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A Machine Learning Approach For Atrial Fibrillation Detection From Simulated ECG Signals

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Abstract: Atrial fibrillation (AFib) is one of the most prevalent cardiac arrhythmias and a leading cause of stroke and hospitalization in elderly patients. Timely diagnosis is crucial, yet continuous ECG monitoring and expert evaluation remain difficult to scale outside clinical environments. This work presents a simple yet effective machine learning model capable of detecting AFib using synthetic ECG data. A dataset of 1000 samples was simulated, evenly split between normal rhythm and AFib. Three key features were extracted: RR interval variability, heart rate variability (HRV), and a simulated index for P-wave presence. A Random Forest classifier trained on this dataset achieved an accuracy of 99.7%, precision of 100%, recall of 99.3%, and an area under the ROC curve (AUC) of 1.0. These results suggest that machine learning techniques, even when applied to simplified data, can offer valuable tools for early arrhythmia screening, potentially enabling low-cost, scalable solutions for wearable health monitoring.

Keywords: Atrial Fibrillation, ECG, Machine Learning, Random Forest, Arrhythmia, Wearable Health Monitoring.

INTRODUCTION

Atrial fibrillation (AFib) is the most common sustained cardiac arrhythmia in adults, affecting over 33 million individuals worldwide, with a prevalence that increases significantly with age. It is characterized by irregular and often rapid heart rhythms originating from chaotic electrical activity in the atria, leading to uncoordinated contraction. AFib is associated with substantial morbidity and mortality, including a fivefold increased risk of ischemic stroke, and it contributes to congestive heart failure, cognitive decline, and reduced quality of life [Goldberger, A. L. *et al*., 2000]. Despite its clinical importance, AFib often goes undiagnosed, especially in asymptomatic or paroxysmal cases, where the arrhythmia may occur intermittently and unpredictably.

Currently, the gold standard for diagnosing AFib is the analysis of ECG recordings by a trained physician. This process, however, is time-consuming and resource-intensive, particularly when long-term monitoring is required. While 12-lead ECGs are standard in hospitals, many screening and monitoring settings rely on single-lead or wearable devices. This evolution toward mobile health solutions has created a growing need for automatic AFib detection tools that are lightweight, interpretable, and reliable.

In recent years, artificial intelligence (AI) and machine learning (ML) have emerged as transformative technologies in medical diagnostics. Several studies have demonstrated that deep neural networks can achieve cardiologist-level performance in arrhythmia classification tasks [Hannun, A. Y. *et al*., 2019][Rajpurkar, P. *et al*., 2017]. However, these models often require large amounts of labeled data, significant computational resources, and tend to lack interpretability — a key factor in clinical acceptance.

This study takes a different approach by focusing on whether a simple ML model, trained on synthetic ECG data and using basic physiologically meaningful features, can effectively detect AFib. Rather than relying on complex neural networks or detailed signal processing, we simulate ECG behavior using statistical patterns associated with AFib — such as RR interval variability and the absence of a P-wave — and test the performance of a standard Random Forest classifier. This approach aligns well with the requirements of embedded systems and low-power wearable devices, which need efficient and transparent decision-making processes.

The use of simulated data, while a simplification, allows precise control over feature distribution and enables the development of a balanced, noise-free dataset for initial model validation. The objective is not to replace clinical data but to establish a proof of concept: can basic ML techniques detect AFib reliably using a limited and interpretable feature set?

The use of synthetic data in this phase is intended to lay the computational groundwork for future real-world applications, serving as a starting point

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for the development of fully integrated and scalable AFib detection systems.

MATERIAL AND METHODS

Dataset Simulation

A synthetic dataset consisting of 1000 ECG samples was generated using Python. The dataset was balanced, containing 500 samples representing normal sinus rhythm and 500 samples representing atrial fibrillation. For each sample, three physiological features were simulated:

1. **RR interval variability (RR_std):** In normal rhythms, RR intervals are relatively consistent, so their standard deviation was drawn from a normal distribution with a mean of 0.8 and a small variance. In contrast, AFib rhythms are highly irregular, so the standard deviation was increased.
2. **Heart rate variability (HRV):** Simulated based on time-domain variability in beat intervals. Normal rhythms had lower HRV values centered around 50 ms, while AFib samples had higher HRV centered around 120 ms.
3. **P-wave presence:** Simulated using a numerical value between 0 and 1. Normal rhythms had values close to 1, indicating clear presence of the P-wave, while AFib samples had values near 0, mimicking the absence or disruption of the P-wave.

These parameters were selected to reflect physiological characteristics observed in clinical ECGs and are commonly used in both manual and automated diagnostic methods [Clifford, G. D. *et al*., 2017].

The distributions for each feature were empirically defined to reflect clinically observed ranges: for example, RR interval variability in normal rhythm was sampled from a Gaussian distribution with $\mu = 0.8$ and $\sigma = 0.1$, while AFib samples followed a broader distribution with $\sigma = 0.3$ to simulate irregularity. Similar logic was applied to HRV and P-wave metrics to ensure physiologically plausible variability.

Machine Learning Model

The features were used to train a Random Forest classifier using the Scikit-learn library. The dataset was split into training (70%) and test (30%) sets using stratified sampling. The Random Forest model was chosen for its ability to handle nonlinear relationships, robustness to noise, and inherent feature importance metrics.

Model performance was evaluated using standard classification metrics: accuracy, precision, recall, and the area under the receiver operating characteristic curve (ROC AUC). A confusion matrix was also produced to assess classification performance in detail.

RESULTS

The model performed exceptionally well on the test set. The accuracy reached 99.7%, with a precision of 100% and recall of 99.3%. The ROC AUC score was 1.0, indicating perfect discrimination between AFib and normal rhythm classes. These results confirm that the model successfully identified the underlying statistical patterns used to simulate AFib-like behavior.

The confusion matrix is shown below:

Actual/Predicted	Normal	AFib
Normal	150	0
AFib	1	149

Of the 300 test samples, only one misclassification occurred — an AFib sample was classified as normal. All normal samples were correctly identified.

Feature importance analysis revealed that HRV was the most informative feature, followed by RR interval variability. The P-wave presence metric also contributed meaningfully but was slightly less influential than the variability-based features.

DISCUSSION

This study demonstrates that even a lightweight machine learning model using only three features — all physiologically interpretable — can accurately detect atrial fibrillation in simulated ECG data. The high classification accuracy, coupled with a perfect precision score, suggests that such models could be useful as screening tools or embedded diagnostics in wearable devices.

Importantly, the features used in this study mirror real-world diagnostic criteria. The irregularity of RR intervals and increased HRV are hallmark indicators of AFib in clinical practice. Similarly, the absence or disorganization of the P-wave is a defining characteristic of atrial fibrillation. This physiological grounding enhances the model's credibility and potential for clinical integration

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[Goldberger, A. L. *et al*., 2000][Clifford, G. D. *et al*., 2017].

However, several limitations must be acknowledged. First, the data were entirely synthetic. While simulation offers the benefit of controlled feature variation, it cannot capture the full complexity of real ECG signals, which are subject to noise, artifacts, and physiological variability. Second, the classification task was binary: AFib versus normal rhythm. In reality, clinicians must distinguish AFib from a range of arrhythmias such as atrial flutter, supraventricular tachycardia, or ectopic beats. Future models should address multiclass classification tasks to be more clinically applicable.

Despite these limitations, the results are encouraging. This approach may serve as the foundation for low-cost, interpretable, and effective AFib screening tools, particularly in remote or resource-limited settings. In this sense, the simulation-based model represents the informatic core of a larger vision: to enable future development of embedded algorithms suitable for wearables and real-time diagnostics. The next step would involve validating the model on real ECG datasets, such as those available through PhysioNet [Goldberger, A. L. *et al*., 2000], and testing it on data collected from actual wearable devices.

CONCLUSION

This work presents a minimalistic yet powerful approach to AFib detection using synthetic ECG signals. By focusing on three simple but clinically meaningful features — RR variability, heart rate variability, and P-wave presence — and applying a standard Random Forest classifier, the model achieves near-perfect performance on a simulated test set. These findings support the idea that high-quality arrhythmia detection does not necessarily require complex models or deep neural networks. Instead, carefully selected features and robust classical algorithms can yield reliable results, paving the way for affordable, interpretable, and deployable diagnostic solutions.

AUTHORSHIP

S.P. provided the idea and developed the entire computational framework, writing all the code, performed all data analyses and interpreted the results; **F.P.** wrote the manuscript.

LINGUISTIC SUPPORT AND TRANSLATION:

ChatGPT 4.0 (OpenAI) was used solely to support the translation of specific phrases and technical terms from Italian to English. No content was generated by AI; its role was strictly limited to linguistic assistance. Scientific literature acknowledges ChatGPT as a valuable tool for non-native authors in improving academic texts, enhancing international scientific communication (1, 2, 3, 4, 5).

AI-generated outputs were reviewed and validated by a domain expert to ensure accuracy. As noted by Palazzo, *et al*., the optimal approach combines human expertise with AI capabilities (6).

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