IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 15, No. 4, August 2026, pp. 3878~3887
ISSN: 2252-8938, DOI: 10.11591/ijai.v15.i4.pp3878-3887

Metaheuristic optimization for atrial fibrillation detection: feature extraction, selection, and hyperparameter tuning

Zaid Nouna[1], Hamid Bouyghf[1], Mohammed Nahid[1], Issa Sabiri[2]
[1]Laboratory of Engineering Sciences and Biosciences, Faculty of Sciences and Techniques, Hassan II University, Mohammedia, Morocco
[2]Laboratory of Systems, Signals and Artificial Intelligence, ENSET, Hassan II University, Mohammedia, Morocco

Article Info

Article history:

Received Aug 10, 2025
Revised Jul 12, 2026
Accepted Jul 21, 2026

Keywords:

Atrial fibrillation
Electrocardiogram signal
Feature extraction
Feature selection
Hyperparameter tuning
Metaheuristic optimization
Neural networks

ABSTRACT

Atrial fibrillation (AF) detection from electrocardiogram (ECG) signals is crucial for early diagnosis and intervention. This study presents a multi-objective optimization approach for AF detection, focusing on feature extraction, selection, and neural network hyperparameter tuning. The methodology uses cross-validation during the training of the two concatenated ECG dataset features and simultaneously minimizes the error rate on the separate validation folds of each dataset and reduces the number of selected features, enhancing model generalization and efficiency. Particle swarm optimization (PSO), grey wolf optimization (GWO), and differential evolution (DE) algorithms were implemented to navigate this multi-objective space. While all three algorithms were explored, the final solution, demonstrating a superior trade-off between accuracy and feature reduction, was obtained using DE. This approach effectively identifies optimal feature subsets and neural network configurations, yielding a robust and compact AF detection model. The proposed approach has shown promising results, with the model achieving accuracies of 96.38% and 90.69%, and corresponding area under the curve (AUC) values of 0.99 and 0.96, for the first and second datasets, respectively, using 10 optimally selected features.

Corresponding Author:

Zaid Nouna
Laboratory of Engineering Sciences and Biosciences, Faculty of Sciences and Techniques
Hassan II University
Mohammedia, Morocco
Email: zaid.nouna-etu@etu.univh2c.ma

1. INTRODUCTION

The prevalence of atrial fibrillation (AF) is expected to increase dramatically in the near future [1], it is the most prevalent type of cardiac arrhythmia and is linked to a five times greater risk of stroke if left untreated [2]. The early and accurate prediction, screening, and timely intervention are of substantial clinical importance [3]. While clinical risk scores can help identify susceptible individuals, their predictive accuracy is limited [4].

The electrocardiogram (ECG) is a widely used tool for diagnosing cardio-vascular conditions. It captures the electrical activity of the heart through surface electrodes placed on the limbs or chest. Intervals between different waves contain diagnostic information about heart diseases. The P wave corresponds to atrial depolarization, the QRS complex indicates ventricular depolarization, and the T wave reflects ventricular repolarization [5]. The efficacy of automated ECG interpretation could be significantly increased by the combination of the increasing availability of digital ECG records and the creation of advanced algorithms designed to analyze large amounts of data [6]. By analyzing the features of these waves, abnormalities in a person's heart function can be detected [7]. Irregular R-R intervals, the lack of clearly defined, repeating P waves, disorganized and irregular atrial activity are among the key features of AF detection [8].

The use of machine learning (ML) and deep learning (DL) for AF detection based on ECG signals is a field of growing interest. A number of studies have explored this domain, Laghari *et al.* [9] developed a deep residual-dense network with a bidirectional recurrent neural network (RNN), and achieved 97.72% accuracy, sensitivity was 93.09%, and specificity was 98.71%. In, Rad *et al.*[10] introduce a system that uses a "voting" approach, where the results of six different AF detection algorithms are combined to make a more accurate final decision in mobile ECG devices, and is evaluated across diverse datasets. Zhao *et al.* [11] propose a single-lead ECGs AF classification approach, which consists of using combined temporal convolutional network (TCN) and residual network architecture. The model achieved a 97% accuracy and an 87% F1-score on the 2017 PhysioNet/CinC dataset.

Jahan *et al.* [12] evaluating several ML algorithms as support vector machine (SVM), decision tree (DT), and random forest (RF) for AF using statistical features extracted from ECG signals. The used dataset for training consists of 23 ten-hour ECG records using leave one group out cross-validation technique, and the best performing model achieved a sensitivity of 85.67%, specificity of 81.25%, positive predictive value of 90.85%, false positive rate of 18.75%, and F1-score of 88.18%. Duranta *et al.* [13] present a novel method for AF detection combining wavelet transform-based filtering and 24 ECG extracted features as input to the neural network classifier. Results demonstrate promising performance, achieving accuracies of 96% (receiver operating characteristic (ROC) 0.95) and 86% (ROC 0.84) on publicly available ECG datasets. Furthermore, 5-fold cross-validation was employed to enhance model robustness, resulting in accuracies of 99% and 90% for the two datasets.

Metaheuristics offer robust solutions to complex optimization problems in artificial intelligence (AI). Specifically, this study apply metaheuristics to optimize neural network performance by efficiently selecting features and tuning hyperparameters. Within wrapper methods, they can be used in selecting features based on the actual performance of a classifier, distinguishing it from filter methods that utilize statistical measures [14].

This study aims to perform metaheuristic algorithm optimization, including number of features minimization and accuracy maximization of two different datasets using proper ECG signal features extractor, hyper-parameters tuning and features selection techniques, to enhance AF detection. The remainder of this paper is structured as follows: section 2 provides an overview of the used datasets, details the preprocessing techniques, and the optimization process steps. Section 3 exposes the experimental setup, the comparison between results of the three algorithms in terms of computations and quality of solution, and then the final chosen model's performance. Section 4 concludes the paper with a summary and outlines potential directions for future research.

2. METHOD

2.1. Datasets

Figure 1 represents the data splitting, respecting randomness to ensure representative samples and reduce bias, stratification to maintain class distributions, and a hold out test set for an unbiased evaluation of the model's final performance. Two publicly available single-lead ECG datasets are used, the first one is collected from the website Mendeley data [15], corresponding to ECG signals from 45 patients, classified into 15 classes of CVD with a sampling frequency of 360 and 10 s as the time of the signal. The second one is 'The PhysioNet in cardiology challenge 2017' [16], and consist of 8,528 single lead data divided into AF, normal rhythm and other rhythm with a sampling frequency of 300. Both datasets are unbalanced; they were adapted by Duranta *et al.* [13] to generate new datasets representing two classes only (AF and normal data). With the authors' permission, these adapted datasets were used in this study and remain publicly available through the source link provided in their original paper.

2.2. Preprocessing

Noise during acquisition and transmission frequently compromises the integrity of ECG signals. This includes baseline wander resulting from patient respiration, power line interference caused by electrical power sources, muscle artifacts generated by muscle movements, and Gaussian noise rising from poor signal transmission, all of which are deviations from the ideal of high-quality, noise-free signal [17]. Wavelet transform denoising is a common technique used in ECG signal processing to improve signal quality. The Symlet-4 (Sym4) wavelet was selected because its near-symmetrical shape closely mirror the morphological peaks of an ECG signal. Artifact removal was achieved by discarding the highest frequency detail coefficients (level 0) to eliminate muscle artifacts and power-line interference, while the lowest frequency coefficients (levels 3 and 4) were removed to eliminate low-frequency artifacts such as respiratory drift.

Only the intermediate coefficients (levels 1 and 2), which capture the essential morphological features of the ECG, were retained for reconstruction. Following ECG signal filtering, P, QRS, and R-peaks were identified, from which 15 features were derived. Subsequently, standardization was applied to these features to ensure uniform scaling, enhancing model performance by allowing each feature to contribute equally. Next step is to select from these features, the ones that characterize the AF, this step is called features selection. This process has become essential for the development of efficient data mining and ML algorithms [18]. After extracting features from the training data, and performing the selection, the resulting feature set (same for both datasets) is concatenated into a single dataset for model training as shown in Figure 2. This approach aims to enhance the model's generalization capabilities.

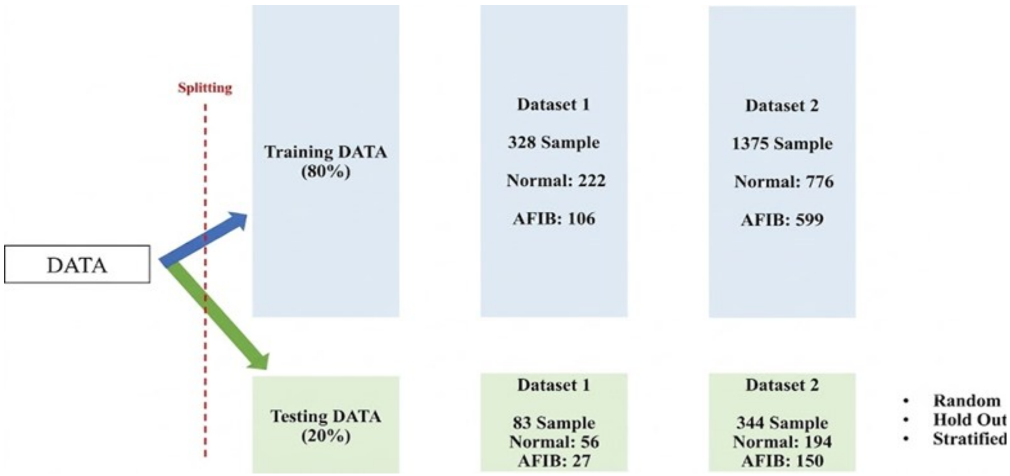


Figure 1. Data splitting

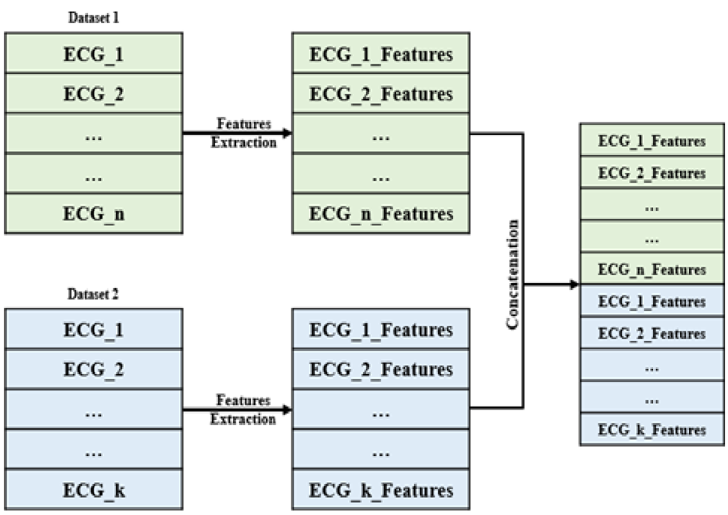


Figure 2. Datasets concatenation

2.3. Features extraction

In the context of ECG signals, feature extraction involves distilling the signal into a set of clinically relevant characteristics that can be used for various diagnostic and analytical purposes. For the case study, we'll focus on extracting each of the P-wave, R-peak, and QRS complexes as shown in Figure 3, and these waveforms served as the foundation for deriving the features used in model analysis. R-peaks were detected using the "find peaks" function from the SciPy library and their number calculated. A minimum distance of 50 samples between detected peaks was implemented to avoid the detection of adjacent peaks. This function returns the peak heights, from which the mean and standard deviation were calculated. Next would be the

R-R intervals calculation in the ECG signal, from which the mean, standard deviation, root mean square of successive differences (RMSSD) of the R-R intervals, and the percentage of successive R-R intervals that differ by more than 50 milliseconds were obtained.

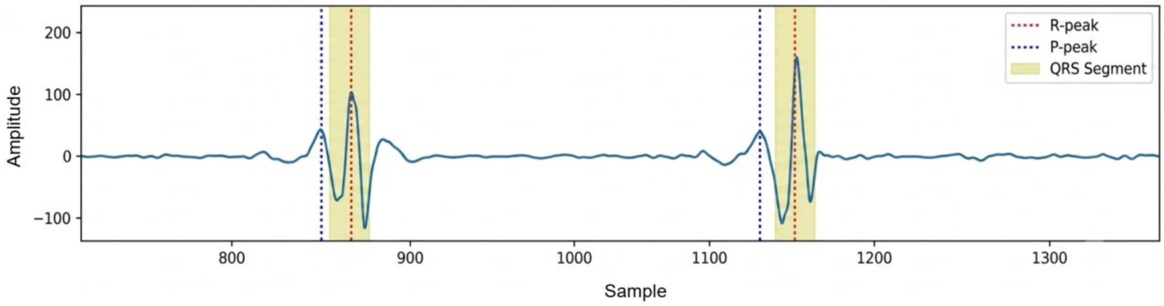


Figure 3. ECG signal

P-peaks are detected using the same function, in a 0.1 s window before R-peak. The mean and standard deviation are determined for each of the P-wave duration and P-wave width, in addition to the P-wave mean area. For the QRS complex, this study focus on the characteristic QRS intervals, from which the mean and standard deviation are extracted as features.

2.4. Metaheuristics

Three different metaheuristics are used during this study, Figure 4 represents the general process of those algorithms. In the particle swarm optimization (PSO) algorithm, particle movement is governed by velocity updates, which are calculated based on a particle's current speed, its personal best position, and the swarm's global best position. This dynamic adjustment enables the swarm to effectively balance exploring the search space and exploiting promising areas [19]. Differential evolution (DE) is a population-based optimization algorithm introduced by Storn and Price [20], that generates new candidate solutions by combining existing ones. It creates 'mutant' vectors from vector differences, blends them with 'target' vectors via crossover to form 'trial' vectors, and selects the fittest for the next generation. The grey wolf optimization (GWO) emulates the hierarchical hunting strategy of gray wolves, utilizing alpha, beta, and delta wolves to guide the search. Omega wolves update their positions based on the leaders, simulating prey encircling and attacking behaviors. This process balances exploration and exploitation, enabling efficient navigation of complex search spaces by iteratively adjusting wolf positions towards promising regions [21]. Electronic circuit design optimization [22]–[25], metaheuristic-optimized ML to identify security breaches in Healthcare 4.0 [26], or even metaheuristic algorithms that create optimal daily schedules for home health care workers by figuring out the best routes and times for their patient visits [27], are a few examples of metaheuristic use cases in the literature.

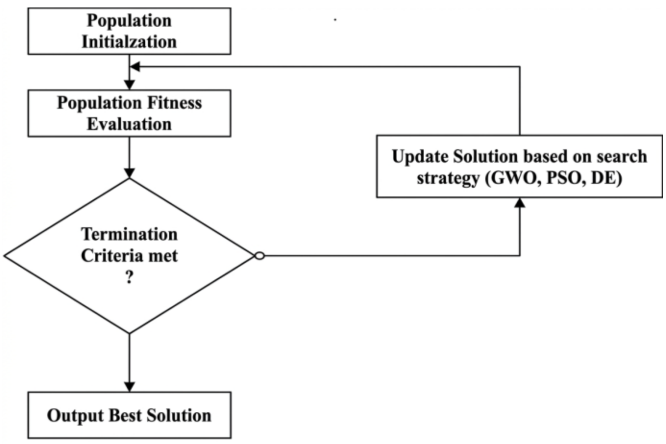


Figure 4. General metaheuristic optimization flowchart

2.5. Optimization process

As shown in Figure 5, this study opted for simultaneous features selection and hyperparameter tuning since the optimal set of features often depends on the chosen hyperparameters, and vice versa. By optimizing these aspects concurrently, the potential for identifying the globally optimal combination is enhanced. Each individual of the population is divided into a feature selection part and a hyperparameter selection part. Once the features and the hyperparameters are selected using a metaheuristic algorithm, the neural network model is built. This study employed 5-fold cross-validation to ensure a robust evaluation of the model's performance and to mitigate the risk of overfitting. For each dataset, the average performance is calculated to enable model evaluation during the iterations of the optimization process and to enable the metaheuristics to explore the solutions space effectively. To balance performance with clinical utility, this study assigned a lower weight to feature reduction (0.1) compared to accuracy (0.45) within the cost function. This deliberate constraint prevents aggressive feature reduction, ensuring the model retains a respectable number of morphological biomarkers essential for interpretability. By avoiding an overly minimalist feature set, the framework maintains the transparency and diversity of data needed to generalize effectively across different patient populations without sacrificing critical diagnostic details. The experiments are conducted on a system with an ASUS Prime H610M- K motherboard, featuring an Intel 12th Gen Core i5-12400F processor (6 cores/12 threads, 2.5 GHz), 16 GB DDR5-4800 RAM, and Windows 10 Professional 64-bit as the operating system.

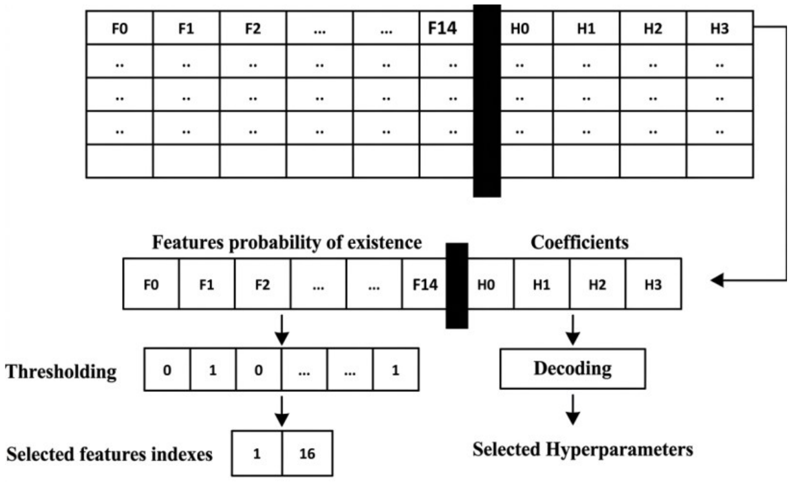


Figure 5. Solution generation

3. RESULTS AND DISCUSSION

3.1. Experimental setup

While the neural network's optimizer, number of epochs, and loss function are fixed at Adam, 20, and binary cross-entropy, respectively, other optimized hyperparameter ranges are exposed in Table 1. The input layer is set as the number of features since it is changing through iterations, and the output layer is a one neuron using sigmoid activation function. Regarding the metaheuristic algorithms, Table 2 resumes the parameter values, and GWO's core mechanism automatically handles the convergence factor and the calculation of "A" and "C" vectors, which are crucial for the encircling and hunting behavior.

3.2. Metaheuristic solutions comparison

Once all parameters are set up, the search for the optimal solution starts. Table 3 represents computation time for each algorithm. The computation time is generally not changing much between program runs, which shows that both GWO and PSO have been about 3 times faster than DE.

Table 1. Hyperparameter ranges and types

Hyperparameter	Range	Type
Learning rate	(1e-4, 1e-1)	Continuous
Number of layers	(2, 5)	Integer
Number of neurons	[8, 16, 24, 32]	Categorical
Activation	['relu', 'sigmoid', 'tanh']	Categorical

Table 2. Metaheuristics parameters

Algorithm	Parameter	Value
General parameters	Number of Iterations	10
	Population Size	10
PSO	w (Inertia)	1
	Wdamp (Damping factor)	0.8
	c1 (Personal coefficient)	2
	c2 (Social coefficient)	2
DE	CR (Crossover rate)	0.5
	F (Scaling factor)	0.8

Table 3. Computation time comparison

Algorithm	GWO	PSO	DE
Computation time (s)	629.7711	710.6278	2017.6134

The convergence curves of the three metaheuristic algorithms are illustrated in Figure 6. Numerically, PSO and GWO exhibit superior convergence speed, reaching a lower global minimum within the first iterations, which suggests high efficiency in minimizing the mathematical cost function. Conversely, DE displays a slower descent. While this might initially imply lower optimization efficiency, it suggests that DE avoids premature convergence by performing a more exhaustive exploration of the search space.

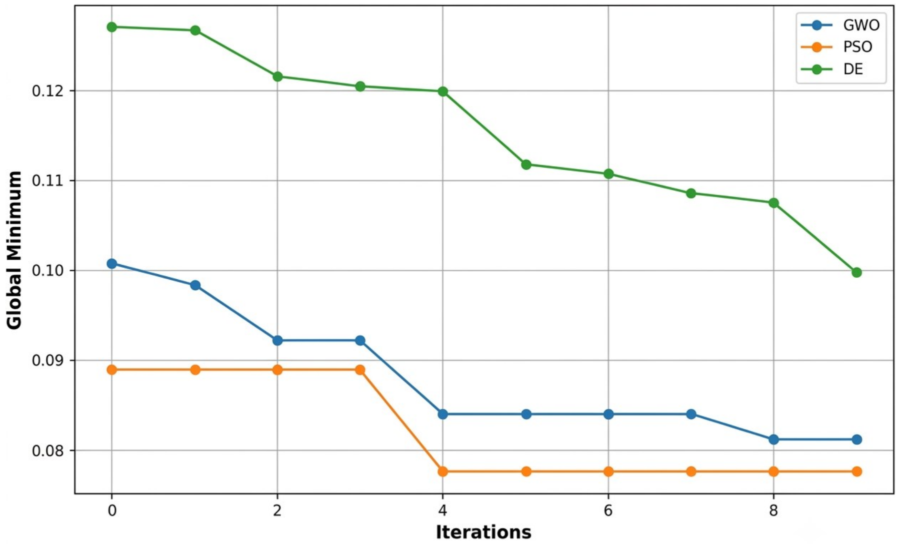


Figure 6. Global minimum convergence

PSO best solution accuracies have achieved 95.18% and 88.66%, area under the curve (AUC) of 0.99 and 0.94, for datasets 1 and 2 successively, using 6 features. GWO best solution has achieved 95.18% and 87.5% accuracies with an AUC of 0.98 and 0.93, using 5 features. DE best solution has achieved 96.38% and 90.69% accuracies with an AUC of 0.99 and 0.96, for datasets 1 and 2 successively, using 10 features, demonstrating the best overall balance across all performance indicators.

3.3. Optimal model

The 10 selected features during the optimization process are detailed in Table 4, and the corresponding model is a neural network with a ten-node input layer corresponding to the number of features and a single-neuron output layer, utilizing a sigmoid activation function, which was implemented to produce a probability score for binary classification. Table 5 shows the selected hyperparameters in the hidden layers using DE algorithm. For each layer, the same activation function is used in all the neurons.

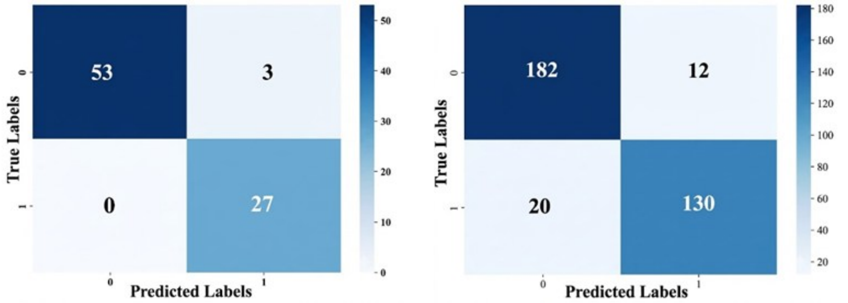
Using the selected features and the discussed hyperparameters, the neural network model achieved high performance across both evaluated datasets, as illustrated in the confusion matrices in Figure 7. Specifically, Figure 7(a) illustrates model’s performance on dataset 1, while Figure 7(b) shows performance on dataset 2. Although the number of test samples in these subsets is smaller compared to the total training pool, the consistency of the results across both datasets confirms the model's robustness and generalizability.

Table 4. DE selected features

Algorithm	Selected features
Differential evolution	Mean R-R intervals R-R standard deviation RMSSD OF R-R intervals Percentage of successive R-R intervals that differ by more than 50 ms R mean height R height standard deviation P wave duration standard deviation P-wave mean area P wave width standard deviation QRS mean interval

Table 5. Hyperparameter values

Hyperparameters	Values
Learning rate	0.0174
Number of hidden layers	3
Numbers of neurons	[32, 24, 16]
Activation function	['tanh','tanh','sigmoid']



(a) (b)

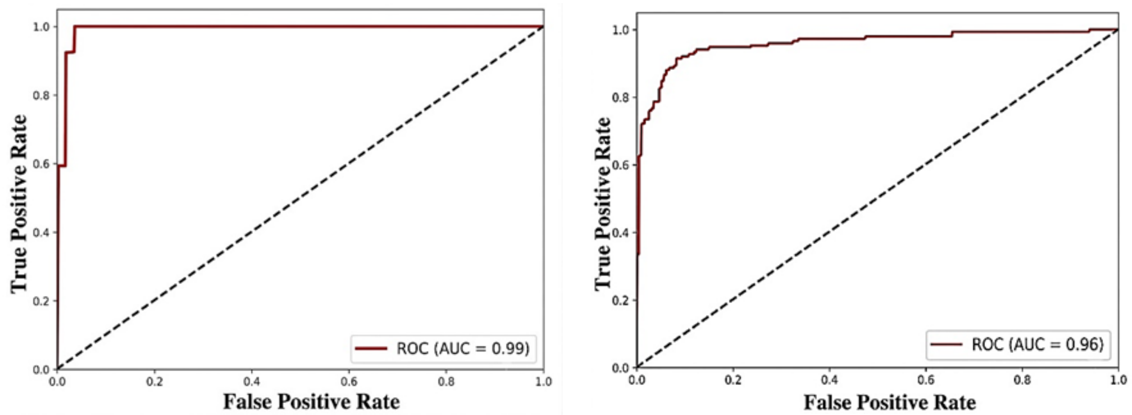
Figure 7. Confusion matrices of (a) dataset 1 and (b) dataset 2

To provide a concise overview of the models' overall performance, Table 6 presents the accuracy, F1-score, precision, and recall for each class, while Figure 8 displays the ROC curves evaluating classification performance. Specifically, Figures 8(a) and 8(b) present the ROC curves for dataset 1 and dataset 2, respectively. The model demonstrates high diagnostic efficacy, with a consistent AF precision of 90 to 92% and high F1-scores (up to 97%), ensuring reliable classification with few false alarms. In dataset 1, the system achieved a perfect 100% recall for AF, though this sensitivity slightly decreased to 87% in dataset 2. These metrics are further supported by the rapid rise of both ROC curves toward the upper-left coordinate, reflecting high discriminative power, maximizing sensitivity while minimizing false positives.

Table 6. Performance of the model

Dataset	Accuracy (%)	Precision (%)		Recall (%)		F1-score (%)	
		Normal	AF	Normal	AF	Normal	AF
Dataset 1	96.38	100	90	95	100	97	95
Dataset 2	90.69	90	92	94	87	92	89

Tables 7 and 8, adapted from [13], present a comparative analysis of AF detection models on datasets 1 and 2, respectively. This study has extended these tables to include the performance of the proposed model. As shown, the model achieves an accuracy of 96.38% on dataset 1 and 90.69% on dataset 2, outperforming the other models. The superior performance of the proposed model is primarily due to the elimination of manual or standard hyperparameter tuning and fixed feature sets, a common limitation in existing studies. Instead of relying on human-biased selection, this study utilized DE to perform a global search for a unified optimal configuration of both features and hyperparameters. By identifying a single set of parameters that remains highly effective across two independent datasets, this study demonstrate that the model captures fundamental physiological markers of AF rather than dataset-specific noise. This dual-optimization approach ensures a more objective, robust, and generalizable diagnostic tool.



(a) (b)

Figure 8. ROC's of (a) dataset 1 and (b) dataset

Table 7. Model comparison (dataset 1)

Model	Year	Accuracy (%)
Deep ANN [28]	2020	93.00
Feedforward NN [29]	2022	84.00
11-layer CNN [30]	2017	94.90
24-Features ANN [13]	2023	96.00
Proposed model	2025	96.38

Table 8. Model comparison (dataset 2)

Model	Year	Accuracy (%)
16 layer 1-D CNN [31]	2017	82.00
LSTM [32]	2020	78.35
DCNN [33]	2018	71.00
24-Features ANN [13]	2023	86.00
Proposed model	2025	90.69

4. CONCLUSION

The main objective of this study is to enhance AF detection based on ECG recordings, by developing a novel detection model trained on a concatenated dataset, and evaluated on hold out, random and stratified test sets. The optimization process has been conducted using three different metaheuristic algorithms, PSO, GWO and DE, that have been compared in terms of solution quality and computation time. The final selected model demonstrated interesting performances, achieving accuracies of 96.38% and 90.69%, AUC scores of 0.99 and 0.96, on both datasets, surpassing the results reported in previous studies. This improvement highlights the effectiveness of the feature extraction and optimization methodology. The successful application of metaheuristic optimization underscores its potential to enhance the accuracy and reliability of AF detection systems. A promising direction for future research is to explore the model's robustness to noise and artifacts in ECG recordings, as well as its performance on larger and more diverse datasets. This work contributes valuable insights towards the development of more precise and efficient AF detection technologies.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Zaid Nouna	✓	✓	✓	✓	✓	✓		✓	✓	✓				
Hamid Bouyghf	✓					✓	✓			✓	✓	✓	✓	
Mohammed Nahid	✓					✓	✓			✓	✓	✓	✓	
Issa Sabiri	✓			✓		✓				✓	✓	✓	✓	

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT
Authors state no conflict of interest.

DATA AVAILABILITY
The adapted data that support the findings of this study are available via the original source link referenced in the main text.

REFERENCES

[1] P. Kirchhof *et al.*, "2016 ESC guidelines for the management of atrial fibrillation developed in collaboration with EACTS," *European Heart Journal*, vol. 37, no. 38, pp. 2893–2962, 2016, doi: 10.1093/eurheartj/ehw210.

[2] T. Hygrell *et al.*, "An artificial intelligence–based model for prediction of atrial fibrillation from single-lead sinus rhythm electrocardiograms facilitating screening," *Europace*, vol. 25, no. 4, pp. 1332–1338, 2023, doi: 10.1093/europace/euad036.

[3] B. Jia, J. Chen, Y. Luan, H. Wang, Y. Wei, and Y. Hu, "Artificial intelligence and atrial fibrillation: a bibliometric analysis from 2013 to 2023," *Heliyon*, vol. 10, no. 15, 2024, doi: 10.1016/j.heliyon.2024.e35067.

[4] Z. I. Attia *et al.*, "An artificial intelligence-enabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: a retrospective analysis of outcome prediction," *The Lancet*, vol. 394, no. 10201, pp. 861–867, 2019, doi: 10.1016/S0140-6736(19)31721-0.

[5] T. Anbalagan, M. K. Nath, D. Vijayalakshmi, and A. Anbalagan, "Analysis of various techniques for ECG signal in healthcare, past, present, and future," *Biomedical Engineering Advances*, vol. 6, 2023, doi: 10.1016/j.bea.2023.100089.

[6] A. Y. Hannun *et al.*, "Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network," *Nature Medicine*, vol. 25, no. 1, pp. 65–69, 2019, doi: 10.1038/s41591-018-0268-3.

[7] A. Azzouz *et al.*, "An efficient ECG signals denoising technique based on the combination of particle swarm optimisation and wavelet transform," *Heliyon*, vol. 10, no. 5, 2024, doi: 10.1016/j.heliyon.2024.e26171.

[8] C. T. January *et al.*, "2014 AHA/ACC/HRS guideline for the management of patients with atrial fibrillation: a report of the American College of Cardiology/American Heart Association task force on practice guidelines and the heart rhythm society," *Journal of the American College of Cardiology*, vol. 64, no. 21, pp. e1–e76, 2014, doi: 10.1016/j.jacc.2014.03.022.

[9] A. A. Laghari, Y. Sun, M. Alhussein, K. Aurangzeb, M. S. Anwar, and M. Rashid, "Deep residual-dense network based on bidirectional recurrent neural network for atrial fibrillation detection," *Scientific Reports*, vol. 13, no. 1, 2023, doi: 10.1038/s41598-023-40343-x.

[10] A. B. Rad *et al.*, "A crowdsourced AI framework for atrial fibrillation detection in Apple Watch and Kardia Mobile ECGs," *Sensors*, vol. 24, no. 17, 2024, doi: 10.3390/s24175708.

[11] X. Zhao, R. Zhou, L. Ning, Q. Guo, Y. Liang, and J. Yang, "Atrial fibrillation detection with single-lead electrocardiogram based on temporal convolutional network–ResNet," *Sensors*, vol. 24, no. 2, 2024, doi: 10.3390/s24020398.

[12] M. S. Jahan, M. Mansourvar, S. Puthusserypady, U. K. Wiil, and A. Peimankar, "Short-term atrial fibrillation detection using electrocardiograms: a comparison of machine learning approaches," *International Journal of Medical Informatics*, vol. 163, 2022, doi: 10.1016/j.ijmedinf.2022.104790.

[13] D. U. S. Duranta *et al.*, "Enhancing atrial fibrillation detection accuracy: a wavelet transform filtered single lead ECG signal analysis with artificial neural networks and novel feature extraction," *Machine Learning with Applications*, vol. 12, 2023, doi: 10.1016/j.mlwa.2023.100472.

[14] Z. O. Hamad, "Review of feature selection methods using optimization algorithm (review paper for optimization algorithm)," *Polytechnic Journal*, vol. 12, no. 2, pp. 203–214, 2022, doi: 10.25156/ptj.v12n2y2022.pp203-214.

[15] P. Pławiak, "Novel methodology of cardiac health recognition based on ECG signals and evolutionary-neural system," *Expert Systems with Applications*, vol. 92, pp. 334-349, 2018, doi: 10.1016/j.eswa.2017.09.022.

[16] G. Clifford *et al.*, "AF classification from a short single lead ECG recording: the Physionet computing in cardiology challenge 2017," *2017 Computing in Cardiology (CinC),* Rennes, France, 2017, pp. 1-4, doi: 10.22489/CinC.2017.065-469.

[17] A. F. Hussein, W. R. Mohammed, M. Musa Jaber, and O. I. Khalaf, "An adaptive ECG noise removal process based on empirical mode decomposition (EMD)," *Contrast Media and Molecular Imaging*, vol. 2022, no. 1, 2022, doi: 10.1155/2022/3346055.

[18] T. Dokeroglu, A. Deniz, and H. E. Kiziloz, "A comprehensive survey on recent metaheuristics for feature selection," *Neurocomputing*, vol. 494, pp. 269–296, 2022, doi: 10.1016/j.neucom.2022.04.083.

[19] A. G. Gad, "Particle swarm optimization algorithm and its applications: a systematic review," *Archives of Computational Methods in Engineering*, vol. 29, no. 5, pp. 2531–2561, 2022, doi: 10.1007/s11831-021-09694-4.

[20] R. Storn and K. Price, "Differential evolution - a simple and efficient heuristic for global optimization over continuous spaces," *Journal of Global Optimization*, vol. 11, no. 4, pp. 341–359, 1997, doi: 10.1023/A:1008202821328.

[21] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," *Advances in Engineering Software*, vol. 69, pp. 46–61, 2014, doi: 10.1016/j.advengsoft.2013.12.007.

[22] K. G. Shreeharsha, R. K. Siddharth, M. H. Vasantha, and Y. B. N. Kumar, "An error bound particle swarm optimization for analog circuit sizing," *IEEE Access*, vol. 12, pp. 50126–50136, 2024, doi: 10.1109/ACCESS.2024.3385491.

[23] I. Sabiri, H. Bouyghf, and A. Raihani, "Optimal interdigitated electrode sensor design for biosensors using differential evolution algorithm," *E3S Web of Conferences*, vol. 351, 2022, doi: 10.1051/e3sconf/202235101031.

[24] K. G. Shreeharsha, R. K. Siddharth, M. H. Vasantha, and Y. B. N. Kumar, "Partition bound random number-based particle swarm optimization for analog circuit sizing," *IEEE Access*, vol. 11, pp. 123577–123588, 2023, doi: 10.1109/ACCESS.2023.3329698.

[25] H. Bouyghf, B. Benhala, and A. Raihani, "Analysis of the impact of metal thickness and geometric parameters on the quality factor-Q in integrated spiral inductors by means of artificial bee colony technique," *International Journal of Electrical and Computer Engineering*, vol. 9, no. 4, pp. 2918–2931, 2019, doi: 10.11591/ijece.v9i4.pp2918-2931.

[26] N. Savanović *et al.*, "Intrusion detection in Healthcare 4.0 internet of things systems via metaheuristics optimized machine learning," *Sustainability*, vol. 15, no. 16, 2023, doi: 10.3390/su151612563.

[27] L. Zhang *et al.*, "BLPAD.Core: a multi-functions optimizer towards daily planning generation in home health care," in *2020 IEEE/ACS 17th International Conference on Computer Systems and Applications (AICCSA),* Antalya, Turkey, 2020, pp. 1-6, doi: 10.1109/AICCSA50499.2020.9316522.

[28] L. Khriji, M. Fradi, M. Machhout, and A. Hossen, "Deep learning-based approach for atrial fibrillation detection," in *The Impact of Digital Technologies on Public Health in Developed and Developing Countries*, Cham: Springer, 2020, pp. 100–113, doi: 10.1007/978-3-030-51517-1_9.

[29] Y. Chen, C. Zhang, C. Liu, Y. Wang, and X. Wan, "Atrial fibrillation detection using a feedforward neural network," *Journal of Medical and Biological Engineering*, vol. 42, no. 1, pp. 63–73, 2022, doi: 10.1007/s40846-022-00681-z.

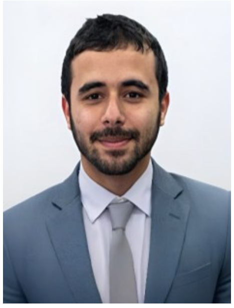
[30] U. R. Acharya, H. Fujita, O. S. Lih, Y. Hagiwara, J. H. Tan, and M. Adam, "Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network," *Information Sciences*, vol. 405, pp. 81–90, 2017, doi: 10.1016/j.ins.2017.04.012.

[31] Z. Xiong, M. K. Stiles, and J. Zhao, "Robust ECG signal classification for detection of atrial fibrillation using a novel neural network," in *2017 Computing in Cardiology (CinC),* Rennes, France, 2017, pp. 1-4, doi: 10.22489/CinC.2017.066-138.

[32] P. Cao *et al.*, "A novel data augmentation method to enhance deep neural networks for detection of atrial fibrillation," *Biomedical Signal Processing and Control*, vol. 56, 2020, doi: 10.1016/j.bspc.2019.101675.

[33] S. Ghiasi, M. Abdollahpur, N. Madani, K. Kiani, and A. Ghaffari, "Atrial fibrillation detection using feature-based algorithm and deep convolutional neural network," in *2017 Computing in Cardiology (CinC),* Rennes, France, 2017, pp. 1–4, doi: 10.22489/CinC.2017.159-327.

BIOGRAPHIES OF AUTHORS



Zaid Nouna got his bachelor's degree in Electrical Engineering and Industrial Computing in 2020, and then an engineering degree in Electrical and Telecommunications in 2023, both at the University Hassan II Mohammedia, Morocco. He is currently a Ph.D. student at Mohammedia-Faculty of Science and Techniques, Hassan II University of Casablanca, in the Laboratory of Engineering Sciences and Biosciences (LSIB). His research and interests are centered on the development and optimization of electronic systems for biomedical engineering and data science techniques for medical applications. He can be contacted at email: zaid.nouna-etu@etu.univh2c.ma.

Hamid Bouyghf got his B.S. and M.S. degrees in Electrical Engineering and Telecom from the University of Science and Technology in Fez, Morocco, in 2007, and his Ph.D. in Electrical Engineering and Telecom from Hassan II University of Casablanca, Morocco, in 2019. From 2015 until 2019, he worked as a research assistant at the Princeton Plasma Physics Laboratory. Since 2019, he has worked as an assistant professor at the Department of Electrical Engineering at Hassan II University's FST Mohammedia in Casablanca, Morocco, and has received his habilitation in Electrical Engineering and Artificial Intelligence in 2023. He conducts research within the Laboratory of Engineering Sciences and Biosciences (LSIB), leading the "circuits and systems" team. In the topic of IC optimization, he has written numerous articles. His research interests include biomedical electronics, analog IC design, electromagnetic fields, low power design, and BLE applications. He can be contacted at email: hamid.bouyghf@gmail.com.

Mohammed Nahid studied electronics and received the B.S. diploma in Electronics at ENSET Institute, Mohammedia, Morocco in 1994, received the Aggregation diploma of electronics and electrical engineering from ENSET institute of Rabat, Morocco in 2000. He received the DESA diploma in computer engineering, telecoms and multimedia in 2004. He conducted doctoral research at images, videos coding and quality assessment under psychovisual quality criteria since 2004 at Mohamed V university of Rabat, Morocco, where he received his Ph.D. in 2010. He is research professor in the Faculty of Science and Techniques of Hassan II University, Mohammedia since 2011, specifically affiliated with the Laboratory of Engineering Sciences and Biosciences located at the Faculty of Sciences and Techniques (FST), conducts research on visual perception and its application to coding, understanding, and display of visual information and to human vision, image quality, and digital imaging. Research and projects are also focused on artificial intelligence, embedded systems, biomedical systems, smart grids, and digital and analog IC design. He can be contacted at email: mohammed.nahid@gmail.com.

Issa Sabiri got a Ph.D. degree in Electrical Engineering and Artificial Intelligence from ENSET Mohammedia-Faculty of Science and Technique, Hassan II University of Casablanca, Morocco, affiliated with the Laboratory of Signals, Distributed Systems and Artificial Intelligence (LSSDIA). His license degree in bio medical instrumentation and maintenance, at the Institute of Health SciencesSettat-Morocco (ISSS) at the University Hassan I, Settat-Morocco. He also got a master's degree in Biomedical Engineering from FST Settat in 2018. His work, studies, and interests are focused on the development, design, and optimization of electronic systems for biomedical engineering, and health sciences. He can be contacted at email: issa.sabiri@etu.fstm.ac.ma.