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Usuda D, Furukawa D, Imaizumi R, Ono R, Kaneoka Y, Nakajima E, Kato M, Sugawara Y, Shimizu R, Inami T, Sakurai R, Kawai K, Matsubara S, Tanaka R, Suzuki M, Shimozawa S, Hotchi Y, Osugi I, Katou R, Ito S, Mishima K, Kondo A, Mizuno K, Takami H, Komatsu T, Nomura T, Sugita M. Sodium glucose transporter 2 inhibitors for heart failure. *World J Cardiol* 2026; 18(3): 118227 [DOI: 10.4330/wjc.v18.i3.118227]

MINIREVIEWS

Mondal S, Raja DP, Muslim NA, Prabhu MA. Electrocardiographic artifacts in clinical practice: A logical approach to recognition and prevention. *World J Cardiol* 2026; 18(3): 116299 [DOI: 10.4330/wjc.v18.i3.116299]

ORIGINAL ARTICLE

Case Control Study

Vuckovic M, Grgurić J, Paic F, Radonic V, Jurin I, Filipec Kanizaj T, Letilovic T. Valvular calcification in liver cirrhosis: A comparison with non-cirrhotic cardiovascular controls. *World J Cardiol* 2026; 18(3): 114077 [DOI: 10.4330/wjc.v18.i3.114077]

Retrospective Study

Teragawa H, Hashimoto Y, Tsuchiya A, Nomura S. Prognostic significance of vascular endothelial dysfunction in patients with vasospastic angina. *World J Cardiol* 2026; 18(3): 116661 [DOI: 10.4330/wjc.v18.i3.116661]

Observational Study

Karbovskaya AD, Marzoog BA, Stroeva A, Suvorov A, Chomakhidze P, Gognieva D, Kuznetsova N, Syrkin A, Fadeev VV, Ismailova SM, Poluboyarinova IV, Kopylov P. Machine learning-based detection of diabetes mellitus from single-lead electrocardiography: A phenotype-stratified approach. *World J Cardiol* 2026; 18(3): 116217 [DOI: 10.4330/wjc.v18.i3.116217]

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Karbovskaya AD, Marzoog BA, Stroeva A, Chomakhidze P, Gognieva D, Kuznetsova N, Syrkin A, Fadeev VV, Poluboyarinova IV, Ismailova SM, Suvorov A, Kopylov P. Discriminating diabetes mellitus from single-lead electrocardiography using machine learning and multinomial regression. *World J Cardiol* 2026; 18(3): 116115 [DOI: 10.4330/wjc.v18.i3.116115]

Basic Study

Hu PF, Bai LY, Zhao M, Ma KY, Xuan LY, Qi X. Landiolol modulates sodium 1.5 ion and connexin-43 to reduce sepsis ventricular arrhythmias. *World J Cardiol* 2026; 18(3): 117821 [DOI: 10.4330/wjc.v18.i3.117821]

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Mylavarapu M, Obi O, Abarca Y, Fatima H, Roshni P, Huda NU, Lysak Y, Gandapur A, Vazquez SC, Siddiqui MA, Mowo-Wale A. Semaglutide in patients with obesity and heart failure with preserved ejection fraction: A systematic review and meta-analysis. *World J Cardiol* 2026; 18(3): 112189 [DOI: 10.4330/wjc.v18.i3.112189]

Ahmed S, Ahmad E, Ashraf H, Ain HU, Ahmad S, Akram U, Basit J, Hassan IN, Ullah I, Ahmed R, Fonarow GC, Cortese B. Nicorandil in ST-segment elevation myocardial infarction patients undergoing percutaneous coronary intervention: A systematic review and meta-analysis. *World J Cardiol* 2026; 18(3): 116789 [DOI: 10.4330/wjc.v18.i3.116789]

CASE REPORT

Li A, Zhu YJ, Ma XX, Jin Y, Yang J, Feng QT. Arrhythmogenic right ventricular cardiomyopathy with atrial tachycardia and sick sinus syndrome: A case report. *World J Cardiol* 2026; 18(3): 117999 [DOI: 10.4330/wjc.v18.i3.117999]

LETTER TO THE EDITOR

Tsai TY, Garg S, Serruys PW. Key considerations in a meta-analysis of physiology-guided percutaneous *vs* surgical revascularization in multivessel coronary artery disease. *World J Cardiol* 2026; 18(3): 115153 [DOI: 10.4330/wjc.v18.i3.115153]

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The primary aim of *World Journal of Cardiology* (*WJC*, *World J Cardiol*) is to provide scholars and readers from various fields of cardiology with a platform to publish high-quality basic and clinical research articles and communicate their research findings online.

WJC mainly publishes articles reporting research results and findings obtained in the field of cardiology and covering a wide range of topics including acute coronary syndromes, aneurysm, angina, arrhythmias, atherosclerosis, atrial fibrillation, cardiomyopathy, congenital heart disease, coronary artery disease, heart failure, hypertension, imaging, infection, myocardial infarction, pathology, peripheral vessels, public health, Raynaud's syndrome, stroke, thrombosis, and valvular disease.

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ORIGINAL ARTICLE

Prospective Study

Discriminating diabetes mellitus from single-lead electrocardiography using machine learning and multinomial regression

Anna Dmitrievna Karbovskaya, Basheer Abdullah Marzoog, Anastasia Stroeva, Peter Chomakhidze, Daria Gognieva, Natalia Kuznetsova, Abromavich Syrkin, Valentin V Fadeev, Irina V Poluboyarinova, Sevindzh M Ismailova, Alexander Suvorov, Philipp Kopylov

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Abstract

BACKGROUND

Current advances in diagnostic and therapeutic strategies remain insufficient to

reduce the prevalence and incidence rate of diabetes mellitus (DM).

AIM

To investigate any association between single-lead electrocardiography (ECG) parameters and the diagnosis of DM.

METHODS

A single center study involved participants of Caucasian origin for the period between May 2, 2022 and August 23, 2025 with or without DM and aged ≥ 18 years. All participants participating in the study passed the cardiologist's, random glucose measurement using a glucometer, single lead-ECG registration (using Cardio-Qvark®) and transthoracic echocardiography. Statistical analysis conducted using the R programming language (version 4.5).

RESULTS

The built logistic regression machine learning model demonstrated diagnostic performance in discriminating (area under the curve) type 1 DM 0.84 (95%CI: 0.76-0.91), type 2 DM 0.69 (95%CI: 0.61-0,76), and healthy control 0.82 (95%CI: 0.76-0.87).

CONCLUSION

The developed model demonstrates an association between single-lead ECG parameters and diabetes status that can support the clinical identification of individuals who would benefit from confirmatory testing. This is probably attributable to relatively stable and long-term physiological alterations associated with the state of the disease.

Key Words: Machine learning; Diabetes mellitus; Diagnosis; Hyperglycemia; Glycated hemoglobin; Glucose

Core Tip: This study pioneers a novel, non-invasive screening strategy for diabetes mellitus by leveraging the ubiquity of single-lead electrocardiography. Using a machine learning model, we demonstrate that the diabetic state leaves a distinct electrophysiological signature on the heart, detectable from a simple, consumer-grade electrocardiography. The model excels at ruling out diabetes with high accuracy and can differentiate between type 1 and type 2 diabetes based on divergent cardiac electrical patterns, such as opposing prolonged QT interval behaviors. This approach transforms a common cardiac tool into a potential frontline, accessible screening method for one of the world's most prevalent metabolic disorders.

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INTRODUCTION

Diabetes mellitus (DM) constitutes a pervasive global health crisis, affecting over 500 million individuals worldwide and serving as a primary driver of significant morbidity and mortality, predominantly through its devastating cardiovascular complications[1-3]. The escalating prevalence of this metabolic disorder underscores an urgent and unmet need for innovative diagnostic strategies that are both accessible and capable of facilitating early intervention[4-6]. Early detection is paramount for effective management and the prevention of long-term sequelae, including neuropathy, retinopathy, nephropathy, and atherosclerotic cardiovascular disease among the 10 articles [7-16]. However, the current diagnostic paradigm, reliant on biomarkers such as fasting plasma glucose, oral glucose tolerance tests, and glycated hemoglobin (HbA1c), presents significant limitations[17,18]. These methods are inherently invasive, require

laboratory infrastructure and trained personnel, and may fail to identify individuals with subclinical disease or early autonomic neuropathy, a common and serious complication of diabetes. Consequently, a substantial number of at-risk individuals remain undiagnosed until complications arise, highlighting a critical gap in our preventive healthcare arsenal.

The electrocardiography (ECG), a cornerstone of cardiovascular assessment, offers a non-invasive window into cardiac electrophysiology and autonomic nervous system function[19]. In recent years, the proliferation of wearable technology and consumer-grade devices capable of recording medical-grade single-lead ECGs has created an unprecedented opportunity for decentralized, continuous health monitoring. These devices provide a low-cost, scalable, and readily accessible platform for population-level screening[20,21]. The ECG signal contains a wealth of data beyond standard intervals; subtle alterations in repolarization, depolarization, heart rate (HR) variability, and signal morphology can reflect underlying metabolic and neuroautonomic disturbances, such as those induced by chronic hyperglycemia and insulin resistance[22-25].

The extraction and interpretation of these subtle, complex patterns from the ECG waveform transcend the capabilities of traditional analysis. This is where the transformative potential of artificial intelligence, specifically machine learning (ML) and deep learning (DL), comes to the fore[26-29]. ML algorithms excel at identifying intricate, multidimensional patterns within large datasets that are often imperceptible to the human eye. Several pioneering studies have demonstrated the feasibility of using ML-based analysis of multi-lead ECGs to detect conditions like atrial fibrillation, left ventricular dysfunction, and even hyperkalemia[30,31]. The logical extension of this research is the application of these powerful analytical tools to the challenge of diabetes diagnosis, leveraging the ubiquitous single-lead ECG as a novel data source.

While the concept is promising, the specific application of ML to single-lead ECG for differentiating not only diabetes from health but also between its principal types (type 1 and type 2) remains a developing field. The pathophysiological pathways leading to type 1 DM (T1DM) (autoimmune beta-cell destruction) and type 2 DM (T2DM) (insulin resistance and progressive secretory defect) impart distinct, yet poorly characterized, impressions on cardiac electrophysiology. A model that can decipher these unique signatures could revolutionize screening protocols and provide profound insights into the cardiac manifestations of different diabetic states[32,33].

Therefore, this study aims to investigate the association between a comprehensive set of parameters derived from a single-lead ECG and the diagnosis of DM. We hypothesize that ML analysis of single-lead ECG features can identify a unique electrophysiological signature associated with DM and develop a validated model capable of distinguishing between healthy individuals, patients with T1DM, and patients with T2DM. By harnessing the synergy of consumer-grade technology and advanced analytics, this research seeks to contribute to the development of a novel, non-invasive, and accessible tool for the early detection and differentiation of DM.

MATERIALS AND METHODS

A single center prospective study conducted at university clinical hospital number 2 for the period between May 2, 2022 and August 23, 2025. The study included participants with *vs* without DM (both first and second type). Patients were recruited from both outpatient and inpatient settings, including those undergoing examination in the endocrinology department. Recruitment was not limited to patients with optimal signal quality at enrollment; however, single exclusions were made based on predefined signal quality criteria as detailed below.

The main logic of the study was to determine the presence or absence of DM without adjustments for covariates – based solely on ECG data and transformations of average complexes. The rationale is straightforward: The algorithm should work quickly, simply, in a screening concept.

Including numerous traditional cardiology covariates would have taken the algorithm out of the screening framework. Additionally, some covariates can be determined very imprecisely (many patients do not know if they had a myocardial infarction, when it occurred, its location, whether they have heart failure, *etc.*). This inevitably leads to significant bias due to retrospective analysis and degradation of model quality. Such an approach would no longer qualify as a screening method that could be used with an electrocardiograph.

We classified diabetes status primarily using fasting plasma glucose measurements (threshold ≥ 126 mg/dL or 7 mmol/L) following World Health Organization recommendations, supplemented by documented clinical history and current medication use. While this approach reflects real-world clinical practice in our setting, we acknowledge it does not incorporate the complete diagnostic algorithm recommended by international guidelines (American Diabetes Association/World Health Organization), particularly the systematic use of HbA1c and specialized testing for diabetes subtype classification.

The study was carried out according to the principles of Good Clinical Practice and Helinski declaration. All participants gave informed written consent to participate in the study and publish any associated results anonymously. The study protocol was approved by the local Ethical Committee of Sechenov University. The study was also registered on the ClinicalTrials.gov website.

Patient inclusion and exclusion criteria

Patients from University Clinical Hospital Number 2 undergoing outpatient or inpatient examination and treatment, including in the Endocrinology Department with a diagnosis of DM, were included in the study. The inclusion and exclusion criteria are presented below.

Inclusion: (1) Patient age over 18 years; and (2) Agreement to participate in the study.

Exclusion: (1) Significant changes in the morphology of the QRS complex (such as bundle branch block, arterial fibrillation, and ventricular extrasystole); (2) Poor quality ECG recorded from the fingers (Parkinson's disease, tremor of any origin, mental disorders); (3) Chronic heart failure with reduced ejection fraction < 40%; (4) Chronic coronary syndrome; (5) Infectious diseases at acute stage; (6) Unsatisfactory quality of ECG and/or photoplethysmograph (PPG); and (7) Withdrawal of consent for further participation in the study.

Clinical data collection

The patients underwent a comprehensive examination.

Clinical examination: (1) Collection of complaints; (2) Auscultation; (3) Palpation; (4) Percussion; (5) Assessment of edema syndrome; (6) Measurement of HR; and (7) Blood pressure (BP) level.

Medical history analysis: (1) Collection of cardiological history; and (2) DM history.

Transthoracic echocardiography: Performed using a GE Vivid 5 device. Assessment of cardiac chamber volumes, wall thickness, diastolic and systolic function status, and detection of valvular apparatus and major cardiac vessel dysfunction according to current guidelines[34].

Standard 12-lead ECG recording: Performed using a SCHILLER AT-5 device. Determination of temporal and amplitude ECG parameters, cardiac electrical axis direction, and assessment of cardiac cycle morphology.

Capillary blood glucose analysis: Fasting blood glucose level measured twice within 1-3 days, in a seated position, adhering to the following requirements: (1) Analysis performed after a 12-hour fast; (2) Abstinence from alcohol 2-3 days prior; (3) Avoidance of stress or heavy physical exertion; and (4) Refraining from tooth brushing, smoking, or consumption of fatty foods, sugary drinks, or confectionery products the day before. The type of DM is classified based on the history of the patients, and the drug they take to manage it. The diagnostic thresholds for DM are a fasting plasma glucose of 126 mg/dL (7 mmol/L) or higher and the presence of DM history.

Single-channel ECG and PPG recording: Recorded using the Qardio-QVARK device (LLC "L Card", Moscow, Russia; registered with the Federal Service for Surveillance in Healthcare number RZN 2019/8124) immediately after each blood glucose analysis. Recordings lasted 1 minute, performed at rest in a seated position. The recorder has a smartphone case form factor and features 2 sensors for recording ECG and PPG. Recordings were transmitted to a cloud-based platform for analysis using proprietary ML algorithms.

Statistical analysis

Statistical analysis was performed using the R programming language (version 4.5). For quantitative variables, the distribution normality was assessed using the Shapiro-Wilk test. Descriptive statistics were calculated, including the mean, standard deviation, median, interquartile range, and minimum and maximum values. For categorical and qualitative variables, proportions (percentages) and absolute frequencies were calculated.

Comparative analysis for independent, normally distributed quantitative variables was performed using Welch's *t*-test (for two groups) or one-way analysis of variance (for more than two groups), followed by *post-hoc* pairwise comparisons. For independent, non-normally distributed quantitative variables, the Mann-Whitney *U* test (for two groups) or the Kruskal-Wallis test (for more than two groups) was employed.

For related (paired) samples, comparative analysis of normally distributed quantitative variables was conducted using a paired Welch's *t*-test (for two groups) or repeated-measures analysis of variance (for more than two groups), again followed by *post-hoc* pairwise comparisons. For related, non-normally distributed quantitative variables, the Wilcoxon signed-rank test (for two groups) or Fisher's test (for more than two groups) was used.

To analyze dynamic changes across visits, Cochran's *Q* test was applied. Where necessary, pairwise comparisons for these dynamic changes were performed using McNemar's test. The Holm-Bonferroni method was used to correct for multiple comparisons. A significance level (α) of 0.05 was adopted for all analyses, corresponding to a 5% probability of committing a type I error.

Mathematical modelling pipeline

The sample size was sufficient to allocate the majority of the data for building associative models (70% of the data), with a separate hold-out set reserved for subsequent validation (20% of the data).

To assess associations with a quantitative outcome (glycemia), a linear regression model with combined L1 and L2 (Elastic Net) regularization was employed. This approach significantly mitigated the risk of multicollinearity and facilitated the selection of factors contributing most substantially to the outcome's variance. Quantitative data were normalized prior to analysis. The model's performance was evaluated on the validation set using the coefficient of determination (R^2), mean absolute error, maximum error, and the correlation coefficient between predicted and true values.

To evaluate the diagnostic properties of single-lead ECG in determining the presence of DM and its types [resulting in three classes: (1) No diabetes; (2) T1DM; and (3) T2DM], a multinomial logistic regression model with L1 (least absolute shrinkage and selection operator) regularization was utilized. This algorithm enabled the selection of the strongest predictors, after which associations were assessed through the conventional calculation of odds ratios (OR), using the non-diabetic class as the reference. The model's performance was evaluated on the validation set using the area under the

curve (AUC), sensitivity, specificity, and positive and negative predictive value (NPV).

RESULTS

A total of 743 patients with data on the presence or absence of T1DM or T2DM were included in the study. The control group included 537 (72.3%), T1DM group included 61 (8.2%), and T2DM included 145 (19.5%) participants. Information on random glucose level at the time of single-lead ECG recording was available for 696 participants; control 145 (19.5%), T1DM 535 (99.6%), and T2DM 100 (69%). The general characteristics of the study group are presented in the Supplementary Table 1. No significant differences were observed in key cardiovascular risk factors, namely sex and age, among the included participants. Body mass index (BMI) demonstrated overall statistical significance (P = 0.032), which was primarily driven by a marked difference between non-diabetic patients and those with T2DM (P = 0.024), with the latter group exhibiting higher values. No significant differences were observed between type 1 and type 2 diabetes groups (Supplementary Figure 1).

Statistical analysis of smoking prevalence revealed a significant overall difference (P < 0.001). Both insulin-dependent and non-insulin-dependent diabetic patients were significantly more likely to smoke compared to healthy controls (P = 0.002 and P = 0.001, respectively). However, no substantial differences were found between the two diabetic groups. Blood group distribution showed significant variations across all compared subgroups (P < 0.001). The most pronounced deviation was observed in the type 2 diabetes subgroup, which demonstrated a predominance of blood group AB (44.8% *vs* 15.7% and 8.2% in other groups, respectively). Systolic BP showed a significant difference in the overall sample (P = 0.005), attributable to lower BP levels in type 2 diabetic patients compared to the control group (P = 0.012; Supplementary Figure 1).

The prevalence of coronary artery disease reached statistical significance (P = 0.005), primarily due to lower disease frequency among type 2 diabetic patients compared to non-diabetic subjects (P = 0.009). The distribution of peak location values showed significant variation (P = 0.004), particularly evidenced by the complete absence of anterior peak cases in the insulin-dependent diabetes group. Finally, glucose levels demonstrated highly significant overall differences (P < 0.001), resulting from substantially elevated values in both diabetic groups compared to healthy controls, while no significant differences were observed between the two diabetic subgroups for this parameter (Supplementary Figure 1). Table of pairwise comparisons for categorical variables (holm correction) represented in Supplementary Table 2.

Features associated with the pulse wave

The greatest number of significant differences was identified in the analysis of pulse wave parameters. Statistically significant differences were observed for the majority of the measured indices. Due to distributions that deviated from normality, central tendency and variability are presented as medians with 25% and 75% (interquartile range). Group comparisons for these parameters are presented in the Supplementary Table 3. Pairwise comparisons (adjusted for multiple comparisons using the Holm method) revealed statistically significant differences not only relative to the non-diabetic control group but also between the two types of DM (Table 1). Of particular interest are those factors that demonstrate significant differences between the two types of DM, as well as those that effectively differentiate either type of diabetes from the control group. Such factors are visualized in the graph below (Figure 1). Thus, the factors that demonstrated significant differences between the three classes were prolonged QT interval (QTc), HFQRS, HFSNR, Pst, P-wave dispersion index (Pfi), QRSst, QRSfi, PpeakN, and RonsF.

Association building by the type of DM

To identify predictors associated with diabetes and its subtypes, a multinomial logistic regression model was employed. The model was initially adjusted for predefined covariates including age, sex, BMI, and smoking status. Continuous variables were standardized using z-score normalization (mean-centered and scaled by standard deviation). The regression model was trained on a randomly selected subset of 519 participants (70% of the total cohort), with validation performed on the remaining 222 participants (30%). Stratified sampling ensured proportional representation of both type 1 and type 2 diabetes cases across both training and validation sets.

Primary predictors selection

Feature selection was performed using L1-regularized multinomial regression to mitigate multicollinearity risks. Model stability was ensured through 10-fold cross-validation. The following predictors were selected: (1) Smoking status (categorized as never smoked, current smoker, or former smoker); (2) QTc; (3) T-wave amplitude (TA); (4) Pan; (5) RA; (6) SA; (7) Pst; (8) T-wave flattening (Tfi); (9) RoffsF; (10) Age; (11) Pfi; and (12) PpeakN.

Validation

These predictors were combined into a single regression equation with estimation of the coefficients, their 95%CI, subsequent exponentiation, and calculation of the OR (Table 2). A multinomial logistic regression model with healthy participants as the reference group, the associations between clinical and electrocardiographic parameters and the likelihood of having either type 1 or type 2 diabetes were analyzed.

T1DM (compared to healthy controls): The presence of type 1 diabetes was statistically significantly associated with the following factors: (1) Smoking: A reduced likelihood of T1DM was observed among smokers (OR = 0.16, 95%CI: 0.11-0.22, P < 0.001), which may reflect potential confounding factors or behavioral characteristics; (2) Prolonged QTc interval (OR =

Table 1 Adjusted pairwise comparisons for multiple comparisons using the Holm method

Factor	No DM: T1DM	No DM: T2DM	T1DM - T2DM
HFNoise	0.660	0.009	0.660
Ventricular activation	0.704	0.009	0.210
Prolonged QT interval	0.000	0.024	0.034
QT_TQ	0.001	0.284	0.022
HFQRS	0.000	0.000	0.000
HFSNR	0.000	0.000	0.000
T-wave amplitude	0.078	0.078	0.697
QRS12energy	0.024	0.541	0.108
QRSE2	0.033	0.639	0.084
QRSw	0.084	0.006	0.878
Pan	0.078	0.128	0.457
RA	0.129	0.129	0.519
SA	0.024	0.484	0.136
Pst	0.000	0.000	0.007
P-wave dispersion index	0.000	0.001	0.001
QRSst	0.000	0.000	0.001
QRSfi	0.000	0.000	0.000
T-wave flattening	0.000	0.000	0.637
PpeakN	0.000	0.000	0.000
Rpeak	0.000	0.721	0.001
Speak	0.001	0.546	0.016
Tpeak	0.158	0.158	0.048
Toffs	0.192	0.192	0.051
RonsF	0.026	0.026	0.002
RoffsF	0.004	0.188	0.002
SDNN	0.018	0.278	0.222

DM: Diabetes mellitus; T1DM: Type 1 diabetes mellitus; T2DM: Type 1 diabetes mellitus.

3.81, 95%CI: 1.22-11.87, $P = 0.021$); (3) Increased TA (OR = 4.03, 95%CI: 1.82-8.94, $P = 0.001$); (4) A decrease in the P-wave terminal force parameter, reflecting atrial electrical activity (OR = 0.71, 95%CI: 0.53-0.96, $P = 0.024$); (5) A reduction in the Pfi (OR = 0.73, 95%CI: 0.54-0.97, $P = 0.033$); and (6) A borderline trend towards statistical significance was also identified for the following predictors: Tfi ($P = 0.072$) and PpeakN ($P = 0.071$).

T2DM (compared to healthy controls): For patients with T2DM, the following statistically significant predictors were identified: (1) QTc interval: An inverse association was observed: A shorter QTc interval was associated with a higher likelihood of T2DM (OR = 0.35, 95%CI: 0.20-0.62, $P < 0.001$); (2) TA: Was strongly associated with an increased likelihood of T2DM (OR = 11.22, 95%CI: 3.78-33.31, $P < 0.001$); (3) Pan parameter, reflecting the spatial characteristics of the P-wave (OR = 4.74, 95%CI: 2.94-7.63, $P < 0.001$); and (4) RA (OR = 2.67, 95%CI: 1.50-4.73, $P = 0.001$).

The remaining parameters, including age, Tfi, SA, and RoffsF, did not demonstrate statistically significant differences between the T2DM group and healthy controls. The most stable predictors of diabetes presence (compared to the control group) were abnormalities in QTc interval, TA magnitude, and atrial activity parameters (Pan, RA, Pfi, Pst). Notably, QTc intervals exhibited divergent directional associations: Prolongation was associated with T1DM, while shortening was linked to T2DM. When validated on the holdout dataset of 222 observations, the model demonstrated the following performance metrics (Table 3, Figure 2). In the one-versus-one classification approach, the highest AUC was observed for differentiating between any type of diabetes and non-diabetic conditions, while the poorest performance was achieved in distinguishing type 1 diabetes from type 2 diabetes (type 1 diabetes *vs* type 2 diabetes) (Table 4).

Table 2 The primary predictors with their coefficient estimation, 95%CI, subsequent exponentiation, and odds ratio

	Type 1 DM			Type 2 DM		
	OR	95%CI	*P* value	OR	95%CI	*P* value
Intercept	0.016	0.005-0.048	< 0.001	1.391	1.049-1.845	0.022
Smoking	0.156	0.110-0.221	< 0.001	0.662	0.100-4.401	0.670
Prolonged QT interval	3.810	1.222-11.875	0.021	0.351	0.197-0.624	< 0.001
T-wave amplitude	4.033	1.819-8.941	0.001	11.218	3.778-33.312	< 0.001
Pan	1.537	0.917-2.577	0.103	4.738	2.943-7.630	< 0.001
RA	1.185	0.846-1.659	0.324	2.668	1.505-4.730	0.001
SA	0.947	0.556-1.611	0.840	1.286	0.940-1.757	0.115
Pst	0.714	0.533-0.957	0.024	0.682	0.442-1.053	0.085
T-wave flattening	0.605	0.350-1.046	0.072	0.972	0.716-1.320	0.854
RoffsF	0.954	0.710-1.282	0.755	0.544	0.133-2.223	0.397
Age	0.954	0.607-1.500	0.839	0.980	0.481-1.997	0.956
P-wave dispersion index	0.725	0.540-0.974	0.033	0.732	0.169-3.177	0.677
PpeakN	1.510	0.965-2.361	0.071	1.946	0.865-4.376	0.108

DM: Diabetes mellitus; OR: Odds ratio.

Table 3 The built machine learning model performance in the differentiation of control, type 1 diabetes mellitus, and type 2 diabetes mellitus, mean (95%CI)

Statistic	No DM	Type 1 DM	Type 2 DM
Area under the curve	0.82 (0.76-0.87)	0.84 (0.76-0.91)	0.69 (0.61-0.76)
Sensitivity	0.65 (0.57-0.72)	0.85 (0.68-1.00)	0.91 (0.81-0.98)
Specificity	0.89 (0.81-0.97)	0.69 (0.63-0.75)	0.42 (0.34-0.49)
Positive predictive value	0.94 (0.89-0.98)	0.21 (0.13-0.32)	0.28 (0.21-0.36)
Negative predictive value	0.51 (0.42-0.60)	0.98 (0.95-1.00)	0.95 (0.89-0.99)

DM: Diabetes mellitus.

Table 4 The one-versus-one classification-built model performance

Groups comparing	Area under the curve	Lower limit 95%CI	Upper limit 95%CI
No DM against T1DM	0.8981013	0.8439558	0.9522468
No DM against T2DM	0.7758087	0.7054986	0.8461189
T1DM against T2DM	0.6366667	0.4914294	0.7819039

DM: Diabetes mellitus; T1DM: Type 1 diabetes mellitus; T2DM: Type 2 diabetes mellitus.

The validation of the diagnostic model revealed statistically significant differences in predictive performance across patient groups depending on diabetic status. The overall diagnostic performance, evaluated by the AUC, demonstrated strong discriminative ability for the absence of diabetes (AUC = 0.82; 95%CI: 0.76-0.87). The model also showed good performance for T1DM (AUC = 0.84; 95%CI: 0.76-0.91). For T2DM, the discriminative capability was comparatively limited, though the confidence interval did not include 0.5 (AUC = 0.69; 95%CI: 0.61-0.76). These results indicate the current model has restricted applicability specifically for detecting T2DM.

In the non-diabetic group, the model exhibited high specificity (0.89; 95%CI: 0.81-0.97) and high positive predictive value (PPV) (0.94; 95%CI: 0.89-0.98). Among diabetic patients, a pronounced asymmetry in performance characteristics

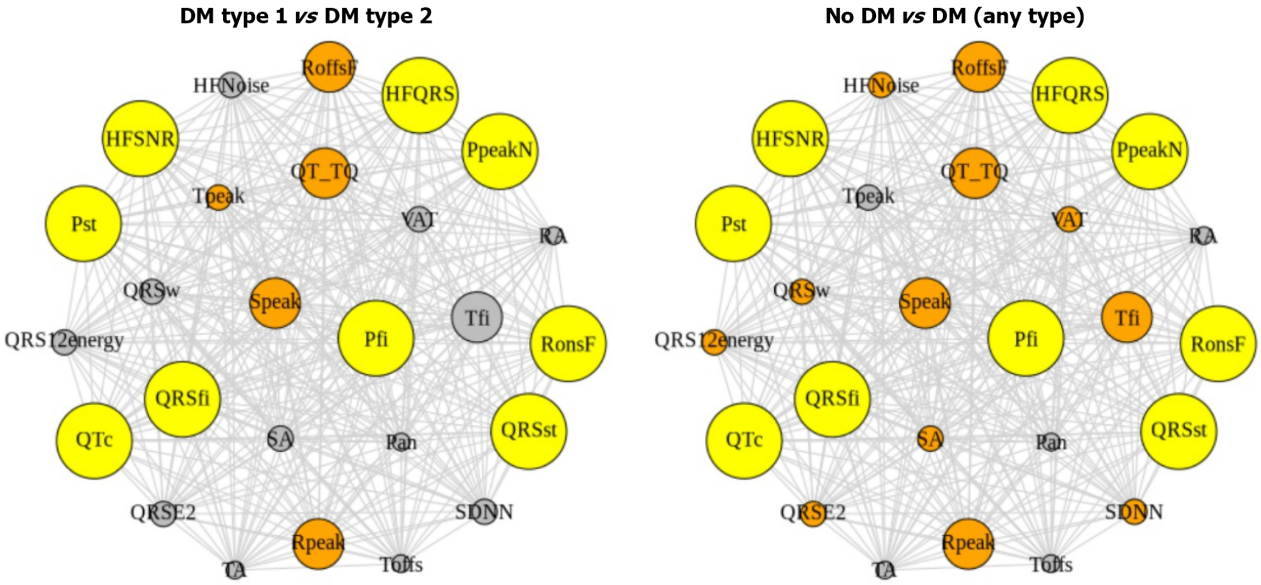

Figure 1 A network of factors demonstrating statistically significant differences in Holm-corrected pairwise comparisons are presented. The largest nodes (depicted in yellow) represent factors that exhibited significant differences across all three groups. Medium-sized nodes correspond to factors differing between any two groups, while the smallest nodes indicate factors significant for only a single group. On the left graph, the nodes are coloured (yellow or orange) according to their ability to differentiate between the types of diabetes. The right graph shows nodes that distinguish the control group from either type of diabetes (significance observed in either "no DM" *vs* "T1DM", "no DM" *vs* "T2DM", or across all three classes). The factors that did not appear in both graphs did not demonstrate statistically significant pairwise comparisons after multiplicity correction. DM: Diabetes mellitus; Tfi: T-wave flattening; Pfi: P-wave dispersion index; QTc: Prolonged QT interval; VAT: Ventricular activation.

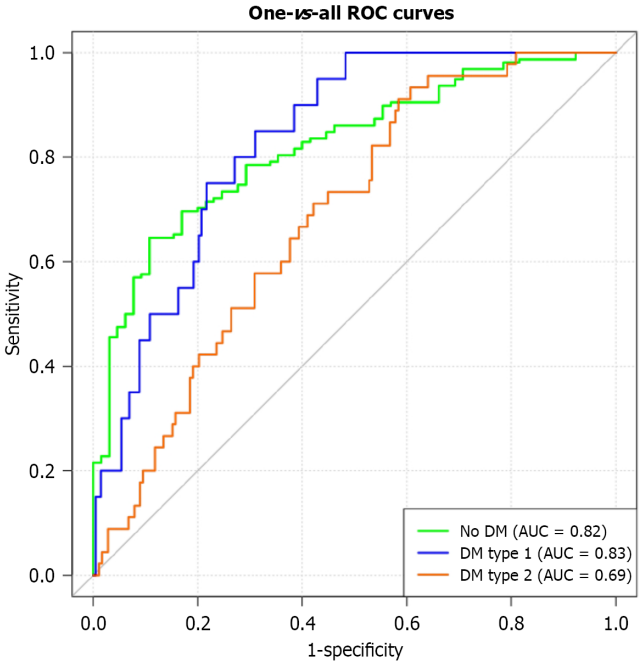

Figure 2 Graphical representation of the diagnostic accuracy of the built model in the diagnosis of diabetes mellitus. AUC: Area under the curve; DM: Diabetes mellitus; ROC: Receiver operating characteristic.

was observed. The model demonstrated high sensitivity in both type 1 (0.85; 95%CI: 0.68-1.00) and type 2 diabetes groups (0.91; 95%CI: 0.81-0.98), coupled with high NPV (0.98 and 0.95, respectively). This supports its potential utility for ruling out pathology in these cohorts. However, the low specificity in the type 2 diabetes group (0.42; 95%CI: 0.34-0.49) resulted in correspondingly low PPV values (0.28; 95%CI: 0.21-0.36), indicating a high rate of false positives for this particular class.

Analysis of associations with glycemic levels

Glycemic level is a more labile parameter than some electrocardiographic-derived features. Nevertheless, an attempt was made to identify associations between glycemic levels and several potential predictors. A linear regression model with combined L1 and L2 regularization (Elastic Net) was employed to identify associations while mitigating multicollinearity risks. The analysis utilized 10-fold cross-validation with mean-centered normalization and scaling by standard deviation for all continuous variables. The Table 5 below presents the coefficient estimates of selected factors from the final model, along with their 95%CI and statistical significance. However, a graphical representation of the data indicated some degree of correspondence between predicted and observed values up to a glycemic level of 5 mmol/L. Beyond this threshold, the predicted values effectively plateaued, exhibiting minimal dependence on the predictor variables (Figure 3). Analysis of standard regression quality metrics revealed suboptimal model performance, characterized by a low coefficient of determination (R^2) 0.217, a moderate mean absolute error 1.35, and a substantially elevated maximum error 14.5. Therefore, the utility of single-lead ECG for predicting glycemic levels appears questionable and should be interpreted with caution, particularly in light of the model's limited explanatory power and elevated maximum error.

DISCUSSION

The results demonstrate a significant and clinically relevant association between features derived from a single-lead ECG and the diagnosis of DM, utilizing a ML framework. Our findings indicate that the electrophysiological and autonomic nervous system alterations inherent to the diabetic state manifest in measurable, albeit subtle, changes in the ECG signal. These changes are sufficiently distinct to allow for the development of predictive models with promising diagnostic accuracy, particularly for differentiating diabetic from non-diabetic states and for identifying T1DM.

The core finding is the robust performance of the multinomial logistic regression model. The AUC values 0.84 for T1DM and 0.82 for the healthy control group signify a strong discriminative capacity. This performance is noteworthy given the non-invasive, low-cost, and highly accessible nature of single-lead ECG technology, which is increasingly integrated into consumer wearables and portable health devices. The model's high sensitivity (0.85 for T1DM, 0.91 for T2DM) and NPV (NPV > 0.95 for both DM types) are its most compelling attributes from a clinical screening perspective. This suggests that such a tool could be highly effective as a rule-out test, potentially identifying individuals who are very unlikely to have diabetes and thus reducing the need for more invasive or resource-intensive testing in a large portion of the population.

However, the model's performance for T2DM was notably weaker (AUC = 0.69), characterized by low specificity (0.42) and a consequently high false-positive rate (low PPV of 0.28). This asymmetry in performance highlights a critical nuance. The electrophysiological signature of T2DM, as captured by our selected features, appears to be less distinct or more heterogeneous than that of T1DM. This could be attributed to the broader pathophysiological spectrum of T2DM, which often coexists with a cluster of other metabolic and cardiovascular conditions like hypertension and obesity, as also seen in our cohort's higher BMI and hypertension prevalence. These comorbid states likely introduce confounding electrophysiological changes that overlap with those caused by hyperglycemia alone, making it challenging for the model to isolate a unique "T2DM fingerprint". Furthermore, the one-*vs*-one analysis confirmed the greatest difficulty lies in distinguishing T1DM from T2DM (AUC = 0.64), underscoring that while both types share the common endpoint of hyperglycemia, their underlying cardiac electrophysiological remodeling may follow different trajectories.

The feature selection process yielded profound insights into the specific ECG parameters most affected by diabetes. The identification of factors like QTc interval, TA, and various P-wave parameters (Pst, Pfi, Pan, RA) points towards diffuse involvement of the heart's electrical system. The divergent behavior of the QTc interval is particularly fascinating. QTc prolongation was associated with T1DM, which aligns with existing literature on diabetic autonomic neuropathy leading to reduced sympathetic tone and potentially prolonged repolarization. Conversely, QTc shortening was associated with T2DM. This counterintuitive finding may be explained by the different autonomic progression in T2DM, often characterized by an early hyperadrenergic state, or by the complex interplay of ischemia, hypertrophy, and electrolyte shifts more common in this population. The strong association of increased TA with both types of DM, but especially T2DM (OR > 11), is a notable finding that warrants further investigation, as it may reflect underlying myocardial strain or altered ventricular repolarization gradients.

The alterations in P-wave parameters (Pst, Pfi, PpeakN) strongly implicate atrial myopathy in the diabetic process. Diabetes is a known risk factor for atrial fibrillation, and these early subclinical changes in atrial conduction and repolarization, detectable on a simple single-lead ECG, could represent a valuable biomarker for assessing atrial fibrillation risk long before overt arrhythmia occurs. This suggests that the utility of this technology may extend beyond diabetes diagnosis to the stratification of cardiovascular complications within the diabetic population.

In stark contrast to diagnosing the disease state, our attempts to predict real-time glycemic levels using ECG features were unsuccessful. The regression model for glycemia exhibited poor performance (R^2 = 0.22, high maximum error), with predictions plateauing beyond 5 mmol/L. This result is, in fact, expected and reinforces a crucial principle: The ECG reflects the end-organ electrophysiological impact of prolonged glycemic exposure and autonomic dysfunction, not the immediate, labile concentration of glucose in the blood. Glycemic levels fluctuate rapidly due to meals, stress, and medication, while the myocardial remodeling and autonomic imbalance that affect ECG parameters develop over months and years. Therefore, the ECG is a biomarker of chronic diabetic disease burden rather than an acute glucometer. This distinction is vital for setting appropriate expectations for this technology.

Table 5 The coefficient estimates of selected factors from the final model, along with their 95%CI

Parameter	Estimated coefficient	Lower limit 95%CI	Upper limit 95%CI	*P* value
Intercept	5.852	4.950	6.753	0.0000000
HFSNR	-0.058	-0.159	0.043	0.261
QRSfi	-0.001	-0.003	0.0009	0.253
T-wave flattening	0.0018	0.001	0.003	0.0000114
PpeakN	-0.0017	-0.004	0.0009	0.202

A weak to moderate correlation was observed between the true and predicted values (Spearman's rho = 0.488, $P < 0.001$).

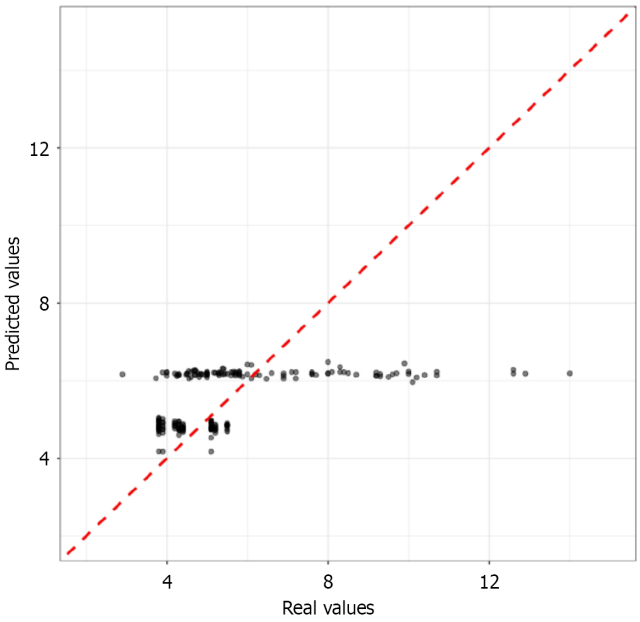

Figure 3 Graphical representation of the predicted *vs* true values plot.

A DL model, IGRNet, was developed to diagnose prediabetes using 12-lead ECGs, achieving an accuracy of 0.781 and an AUC of 0.777. This suggests potential for non-invasive, real-time prediabetes diagnosis[35]. Another study proposed a novel approach using single-lead ECGs to detect HbA1c levels, achieving an accuracy of 0.9015 and an AUC of 0.9899. This method highlights the potential for non-invasive and fast detection of diabetes-related metrics[36].

The DiaBeats algorithm, using ECG signal data, accurately predicted diabetes and pre-diabetes classes with a precision of 97.1% and an accuracy of 96.8%. This model utilized leads III, aVL, V4, V5, and V6, indicating the significant role of specific ECG leads in diabetes detection[21]. Combining single-lead ECG with other sensors (*e.g.*, glucose, accelerometer) has shown improved accuracy in diabetes prediction. A multisensor combination achieved a prediction accuracy of 98.2%, significantly higher than using single sensors alone[37].

A study utilized multi-resolution analysis of single-lead ECG signals to develop a system for detecting diabetic patients. The system achieved a classification accuracy of 91.5%, demonstrating the effectiveness of ML in identifying diabetes through ECG analysis[38]. Another framework used intrinsic time-scale decomposition and ML to screen for diabetes using single-lead ECG signals, achieving an accuracy of 86.9 %. This approach is suitable for resource-limited environments and highlights the potential for widespread screening[25]. The single lead ECG using Cardio_Qvark studied to diagnose ischemic heart disease and showed an improvement in the diagnostic accuracy comparing to the physical ECG-stress test[39].

DM induces distinct cardiac alterations through chronic hyperglycemia and insulin resistance, which create a detectable electrophysiological signature on a single-lead ECG. Key pathophysiological pathways include cardiac autonomic neuropathy, which disrupts sympathetic-parasympathetic balance and causes heterogeneous ventricular repolarization, and the accumulation of advanced glycation end-products that promote myocardial fibrosis. These processes directly impair the heart's electrical properties by slowing impulse conduction and destabilizing repolarization.

The integration of these subtle changes – manifested as Tfi, QTc, slowed ventricular activation (VAT), and altered P-wave morphology – creates a composite biomarker for diabetes. While individually minor, these features collectively form a distinct pattern that ML models can decode from a single-lead ECG, effectively identifying the integrated cardiac impact of diabetes before overt clinical disease develops (Figure 4).

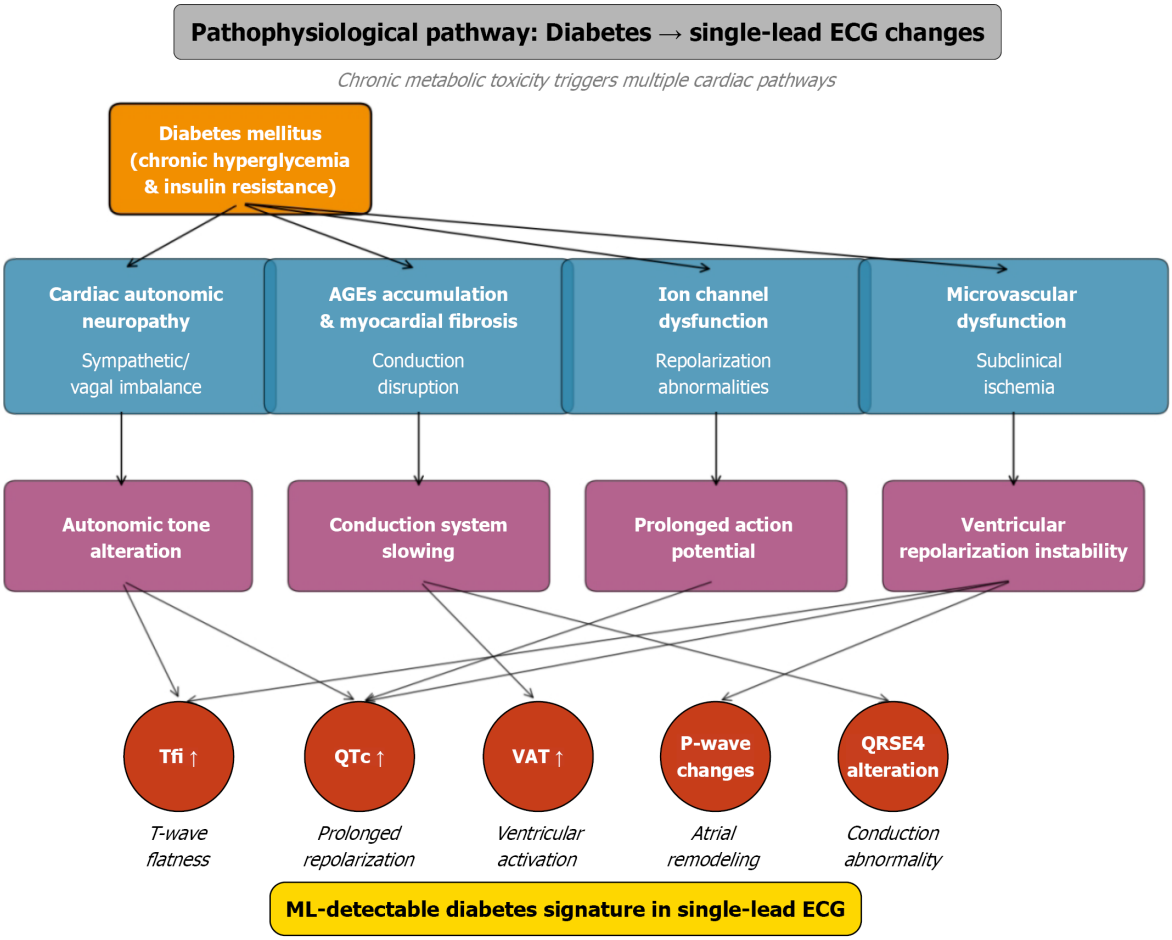

Figure 4 Pathophysiological pathway of diabetes-induced cardiac electrophysiological changes detected by single-lead electrocardiography and machine learning. Chronic hyperglycemia initiates four core mechanisms: Autonomic neuropathy, myocardial fibrosis, ion channel dysfunction, and microvascular impairment. These collectively alter cardiac electrophysiology, generating specific electrocardiography biomarkers including T-wave flattening (↑), prolonged QT interval (↑), and conduction abnormalities (ventricular activation↑, QRSE4). Machine learning integration of these features enables diabetes detection, with optimal performance in high-prevalence, moderate-cardiovascular diseases populations (cluster 4; area under the curve = 0.880). AGE: Advanced glycation end products; ECG: Electrocardiography; Tfi: T-wave flattening; QTc: Prolonged QT interval; VAT: Ventricular activation.

The integration of these subtle changes – manifested as Tfi, QTc, slowed ventricular activation, and altered P-wave morphology – creates a composite biomarker for diabetes. While individually minor, these features collectively form a distinct pattern that ML models can decode from a single-lead ECG, effectively identifying the integrated cardiac impact of diabetes before overt clinical disease develops.

Our study has several limitations. Firstly, it is a single-center study with a predominantly Caucasian cohort, which may limit the generalizability of our findings to other ethnicities and healthcare settings. Secondly, the imbalance in group sizes, particularly the smaller T1DM group, can affect the stability of the estimates for that subclass. Thirdly, while we adjusted for key confounders like age, sex, and BMI, residual confounding from unmeasured factors (*e.g.*, duration of diabetes, specific medications, presence of subclinical coronary artery disease) is possible. The diagnosis of DM was not solely based on HbA1c or oral glucose tolerance tests in all cases, relying partly on medical history, which could introduce misclassification bias. Finally, the model's performance, especially for T2DM, requires significant improvement before clinical implementation can be considered. One of the important limitations that the ECG recording was performed after the diagnosis of DM have been made, which means that this model reflects secondary electrophysiological changes caused by established disease rather than early screening potential. While this makes our model a potent tool for identifying individuals with existing diseases, it inherently limits our conclusions regarding its utility for *de novo* screening or early prediction. The model detects the cardiac sequelae of diabetes, not its prodromal phase. Therefore, our results demonstrate high performance in "diagnosing" the condition in a cross-sectional setting where the disease is already present, but they do not provide evidence that these ECG changes precede the conventional diagnosis. The high sensitivity and NPV are particularly valuable in this context, suggesting the model could be used to "rule out" significant diabetic cardiac involvement or to identify undiagnosed cases in high-prevalence settings, but it would likely miss individuals in the earliest stages of the disease, before substantial electrophysiological alterations have occurred. Longitudinal studies are essential to determine whether subtle ECG alterations can be detected during the prediabetic stage or in at-risk individuals before the onset of overt hyperglycemia. Such research is needed to truly unlock the potential of this technology for primary prevention and early intervention.

Future research directions should include multi-center, multi-ethnic validation studies with larger, balanced cohorts to improve model robustness and generalizability. Incorporating additional data streams from wearables, such as activity level and HR variability over time, could enhance predictive power. Exploring more complex DL architectures that analyze the raw ECG signal directly might capture features invisible to conventional parameterization. Furthermore, longitudinal studies are needed to determine if these ECG changes can predict the future development of diabetes or its complications, positioning single-lead ECG as a tool for risk stratification and prevention, not just diagnosis.

The optimal application of this technology would be in clinical settings where it serves as a decision-support tool to identify patients requiring definitive biochemical evaluation, rather than as a standalone diagnostic or broad population screening method. Our model detects electrophysiological changes associated with established diabetes rather than predicting future development of the disease. It should be viewed as an adjunct to, not a replacement for, established diagnostic criteria including fasting glucose, HbA1c, and oral glucose tolerance testing.

Diabetic state leaves a discernible imprint on the heart's electrical activity, detectable through ML analysis of a single-lead ECG. While not a replacement for standard glycemic tests, this technology shows potential as a supplementary clinical tool to identify individuals who may benefit from confirmatory glycemic testing, particularly in settings where standard diagnostic approaches are limited or when diabetes status is uncertain. It represents a significant step towards leveraging ubiquitous digital health technology for the early detection and management of one of the world's most prevalent chronic diseases.

CONCLUSION

The developed models demonstrate a stronger association between single-lead ECG parameters and the diagnosis of DM. This is likely attributable to the relatively stable and long-term physiological alterations associated with the state of disease. In contrast, single-lead ECG indicators do not adequately account for the values or variance in glycemic fluctuations.

REFERENCES

1 **Hossain MJ**, Al-Mamun M, Islam MR. Diabetes mellitus, the fastest growing global public health concern: Early detection should be focused. *Health Sci Rep* 2024; **7**: e2004 [*RCA*] [PMID: 38524769 DOI: 10.1002/hsr2.2004] [FullText] [Full Text(PDF)]

2 **Siam NH**, Snigdha NN, Tabasumma N, Parvin I. Diabetes Mellitus and Cardiovascular Disease: Exploring Epidemiology, Pathophysiology, and Treatment Strategies. *Rev Cardiovasc Med* 2024; **25**: 436 [*RCA*] [PMID: 39742220 DOI: 10.31083/j.rcm2512436] [FullText] [Full Text (PDF)]

3 **Conning-Rowland M**, Cubbon RM. Molecular mechanisms of diabetic heart disease: Insights from transcriptomic technologies. *Diab Vasc Dis Res* 2023; **20**: 14791641231205428 [*RCA*] [PMID: 38116627 DOI: 10.1177/14791641231205428] [FullText] [Full Text(PDF)]

4 **Ershova AI**, Ivanova AA, Kiseleva AV, Sotnikova EA, Meshkov AN, Drapkina OM. From biobanking to personalized prevention of obesity, diabetes and metabolic syndrome. *Cardiovasc Ther Prev* 2022; **20**: 3123 [*RCA*] [DOI: 10.15829/1728-8800-2021-3123] [FullText]

5 **Toscano A**, Barca E, Musumeci O. Update on diagnostics of metabolic myopathies. *Curr Opin Neurol* 2017; **30**: 553-562 [*RCA*] [PMID: 28763305 DOI: 10.1097/WCO.0000000000000483] [FullText]

6 **Furuta Y**, Tinker RJ, Hamid R, Cogan JD, Ezell KM, Oglesbee D, DeBerardinis RJ, Phillips JA 3rd; Undiagnosed Diseases Network. A review of multiple diagnostic approaches in the undiagnosed diseases network to identify inherited metabolic diseases. *Orphanet J Rare Dis* 2024; **19**: 427 [*RCA*] [PMID: 39543639 DOI: 10.1186/s13023-024-03423-3] [FullText] [Full Text(PDF)]

7 **Chandra TB**, Reddy AS, Adarsh A, Jabbar MA, Jyothi BN. Diabetes Prediction Using Gaussian Naive Bayes and Artificial Neural Network. 2024 International Conference on Distributed Computing and Optimization Techniques (ICDCOT); 2024 Mar 15-16; Bengaluru, India. Bengaluru: IEEE, 2024: 1-5 [DOI: 10.1109/icdcot61034.2024.10516226] [FullText]

8 **Viberti G**. Thiazolidinediones-benefits on microvascular complications of type 2 diabetes. *J Diabetes Complications* 2005; **19**: 168-177 [*RCA*] [PMID: 15866064 DOI: 10.1016/j.jdiacomp.2004.04.001] [FullText]

9 **Fan W**, Wong ND. Diabetes mellitus and macrovascular disease: epidemiology and cardiovascular risk assessment. In: Krentz AJ, Chilton RJ, editors. Cardiovascular Endocrinology and Metabolism: Theory and Practice of Cardiometabolic Medicine. Netherlands: Elsevier, 2023: 11-38

10 **Simon Machado R**, Mathias K, Joaquim L, Willig de Quadros R, Petronilho F, Tezza Rezin G. From diabetic hyperglycemia to cerebrovascular Damage: A narrative review. *Brain Res* 2023; **1821**: 148611 [*RCA*] [PMID: 37793604 DOI: 10.1016/j.brainres.2023.148611] [FullText]

11 **LeRoith D**. Hyperglycemia, Hypertension, and Dyslipidemia in Type 2 Diabetes Mellitus: Goals for Diabetes Management. *Clin Cornerstone* 2008; **9**: S8-S16 [DOI: 10.1016/S1098-3597(09)60021-1] [FullText]

12 **Beckman JA**, Creager MA. Vascular Complications of Diabetes. *Circ Res* 2016; **118**: 1771-1785 [*RCA*] [PMID: 27230641 DOI: 10.1161/CIRCRESAHA.115.306884] [FullText]

13 **Pedro-Botet J**, Chillarón JJ, Benaiges D, Flores-Le Roux JA. [Cardiovascular prevention in diabetes mellitus: A multifactorial challenge]. *Clin Investig Arterioscler* 2016; **28**: 154-163 [*RCA*] [PMID: 26655375 DOI: 10.1016/j.arteri.2015.10.003] [FullText]

14 **Viigimaa M**, Sachinidis A, Toumpourleka M, Koutsampasopoulos K, Alliksoo S, Titma T. Macrovascular Complications of Type 2 Diabetes Mellitus. *Curr Vasc Pharmacol* 2020; **18**: 110-116 [*RCA*] [PMID: 30961498 DOI: 10.2174/1570161117666190405165151] [FullText]

15 **Sone H**. Diabetes Mellitus. In: Vasan RS, Sawyer DB, editors. Encyclopedia of Cardiovascular Research and Medicine. Netherlands: Elsevier, 2017: 9-16

16 **Szuszkiewicz-Garcia MM**, Davidson JA. Cardiovascular disease in diabetes mellitus: risk factors and medical therapy. *Endocrinol Metab Clin North Am* 2014; **43**: 25-40 [*RCA*] [PMID: 24582090 DOI: 10.1016/j.ecl.2013.09.001] [FullText]

17 **Cavagnolli G**, Comerlato J, Comerlato C, Renz PB, Gross JL, Camargo JL. HbA(1c) measurement for the diagnosis of diabetes: is it enough? *Diabet Med* 2011; **28**: 31-35 [*RCA*] [PMID: 21210540 DOI: 10.1111/j.1464-5491.2010.03159.x] [FullText]

18 **Salarizadeh N**, Shojai S, Pebdeni AB, Nojoki F, Zargar SJ, Rezaei MH. Classical and new candidate biomarkers for developing biosensors in diagnosing diabetes and prediabetes; past, present and future. In: Barhoum A, Altintas Z. Advanced Sensor Technology: Biomedical, Environmental, and Construction Applications. Netherlands: Elsevier, 2022: 337-381

19 **Hou R**, Dou J, Wu L, Zhang X, Li C, Wang W, Gao Z, Tang X, Yan L, Wan Q, Luo Z, Qin G, Chen L, Ji J, He Y, Wang W, Mu Y, Zheng D. Development and validation of a machine learning-based model to predict isolated post-challenge hyperglycemia in middle-aged and elder adults: Analysis from a multicentric study. *Diabetes Metab Res Rev* 2024; **40**: e3832 [*RCA*] [PMID: 39031573 DOI: 10.1002/dmrr.3832] [FullText]

20 **Angelaki E**, Barmparis GD, Fragkiadakis K, Maragkoudakis S, Zacharis E, Plevritaki A, Kampanieris E, Kalomoirakis P, Kassotakis S, Kochiadakis G, Tsironis GP, Marketou ME. Diagnostic performance of single-lead electrocardiograms for arterial hypertension diagnosis: a machine learning approach. *J Hum Hypertens* 2025; **39**: 58-65 [*RCA*] [PMID: 39424986 DOI: 10.1038/s41371-024-00969-4] [FullText]

21 **Kulkarni AR**, Patel AA, Pipal K V, Jaiswal SG, Jaisinghani MT, Thulkar V, Gajbhiye L, Gondane P, Patel AB, Mamtani M, Kulkarni H. Machine-learning algorithm to non-invasively detect diabetes and pre-diabetes from electrocardiogram. *BMJ Innov* 2022; **9**: 32-42 [DOI: 10.1136/bmjinnov-2021-000759] [FullText]

22 **Glass GF**, Sudhir A, Pandit AAK. The ECG and Metabolic Abnormalities. In: Brady WJ, Lipinski MJ, Darby AE, Bond MC, Charlton NP, Hudson K, Williamson K, editors. Electrocardiogram in Clinical Medicine. Hoboken: John Wiley and Sons Ltd, 2020: 307-313

23 **Wald DA**. ECG manifestations of selected metabolic and endocrine disorders. *Emerg Med Clin North Am* 2006; **24**: 145-157, vii [*RCA*] [PMID: 16308117 DOI: 10.1016/j.emc.2005.08.010] [FullText]

24 **Darby AE**. Nontraditional Rhythm Disorders: Dysrhythmias Related to Metabolic and Toxicologic Conditions. In: Brady WJ, Lipinski MJ, Darby AE, Bond MC, Charlton NP, Hudson K, Williamson K, editors. Electrocardiogram in Clinical Medicine. Hoboken: John Wiley and Sons Ltd, 2020: 187-192

25 **Gupta K**, Bajaj V. A Robust Framework for Automated Screening of Diabetic Patient Using ECG Signals. *IEEE Sens J* 2022; **22**: 24222-24229 [DOI: 10.1109/JSEN.2022.3219554] [FullText]

26 **Sun JY**, Shen H, Qu Q, Sun W, Kong XQ. The application of deep learning in electrocardiogram: Where we came from and where we should go? *Int J Cardiol* 2021; **337**: 71-78 [*RCA*] [PMID: 34000355 DOI: 10.1016/j.ijcard.2021.05.017] [FullText]

27 **Sleiman J**, Daher M, Khalil M, Diab A, Kassem A. Biological age estimation from ECG using Artificial Intelligence approaches. 2024 2nd Jordanian International Biomedical Engineering Conference (JIBEC); 2024 Nov 27; Amman, Jordan. Bengaluru: IEEE, 2024: 78-83

28 **Buyya A**, Ogeti T, Suhas G, Kashapogula P, Panigrahy AK. Arrhythmias Classification by using STFT-based Spectrograms, Transfer Learning and Concatenation of features. 2023 4th International Conference for Emerging Technology; 2023 May 26-28; Belgaum, India. Bengaluru: IEEE, 2023 [DOI: 10.1109/INCET57972.2023.10170089] [FullText]

29 **Naik S**, Debnath S, Justin V. A Review of Arrhythmia Classification with Artificial Intelligence Techniques: Deep vs Machine Learning. 2021 2nd International Conference for Emerging Technology (INCET); 2021 May 21-23; Belagavi, India. Bengaluru: IEEE, 2021: 1-14

30 **Bergquist JA**, Zenger B, Brundage J, MacLeod RS, Shah R, Ye X, Lyones A, Ranjan R, Tasdizen T, Bunch TJ, Steinberg BA. Comparison of Machine Learning Detection of Low Left Ventricular Ejection Fraction Using Individual ECG Leads. *Comput Cardiol (2010)* 2023; **50**: 10.22489/cinc.2023.047 [*RCA*] [PMID: 39193485 DOI: 10.22489/cinc.2023.047] [FullText] [Full Text(PDF)]

31 **Kuznetsova N**, Sagirova Z, Suvorov A, Dhif I, Gognieva D, Afina B, Poltavskaya M, Sedov V, Chomakhidze P, Kopylov P. A screening method for predicting left ventricular dysfunction based on spectral analysis of a single-channel electrocardiogram using machine learning algorithms. *Biomed Signal Process Control* 2023; **86**: 105219 [DOI: 10.1016/j.bspc.2023.105219] [FullText]

32 **Moussaoui R**, Salem O, Mehaoua A. Analysis of Different Machine Learning Models for Diabetes Prediction. 2023 IEEE International Conference on E-health Networking, Application and Services (Healthcom); 2023 Dec 15-17; China. Bengaluru: IEEE, 2023: 43-48

33 **Wijoseno MR**, Permanasari AE, Pratama AR. Machine Learning Diabetes Diagnosis Literature Review. 2023 10th International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE); 2023 Aug 31-Sep 1; Semarang, Indonesia; Bengaluru: IEEE, 2023: 304-308

34 **Lancellotti P**, Zamorano JL, Habib G, Badano L. The EACVI textbook of echocardiography. Oxford: Oxford University Press, 2017

35 **Wang L**, Mu Y, Zhao J, Wang X, Che H. IGRNet: A Deep Learning Model for Non-Invasive, Real-Time Diagnosis of Prediabetes through Electrocardiograms. *Sensors (Basel)* 2020; **20**: 2556 [*RCA*] [PMID: 32365875 DOI: 10.3390/s20092556] [FullText] [Full Text(PDF)]

36 **Li J**, Lu J, Tobore I, Liu Y, Kandwal A, Wang L, Zhou J, Nie Z. Towards noninvasive and fast detection of Glycated hemoglobin levels based on ECG using convolutional neural networks with multisegments fusion and Varied-weight. *Expert Syst Appl* 2021; 186 [DOI: 10.1016/j.eswa.2021.115846] [FullText]

37 **Site A**, Nurmi J, Lohan ES. Machine-Learning-Based Diabetes Prediction Using Multisensor Data. *IEEE Sens J* 2023; **23**: 28370-28377 [DOI: 10.1109/JSEN.2023.3319360] [FullText]

38 **Jain A**, Verma A, Verma AK, Bajaj V. Tunable Q-factor wavelet transform based identification of diabetic patients using ECG signals. *Comput Methods Biomech Biomed Engin* 2024; 1-10 [*RCA*] [PMID: 38635476 DOI: 10.1080/10255842.2024.2342512] [FullText]

39 **Marzoog BA**, Chomakhidze P, Gognieva D, Silantyev A, Suvorov A, Abdullaev M, Mozzhukhina N, Filippova DA, Kostin SV, Kolpashnikova M, Ershova N, Ushakov N, Mesitskaya D, Kopylov P. Development and validation of a machine learning model for diagnosis of ischemic heart disease using single-lead electrocardiogram parameters. *World J Cardiol* 2025; **17**: 104396 [*RCA*] [PMID: 40308623 DOI: 10.4330/wjc.v17.i4.104396] [FullText] [Full Text(PDF)]

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