Near-Term Prediction of Ventricular Arrhythmias from Implantable Cardioverter Defibrillator Time-Series Data – A Proof-of-Concept Study

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Abstract

Ventricular arrhythmias (VA) remain a major public health concern and are frequently managed in high-risk patients using implantable cardioverter-defibrillators (ICDs). Beyond their therapeutic function, ICDs continuously capture physiological data that provide early warning of impending arrhythmic events. This study aimed to assess the feasibility of predicting VA occurrence from routine collectedly ICD-derived data. We retrospectively analyzed two patient groups: patients who experienced at least one VA episode and a control group without documented VAs. Eleven daily physiological parameters, including mean heart rate and shock impedance, were extracted, and deviations from a reference follow-up were quantified using linear mixed-effects models, yielding 44 candidate predictive features. The 10 most informative variables were identified through clinical review and Morris sensitivity analysis. A gradient-boosting machine-learning model was then trained, with performance evaluated via 10-fold cross-validation. The model achieved a correct classification rate of 77% and an area under the receiver operating characteristic curve of 0.76. This study provides proof of concept that routinely collected ICD data can enable short-term VA prediction, opening a potential avenue for timely, preventive clinical interventions.

1. Introduction

Sudden cardiac death (SCD) affects an estimated 4-5 million individuals worldwide each year, accounting for up to 20% of all-cause mortality [1]. It is defined as unexpected, natural cardiac death resulting from a malignant ventricular arrhythmia (VA).

The abrupt onset of VA and the requirement for immediate intervention are critical determinants of prognosis. Cardiopulmonary resuscitation and external defibrillation must be initiated within minutes of VA onset to maximize survival. Although overall survival rates remain low (less than 10%), immediate recognition and prompt resuscitation can achieve survival rates approaching 80% in ideal scenarios [1,2].

Contrary to the notion that SCD always occurs "out of the blue," studies have shown that up to half of patients experience warning symptoms shortly before collapse [3]. This observation supports the emerging concept of *near-term prevention*, whereby timely recognition of physiological changes could enable rapid preventive or therapeutic intervention [4,5]. Since the 1990s, implantable cardioverter defibrillators (ICDs) have been recommended for patients at high-risk of SCD [1,6]. In addition to delivering life-saving therapies, modern ICDs can record intracardiac electrograms during clinically significant arrhythmias and capture daily physiological metrics such as physical activity levels.

Given the practical limitations of storing large volumes of electrogram data over extended periods, we propose an alternative strategy: predicting VA events using routinely collected physiological parameters from ICDs.

2. Study design

This work is part of the Implantable Automatic Defibrillator – Primary Prevention (DAI-PP) research consortium, a national multicentre programme aimed at improving the prediction of SCD/VAs, as well as optimizing the net clinical benefit of ICDs. Among its ongoing investigations, the flagship DAI-PP cohort study seeks to enroll 10,000 patients (recruitment began in 2018) and follow them for 10 years using a continuous follow-up strategy enabled by ICDs connected to remote monitoring systems. Feasibility of such a collaborative approach was demonstrated through a pilot study [7]. Device data are collected from all manufacturers.

2.1. Data base

Given the heterogeneity of physiological data recorded across device manufacturers, this proof-of-concept study was restricted to patients implanted with a Biotronik ICD. Two distinct patient groups were analyzed:

- VA group: 64 patients who experienced at least one documented episode of VA. To exclude false positives such as supraventricular arrhythmia or artefacts, all corresponding electrograms (EGMs) were reviewed by an experienced cardiologist.
- Control group: 776 patients without any documented VA during follow-up.

The recruitment pathways for these two groups are illustrated in Figures 1 and 2, respectively.

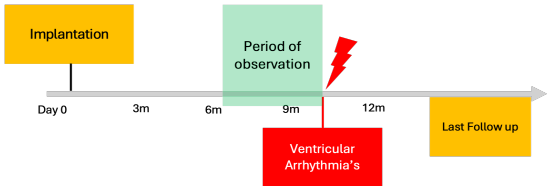

Figure 1. Recruitment procedure for the VA group.

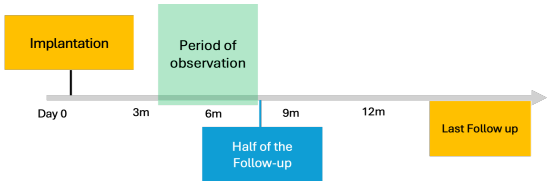

Figure 2. Recruitment procedure for the control group

2.2. The physiological features set

Eleven daily physiological variables (table 1) were available for analysis, representing a compromise between the parameters recorded by single-, dual- and triple-chamber Biotronik ICDs.

Table 1. Physiological variables included in the analysis.

V1	Mean ventricular rate
V2	Mean resting ventricular rate
V3	Right ventricular lead impedance
V4	Shock impedance
V5	Mean sensitivity threshold
V6	Minimum sensitivity threshold
V7	Percentage of right ventricular pacing
V8	Intensity of Physical activity
V9	Number of supraventricular tachycardias
V10	Number of non-sustained ventricular tachycardias
V11	Number of ventricular tachycardias in zone 1

2.3. Selection of control patients

Given the limited number of patients in the VA group, control patients were selected at a 2:1 ratio (two controls per VA patient). This approach ensured greater homogeneity of the dataset, which is essential for valid comparison between groups. Statistical matching was performed to align the control and VA groups. Exact matching was applied for sex, type of heart disease, and indication for implantation. Additionally, matching was carried out for age and left ventricular ejection fraction using the Mahalanobis distance, which accounts for the covariance structure of the variables when assessing similarity between individuals.

3. Methods

Analysis was restricted to the 30-day period preceding the occurrence of a ventricular arrhythmia (VA). Day 0 was defined as 30 days before the VA episode, and day 29 as the day immediately preceding the event. In a first step, the characteristics of the database were explored. Temporal representations of the multidimensional data revealed distinct patterns between VA and control patients—for example, a progressive increase in mean heart rate before ventricular tachycardia. These findings informed the selection of relevant attributes and the choice of an appropriate classification method, which are described below.

3.1. Definition of the set of variables

Preliminary analyses indicated that several variables exhibited temporal variation. To capture this information, we considered not only the daily raw data but also two derived measures: (i) the day-to-day difference between consecutive measurements, and (ii) the temporal trend estimated using a linear mixed-effects model.

3.2. Temporal difference

Let $x_{i,j}(t)$ denote the jth explanatory variable of patient i at time t. A simple way to capture temporal change is to compute the difference between two time points:

$$\Delta_{ij} = x_{ij}(ta) - x_{ij}(to)$$

where *to* is the reference time and *ta* is the time point selected for comparison.

3.3. Modeling by linear mixed effects

A linear mixed-effects model incorporates both fixed effects, which influence the mean response, and random effects, which account for variability between individuals. In this study, each patient had repeated measurements of each variable over the 30-day observation window. This structure was modelled by introducing patient-specific random effects. For each variable j and patient i, the model

is expressed as:

$$x_{ij}(t) = b_{oij} + a_{1ij}t + \epsilon_{ij}(t)$$

where :

- $b_{0ij} = \beta_0 + \beta_{ij}$ is the mixed intercept, with β_0 as the fixed intercept and β_{ij} as the patient-specific random intercept.
- $a_{1ij} = \alpha_1 + \alpha_{aij}$ is the slope, with α_1 as the fixed slope coefficient and α_{aij} as the patient-specific random slope.
- $\varepsilon_{ij}(t)$ is the residual error term.

In summary, for each variable, four derived measures were considered: *i)* the daily raw value $x_{i,j}(t)$ ($t \in [0, 1, ...29]$), *ii)* the temporal difference Δ_{ij}, *iii)* the intercept b_{oij}, *iv)* the slope a_{1ij} leading to a total of 44 explanatory variables capturing the temporal dynamics of the physiological parameters over the 30-day period.

3.4. Gradient boosting model

Several classification algorithms were tested and evaluated. Gradient boosting (GB) achieved the highest performance in terms of area under the receiver operating curves (AUC), F1-score, and accuracy. Gradient boosting is a supervised learning technique primarily used for regression and classification. It constructs a strong predictive model by sequentially combining multiple weak learners, typically shallow decision trees. Each successive tree is trained to correct the residual errors of the preceding ensemble, with the correction process guided by gradient descent optimization of a specified loss function. In this study, the Extreme GB (XGBoost) implementation was used, owing to its computational efficiency, regularization capabilities, and proven performance in tabular data prediction tasks.

4. Results

Results were obtained through an iterative process involving the selection of the most informative variables, the optimization of the observation period and the final performances.

4.1. Selection of the relevant variables

Given the limited number of observations in the VA group, the input dimensionality of the model was reduced while retaining the relevant informative predictors. Three criteria were applied to guide variable selection: clinical relevance, discriminant analysis and Morris's sensitivity analysis.

Clinical relevance: Selected variables had to be interpretable and meaningful to clinical experts. For example, an increase in heart rate is a well-recognised phenomenon preceding ventricular arrhythmia [8].

Discriminant analysis: Stepwise discriminant analysis was used to assess the contribution of each variable in distinguishing between the VA and control groups.

Morris sensitivity analysis: Following model training, sensitivity analysis was conducted to identify variables whose modification produced the largest changes in classification performance.

By combining these three approaches, ten variables were ultimately retained for model development.

Table 2. The ten selected variables (V1 and V11 are detailed in Table 1).

Variables	Day	Intercept	Slope	Δ
V1		X	X	X
V2	X			
V3				
V4		X		
V5		X		
V6			X	
V7				
V8		X		
V9				
V10			X	
V11			X	

4.2. Optimization of the analysis window

The optimal duration of the analysis window was determined empirically. Time windows ranging from 5 to 30 days were tested to train the GB model. Model performance (assessed by AUC, F1-score and accuracy) for each window length is presented in Figure 3. The highest performance was achieved with a 19-day window.

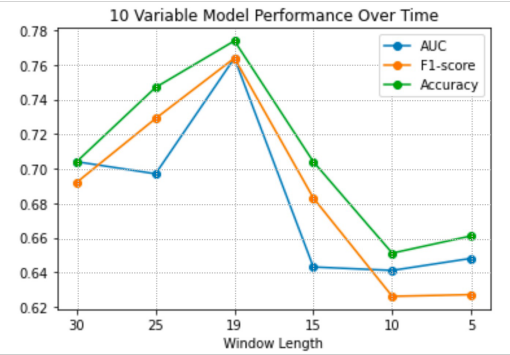

Figure 3. Performance according to the window size.

4.3. The final performance

This analysis included 186 observations described by 10 variables. Model evaluation was performed using 10-fold cross-validation. A 19-day sliding window is applied across the 30-day pre-event period.

The results of the optimized GB model are shown in Figure 4. Performance was close to random when the analysis window was distant from the VA event. In contrast, predictive accuracy improved progressively as

the window approached the date of the arrhythmia.

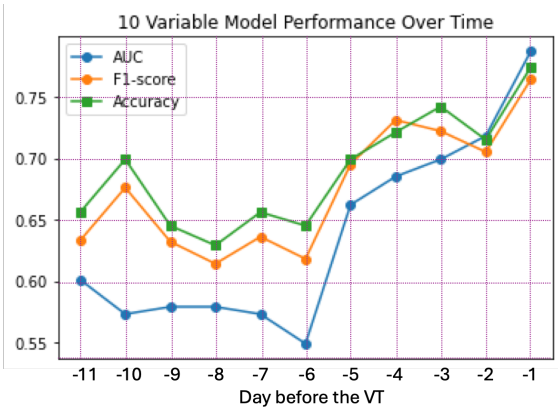

Figure 4. Performance according to the number of days before the VA event.

5. Discussion

This proof-of-concept study was designed to assess the feasibility of predicting VAs occurrence using physiological data routinely collected by ICDs. Our findings demonstrate that patients at increased risk of VA can be identified with a good classification performance (accuracy = 0.77). These results are consistent with those reported by Ginder et al. in 2023 [8], who reached similar conclusions.

A second objective was to identify variables most relevant for prediction. Morris sensitivity analysis applied to the 44 candidate variables highlighted ventricular rate and the number of non-sustained ventricular tachycardia episodes in the preceding days as associated risk factors—findings in line with prior literature [9]. Physiologically, these associations may reflect heightened sympathetic nervous system activity. In addition, consistent with the observations of Ginder et al. [8], our study identified shock impedance as a potential risk factor.

Despite encouraging results, the misclassification rate remained relatively high (approximately 20%). The most likely explanation is the limited sample size in this proof-of-concept study and heterogeneity in the type of ICD where, to assure homogeneity, certain parameters, potentially informative, were excluded from the analysis, which may have reduced predictive performance.

6. Conclusion

The significance of this study lies in providing a robust proof of concept for predicting ventricular arrhythmias using physiological data obtained through ICDs. Its novelty resides in the application of linear mixed-effects models to capture dynamic temporal trends in predictive variables. Future research will build on the large-scale DAI-PP Biotronik database, which currently includes 500 patients with documented VAs and more than 2,000 controls. This expanded dataset will enable the development and validation of advanced deep-learning architectures which have already shown promising results [10,11]. Furthermore, incorporating data from other device manufacturers represents an important next step to enhance model generalizability and predictive accuracy.

Acknowledgments

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