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Early Heart Disease Detection Based on Anomaly Behavior in ECG Data Using Cross-Correlation and Machine Learning

Muhamad Ariff Izzudin Mohamat Zamri[1], Mohamad Sabri Sinal @ Zainal[1]*, Muhammad Nur Adilin Mohd Anuardi[2]

[1] *School of Computing, Universiti Utara Malaysia, Sintok 06010, Kedah, MALAYSIA*

[2] *Graduate School of Advanced Science and Engineering is part of Hiroshima University. 1-7-1 Kagamiyama, Higashi-Hiroshima, Hiroshima 739-8521, JAPAN*

*Corresponding Author: msabri@uum.edu.my
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Abstract

The importance of early detection of electrocardiogram anomalies primarily lies in its potential to facilitate timely diagnosis of heart diseases and improve patient outcomes. Existing detection approaches continue to adopt intricate feature selection, often leading to increased complexity of the model without significant improvement in the detection performance. In addressing the challenge, the current study seeks to develop a hybrid model that incorporates SVM with cross-correlation for feature extraction and ECG signal classification, namely, Normal Sinus Rhythm and Atrial Fibrillation. The developed model was trained and validated with a dataset of 36 ECG recordings that had been carefully segmented and preprocessed to enhance the focus and precision of the features. The developed model was able to cross correlate for feature extraction over the impulse response and pattern recognition for classification and demonstrated excellent performance in differentiating NS from AF ECG signals. The study attains the important benchmarking of 100% accuracy, sensitivity and specificity on the dataset, thereby, demonstrating its potential to reliably detect rhythm disturbance. This study represents a considerable contribution to the ECG analysis by proposing a diagnostic model that integrates cross-correlation based feature extraction and SVM classification. The model's precise functioning with a well-annotated dataset and the slight need for preprocessing and minimal data shows the opportunity for the model to be scaled and implemented more objectively for practical use in clinical settings for the detection of heart disease in early stages.

1. Introduction

Heart disease continues to be one of the leading global killers, which further highlights the need for timely identification to decrease casualties and complications [1]. Although electrocardiograms (ECGs) are used as diagnostic instruments, traditional methods of analysis are typically based on manual gateway which eats up time and is subject to blunders [2]. Goldberger [3] noted that clinical practice often neglects subtle already borderline ECG changes associated with early cardiac dysfunction in the absence of an expert analysis, highlighting the need for automation in timely and accurate diagnostics for heart conditions of great volume and remote locations.

Long ECG recordings pose significant analytic challenges, especially in terms of maintaining waveform fidelity. Distortions caused by skeletal muscle activity, breathing, electrode shifting, and physiological and environmental phenomena complicate discernable insights. These aspects prove the need for advanced supervised machine learning (ML) tools complemented by powerful disease-specific feature extraction. Previous research has attempted to solve the problem of small telemetry ECG datasets, including the use of synthetic data generation [4], few-shot learning [5], and augmentation techniques such as segmentation and rearranging signals [6]. Although promising, these techniques frequently struggle with reproducibility and generalization. Advanced feature extraction such as cross-correlation, complemented by noise reduction and normalization, has been shown to capture vital signals well [7]. Subsequent integration of cross-correlation and Support Vector Machines (SVM) improves classification by maintaining powerful alignment of critical ECG patterns [8], as well as additional supervised models like Random Forests (RF) and Decision Trees (DT) proficient in feature detection of RR interval variability and PQRST wave morphology [9], and K-Nearest Neighbors (KNN) for small, well pre-processed datasets [10]. These methods collectively strengthen the practical foundation for transparent and interpretable automated ECG analysis systems.

Cardiac conditions can be classified into two groups: normal and abnormal. Abnormal conditions can include an array of pathologies such as coronary artery disease and heart failure. Within such arrhythmias, AF is particularly common and serious, being responsible for more than 20% of sudden cardiac deaths of those who have it [11]. Without a doubt, this emphasizes the need for more AF detection and adequate management of the condition in attempt to lessen the overall mortality and improve prognosis for such patients. Continuous monitoring of AF is critical to the management of cryptogenic ischemic stroke, assessing the effectiveness of interventional ablation, and tailoring antiarrhythmic agents. Such monitoring is vital for analyzing the effectiveness of the treatment and guiding clinical practice. The detection of Paroxysmal Atrial Fibrillation (ParAF), particularly for episodes of up to seven days, is during short periods of monitoring rests a fundamental and salient monitoring issue. Thus, prolonged tracking is crucial for detecting ParAF episodes that standard evaluations may miss after any kind of interventions. Additionally, persistent rhythm monitoring is critical since AF signs and symptoms may still be present without apparent abnormalities [12]. Studies have shown that prolonged monitoring increases the chances of an accurate diagnosis and identifying complex phenomena that shorter intervals tend to bypass [13]. The use of sophisticated computer algorithms enhances the utility of prolonged monitoring for detecting AF episodes embedded in complex and noisy data sets [14]. All this information reinforces the fundamental need for advanced monitoring capabilities to solve the complex issues in detecting ParAF described above.

To overcome existing gaps, this study applies ML and statistics, particularly cross-correlation, to anomalous pattern detection in ECG data. This technique, using cross-correlation for feature extraction, aids in capturing and understanding finer deviations within and provides deeper understanding toward cardiovascular issues. Critical in the design and assessment of the proposed framework for automated ECG anomaly detection is the PhysioNet dataset [15]. With the intention of assisting anomaly detection aimed to automate the analysis to allow the retrieval of ECG data and reveal anomaly detection results that are often too cumbersome and missed using traditional methods, automated ECG anomaly detection system is proposed to enable the analysis of data that fill the gaps and are usually missed in current methodologies. Signal preprocessing methods, including noise removal, normalization, and specialized feature extraction aimed at the PQRST complex and RR intervals, which are a strong indicator of cardiovascular pathology, will be applied to these models. Cross-correlation is used to find and synchronize key parts of ECG to enhance the effectiveness of feature extraction. SVM, RF, and Autoencoders will be used in the modeling of the extracted features to perform ML. Rigorously, the proposed metrics of accuracy, sensitivity, and specificity will be utilized to evaluate the model to ascertain its acceptability. Utilizing the annotated ECG recordings in the PhysioNet dataset helps compliance in training and testing with real world data, adding to the robustness of results [3] Practically, the aim is to build a reliable platform that drives higher accuracy in diagnostics and extends to multiple clinical and non-clinical uses.

This particular research aims at exploring differentiating NS from other rhythms of which AF is a subset by pinpointing distinctive ECG patterns. NS is characterized by standard PQRST waveforms by a set of RR intervals, being the reference [16]. In contrast, AF is characterized by split P waves, the absence of P waves, and RR intervals which are variable in number and length which is possibly a reflection of the pathology of the heart [17]. These distinct features are used to develop ML algorithms to improve on the deviation determination used in diagnostical work in order to improve the precision and efficacy of the de procedures. The rest of the paper is organized in the following structure: The literature review examines prior works that focus on the ECG and heart disease ML and statistical analysis. The methodology examines the proposed ML model and its deployment. The results and discussion section answers the question on what the model has learned and evaluates its performance on differentiating NS and AF. In the last part of the paper which is conclusion, the focus is on what the model has learned, the developments in the study, the limitations encountered, and propose future areas that can be built on.

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2. Literature Review

Cardiovascular diseases continue to be a leading cause of death across the globe, emphasizing the importance of rapid, accurate, and timely diagnostic approaches to help save lives and improve patient outcomes [1]. Detecting cardiac irregularities incorporates the use of the ECG, however, the conventional analytical approaches do not guarantee optimal accuracy and efficiency, and most of the time do not guarantee widespread availability [3]. For this reason, ML developed and continues to improve diagnostic tools by executing highly complex data processing and pattern recognition [18]. The current review addresses the most relevant studies directed to the use of ML to automate the diagnosis of cardiovascular diseases using the ECG, specifically focusing on 4 studies that document the most promising advancements in this dynamic area of cardiovascular technology [19][20].

In their research, Syed Ali Nawaz et al. [21] assessed the use of different ML techniques, SVM, RF, LR, and DT, for the classification of ECG signals into normal, abnormal, and COVID-19-affected categories. Utilizing a dataset of different patterns of ECG, the study achieved SVM model with 84% as the highest accuracy. This study demonstrates the potential of ML in ECG analysis, particularly for improving the diagnostic capacity for distant areas and for the lack of clinical skills in poorly resourced areas. However, the performance of the model also needs external dataset as clinical validations for practical use.

A convolutional neural network (CNN) was used in an attempt to predict the 10-year risk of heart failure in a study by Butler et al. [22]. This was built on raw 12-lead ECG data, with model training occurring in the Atherosclerosis Risk in Communities (ARIC) cohort and later validation in the Multi-Ethnic Study of Atherosclerosis (MESA) dataset. Using deep learning as a means of automated feature extraction, substantial predictive power was displayed, with AUC figures reaching 0.81 indicating positive predictive power and demonstrating utility for long-term cardiovascular risk assessment. Its immediate real-world clinical application, however, remains limited due to the model's requirement of high-quality, research-grade ECGs and comprehensive annotations. Most original clinical data contain noise and lack a high-quality framework, and as such, its generalizability beyond the bounds of the research environment is even more likely to be inaccurate.

Subbba et al. [23] highlighted the crucial value of prompt detection of arrhythmia and provided a ML pipeline that utilized preprocessing techniques of noise reduction, advanced feature extraction, and the use of classifiers such as Artificial Neural Networks (ANN), SVM, and RF. Their study performed Slow Wavelet Transforms and Fast Fourier Transforms (FFT) feature engineering for the MIT-BIH Arrhythmia dataset with RF showing the best results. Despite the strong results, the study highlighted limitations such as computational intensity, class imbalance, and the challenge of separating morphologically similar heartbeat types. These limitations, in combination, dilute the clinical utility of the study.

Telmoud et al. [24] assessed and contrasted multiple ML models, namely RF, DT, LR, SVM, KNN, gradient boosting and NN, focusing on heart disease prediction and ECG classification. For this purpose, the researchers trained the models on three benchmark datasets, and achieved remarkable results, particularly RF and DT which on prediction of heart disease achieved 99% and 97% on classification of ECGs. These results, though, raise enthusiasm towards the potential of ML in designing diagnostic tools, the possible clinical utility of the models in the study might be overstated. This is primarily due to the datasets used in the study, which although well-curated, offered little diversity in demographic factors. This fundamental reliance on benchmark datasets calls into question the potential utility of the models in real-world clinical practice, which is often heterogeneous, noisy and disorganized.

In their work, Sraitih et al. [10] built an automated arrhythmia detection system which leverages different ML algorithms which includes the SVM, KNN, RF, and voting ensembles. The authors presented their findings based on the MIT-BIH Arrhythmia Database and focused on the inter-patient approach. SVM was the best performing model, with the model achieving 83% accuracy, 0.64 precision, 0.59 recall, and 0.55 F1. While the described approach illustrated the potential for ML methods in the detection of arrhythmias, it was noted that the models had trouble recognizing the left bundle branch block and premature atrial contraction minority classes. This points out the issues of class imbalance and the limited generalizability of such models to other patient populations.

A comparative study carried out by Das et al. [25] analyzed the performance of six machine learning algorithms: XGBoost, Bagging, RF, DT, KNN, and Naïve Bayes in heart disease prediction. Using the Behavioral Risk Factor Surveillance System dataset by the CDC, and consisting of over 319,000 records, the authors found that XGBoost was the most powerful algorithm and achieved an 91.3% overall accuracy, 92% sensitivity, an F1 score of 95.4% and an AUC of 0.83. These outcomes are excellent and highly commendable considering the study's use of large epidemiological data. Importantly, though, the study's major weakness is lacking the use of objective data and relies to a great extent on self-reported survey data, which is highly biasing and limits the study's usefulness in real clinical practice where objective clinical diagnostic data are critical in making a sound clinical decision.

Kumar et al. [26] conducted a thorough study of the ML techniques used for the prediction of heart disease and examined classical approaches which include LR and SVM alongside the more complex frameworks like the hybrid CNN-LSTMs. The authors worked with several datasets, namely the UCI Cleveland, the Framingham, and the PhysioNet along with IoT-enabled health records and arrived at a conclusion whereby the predictive performance of the hybrid deep learning models improved with a sensitivity, specificity and AUC metrics of more than 97% and most importantly, more than 97% for each parameter individually. Regardless of the notable results, the study analyzed the persistence of several issues, including the imbalance of data, the high costs of computation, the limited interpretability of models, and the ethical issues involved. The issues raised serve to undermine the dependable and accountable use of these models within clinical practice.

Ahmad et al. [27] created a deep learning architecture that combined ECG signal reconstruction with multiple transfer learning approaches, such as VGG16, VGG19, ResNet50, InceptionNetV2, and GoogleNet and provided optional SVM integration for classification. This was evaluated using a well-constructed dataset containing 674 annotated 12-lead ECG images obtained from multiple cardiac institutes across Pakistan. The combined VGG19 + SVM hybrid model was able to obtain an unprecedented 100% accuracy for multi-class ECG classification and 98.51% accuracy for defining abnormal cases from myocardial infarction (MI). Although these results show great promise in the potential of transfer learning combined with traditional classifiers, the limited size and highly curated dataset the study relies upon considerably weakens its robustness and limits the potential for real-world clinical integration.

Building upon the work of Lilhore et al. [28], the proposed integrated deep learning framework fused the Modified Multiclass Attention Mechanism (M2AM) with BiLSTM, further polished by advanced Wavelet transformed based Improved Adaptive Bandpass Filter timed Preprocessing Methods. Evaluation of the Attention BiLSTM framework was performed over 6,000 ECGs from the MIT-BIH and INCART which yielded marvelous results of 98.82% Accuracy, 97.20% Precision, 98.34% Recall, and 98.92% F1-score. These results indicate the power of Attention Mechanisms + Recurrent NNs for Arrhythmia Detection, however, the proposed method suffers from extreme computational costs that limits real-time clinical use. Furthermore, the proposed method does not provide a concrete solution to the problem of class-imbalance, which exacerbates the challenge of real-time clinical applicability.

There is a robust literature demonstrating advances in ECG-based heart disease ML applications, particularly in advanced systems for arrhythmia detection, deep learning frameworks for large cohorts, extensive benchmarking, advanced ensemble techniques, and prediction systems at the population level. Current literature also emphasizes the utility of hybrid systems such as CNN-LSTM, the combination of transfer learning with classical classifiers, and recurrent networks with attention in the field. The development of such diverse methodologies and their extensions into diagnosing advanced systems have underscored the diagnostic potential of the field.

Although progress has been made, the acceptance of current ML frameworks has not been made in the clinics. Concerns about performance are primarily due to ML models reliance on well curated benchmark datasets which to some extents are overfitted, raising questions about their generalizability to the variability encountered in actual clinical practice. Added to that, class imbalance and the lack of diversity in the dataset also erode robustness. Inversely, the 'black-box' nature of some deep learning models which emphasize predictive performance and not interpretability impedes their clinical use. In practice, the so-called state of the art hybrid and attention models available in the literature [26][27][28] remain underdeveloped in the clinical ML literature due to their exorbitant computational needs and their small, and of even greater concern, non-representative datasets.

The proposed methodology overcomes the limitations described above by using cross-correlation for interpretable feature extraction combined with a SVM for fast and uncomplicated robust classification. In contrast to the overreaching and data-consuming paradigms of deep learning, this approach retains its usefulness under conditions of scarce data. Moreover, its compatibility with diagnostic reasoning involving clinical waveforms augments the diagnostic justification. In the anticipated future of clinically useful and scalable ML-integrated cardiac diagnostic systems, one will need to bridge the gaps of ECM multi-institutional datasets and ML with the Internet of Medical Things, targeting a strategic trade-off among accuracy, interpretability, and computational efficiency [29]. In Table 1, existing methodologies, datasets, performance metrics, and limitations are summarized and paired with the respective explanations.

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Table 1 *Comparative analysis of existing studies*

Author	Method/Model	Dataset	Metrics	Limitations
Butler et al. [22]	CNN	ARIC cohort (training) & MESA dataset (validation)	AUC up to 0.84 for 10-year heart failure risk prediction	Relied on high-quality research ECGs; generalizability to noisy, real-world data uncertain
Subba et al. [23]	DT, LR, SVM, KNN, RF (with wavelet transforms, FFT for feature extraction)	MIT-BIH Arrhythmia dataset	RF: 98% accuracy, 97.2% precision, 87.8% F1-score	Computational complexity, class imbalance, difficulty distinguishing similar heartbeat types
Telmoud et al. [24]	RF, DT, LR, SVM, KNN, Neural Networks	Heart Disease dataset, HDP dataset, MIT-BIH dataset	Up to 99% accuracy (Heart Disease), 97% accuracy (MIT-BIH ECG classification)	Benchmark datasets with limited demographic diversity to reduced clinical generalizability
Sraitih et al. [10]	SVM, KNN, RF, Voting Ensemble	MIT-BIH Arrhythmia Database (inter-patient paradigm)	SVM: Accuracy 0.83, Precision 0.64, Recall 0.59, F1-score 0.55	Struggled with minority classes (e.g., LBBB, PAC), dataset imbalance, limited generalization
Das et al. [25]	XGBoost, Bagging, RF, DT, KNN, Naïve Bayes	CDC BRFSS survey dataset (319,795+ cases, 18 variables)	XGBoost: Accuracy 91.3%, Sensitivity 92%, F1-score 95.4%, AUC 0.83	Reliance on self-reported survey data introduces bias; clinical applicability may be limited
Kumar et al. [26]	LR, SVM, CNN-LSTM hybrids (review of ML approaches)	UCI Cleveland, Framingham, PhysioNet, IoT-enabled health records	Hybrid deep learning often exceeded 97% sensitivity, specificity, AUC	Dataset imbalance, high computational requirements, limited interpretability, ethical concerns in deployment.
Ahmad et al. [27]	Deep learning + transfer learning (VGG16, VGG19, ResNet50, InceptionNetV2, GoogleNet) + optional SVM	674 annotated 12-lead ECG images (multiple cardiac institutes, Pakistan)	100% accuracy (multi-class), 98.51% accuracy (abnormal vs MI)	Small, curated dataset; limited robustness and generalizability in real-world settings.

Author	Method/Model	Dataset	Metrics	Limitations
Lilhore et al. [28]	Modified Multiclass Attention Mechanism (M2AM) + BiLSTM with preprocessing (bandpass filter, wavelets)	6,000 ECG samples (MIT-BIH and INCART databases)	98.82% accuracy, 97.20% precision, 98.34% recall, 98.92% F-measure	High computational complexity; class imbalance challenges; barriers for real-time clinical deployment.

3. Methodology

In this section, the proposed model for early detection of heart diseases is explained. It consists of four stages: ECG preprocessing, feature extraction, classification using SVM, and evaluation. The outlined framework is lightweight, clinically interpretable, and robust in differentiating NS from AF.

3.1 Proposed Framework for Heart Disease Detection

The architecture of the proposed framework is represented in Figure 1. The workflow consists of four stages: preprocessing the ECG, feature extraction through cross-correlation, using an SVM classifier, and making the final decision. This modular design was aimed at overcoming some of the challenges of the existing literature, which include dependence on large datasets [25][26][27], excessive computational resource intake, and a lack of transparency in clinical reasoning.

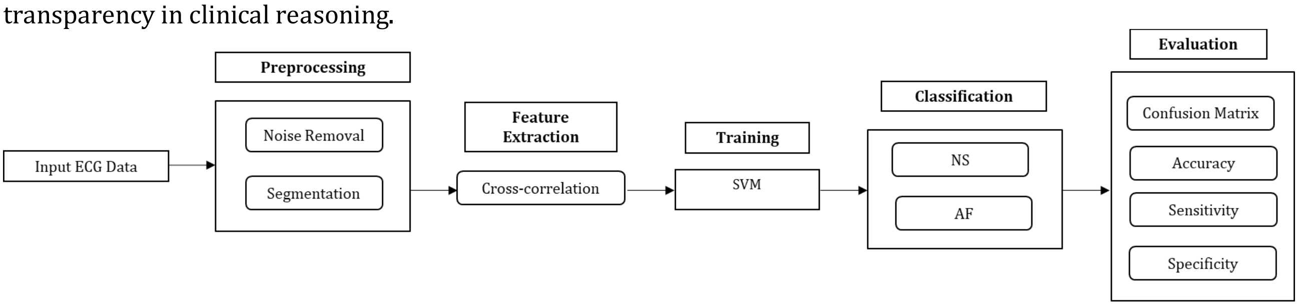

Fig. 1 *Flowchart of ECG-based early heart disease detection model*

3.2 ECG Preprocessing

In order to prepare the raw ECG signals for reliable feature extraction, preprocessing techniques were implemented to improve the quality of the data. Two primary steps were carried out:
a) Noise removal: In order to improve the clarity of the signals, baseline wander, powerline interference, and motion artifacts were filtered. This reduces the potential for misclassification due to artifacts.
b) Segmentation: ECG signals were segmented into individual heartbeats in order to preserve temporal uniformity and facilitate an analysis that corresponds to the clinically relevant periods of the heart.

3.3 Feature Extraction via Cross-Correlation

Feature extraction was performed utilizing cross-correlation, which quantifies the likeness of ECG signal segments. The cross-correlation function is given by:

$$R_{xy}(k) = \sum_{n=0}^{N-1-k} x[n].y[n+k] \quad (1)$$

where $R_{xy}(k)$ represents the correlation at lag k , $x[n]$ and $y[n]$ are ECG sequences of length N, and k is the time shift. Correlation values range from −1 to 1, with +1 indicating maximum similarity, 0 no relationship, and −1 complete dissimilarity. This study focuses primarily on Lag 0, which directly measures the alignment of waveforms. This has clinical relevance, as the irregular shapes associated with AF reduce the consistency of alignment as compared to NS. Cross-correlation emulates the clinical activities of cardiologists, who diagnose by visually inspecting and comparing the shape of the waveforms [30][31]. This guarantees that the features extracted are interpretable, trustworthy, and computationally inexpensive.

3.4 Classification with SVM

SVM was used for classification on the extracted features. This type of classifier was selected because SVMs are effective with small-sized ECG datasets, as well as being resilient to noise, outliers, and complex pattern recognition via the use of kernel functions [32]. During model training, to reduce bias and improve performance on unseen data, 5-fold cross-validation was used. The proposed framework is reliable and computationally simple in distinguishing NS from AF, because it combines intuitive cross-correlation features with the consistent performance of SVMs.

3.5 Evaluation

For the evaluation phase, the performance metrics of the SVM model include the following:
a) Confusion Matrix. This matrix summarizes the classification results in terms of true positives, false positives, true negatives, and false negatives, and helps to outline the model's performance in detail.
b) Accuracy. To assess how well the model classifies the ECG signals, the overall accuracy of the model is computed.
c) Sensitivity and Specificity. Sensitivity assesses the model's performance in detecting AF and specificity assesses the model's performance in recognizing NS.

3.6 Summary of Methodology

The framework integrates interpretable feature extraction and strong classification methods to create a lightweight, efficient system for the early detection of heart disease. This model overcomes the primary obstacles associated with previous attempts to integrate noise-filtered, segmented ECG signals, cross-correlation features, and SVM classification. These obstacles are excessive data requirements, high computational costs, and weak interpretability. The framework was aimed to offer accuracy as well as interpretability and real-world applicability, ensuring that it is appropriate for use in clinical environments that are both real-world and low-resources.

4. Results and Performance Evaluation

This section provides an overview of the development of the proposed model and its capability to classify ECG signals as either NS or AF based on the selected features. Sections 4.1 and 4.2, respectively, outline the details of the dataset and the evaluation strategy. Section 4.3 elaborates on the model training and evaluation process, presenting the performance results using the specified ECG features.

4.1 Dataset for Evaluation

The evaluation set uses data from the MIT-BIH Atrial Fibrillation Database and the MIT-BIH Normal Sinus Rhythm Database [15]. These combined resources span 36 patient recordings, in which 18 recordings pertain to patients with AF and 18 recordings to patients with Normal Sinus Rhythm, as described in Table 2. Every recording corresponds to 10 hours of continuous ECG signal capturing, which corresponds to several million data points and thousands of heartbeats. This data is critical to building models for AF detection, as well as validating models for NS and other rhythm disorder models [3]. The ECG recordings in the dataset particularly for the early detection of coronary heart disease, provide excellent material for the design and implementation of ML models, due to the extensive annotations and variety. Data preparation consisted of extracting the annotated NS and AF recordings from the PhysioNet database. Identifying wave form segments and R-R intervals are essential in determining the features of the ECG signals, which can indicate possible cardiac irregularities [33]. Analysis of rhythm abnormalities included some passes of preprocessing steps, including the normalization of the sampling rates to 128Hz for NS recordings and 250Hz for AF recordings [34].

Table 2 *Patient distribution and ECG dataset*

Category	Sample Size
Normal Sinus Rhythm (NS)	18
Atrial Fibrillation (AF)	18

4.2 Evaluation Strategy

The effectiveness of the proposed hybrid model was evaluated using three key performance metrics: accuracy, sensitivity, and specificity. Accuracy measures how many of the total cases were correctly classified. Sensitivity, or true positive rate, measures how well the model classifies cases of abnormal rhythms such as AF among all cases that are actually abnormal. The specificity, or true negative rate, measures how well it classifies normal rhythms such as NS as non-abnormal [35]. The calculations are carried out and given in detail below.

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \quad (2)$$

$$Sensitivity = TP / (TP + FN) \quad (3)$$

$$Specificity = TN / (TN + FP) \quad (4)$$

where,
True Positive (TP): The count of AF data points that the model correctly identified as AF data.
True Negative (TN): The count of NS data points that the model correctly identified as NS data.
False Positive (FP): The count of NS data points that the model incorrectly identified as AF data.
False Negative (FN): The count of AF data points that the model incorrectly identified as NS data.

4.3 Performance Evaluation

This section discusses the hybrid model proposed, which uses cross-correlation for feature extraction and SVM classifies for heart disease early detection. The model also classifies the ECG signals as NS or AF. To assess the effectiveness of the model in detecting abnormal heart rhythms, parameters such as accuracy, sensitivity, and specificity, which rely on the confusion matrix, are considered. Figure 2 presents the cross-correlation of two NS ECG signals. The signals are shown to be NS and periodic as indicated by the strong, peak correlation at lag= 0. The correlation value of 0.08 further reinforces that NS signals are stable and can serve as reference to properly differentiate normal and abnormal heart rhythms. The baseline is important for AF detection because a drop in the baseline correlation is indicative of irregular, disordered heart activity.

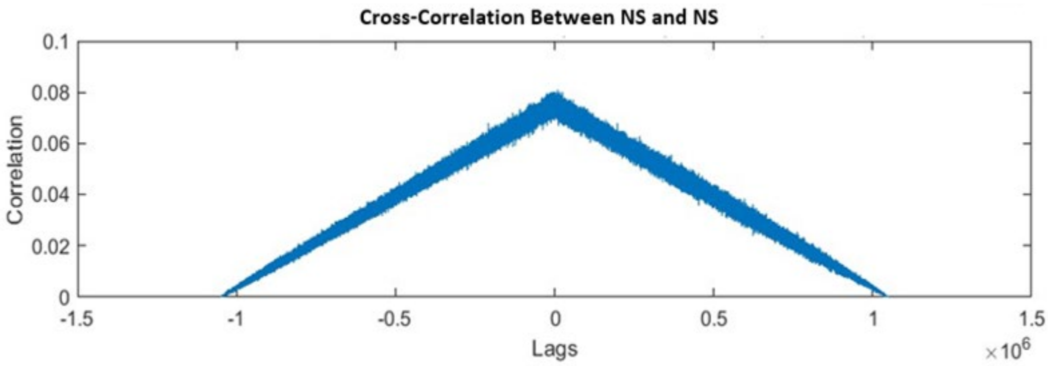

Fig. 2 *Cross-correlation patterns of NS*

Figure 3 illustrates how well the model performs in classifying NS and AF signals. As weak correlation pertains to NS and AF ECG signals, this demonstrates the distinctiveness of their waveforms, thus confirming the efficacy of employing cross-correlation as a technique for feature extraction.

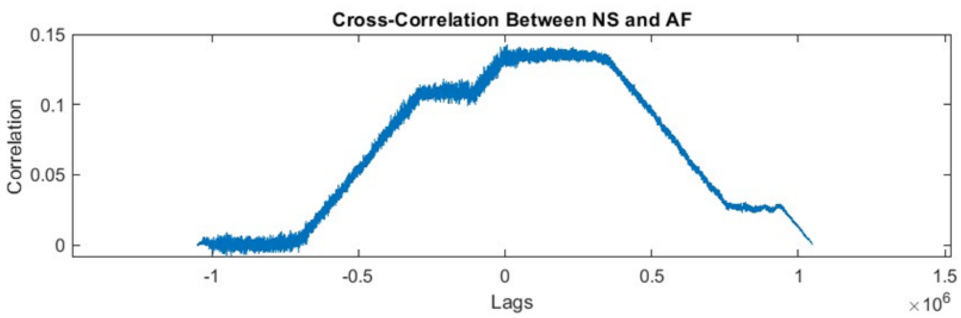

Fig. 3 *Performance evaluation of ECG classification*

Table 3 *Classification performance of the proposed model, with 95% confidence intervals determined using the Wilson Score Interval. Despite the model attaining perfect scores, the confidence intervals indicate the presence of statistical uncertainty, which can be attributed to the small number of patient recordings (n=36)*

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Performance Metrics	Result (%)	95% Confidence Interval
Accuracy	100	[88.4%, 100%]
Specificity	100	[78.8%, 100%]
Sensitivity	100	[78.8%, 100%]

Although the model demonstrated full classification accuracy under the conditions tested, as presented in Table 3, such results are rare with real-world clinical data and should be taken with caution. To avoid overfitting, the model employed 5-fold cross-validation. Even though the number of recordings was modest (n = 36), each ECG file in the PhysioNet database is very large, containing millions of high-resolution data points, which allows for significant waveform variation. This variation in data points likely played a role in the model's positive results. NS signals contained periodic and consistent patterns while AF signals contained irregularities consistent with clinical expectations, which was helpful in reinforcing classification accuracy. Moreover, ECG segments went through effective noise reduction, normalization, and segmentation to simplify features prior to signal classification using the SVM. This is what resulted in the model distinguishing NS and AF signals while attaining full classification across accuracy, sensitivity, and specificity. To examine the results in a different light, 95% confidence intervals (CIs) using the Wilson Score Interval method were also calculated. Even though the performance metrics were perfect, the small sample size was the reason the CIs contained uncertainty. In particular, the confidence interval for accuracy varied between 88.4% and 100%, whereas for both sensitivity and specificity, the confidence intervals ranged from 78.8% to 100%. These intervals suggest that although the model performs exceptionally well on the current dataset, its generalizability must be tested further. Therefore, external validation using larger and more diverse ECG datasets is recommended to assess scalability and robustness in real clinical environments.

4.4 Baseline Model Setup

For the evaluation of the proposed SVM model, performance was benchmarked against three other classifiers namely, KNN, NN and LR. All classifiers utilized the same pre-processed ECG data and features which were consistently extracted using cross-correlation at Lag 0. A comparison of performance was undertaken using hyper-parameter optimisations for each classifier which were achieved using grid searches, 5-fold cross validation was used for training and evaluation of each classifier. This created controlled conditions which reduced possible biases and allowed for an equitable performance comparison of the classifiers in a like for like scenario. As fully illustrated in Table 4, the SVM model was the only model to attain 100% accuracy and was therefore classified as the best classifier. This was in stark contrast to KNN, NN and LR which achieved accuracy scores of 57.1%, 65.7% and 62.9% respectively. This demonstrated the accuracy of the SVM approach in differentiating between NS and AF signals. It was particularly notable that this was achieved using a limited data set.

Table 4 *Comparative performance of ML models using the same ECG dataset*

Technique	Accuracy (%)
KNN	57.1
NN	65.7
SVM (Proposed Method)	100
LR	62.9

McNemar's Test was used to evaluate the significance of the results, specifically to determine whether the difference in performance between the SVM model and the baseline classifiers was statistically significant. The results of this test, shown in Table 5, indicate that there are statistically significant differences between SVM and each of the baseline models. Specifically, the χ^2 values were 15.0 (KNN), 12.0 (NN), and 13.0 (LR), all exceeding the critical value of 3.841 at a 0.05 significance level. These results confirm that the improved performance of the SVM-based model is not due to random variation but reflects a genuine performance gain in classifying ECG signals.

Table 5 *Results of McNemar's test comparing the proposed SVM model with other classifiers. Significance is determined based on a critical χ^2 value of 3.841 ($p < 0.05$)*

Model Compared	McNemar's χ^2	Significance ($p < 0.05$)
SVM vs KNN	15.0	Yes
SVM vs NN	12.0	Yes
SVM vs LR	13.0	Yes

Table 6 *Evaluation of proposed method against existing studies*

Author	Method/Model	Metrics (Acc/Sens/Spec)
Butler et al. [22]	CNN	81% / 75% / 72%
Subba et al. [23]	DT, LR, SVM, KNN, RF (with wavelet transforms, FFT for feature extraction)	98% / 81.2% / –
Telmoud et al. [24]	RF, DT, LR, SVM, KNN, NN	99% / – / –
Sraitih et al. [10]	SVM, KNN, RF, Voting Ensemble	83% / – / –
Das et al. [25]	XGBoost, Bagging, RF, DT, KNN, Naïve Bayes	91.3% / 92% / –
Proposed Method	Cross-Correlation + SVM (with 5-fold CV)	100% / 100% / 100%

Table 6 shows that the method proposed achieves perfect scores in classification of ECG signals, with an accuracy, sensitivity, and specificity of 100%, surpassing previous works in the literature. For example, Butler et al. [22] reported an accuracy of 81%, and sensitivity and specificity of 75% and 72%, respectively. Subba et al. [23] reported an accuracy of 98% with sensitivity of 81.2%, but did not report specificity. Telmoud et al. [24] achieved 99% accuracy, but did not report sensitivity and specificity, which lowers the comparability of the results. Sraitih et al. [10] reported accuracy of 83%, but also did not report sensitivity and specificity. Das et al. [25] reported an accuracy of 91.30% and sensitivity of 92%, but did not report specificity. In contrast with these works, the proposed method achieves the most comprehensive results in all metrics on the current dataset, illustrating its effectiveness in revealing the ECG signal anomalies and addressing the limitations of previous works. The use of cross-correlation makes a significant contribution to this, as it aids in feature alignment and signal quality enhancement. Accuracy in identifying subtle differences enhances the effectiveness of cross-correlation in recognizing ECG patterns and decreases the chances of misclassification, thereby improving the model's robustness and overall performance. Even though the model proposed in the study attained perfect classification results, with 100% accuracy, sensitivity, and specificity, these results must be taken with caution as, in real-life clinical practice, this type of performance is far from the standard and may indicate overfitting, especially with small samples of patients. For instance, while each ECG file is very large, the number of distinct patients, n = 36, is small relative to the size of the dataset. To counter this, 5-fold cross-validation was used to ensure robustness and mitigate bias. Still, to confirm the applicability of the model in the everyday clinical setting, other diverse datasets should be used as validation. Going forward, these efforts will concentrate on external validation and real-time testing to best evaluate the model's capacity and dependability on the scale and perform in everyday practical settings.

5. Conclusion

This research presented a new hybrid model that integrates the SVM method with cross-correlation for detecting arrhythmias in ECG data. The model's use of cross-correlation facilitates the preprocessing of ECG signals through feature alignment and the recognition of subtle differences, which results in a more precise and dependable classification. The proposed model achieved complete classification of all the metrics, under the existing testing parameters, for the classification of NS and AF. The results obtained demonstrate the effectiveness and dependability of the SVM model and its promise of early heart disease detection. This research is a contribution towards improving the techniques used in ECG analysis and builds a solid groundwork towards the development of scalable and robust diagnostic systems. For future investigations, the proposed method should be tested on more extensive and real-world data sets to analyze its generalizability and increase its use in the clinic.

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Declaration of AI Use in Manuscript Preparation

The authors used Grammarly and QuillBot to assist with grammar checking and language editing. All content generated was thoroughly reviewed and verified by the authors, who take full responsibility for the final submission.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Author Contribution

Author contributions are as follows: ***study conception and design:*** *Muhamad Ariff Izzudin bin Mohamat Zamri, Mohamad Sabri bin Sinal @ Zainal, Muhammad Nur Adilin bin Mohd Anuardi;* ***data analysis and manuscript preparation:*** *Muhamad Ariff Izzudin bin Mohamat Zamri;* ***supervision:*** *Mohamad Sabri bin Sinal @ Zainal, Muhammad Nur Adilin bin Mohd Anuardi. All authors reviewed the results and approved the final version of the manuscript.*

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