

AI for the Prediction of Atrial Fibrillation or Atrial Tachycardia Episodes in Patients with Pacemakers

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Abstract

Background: Predictive medicine relies on algorithms to determine clinical treatments tailored to each patient's individual characteristics. Predictive models based on AI have shown promise in identifying Atrial Fibrillation (AF) episodes; however, they rarely focus on short-term dynamic prediction.

Objective: This study aims to evaluate the use of an AI model and remote monitoring data extracted from pacemaker devices to predict the onset or worsening of arrhythmias in the short term.

Methods: This was an observational, prospective, multicenter study in which data from 314 patients were analyzed. A total of 65,243 data sequences were collected, of which 55,532 were used to train the algorithm. This model used 31-day records to predict whether the number of arrhythmic episodes increased, decreased, or remained the same in the following 14 days.

Results: The sensitivity and specificity of the generated predictions were calculated from 9,711 prediction/observation pairs. The global sensitivity was 66.4% and specificity was 77.4%; with a sensitivity of 76.8% and specificity of 39.6% in patients with baseline arrhythmia; and a sensitivity of 39% and a specificity of 81% in patients without baseline arrhythmia. The analysis for the patient subgroup without prior history of AF yielded a 69% sensitivity and an 80% specificity.

Conclusions: This model was capable of predicting short-term increases or decreases in arrhythmic episodes with reasonable sensitivity and specificity, using data collected through remote monitoring of implantable devices. The model's performance is expected to improve progressively as more data samples become available, including demographic and clinical records. Clinical Trial: Trial code: IA-Pacing Spain

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Original Manuscript

Acronyms

AF Atrial Fibrillation.

AI Artificial Intelligence.

AV Atrioventricular.

COPD Chronic Obstructive Pulmonary Disease.

CV Cardiovascular.

ECG Electrocardiogram.

ML Machine Learning.

1. Introduction

In recent years, the use of Artificial Intelligence (AI) for the diagnosis, prognosis, and the evaluation of risk factors and the response to treatment of different pathologies has shown significant advancements. This has had a positive impact on healthcare systems, improving the medical handling efficiency and reducing the number of adverse events [9, 15].

Cardiac electrophysiology has emerged as one of the fastest growing sub-specialties within cardiology over the last few decades [2, 18], which is evidenced by numerous technological advancements aimed at detecting, predicting, and managing cardiac arrhythmias [6, 14]. Among those, the prediction of cardiac arrhythmias is especially relevant for patients with Atrial Fibrillation (AF), who are 5 times more likely to suffer thromboembolic events than AF-free patients [12].

Additionally, training information systems from enormous data quantities from clinical reports and complementary tests from millions of patients not only enables episode prediction in AF-diagnosed patients, but also allows the diagnosis of asymptomatic patients, allowing early intervention and reducing the number of clinical events [8].

Although several authors have published many AI- and Machine Learning (ML)-based models for AF prediction in different contexts with good results [4, 10, 11], these models were primarily trained and evaluated for predictions over extended periods (often up to one year), which provided them with a great amount of input data. However, none of the existing algorithms support short-term, dynamic AF prediction in patients with implantable cardiac devices.

For that reason, this study aims to evaluate the use of AI on data extracted from remote pacemaker monitoring for short-term prediction of the onset or increase of AF episodes.

2. Materials and Methods

2.1. Study Design

This was an observational, prospective, multicenter study in which we analyzed data from 314 patients enrolled in the *IA Pacing* study between May 2022 and May 2024 across 12 centers in Spain.

All procedures were performed in compliance with relevant laws and institutional guidelines and have been approved by the ethics committee at each participating center. Signed informed consent was obtained from each patient prior to enrollment. The study protocol conforms to the ethical guidelines of the 1975 Declaration of Helsinki as reflected in a priori approval by the institution's human research committee.

Inclusion criteria for the study and complete patient recruitment by hospital can be seen in the

appendices in the Supplementary Material (Section A).

2.2. Baseline Characteristics

Medical records were used to assess patients' baseline characteristics, including demographic data, cardiovascular risk factors, history of arrhythmias, details of the implanted device, procedural data, and pharmacological treatment.

2.3. Arrhythmia Prediction

To calculate arrhythmia predictions, we used data generated through remote monitoring of patients' pacemakers, which included the following variables:

- **General variables:** activity level, respiratory rate, and maximum and mean heart rate.
- **Atrial fibrillation-related variables:** total number of arrhythmia episodes per day, total duration of those arrhythmias, atrial tachycardia response (mean and maximum ventricular rate during rapid ventricular response events) and apnea-hypoapnea index.
- **Heart failure-related variables:** percentage of left ventricular pacing, and standard deviation of the average NN intervals every 5 minutes (SDANN).

When considering arrhythmia episodes per day, we considered only those arrhythmias that were of the type "Supraventricular tachycardia" or "Atrial fibrillation".

The algorithm divided the data into sequences of 45 days. The first 31 days were used for the algorithm to analyze and predict what would happen in the following 14 days. Therefore, after observing the telemetry data for 31 days, a prediction was generated about the next 14 days. The appearance or absence of arrhythmias was categorized into 4 categories according to:

1. **Increase:** Patient already has arrhythmias during the 31 days of observation and the average number of arrhythmias during the 14 days of prediction increases.
2. **Decrease:** Patient already has arrhythmias during the 31 days of observation but the average number of arrhythmias during the 14 days of prediction decreases.
3. **Remains at 0:** Patient doesn't have arrhythmias during the 31 days of observation and the average number of arrhythmias during the 14 days of prediction remains at 0.
4. **Goes from 0 to something:** Patient doesn't have arrhythmias during the 31 days of observation but some arrhythmias occur during the 14 days of prediction.

Subsequently, to simplify the analysis, the previous 4 categories were regrouped into 2:

1. **Increased:** Average number of arrhythmias during the day increases (categories 1 and 4).
2. **Maintained or decreased:** Average number of arrhythmias during the day remains or decreases (categories 2 and 3).

Detailed information about the categorization in these categories is provided in the Supplementary Material (Section B). Similarly, information about data preprocessing and final data volume is given in the Supplementary Material (Section C). Finally, the creation of the predictive model using AI, along with its parameters, its training, and its final results over the *test* data, is detailed in the Supplementary Material (Section D).

Furthermore, to generate explanations in the model, a specialized tool called SHAP was used, which leverages game theory-based results to identify the variables that had the greatest importance in making each prediction. In Appendix E in the Supplementary Material, the average results for the predictions of each class can be observed, where some clinically relevant variables stand out, such as the presence of apneas or the SDANN. Alongside SHAP, the entropy of the classification was used as a measure of uncertainty to obtain confidence estimations for each

prediction, as explained in Appendix F in the Supplementary Material. These tools combined reduce the opacity of AI models, increasing trust in them as a tool for clinical decision-making.

2.4. Statistical Analysis

Categorical variables are presented as frequency (%), while quantitative variables are expressed as mean $\pm$ SD (Standard Deviation). The sensitivity and specificity of the arrhythmia prediction were calculated from a 2 $\times$ 2 contingency table, considering prediction and reality during the follow-up period. Sensitivity and specificity were calculated from 9,711 prediction/observation pairs. Statistical analyses were performed using SPSS version 17.0.

3. Results

For this study, a total of 65,243 data sequences were collected. Of these, 55,532 were used to train the algorithm, and the remaining 9,711 were used to analyze the sensitivity and specificity of the generated predictions.

3.1. Clinical Characteristics of the Population

Table 1 shows the clinical characteristics of the participating patients.

Sixty-one percent of patients were male, and the mean age was 77 $\pm$ 9 years. The most common indication for pacemaker implantation was atrioventricular block, while the predominant pacing site was the right ventricular apex. Sixty-eight percent of patients had at least one cardiovascular hospitalization in the year prior to enrollment.

Regarding cardiovascular risk factors, most patients had hypertension and dyslipidemia, while the prevalence of diabetes mellitus was 39.9% of patients. The mean CHA₂DS₂-VASc score was 3.5 $\pm$ 1.5. A history of prior Atrial Fibrillation was present in 15.3% of the patients.

3.2. Prediction of Arrhythmia Onset Using AI

The sensitivity of the AI-based predictive model was 66.4% for the full sample, with a 95% confidence interval (CI) of 64.3–68.3, while specificity was 77.4% (95% CI: 76.4–78.4).

Next, we grouped the patients based on whether they had presented arrhythmias during the initial 31-day period used by the algorithm to generate predictions. Two groups were defined:

1. Patients with arrhythmias during the baseline period: those classified in the “increase” or “decrease” categories.
2. Patients without arrhythmias during the baseline period: those in the “remains at 0” or “goes from 0 to something” categories.

Based on the contingency tables generated, we obtained a sensitivity of 76.8% (95% CI: 74.6–78.8) and specificity of 39.6% (95% CI: 35.8–43.5) in patients with arrhythmias during the baseline period, and a sensitivity of 39% (95% CI: 35.1–43) and specificity of 81% (95% CI: 80–81.9) in patients without arrhythmias during that period.

Also, using data sequences from patients with no prior history of AF (n = 232 patients, 7,259 data points), we calculated the model's sensitivity and specificity for arrhythmia prediction, considering both supraventricular tachycardia and AF as the presence of arrhythmia. These were 69% (95% CI: 66.5–71.5) and 80% (95% CI: 79.3–81.3), respectively.

The raw values from the contingency table for each group can be observed in Table 2.

3.3. Web Application Development

Based on the AI-generated predictions of arrhythmias for the following 14 days and the explanations based on SHAP and confidence estimation, a web application was developed to allow

medical personnel to monitor each patient. This interface can be seen in Figure 1 and presents the prediction along with its confidence score (expressed as a percentage), aiding clinical decision-making.

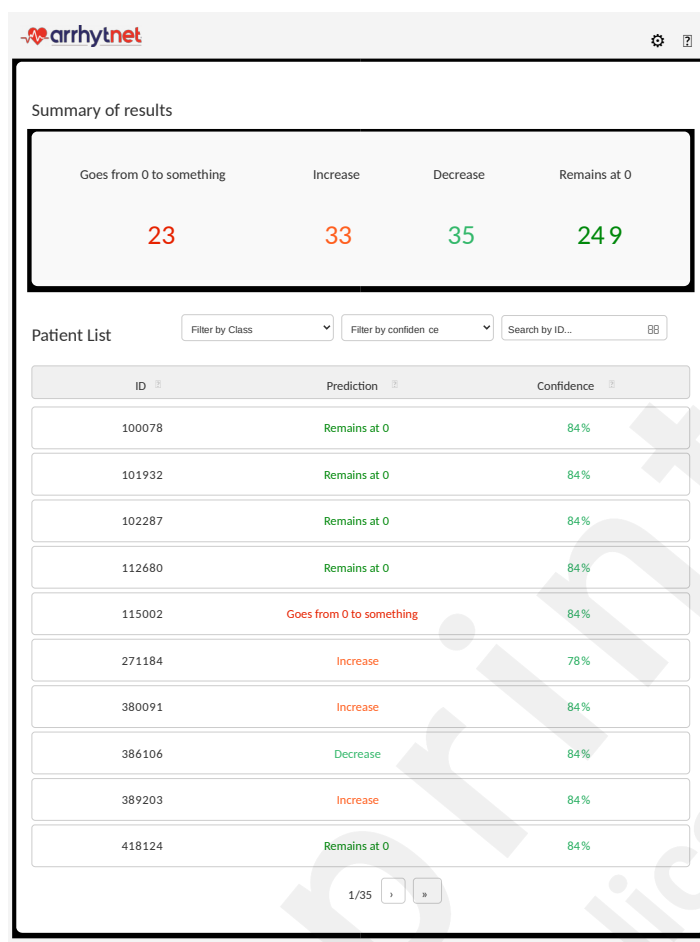
Table 1: Baseline characteristics of the patients (n = 314). Data are expressed as frequency (n (%)) or mean $\pm$ SD.

Baseline characteristics	Statistic
Demographics	
Male	192 (61.3)
Age (years)	77 $\pm$ 9.2
Pacemaker indication	
AV block	240 (76.7)
Sinus bradycardia	24 (7.7)
Other indications	49 (15.7)
Pacing type	
Right ventricular apex	259 (83.5)
Left branch	51 (16.5)
CV hospitalizations in the last year	
0	35 (18.1)
1	132 (68.4)
> 2	26 (13.5)
CV risk factors	
Arterial hypertension	236 (76.6)
Diabetes mellitus	118 (39.9)
Dislipidemia	202 (66.9)
Obesity	54 (19.8)
Current smoking	22 (7.7)
Current alcoholism	14 (5.1)
Cardiovascular history	
NYHA I	101 (54)
Ischemic cardiopathies	52 (18.8)
Valvulopathies	77 (27.1)
Miocardopathies	34 (12.2)
AIT/ACVA	36 (13)
Peripheral vascular disease	21 (7.8)
CHA2VASc	3.5 $\pm$ 1.5
Arrhythmia history	
Atrial fibrillation	42 (15.3)
Ventricular arrhythmia	5 (1.6)
Other comorbidities	
COPD	24 (8.8)
Asthma	17 (6.3)
Pharmacological treatment	
Antiaggregants	124 (39.4)
Anticoagulants	57 (18.2)

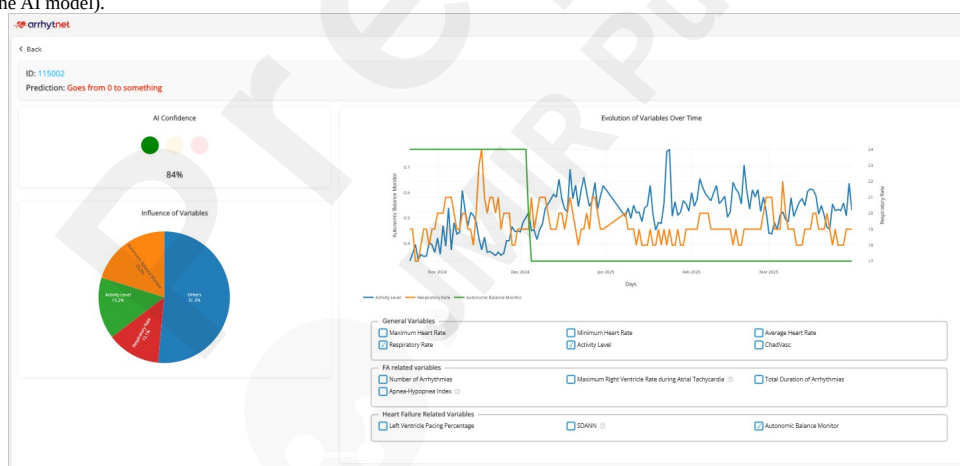
IECA/ARAI/ARNI	178 (56.7)
Beta-blockers	79 (25.2)
Loop diuretics	66 (21)

Table 2: Arrhythmic episodes prediction and ground truth for various patient groups.

AIarrhythmiaprediction	Follow-upground-truth		Sensitivity	Specificity
	Increased	Maintained/Decreased		
Total patients				
Increased	1456	1696	66.4%	77.4%
Maintained or decreased	738	5821		
With arrhythmia in last 31 days				
Increased	1219	393	76.8%	39.6%
Maintained or decreased	368	258		
Without arrhythmia in last 31 days				
Increased	237	1303	39.0%	81.2%
Maintained or decreased	370	5563		
With no prior AF history (n=232)				
Increased	951	1157	69.1%	80.3%
Maintained or decreased	426	4725		



(a) Main view of the web platform, showing the list of patients with their predictions and estimated confidence along with a summary of the patients' results and search filters to aid doctors (quantity of patients is higher since predictions can be made on patients with 31 < days of measurement < 45 instead of just > 45 used to validate the AI model).



(b) Details of a patient with its prediction, estimated confidence, most important variables for the decision-making based on SHAP(pie chart) and variables evolution.

Figure 1: Final version of the web application developed for the visualization of clinical predictions.

4. Discussion

AI implementation is transforming healthcare in cardiology, especially in the context of heart rhythm related disorders. This study is, to the best of our knowledge, the first to use data exclusively from remote pacemaker monitoring to dynamically predict arrhythmia onset in AF patients in the short term (in the 14 days following the monitoring period).

Given how important arrhythmia detection is for the identification of patients at risk of having a stroke or systemic embolism, AI algorithms have lately been used for detection, prediction and

treatment tailoring of AF patients [8].

Focusing on AF episode prediction, several authors have achieved significant advancements in developing AF-predicting algorithms in varying time periods from initial measured data. Kao *et al.* [7] have developed a model able to predict new arrhythmic episodes in the span of a year with a 98.7% specificity using a database of clinical data gathered for 3 years from elderly patients with no electrocardiographic data.

Similarly, Hill *et al.* [4] implemented a ML model to detect, from medical record data, risk factors for developing AF in asymptomatic patients.

Another author used data from 100,000 ECGs, taken from 40,000 patients in a mean of 2 years of followup, to predict the time before a new arrhythmic episode, obtaining similar results to medical record-based predictions [10].

In our study, unlike the studies cited before, no medical record was used to train the system. The algorithm actually compares daily data from the remote monitoring of the implantable device. We consider this a strength of the study since only relatively few data are needed to estimate the risk of suffering an arrhythmic episode in any patient with a remote monitoring implantable device.

Although our algorithm does not compute the time before a new arrhythmic episode, it does enable the identification of the patients at risk of suffering episodes of supraventricular arrhythmias in the short term (14 days following the measurement), which would improve their medical care.

Our predictive model correctly predicted whether arrhythmias would rise in almost 75% of the cases, with 66.4% global sensitivity and 77.4% specificity.

In patients with no registered prior history of arrhythmia (n=232), who constitute the group most likely to benefit from early therapeutic interventions, the analysis showed higher values of sensitivity and specificity, 69% and 80%, respectively.

These data are similar to those reported by the model by Tiwari *et al.* [17], whose model achieved 75% sensitivity and 85% specificity.

The fact that our algorithm predicted the occurrence of arrhythmias with a similar performance to the model by Tiwari *et al.* (whose model predicted arrhythmias in a 6-month time window from clinical records from 2 million younger patients) with relatively few data is a promising starting point to continue enhancing the AI training and, therefore, the obtained results. Like Tiwari *et al.*, we deem it necessary to optimize the AI models to increase their sensitivity and reduce false positives.

One strength of our approach is that it requires only a small amount of data for training, because the implantable devices continuously monitor cardiac activity. We also employed a tool to standardize variable names across devices, which allowed us to combine datasets and increase the amount of data for the training, which is another strong point of the study.

It is worth mentioning some limitations of the proposed model. Firstly, the training didn't consider demographic variables. Including these factors could increase the predictive capabilities and justify the use of AI over classical risk factor predictors [1].

Moreover, it has been observed that the models encompassing more than one type of variable — like clinical data and ECG, echocardiogram or magnetic resonance imaging, for instance — increase the prediction sensitivity [13]; this should be taken into account when designing and training future AI algorithms.

Secondly, although the number of prediction/reality sequences is high (more than 9,000), data pairs were taken from a cohort of 314 patients, which could be considered low. The size of the cohort could then be increased to augment the training database and refine the output of the model, optimizing AI training. Additionally, the ability of cardiac devices to differentiate arrhythmia types should be considered when using the extracted data to train the model [5, 16].

Further research could focus on increasing the prediction period, and on differentiating types of arrhythmias, given the clinical implications of *de novo* episodes of AF and the need for

anticoagulation therapy.

Lastly, we would like to mention the importance of an intuitive web design to present the obtained data. It has been proven that the use of mobile applications in the healthcare system is determined by how user-friendly and intuitive they are, and the quantity of data that is to be provided for their use [3]. If the application quickly displays the prediction along with the patient's arrhythmia risk percentage, it is more likely that healthcare professionals will use these tools.

In conclusion, our study proves that an increase or decrease in arrhythmias can be predicted with reasonable sensitivity and specificity using data from implantable devices. We believe that the model could improve the prediction performance as it is trained on more data, including demographic and clinical data. All the previously mentioned factors, together with the user-friendly visualization of the prediction on a simple app, make this first phase of the study a good starting point. This allows us to continue working on improving the monitoring and treatment of patients with implantable devices for cardiac pacing.

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Supplementary Files

Multimedia Appendixes

Supplementary material.

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TOC/Feature image for homepages

Graphical Abstract.

