In various machine learning systems, algorithms such as Decision Tree, Naive Bayes, Multilayer Perceptron, K-Nearest Neighbors, Single Conjunctive Rule Learner, Radial Basis Function, and Support Vector Machine have been applied, both individually and together, using ensemble learning methods on the Cleveland Heart Disease dataset to assess the performance of each technique [6]. Gudadhe et al. developed a model using both MLP network and the SVM classifier, achieving an accuracy of 80.41% in distinguishing between two classes: the presence or absence of heart disease.Non-invasive blood glucose monitoring using ECG (electrocardiogram) signals is an emerging field that seeks to provide a painless and continuous alternative to traditional invasive methods like finger- prick tests. The core idea behind these methods is that blood glucose levels can influence the electro physiological properties of the heart, which are reflected in the ECG signal. Researchers have identified small changes in ECG features, such as heart rate variability (HRV), QT interval, P wave duration, and other waveform characteristics.

TABLE II: DIFFERENT CLASSIFIERS AND THEIR MAXIMUM ACCURACIES OBTAINED IN THE CLASSIFICATION OF BLOOD GLUCOSE LEVEL

Classifier	Maximum Accuracy%
SVM	94.2%
Random forest	89.6%
KNN	85.1%
Decision Tree	84.0%
ANN	90.5%

IV. PROPOSED METHODOLOGY

Diseases related to ECG abnormalities come from changes in important ECG features like the P-wave, Q-wave, R-wave, S-wave, T-wave, QRS complex, PR interval, and ST segment.To classify these conditions, it is important to extract useful features from the ECG waveform [7]. In this work, feature extraction is performed in MATLAB using Wavelet Transform algorithm.The extracted features are stored in a file, on the Random Forest algorithm application. Using this approach, the following blood glucose categories are predicted:

- Hyperglycemia
- Hypoglycemia
- Normal

Proposed Methodology for Non-Invasive Blood Glucose Monitoring Table.2 using ECG signal leverages machine learning techniques to establish a reliable and accurate prediction model. By capturing subtle physiological changes in the ECG signal that correlate with blood glucose levels, the system processes and extracts meaningful features through signal processing and feature engineering techniques[8]. These features are input to machine learning algorithm like regression models, support vector machine, or neural network.ECG signals collected from the human body are often impacted by noise and distortions. They are frequently contaminated with different types of noise and artifacts, the primary goal of preprocessing is to enhance signal quality and prepare it for accurate feature extraction.

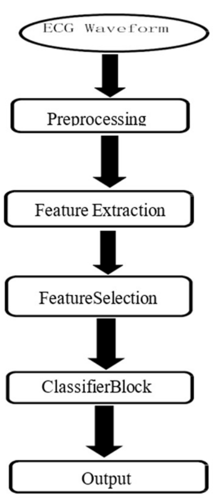

Fig.2 FlowDiagram of Signal Analysis

In the block, the ECG signals are analyzed to remove noise and artifacts noise removal techniques to eliminate common interferences such as baseline wander, power line noise (50/60 Hz), muscle artifacts (EMG), and motion- related disturbances. Filters such as band pass filters and notch filters are commonly used to preserve the key morphological components of the ECG irrelevant noise.To learn complex patterns and relationships. Through continuous training and validation on large, diverse datasets, the model improve its predictive accuracy, offering again less, real- time, and user-friendly solution for glucose monitoring without the need for traditional invasive methods. Before extracting features from the ECG signal, it is important to remove the artifacts. Therefore, the steps in are necessary for ECG signal analysis.

- Preprocessing Block: The block aims to suppress artifacts present in the ECG signal, including power line interference baseline drift, high frequency noise, and disturbances introduced by instrumentation conditions.
- Feature Extraction Block: After preprocessing removes the undesired components, relevant feature are extracted from the clean ECG signal to enable accurate characterization and subsequent analysis.
- Feature Reduction Block: This block is optional and is not utilized in all ECG analysis methodologies. It is purpose is to reduce the dimensionality of the extracted feature set. Minimizing the number of features enhances computational efficiency and improves the processing speed of the algorithms used for ECG analysis.
- Classifier Block: Different diseases have unique features that indicate their presence. Therefore, it is important to classify the features after extraction. The classifier block performs this function.
- Output Block: This block provides the final result or judgment of the ECG analysis.

The preprocessing stage plays a main role in the overall framework of non-invasive blood glucose monitoring using ECG signals Fig.2 Since ECG signals collected from the human body are often contaminated with various types of noise and artifacts, the primary goal of preprocessing is to enhance signal quality and prepare it for accurate feature extraction. In the block, the ECG signals are processed to noise removal techniques to eliminate common interferences such as baseline wander, power line noise (50/60 Hz), muscle artifacts (EMG), and motion- related disturbances. Filters such as band pass filters and notch filters are commonly used to preserve the key morphological components of the ECG while discarding irrelevant noise. Next, the signals undergo normalization or standardization to ensure amplitude and scale uniformity, which is essential for comparing signals across different subjects or sessions. This step helps in reducing inter-subject variability and improving model robustness[9]. Following that, R-peak detection algorithms are applied to identify and segment individual cardiac cycles. Accurate segmentation is crucial for computing heartbeat-based features such as RR intervals, heart rate variability (HRV), and QT intervals—all of which have been shown to correlate which change in blood glucose levels.Feature extraction a critical component to process by the non-invasive blood glucose monitoring using ECG signals. This block focuses on deriving meaningful quantitative parameters from the pre-processed ECG data that can reflect physiological changes associated with variations in blood glucose levels[10].After prepossessing ,the clean and segmented ECG signals are analyzed to extract algorithms, the Random Forest (RF) algorithm has shown promising results due to its robustness, ability to handle nonlinear relationships, and resistance to over fitting. When compared to other commonly used algorithms like Support Vector Machines, k-Nearest Neighbors, and Artificial Neural Networks, RF generally provides a better balance between accuracy, interpretability, and computational efficiency.In many studies, Random Forest has demonstrated around 85–90% prediction accuracy, whereas algorithms like SVM and KNN typically range between 75–85%, and ANN, while powerful, may achieve 90% or more accuracy but at the cost of higher comp Overall, Random Forest is preferred in many cases because it offers high accuracy (~88%), fast training time, and good generalization. This makes it a strong candidate for practical use in a real time or wearable ECG-based glucose monitoring system[11].

After completion of feature extraction in non- invasive blood glucose monitoring using ECG signal, the next crucial step is model training and prediction. The extracted features—such as heart rate variability (HRV), QT interval, RR interval, and other time and frequency domain parameters—are fed into a machine learning model to establish the connection between ECG characteristics and blood glucose levels. [12]. Depending on the approach, this model may be a regression model (for continuous glucose value prediction) or a classification model (to categorize glucose levels into low, normal, or high). The dataset has been split into training and testing sets; The model learns patterns related to glucose changes using the training data. After training, it is validated and tested on new data to assess its performance with metrics like mean absolute error, root mean square error, accuracy, sensitivity, and specificity. Once validated, the trained model can predict blood glucose levels continuously from live ECG data. This make the system as valuable tool for non-invasive, comfortable, continuous glucose monitoring.

V. Result

```
Mean Absolute Error (MAE): 0.1665
Mean Squared Error (MSE): 0.0457
Enter 12 ECG signal values:
ECG value 1: 60
ECG value 2: 30
ECG value 3: 80
ECG value 4: 10
ECG value 5: 100
ECG value 6: 70
ECG value 7: 19
ECG value 8: 36
ECG value 9: 44
ECG value 10: 0
ECG value 11: 89
ECG value 12: 55
/usr/local/lib/python3.11/dist-packages/sklearn/utils/validat
  warnings.warn(
Predicted Blood Glucose Level (average of 12 inputs): 139.92

Warning: High blood glucose level detected!
```

Fig. 3 Predicted Blood Glucose

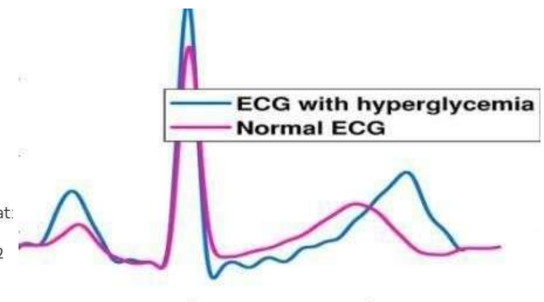

Fig.4 High glucose level ECG Waveform

Hyperglycemia, or high blood glucose, can influence ECG signals by causing changes such as prolonged QT intervals, which may increase the risk of cardiac arrhythmias Fig. 3 Common symptoms include frequent urination, excessive thirst, tiredness, and blurred vision [13]. Severe hyperglycemia may lead to altered heart rhythms detectable on an ECG, indicating potential cardiovascular stress Fig.4.

```
Enter 12 ECG signal values:
ECG value 1: 70
ECG value 2: 23
ECG value 3: 19
ECG value 4: 15
ECG value 5: 36
ECG value 6: 25
ECG value 7: 75
ECG value 8: 30
ECG value 9: 15
ECG value 10: 2.3
ECG value 11: .9
ECG value 12: 25
/usr/local/lib/python3.11/dist-packages/sklearn/utils/validation.py:2
  warnings.warn(
Predicted Blood Glucose Level (average of 12 inputs): 121.75

Blood glucose level is within normal range.
```

Fig.5 Predicted Blood Glucose

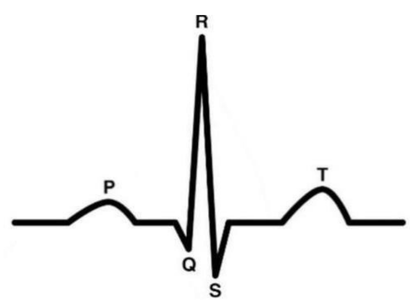

Fig.6 Normal glucose level ECG Waveform

Euglycemi are fersto normal blood glucose levels, Which support stable metabolic can dcardiac function Fig.5 . In this state, ECG signals typically remain normal with regular heart rhythm and no significant abnormalities. There are usually no symptoms, as the body is in a balanced, healthy glucose state Fig.6.

VI. Conclusion

Non-invasive blood glucose monitoring using ECG signals presents a promising, painless alternative to traditional invasive methods. By analyzing the specific changes in the ECG pattern, such as the QT interval variations and heart rate changes, researchers can correlate them with blood glucose levels. This method offers the potential for continuous, real-time monitoring, improving diabetes management and patient compliance. It also reduces the risk of in fections and discomfort associated with finger-prick tests.With progress of machine learning the signal processing, accuracy and reliability of ECG-based glucose prediction are improving. However, individual variability and external factors still pose challenges to standardization. More clinical validation and large-scale studies are needed. Integration with wearable technologies could further enhance usability. Overall, ECG-based glucose monitoring holds great potential as a non-invasive, user- friendly solution for glucose tracking.

Future Work

Future research in non-invasive blood glucose monitoring using ECG signals, the focus should be improving the accuracy and reliability of glucose prediction models for different populations. Machine learning and deep learning algorithms can help to achieve improve the capture the subtle ECG changes related to glucose variations. Integrating multi-modal bio signals, such as PPG (photoplethysmography) and skin impedance, with ECG could enhance prediction reliability. Additionally, efforts should made the miniaturize and integrate the technologies into the wearable devices for continuous, real-time monitoring. Long-term clinical trails are essential to validate these systems in real-world settings. Personalized calibration techniques may also be explored to account for individual physiological differences and external factors like stress, activity, and hydration.

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