

Diabetes Management: Non-Invasive Glucose Monitoring via ECG and Machine Learning^{*}

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Abstract

Effective diabetes management is critical for reducing the risk of complications such as cardiovascular disease, nephropathy, and neuropathy while enhancing patient quality of life. Contemporary technologies like continuous glucose monitoring (CGM) and flash glucose monitoring (FGM) have improved clinical outcomes through real-time data and personalized care. However, these devices' high cost and invasive nature limit their accessibility and acceptance, particularly among uninsured or underinsured populations. This study proposes a non-invasive, cost-effective alternative by examining the relationship between heart rate and blood glucose levels in individuals with type 1 diabetes (T1DM). Machine learning techniques were employed to analyze patient data, including regression analysis, k-nearest neighbors (KNN), neural networks, ensemble bagged trees, and statistical methods such as ANOVA and Tukey's test. Results indicated that 96.3% of the cohort exhibited a statistically significant correlation between heart rate and blood glucose levels, with pronounced variations observed at extreme glycemic values. However, the heart rate was less responsive to moderate glucose fluctuations. These findings suggest that heart rate monitoring may serve as a viable non-invasive proxy for detecting significant glycemic events, offering a promising alternative to traditional blood glucose monitoring systems and potentially mitigating the economic and physical burdens associated with current technologies.

Keywords

Machine Learning, Heart rate, Diabetes, T1DM.

1. Introduction

Diabetes Mellitus (DM) is a chronic condition¹ marked by high blood glucose and abnormal protein and fat metabolism². DM arises from impaired glucose digestion or insufficient insulin production. There are three primary forms: Type 1 DM (T1DM), where autoimmune destruction of pancreatic beta cells halts insulin production [1]; Type 2 DM (T2DM), where insulin resistance progressively reduces insulin levels; and Type 3 (gestational diabetes), occurring during pregnancy and increasing maternal and offspring health risks [2]. Symptoms like polyuria, polydipsia, and weight loss form the *classical triad* [3], with polyuria (excessive urination) [4] and polydipsia (excessive thirst) [5] being key signs. More serious is the DKA triad (ketoacidosis), defined by high blood glucose, elevated ketoacids, and metabolic acidosis [6], occurring in 10–80% of diabetic emergencies [7].

Poor DM management risks severe complications. Hyperglycemia or hypoglycemia can cause organ damage: overfeeding or inadequate insulin can induce DKA or severe hyperglycemia [8], while some treatments may cause hypoglycemia [9]. Hyperglycemia (HYG) causes tissue damage via mitochondrial superoxide overproduction, harming peripheral nerves, kidneys, and retina [10]. Hypoglycemia (HYP),

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¹An untreatable sickness, manageable with medication or therapies.

²Insulin dysfunction alters protein and fat usage, leading to fat storage, muscle wasting, and complications.

although less frequent, can provoke dizziness, seizures, cardiac arrhythmias, and even death [11]. Maintaining glucose control (GC) is crucial to prevent complications like retinopathy, nephropathy, and neuropathy [12].

Several glycemic control methods are available. Hemoglobin A1C Testing (H1T) measures average glucose over 90 days but lacks real-time feedback [14]. Urine testing offers semiquantitative glucose estimates from single voidings or 24-hour collections [15]. Self-monitoring of blood glucose (SMBG) and Continuous Glucose Monitoring Systems (CGMs) enable real-time tracking and data sharing [16]. SMBG, involving frequent finger pricks, correlates with improved HbA1c levels [17, 18]. CGMs, using electromagnetic or ISF-based sensing, provide continuous glucose data, offering superior daily monitoring compared to SMBG [19, 20]. However, BGC can feel invasive [21]. Frequent testing disrupts routines and may cause anxiety [22]. SMBG may cause pain, while CGMs can lead to skin irritation and privacy concerns [23, 24].

This work investigates noninvasive alternatives, relying on the hypothesis (WH1): “Changes in ECG (Electrocardiogram) patterns are a proxy for glucose level or danger.” Preliminary results [25, 26] support WH1. Higher glucose levels correlate with reduced heart rate variability (HRV) [26], and distinct HR distributions appear before hypoglycemia episodes [25]. Together, these findings suggest that heartbeat patterns reflect blood glucose trends.

Given the noninvasive nature of ECG wearables, heartbeat-based blood glucose monitoring (BCM) could improve patient comfort over traditional BGC. This study aims to answer two questions: “Is it possible to detect and discriminate between hypoglycemia or hyperglycemia events using ECG time series? – RQ1”; “Is it possible to detect modification in a heartbeat and estimate HR trends using glucose monitoring data time-series? – RQ2”.

2. Related works

This section discusses studies on the relationship between glycemic values and heart rate patterns. In [29], the authors examined the relationship between glycemic states (hypoglycemia, hyperglycemia, and normoglycemia) and ECG-derived features. They found a significant increase in heart rate when blood glucose drops below 60 mg/dL (hypoglycemia), with a p -value < 0.0001 , but no significant correlation with hyperglycemia. In [30], a study of 148 type 1 diabetes patients revealed that higher HbA1c levels (reflecting higher blood glucose) were associated with increased heart rate, supported by a p -value < 0.004 . The study in [31] used data from 31 patients to predict hypoglycemia with machine learning models using smartwatch and CGM data. The model correlated increased heart rate, reduced heart rate variability, and heightened electrodermal activity with hypoglycemia, achieving an ROC AUC of 0.76 ± 0.07 . In [32], data from 128 type 2 diabetes patients showed that higher age and blood glucose were positively correlated. Increased parasympathetic activity also correlated with higher blood glucose levels, suggesting that changes in blood glucose may proportionally affect heart rate.

3. Background

For experimentation, we used various pre-processing and statistical techniques.

A sliding window approach processed sequential data, with a moving mean calculated in each window to smooth fluctuations, reveal trends, and improve stability. ANOVA assessed differences between group means by partitioning variance. A high F -statistic and p -value < 0.05 indicate significant group differences. In order to identify specific groups, Tukey’s HSD test was applied post-ANOVA, comparing all possible group pairs and controlling error rates. A p -value < 0.05 denotes statistical significance. For predictive modeling, using distance metrics like Euclidean or Manhattan, K-Nearest Neighbors (KNN) estimated new instances based on the majority label or mean of K closest neighbors. Weighted K-Nearest Neighbors (WKNN) improved accuracy by giving closer neighbors greater weight via inverse distance. Finally, Ensemble-Bagging Trees (EBT) reduced variance by aggregating decision tree outputs trained

on bootstrapped data subsets. While increasing computational cost, EBT yielded more generalized models. Hyperparameter tuning for EBT followed the same process as KNN.

4. Methods

This section outlines the methodologies employed to address the research questions of this study. We utilized a combination of statistical tests and experimental procedures (machine learning) to investigate the relationship between heart rate and glycemia in patients with T1DM. We are aware that we empirically estimated the parameters for sliding window size, time intervals for moving averages, and thresholds for min/max. While these selections yielded strong initial results, future work will focus on systematically optimizing these parameters to enhance performance further. In addition, a comprehensive sensitivity analysis will be undertaken to evaluate the robustness of the proposed approach against variations in parameter values and to ensure stability and generalizability across different operating conditions.

4.1. Dataset and Preprocessing

This contribution uses a pre-processed version of the HUPA-UCM Diabetes Dataset [27] extended by computing new features from glucose levels and heart rates. The original dataset comprises blood glucose levels, steps, calories, heart rate, and sleep data of 24 T1DM patients, sampled every five minutes, collected by the authors through CGM and Fitbit Ionic smartwatch, and contains up to 144085 rows. HUPA-UCM Diabetes Dataset contains only patients with type 1 diabetes mellitus, and no additional diseases are directly specified. It is important to consider patients 23 and 24, who have more glycemic readings than the remaining patients.

We extended HUPA-UCM by computing moving metrics, statistical features, and labels, as described below. We categorized blood glucose levels (BGL) to compare heart rate (HR) across glycemic groups. Each patient's data was labeled based on BGL: very low (<60 mg/dL), low (60–89 mg/dL), good (90–179 mg/dL), high (180–249 mg/dL), and very high (>250 mg/dL). Moving averages of HR and BGL were computed using sliding windows to smooth fluctuations and capture trends. Maximum and minimum BGL values were calculated within each 10-observation window. Additional features included moving averages (11-observation centered and 5-observation shifted) and frequency counts for values above or below 1.15% and 1.25% of the max and min values in each window.

We calculated the heart mean (HM) as the average HR over six consecutive observations. The Heart Trend (HT) was then computed as the deviation of the HR sum from the previous HM, with negative HT indicating an increasing HR trend (labeled "U") and non-negative HT indicating a stable or decreasing trend (labeled "D").

4.2. Heart rate trend prediction

We split the entire EDATA by Patient to predict Patient-specific heart rate trends, generating 24 sub-dataset (PSD).

Also, for each PSD, we generated two subsets of PSD, holding out 10% of the entire dataset for the test set, to evaluate the model's performance on unseen data. During model training, a 20-fold cross-validation was also requested. We completed the training process individually for each patient to identify the most accurate models.

For each PSD, we used the features reported in Table 1 as prediction features and *heart rate trend* as the prediction class.

4.3. Statistical Analysis

The ANOVA was used to test whether there was a statistically significant difference in heart rate as a function of different glycaemic levels in patients with DM: it was used to test for significant differences

Feature Name	Description
Glucose	Blood glucose levels of the patient.
Calories	The caloric intake associated with the patient.
Glucose Rate Moving Average (column_glucose_rate_moving)	A moving average centered on 11 observations for blood glucose levels (BGL).
Heart Rate Moving Average (heart_rate_moving_avg)	A moving average centered on 11 observations for heart rate (HR).
Glucose Rate Left Shifted Average (glucose_rate_left_avg)	A left-shifted moving average calculated over five observations for blood glucose levels (BGL).
Heart Rate Left Shifted Average (heart_rate_left_avg)	A left-shifted moving average calculated over five observations for heart rate (HR).
Max in Window (max_in_window)	The maximum blood glucose level within a sliding window.
Frequency Above Threshold 1.15 (count_above_max_1.15)	The frequency of glucose values above 1.15% of the maximum value within a sliding window.
Frequency Above Threshold 1.25 (count_above_max_1.25)	The frequency of glucose values above 1.25% of the maximum value within a sliding window.
Min in Window (min_in_window)	The minimum blood glucose level within a sliding window.
Frequency Below Threshold 1.15 (count_below_min_1.15)	The frequency of glucose values below 1.15% of the minimum value within a sliding window.
Frequency Below Threshold 1.25 (count_below_min_1.25)	The frequency of glucose values below 1.25% of the minimum value within a sliding window.

Table 1

Features used for prediction in MCLT.

Table 2

Performance metrics of the model during validation

ID	Best Model	Accuracy (%)	TP	TN	FP	FN	Precision (%)	Recall (Sensitivity) (%)	Specificity (%)	F1-Score (%)	FPR (%)	FNR (%)	AUC (%)
1	EBT	67.8%	1419	1073	536	649	66.69%	62.31%	72.58%	64.43%	27.42%	37.69%	74.46%
2	EBT	66.7%	1143	758	418	529	73.22%	68.36%	64.46%	70.71%	35.54%	31.64%	72.79%
3	EBT	70.9%	1487	912	427	558	77.69%	72.71%	68.11%	75.12%	31.89%	27.29%	77.28%
4	EBT	79.0%	1938	318	176	424	81.37%	91.67%	82.05%	64.37%	86.60%	35.63%	81.37%
5	EBT	81.3%	2327	493	225	422	91.18%	84.65%	68.66%	87.79%	31.34%	15.35%	84.93%
6	EBT	73.8%	834	681	237	300	77.87%	73.54%	74.18%	75.65%	25.82%	26.46%	81.25%
7	EBT	68.0%	1353	1000	486	623	73.57%	68.47%	67.92%	70.93%	32.71%	31.53%	74.77%
8	EBT	69.2%	1408	961	475	577	74.77%	70.93%	66.92%	72.80%	33.08%	29.07%	76.94%
9	WKNN	73.8%	397	1573	440	259	47.43%	60.52%	78.14%	53.18%	21.86%	39.48%	75.10%
10	EBT	68.3%	1306	1049	495	596	72.52%	68.66%	67.94%	70.54%	32.06%	31.34%	74.90%
11	WKNN	65.5%	1285	965	560	627	69.65%	67.21%	63.28%	68.41%	36.72%	32.79%	72.17%
12	WKNN	64.5%	1144	1051	598	610	65.67%	65.22%	63.74%	65.45%	36.26%	34.78%	70.87%
13	EBT	68.4%	1350	1005	477	610	73.89%	68.88%	67.81%	71.30%	32.19%	31.12%	74.99%
14	EBT	70.0%	1312	948	430	540	75.32%	70.84%	68.80%	73.01%	31.20%	29.16%	76.51%
15	EBT	66.8%	1410	925	516	645	73.21%	68.61%	64.19%	70.84%	35.81%	31.39%	72.79%
16	WKNN	67.1%	988	1247	560	535	63.82%	64.87%	69.01%	64.34%	30.99%	35.13%	73.81
17	EBT	68.3%	1052	700	361	453	74.45%	69.90%	65.98%	72.10%	34.02%	30.10%	74.84%
18	EBT	67.5%	787	629	300	383	72.40%	67.26%	67.71%	69.74%	32.29%	32.74%	73.94%
19	EBT	66.8%	1349	1064	545	653	71.22%	67.38%	66.13%	69.25%	33.87%	32.62%	73.28%
20	EBT	66.7%	1338	1008	525	647	71.82%	67.41%	65.75%	69.54%	34.25%	32.59%	73.43%
21	EBT	72.1%	1040	836	318	408	76.58 %	71.82%	72.44%	74.13%	27.56%	28.18%	78.62%
22	EBT	71.8%	1672	910	449	565	78.83%	74.74 %	66.96%	76.73%	33.04 %	25.26%	78.21%
23	EBT	64.3%	13559	9914	5796	7262	70.05%	65.12%	63.11%	67.50%	36.89%	34.88%	70.03%
24	EBT	60.4%	7684	6387	4162	5069	64.87%	60.25%	60.55%	62.47%	39.45%	39.75%	64.91%

Table 3

Performance metrics of the model during testing

ID	Best Model	Accuracy (%)	TP	TN	FP	FN	Precision (%)	Recall (Sensitivity) (%)	Specificity (%)	F1-Score (%)	FPR (%)	FNR (%)	AUC (%)
1	EBT	69.6%	160	124	57	67	73.73%	70.48%	68.51%	72.07%	31.49%	29.52%	75.87%
2	EBT	68.7%	130	87	44	55	74.71%	70.27%	66.41%	72.42%	33.59%	29.73%	74.31%
3	EBT	72.0%	169	101	43	62	79.72%	73.16%	70.14%	76.30%	29.86%	26.84%	75.00%
4	EBT	72.2%	219	32	15	51	93.59%	81.11%	68.09%	86.90%	31.91%	18.89%	80.13%
5	EBT	82.3%	265	52	18	50	93.64%	84.13%	74.29%	88.63%	25.71%	15.87%	90.33%
6	EBT	74.4%	90	79	28	30	76.27%	75.00%	73.83%	75.63%	26.17%	25.00%	83.27%
7	EBT	65.9%	144	109	60	71	70.59%	66.98%	64.50%	68.74%	35.50%	33.02%	70.50%
8	EBT	75.8%	174	114	36	56	82.86%	75.65%	76.00%	79.09%	24.00%	24.35%	81.41%
9	WKNN	76.7%	49	178	44	25	52.69%	66.22%	80.18%	58.68%	19.82%	33.78%	76.23%
10	EBT	64.9%	144	104	56	78	72.00%	64.86%	65.00%	68.25%	35.00%	35.14%	73.24%
11	WKNN	67.7%	140	118	65	58	68.29%	70.71%	64.48%	69.48%	35.52%	29.29%	71.59%
12	WKNN	60.6%	122	107	72	77	62.89%	61.31%	59.78%	62.09%	40.22%	38.69%	68.63%
13	EBT	66.8%	145	110	58	69	71.43%	67.76%	65.48%	69.54%	34.52%	32.24%	72.69%
14	EBT	72.3%	152	107	41	58	78.76%	72.38%	72.30%	75.43%	27.70%	27.62%	78.33%
15	EBT	73.5%	166	119	48	55	77.57%	75.11%	71.26%	76.32%	28.74%	24.89%	78.94%
16	WKNN	65.7%	109	134	63	64	63.37%	63.01%	68.02%	63.19%	31.98%	36.99%	72.69%
17	EBT	67.4%	121	71	36	57	77.07%	67.98%	66.36%	72.24%	33.64%	32.02%	75.13%
18	EBT	66.1%	86	68	34	45	71.67%	65.65%	66.67%	68.53%	33.33%	34.45%	75.32%
19	EBT	69.8%	161	119	49	72	76.67%	69.10%	70.83%	72.69%	29.17%	30.90%	75.61%
20	EBT	71.8%	158	122	49	61	76.33%	72.15%	71.35%	74.18%	28.65%	27.85%	77.64%
21	EBT	75.4%	117	101	34	37	77.48%	75.97%	74.81%	76.72%	25.19%	24.03%	82.93%
22	EBT	72.7%	191	99	45	64	80.39%	74.90%	68.75%	77.80%	31.25%	25.10%	78.08%
23	EBT	64.7%	1515	1110	636	798	70.43%	65.50%	63.57%	67.88%	36.43%	34.50%	70.64%
24	EBT	60.7%	859	712	457	561	65.27%	60.49%	60.91%	62.79%	39.09%	39.51%	65.39%

between the heart rate averages in the various blood glucose groups defined above. In our case, p-value < 0.05 is considered the threshold for determining significance, suggesting that the variability in heart rate between glycemic groups is not due to chance.

In this T1DM scenario, if the p-value is less than 0.05, there is a significant difference in heart rate between at least two of the glycemic groups. Therefore, the blood glucose level could significantly impact heart rate, warranting further analysis. Also, a high F value indicates that the group variation is

much greater than the internal variation, suggesting significant differences.

The ANOVA Test does not allow for a precise understanding of the effect of blood glucose categories (glucose_label) on heart rate, so Tukey’s posthoc test was applied. Tukey’s test was applied to all patients who showed a p -value < 0.05 after the ANOVA Test to identify which blood glucose groups show significant differences in heart rate.

5. Results and Discussion

Tables 2 and 3 summarize each patient’s validation and testing accuracies. Ensemble Bagged Trees emerged as the top performer in 20 out of 24 patients, while Weighted K-Nearest Neighbors led in the remaining four. Across patients, validation accuracy ranged from 60.4 % to 81.3 %, with a similar spread in test performance. This variability underscores that, although ECG-based predictors can capture glycemic trends, their reliability is patient-dependent.

Table 4

Merged Tukey and ANOVA Results for Each Patient

PID	F value	Pr(>F)	SC (%)	MeD	MaD	MiD
1	51.01	$<2e-16$	80%	-1.23	11.12 (VLVH)	-7.59 (VHH)
2	14.96	$4.04e-12$	70%	-0.98	8.28 (VLVH)	-6.56 (VHH)
3	84.81	$<2e-16$	90%	0.89	13.21 (VLG)	-10.38 (VHG)
4	49.62	$<2e-16$	75%	-0.45	7.00 (VLVH)	-5.88 (VHL)
5	14.41	$1.11e-11$	85%	1.11	12.74 (VLVH)	-7.06 (VHG)
6	12.66	$3.43e-10$	80%	-1.67	6.19 (VLVH)	-7.66 (VHL)
7	30.49	$<2e-16$	75%	0.55	8.40 (VHL)	-6.69 (VLH)
8	10.76	$4.85e-07$	50%	-0.34	3.18 (VHG)	-1.41 (GH)
9	15.57	$1.29e-12$	70%	0.23	8.27 (VLVH)	-6.12 (VLH)
10	52.34	$<2e-16$	90%	2.02	13.19 (VLVH)	-7.59 (LH)
11	55.83	$<2e-16$	80%	1.12	7.63 (VHL)	-7.80 (VHG)
12	12.19	$7.55e-10$	65%	0.78	6.45 (VLG)	-4.48 (GL)
13	73.36	$<2e-16$	75%	1.56	10.28 (VLG)	-9.65 (VLL)
14	20.89	$<2e-16$	70%	0.89	5.93 (VHL)	-5.74 (VHG)
15	73.02	$<2e-16$	85%	2.34	7.84 (VHL)	-7.84 (VHG)
16	45.41	$<2e-16$	60%	-1.34	11.07 (VLG)	-8.69 (VLL)
17	24.26	$<2e-16$	90%	0.87	11.12 (VHG)	-7.62 (VLL)
18	21.88	$<2e-16$	65%	-0.45	5.73 (VLG)	-6.55 (VHH)
19	24.29	$<2e-16$	80%	-1.12	6.65 (VHL)	-4.79 (VLL)
20	21.19	$<2e-16$	70%	0.43	5.99 (VHG)	-3.32 (LH)
21	26.22	$<2e-16$	75%	-0.56	7.98 (VHH)	-6.76 (LG)
22	2.04	0.106	–	–	–	–
23	403.2	$<2e-16$	85%	1.22	14.60 (VHL)	-13.89 (VHVL)
24	48.08	$<2e-16$	85%	1.22	14.60 (VHL)	-13.89 (VHVL)

ANOVA outcomes (Table 4) reveal that 23 of 24 patients (95.8 %) exhibited significant differences between heart rate distributions across glycemic categories ($p < 0.05$). Patient 22 was the lone exception ($p \geq 0.05$; $F = 1.74$), indicating no clear heart rate stratification by glycemic state and suggesting that, in some individuals, ECG features may lack sensitivity to glucose shifts. The high F -values observed in the other patients confirm pronounced effect sizes, particularly when contrasting extreme glycemic bands.

Post hoc Tukey comparisons (Table 4) further clarify these effects. The largest mean differences occurred between “Very Low” and “Very High” glycemic states (MaD), with confidence intervals excluding zero—evidence of robust heart rate modulation at glycemic extremes. In contrast, adjacent labels such as “Good” versus “High” rarely reached statistical significance, implying that mid-range glucose changes induce subtler cardiovascular responses that may fall below the detection threshold of consumer-grade wearables.

Our findings align with prior work showing that ECG-derived metrics can flag hypo- and hyperglycemia, but add nuance by quantifying patient-level variability. Narasimhan et al. (2023) reported population-average heart rate increases of 5–7 bpm during hypoglycemic episodes, yet noted inter-subject standard deviations exceeding 3 bpm—which mirrors our observed 20 % spread in model accuracy. Likewise, González et al. (2021) highlighted the need for personalized calibration to reach clinical-grade sensitivity, a recommendation reinforced by our patient-specific performance gaps.

Clinically, these results suggest two pathways forward. First, the consistent accuracy of Ensemble Bagged Trees in most patients indicates that tree-based ensembles can robustly capture non-linear ECG–glycemia relationships, making them strong candidates for embedded algorithms in wearable platforms. Second, the pronounced failure in certain individuals (e.g., Patient 22) and the modest performance on mid-range glucose shifts underscore the necessity of integrating complementary signals—such as photoplethysmography, activity level, or stress markers—to boost sensitivity and reduce false negatives in critical glycemic ranges.

However, consumer wearables—used here for heart rate capture—can suffer from motion artifacts and variable signal fidelity, particularly during exercise or when there is poor sensor contact. Our moving-average smoothing mitigated some noise, but real-world deployment will demand adaptive filtering and on-device quality checks. Furthermore, the five-minute sampling interval may miss rapid glycemic excursions; integrating continuous or higher-frequency monitoring could unveil transient ECG patterns predictive of imminent hypo- or hyperglycemia.

Lastly, beyond model optimization, patient engagement and data privacy are pivotal. Personalized model training requires substantial amounts of labeled data, which can be burdensome for users. Federated learning approaches could reconcile the need for individualized calibration with privacy preservation, as has been trialed successfully in diabetes glucose prediction (Li et al., 2024). Future studies should therefore not only refine algorithmic approaches but also develop scalable pipelines for secure data collection, model updating, and clinical validation in diverse T1DM cohorts.

6. Conclusion

With the advent of modern FGM and CGM sensors, glycemic control in T1DM patients has become faster and more accurate. However, these technologies can be perceived as invasive and suffer from limited user acceptance. This study investigated whether non-invasive ECG tracking via consumer smart devices could serve as a viable alternative by exploring the relationship between blood glucose levels (BGL) and heart rate (HR). Two research questions were formulated (Section 1: Introduction) to examine both the existence of a statistical link and the feasibility of predictive modeling.

To address RQ1, we applied ANOVA and Tukey’s post-hoc tests to data from 24 T1DM patients. ANOVA revealed that 23 of 24 patients exhibited significant HR differences across glycemic categories ($p < 0.05$), with the most pronounced effects observed when comparing extreme glycemic states. Tukey’s tests localized these differences, confirming that HR variability tracks BGL fluctuations in a statistically robust manner. Collectively, these findings provide strong evidence of a positive correlation between BGL and HR in T1DM.

RQ2 was explored through supervised machine learning models (KNN, WKNN, and Ensemble Bagged Trees), which exploit features such as glycemic rate of change, threshold counts, and caloric intake. The Heart Trend (HT) parameter successfully classified HR shifts as rising (‘U’) or stable/decreasing (‘D’), demonstrating that HR dynamics inferred from BGL trends can be predicted with moderate to high accuracy. Ensemble Bagged Trees achieved the best performance in most patients, highlighting the utility of non-linear ensemble methods for capturing complex ECG–glycemia relationships.

Our results underscore the potential of integrating ECG-based monitoring into routine diabetes management. Together, statistical analysis, machine learning and wearable devices could provide continuous, non-invasive alerts for impending hypo- or hyperglycemic events, reducing finger-prick frequency and improving patient comfort.

7. Limitations and Future Work

Although the examination of the relationship between heart rate patterns and glycemic states yields promising results for non-invasive glucose monitoring in patients with T1DM, several limitations should be considered when interpreting the findings and applying the methodology in clinical practice.

First, our cohort consisted of only 24 T1DM patients, without non-diabetic controls, which limited external validity. Also, this study focuses exclusively on patients with T1DM and cannot be generalized to T2DM, which accounts for approximately 90–95% of all diabetes cases and involves different pathophysiological mechanisms that may affect the heart rate–glucose relationship. Moreover, the lack of control subjects without diabetes limits the ability to isolate diabetes-specific effects on cardiac dynamics.

Second, the five-minute sampling interval and reliance on consumer-grade wearables introduce temporal gaps and measurement noise that may obscure rapid glycemic excursions or subtle heart rate variability. Third, model parameters—such as sliding window size, moving-average intervals, and classification thresholds—were tuned empirically; the absence of a formal sensitivity analysis raises concerns about robustness across different populations and operating conditions. Fourth, potential confounders (sleep quality, BMI, physical activity, emotional stress, medication) were recorded but not integrated into the predictive framework, limiting insight into multifactorial influences on HR–BGL dynamics.

To address these issues, future studies should:

- Use bigger cohorts (including healthy controls) and balance glycemic reading distributions.
- Increase sampling frequency or fuse multi-sensor data (e.g., continuous ECG, PPG, accelerometry) to capture transient events.
- Perform systematic parameter optimization (e.g., grid search, genetic algorithms[33], wavelet transforms) and comprehensive sensitivity analyses.
- Develop personalized and privacy-preserving modeling strategies—such as patient-specific models, transfer learning (Digital Twins), or federated learning—to accommodate inter-individual variability.
- Incorporate additional physiological and behavioral variables (sleep metrics, BMI[34], stress markers, medication timing) and apply explainability methods (LIME, SHAP) to ensure clinical interpretability.
- Develop a multimodal system that can analyze extra data, like electrodermal activity (EDA).

These efforts will be crucial in translating ECG-based approaches into reliable, non-invasive tools for diabetes management.

Despite these limitations, this research aims to establish a preliminary foundation for non-invasive ECG-based glucose monitoring approaches.

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Declaration on Generative AI

During the preparation of this work, the author(s) used Grammarly to check grammar and spelling. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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