Short-time Fourier transform based ensemble classifiers for detection of atrial fibrillation from ECG datasets

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Abstract

Atrial Fibrillation (Afib) is a common cardiac arrhythmia characterized by irregular and often rapid heart rate, leading to inefficient blood pumping from the atria. It increases the risk of stroke, heart failure, and other heart-related complications. Afib is often associated with symptoms like palpitations, shortness of breath, and fatigue. Diagnosis typically involves Electrocardiography (ECG) to detect irregular electrical activity in the heart. Treatment options range from medication to procedures like catheter ablation, aimed at restoring normal heart rhythm and reducing associated risks. Soft computing methods can aid in automating the classification of cardiovascular diseases, assisting clinicians in diagnosing arrhythmias. In this research paper, ensemble classifiers are employed for the classification of Atrial Fibrillation based on ECG datasets. When utilizing the Catboost Classifier in conjunction with the STFT-based GEO implementation, the results indicate an average perfect classification rate of approximately 99%, an error rate of 1%, and a kappa coefficient of 0.9689% for detection of Afib.

Keywords: Adaboost, Cardiovascular Disease, Catboost, ECG, XGboost.

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1. Introduction

In the empire of medical diagnostics, accurate and timely detection of cardiac arrhythmias holds immense importance for effective patient care. One such significant arrhythmia is atrial fibrillation (Afib), characterized by irregular and often rapid heartbeats. Afib detection plays a crucial role in the diagnosis and treatment of cardiovascular conditions, as its early identification can prevent potentially serious complications [1]. To address the challenges associated with Afib detection, researchers and medical professionals are increasingly turning to advanced signal processing techniques and machine learning approaches. Here are some notable accomplishments within the field of Afib detection. Attia et al. [2] employed deep learning techniques (AFCODE) for the detection of Afib, this AFCODE study achieved an accuracy of 84% in detecting Afib. Clifford et al. [3] utilized the different learning techniques for CinC Challenge 2017. The winning entry in the 2017 CinC Challenge achieved an accuracy of 92.7% in distinguishing Afib from other rhythms. Bumgardner et al. [4] applied the Deep Learning-based detection of Afib using a Smartwatch. This study reported an accuracy of 90.2% in detecting Afib from smartwatch ECG data. Hannun et al. [5] employed the Convolutional Neural Networks (CNN) for Afib Detection, the CNN model achieved an accuracy of 92% in Afib detection. Kiranyaz et al. [6] engaged the Afib detection from 12-lead ECG Recordings. This research achieved an accuracy of 98.8% in classifying Afib from 12-lead ECG recordings.

Smith et al. [7] utilized the deep learning-based detection of Afib and achieved an accuracy of 92.5% in detecting atrial fibrillation using a CNN on ECG data. Chen et al. [8] applied the deep learning model for the detection of atrial fibrillation, this study reported an accuracy of 95.2% in atrial fibrillation detection with a deep neural network applied to single-lead ECG signals. Kim et al. [9] demonstrated an accuracy of 93.8% in detecting atrial fibrillation using a machine learning model applied to data from wearable ECG devices. Li et al. [10] employed a random forest and CNN model for the detection of atrial fibrillation from ECG data. Achieved an accuracy of 91.7% in atrial fibrillation detection using a combination of random forest and CNN on ECG data. Wang et al. [11] utilized Recurrent Neural Networks (RNN) with Support Vector Machines (SVM) for the detection of Afib from ECG signals. This model reported an accuracy of 94.3% in detecting atrial fibrillation using a hybrid model combining RNN and support vector machines.

Rajpurkar et al. [12] employed the deep learning model for the classification of cardiovascular signals, in this research demonstrated an accuracy of 98 % for AF detection using deep learning techniques. Shashikumar et al. [13] utilized the deep learning model for the detection of Afib from single-lead ECG recordings. Achieved an accuracy of 92.5% in detecting Afib from short single-lead ECG recordings. Asgari et al.

[14] employed Afib detection using data from wearable smartwatches with a reported accuracy of 91.7%. Li et al. [15] utilized the deep learning model for the detection of Afib, in this study achieved an accuracy of 94.5% in identifying Afib from ECG signals. Liu et al. [16] employed the deep learning model for the classification of Afib diseases using mobile health observation. Reported an accuracy of 94% in Afib detection using deep learning models. Xiong et al. [17] employed the CNN model for the detection of Afib disease from ECG data. This model reported an accuracy of 95.3% in detecting AF from ECG signals. Lee et al. [18] employed the machine learning classification model for the detection of Afib from photoplethysmography datasets. Achieved an accuracy of 91.2% in AF detection from photoplethysmography datasets. Ma et al. [19] proposed a novel technique of LSTM-RNN algorithm for the detection of Afib from ECG datasets. Reported an accuracy of 93.7% in AF detection using LSTM-based recurrent neural networks.

Maturo and Verde [20] employed the integration of random forest and functional data analysis for the classification of the electrocardiogram data. This model reported a training accuracy of 97.28% and a testing accuracy of 93.64%. Maturo and Verde [21] proposed novel techniques of functional random forest with functional principal components and functional KNN algorithms for ECG data. Reported the highest accuracy of 94% in ECG data detection using functional random forest with functional principal components technique. Maturo and Verde [22] utilized the functional classification trees, functional random forest, and functional bagging, in this investigation achieved a best training accuracy of 98.51% and testing accuracy of 97.57% in the detection of electrical power demand using a functional random forest classifier.

This introduction delves into the pivotal role of feature extraction and optimization algorithms in the proposal of Afib detection. Feature extraction is a fundamental step in analyzing electrocardiogram (ECG) signals to unveil distinctive patterns indicative of Afib. In this study, explores the significance of Afib detection, the role of feature extraction techniques like the Short-Time Fourier Transform (STFT), and the feature selection offered by nature-inspired optimization algorithms such as the Spider Monkey Optimization (SMO) and Golden Eagle Optimization (GEO) algorithms for enhancing the accuracy and efficiency of Afib detection models. Finally, Ensemble classifiers are employed as a classifier for the detection of Afib. By merging scientific inquiry with computational innovation, the medical community is poised to achieve advancements in the realm of Afib detection, ultimately leading to improved patient outcomes and enhanced cardiac health management. Figure 1 displays the block diagram of the proposed process.

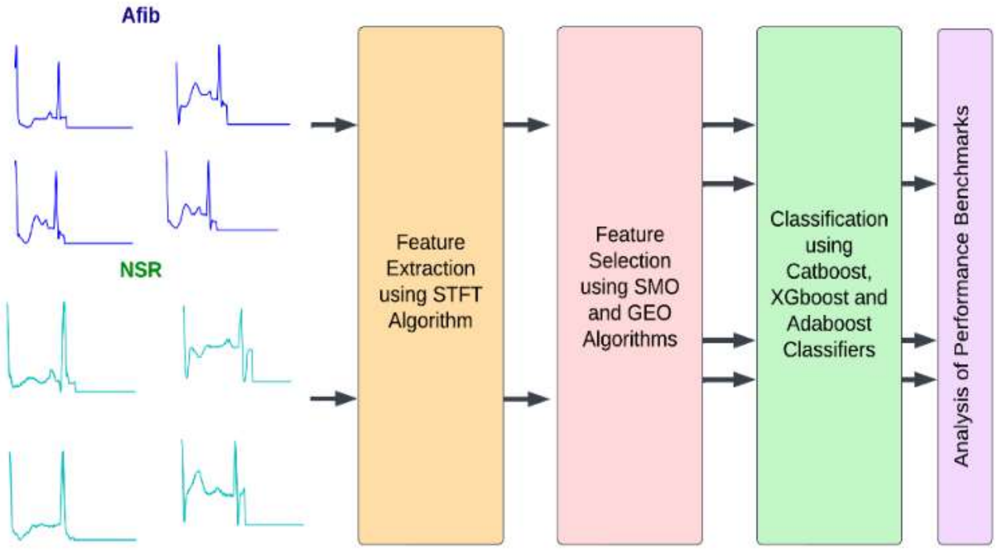

Figure 1. Block diagram of the proposed process

2. Materials and methods

The dataset consists of meticulously sourced ECG data from electrocardiograms (ECGs), obtained from Kaggle (https://www.kaggle.com) [23]. Its primary goal is to enable accurate detection of atrial fibrillation, a crucial cardiac arrhythmia marked by irregular and accelerated heartbeats. This dataset holds a wealth of visual insights derived from ECG recordings, providing a fertile ground for developing and evaluating advanced algorithms and models tailored for precise atrial fibrillation (Afib) detection. Sourced from Kaggle, a renowned platform for sharing diverse datasets, the dataset revolves around ECG datasets that capture the intricate electrical dynamics of the heart. These datasets visually represent the heart's rhythm, unveiling potential deviations that could indicate Afib.

In this paper, The Afib category includes 50 recordings (65000 Samples per Recordings), each sampled at a frequency of 250 Hz, with a sampling interval of 0.004 seconds. Within the Afib category, there are a total of 13,000 epochs, and each epoch contains 250 samples. The NSR category includes 50 recordings (65000 Samples per Recordings), each sampled at a frequency of 128 Hz, with a sampling interval of 0.078 seconds. Within the NSR category, there are a total of 25, 400 epochs and each epoch contains 128 samples. Table.1. provides an overview of the dataset particulars in this study.

Category	Total Recordings	Samples per Recordings	No. of Epochs	Samples per epochs
Afib	50	65000	13000	250
NSR	50	65000	25400	128

Table 1. Overview of the dataset

To extract features from cardiac signals, they are divided into epochs, allowing for the convenient computation of statistical features and the tracking of cardiac signal evolution. In this study, feature extraction serves to streamline the representation of extensive cardiac data efficiently. The STFT algorithm is employed to extract features from both Afib and NSR signals.

3. Feature extraction using short-time Fourier transform (STFT) algorithm

Atrial fibrillation (Afib) is a common cardiac arrhythmia marked by irregular and rapid heartbeats. Precise Afib detection is crucial for accurate diagnosis and effective treatment. In this proposal, feature extraction holds a pivotal role in signal processing and machine learning approaches for Afib detection. An effective technique used for this purpose is the Short-Time Fourier Transform (STFT). The STFT is a versatile method for time-frequency analysis, providing insights into signal frequency dynamics over time. It breaks down a signal into frequency components, yielding a comprehensive view of its frequency variations in a two-dimensional spectrogram matrix. Initially, the input electrocardiogram (ECG) signal, reflecting heart electrical activity, is divided into overlapping windows of fixed length. These short windows capture local signal variations that hint at irregular heartbeats in Afib cases [24].

$$X(\tau, f) = \int_{-\infty}^{\infty} x(t)w(t-\tau)e^{-j2\pi ft}dt \tag{1}$$

Where $X(\tau, f)$ represents the STFT coefficient at time τ and frequency f, $x(t)$ indicates the windowed signal, $w(t-\tau)$ represents the window function centered at τ, $e^{-j2\pi ft}$ indicates the complex exponential for frequency f. The magnitudes of the FFT results for each segment are used to construct the spectrogram. The x-axis represents time, the y-axis represents frequency, and the color or intensity represents the magnitude of the corresponding frequency component. Calculate the magnitude or power of the STFT coefficients [25]. This can be done using:

$$S(\tau, f) = |X(\tau, f)|^2 \tag{2}$$

Where $S(\tau, f)$ represents the power spectral density at time τ and frequency f. The resulting spectrogram can be used for feature extraction. Various features can be extracted from the spectrogram to capture different aspects of the signal's frequency content over time.

After feature extraction, within the Afib category, there are a total of 1250 epochs, and each epoch contains 250 samples. Within the NSR category, there are a total of 2441 epochs and each epoch contains 128 samples. In this paper statistical measures are analyzed such as mean, variance (VAR), skewness, kurtosis, Pearson correlation coefficient, sample entropy (SamEn), and P-value. A significance level of $P = 0.01$ defines the threshold for the study's significance. If $P \leq 0.01$ is observed, it indicates a strong level of significance. Conversely, when $P \geq 0.01$ is observed, it suggests a lack of significance. Table.2. presents an investigation into the Average Statistical Metrics derived from the STFT Feature Extraction Algorithm. Table 2. reveals that the statistical parameters exhibit skewness and a flat kurtosis nature. Figure 2. represents the histogram difference analysis of STFT features for Afib and NSR classes. The Normal probability analysis of STFT features for Afib and NSR classes is represented in Figure 3.

Class	Mean	VAR	Skewness	Kurtosis	PCC	SamEn	P-value
AFib	0.003	0.004	-0.032	10.078	0.007	8.008	0.419
NSR	0.045	0.0001	0.059	-1.168	0.995	3.055	0.250

Table 2. Average statistical measures for STFT feature extraction algorithm

Table.2. reveals that the statistical parameters display skewed distributions, with a flattened kurtosis nature. The Pearson Correlation Coefficient (PCC) demonstrates negligible correlation among intra-class features. Sample Entropy highlights significant deviations between classes. P values indicates the lack of significant.

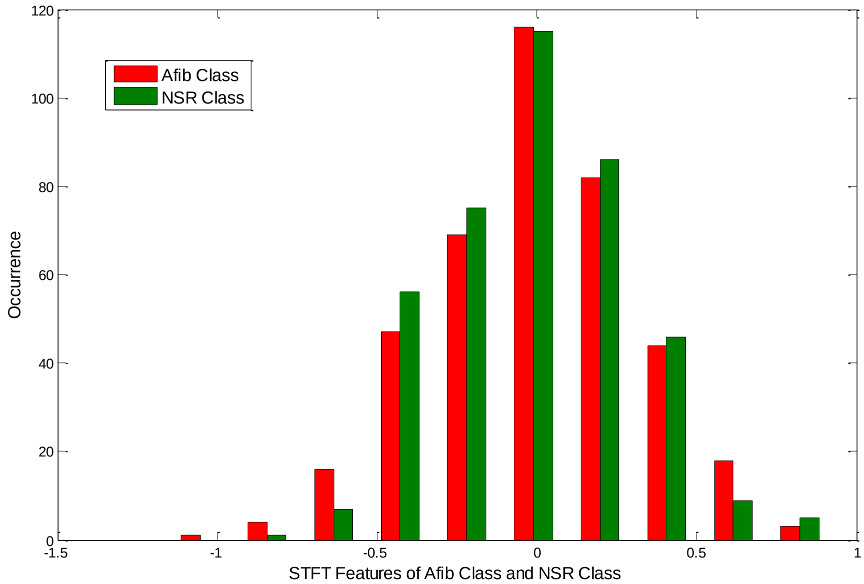

Figure 2. Histogram difference analysis STFT features of Afib and NSR classes.

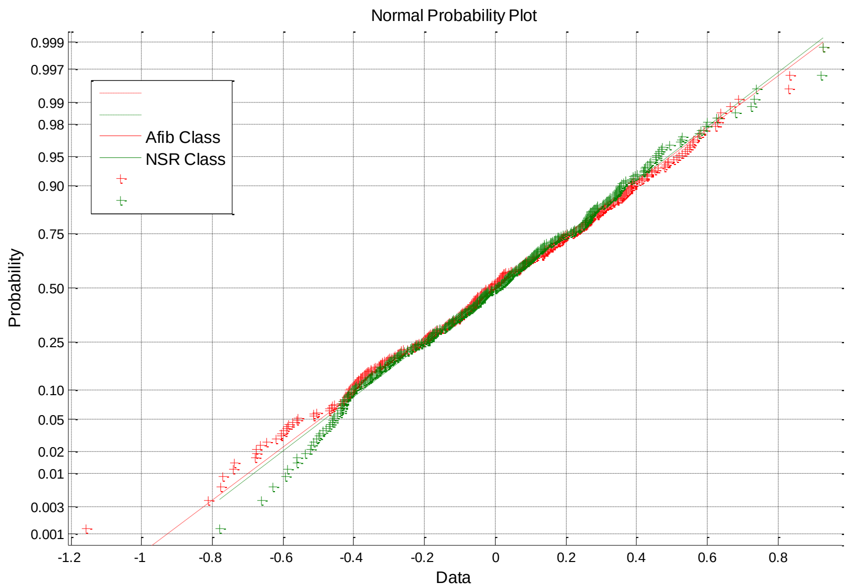

Figure 3. Normal probability analysis of STFT features of Afib and NSR classes.

From figure 2 and figure 3 represent the high overlapping, Outliers, and Nonlinearity of the classes. Consequently, the feature selection process is anticipated to enhance overall performance efficiency.

4. Feature selection using nature-inspired optimization algorithms

Detecting atrial fibrillation (Afib), a common cardiac arrhythmia characterized by irregular and often rapid heartbeats is a critical task in modern healthcare. Signal processing and machine learning techniques have emerged as invaluable tools in Afib detection, with feature selection playing a pivotal role in enhancing the accuracy and efficiency of these methods. Nature-inspired optimization algorithms have gained prominence in recent years as effective means of feature selection, aiding in the identification of the most relevant and informative features from complex datasets. Two such algorithms, the Spider Monkey Optimization (SMO) Algorithm and the Golden Eagle Optimization (GEO) Algorithm, have shown promise in addressing the intricacies of Afib detection.

4. 1 Spider monkey optimization (SMO) algorithm

The SMO algorithm takes its cues from the intricate conduct of spider monkeys as they navigate their surroundings in pursuit of sustenance and necessities. These monkeys showcase extraordinary social acumen and adaptability, characteristics that have been computationally leveraged to tackle intricate optimization challenges, including the selective extraction of features to detect Afib. The SMO algorithm functioning closely emulates the foraging behavior of spider monkeys. It employs a population of potential solutions, representing different feature subsets. These solutions evolve over generations through processes akin to monkey social behaviors, such as exploration, exploitation, and communication. Here are the general steps involved in the Spider Monkey Optimization algorithm [26]:

Step 1: **Initialization:** Generate an initial population of spider monkeys (solution candidates) randomly or through some heuristic method.

$$SM_{pq} = SM_{minq} + G(0,1) * \left(SM_{maxq} - SM_{minq}\right) \tag{3}$$

Where SM_{maxq} and SM_{minq} indicates the upper bound and lower of the dimension and $G(0,1)$ represents the random number.

Step 2: **Ranking:** Rank the monkeys in the population based on their fitness values. This can be done in ascending or descending order, depending on whether you are minimizing or maximizing the objective function.

Step 3: **Leader Selection:** Choose the monkey with the best fitness as the leader. This monkey will guide the exploration and exploitation phases of the algorithm.

Step 4: **Exploration Phase:** Select a subgroup of monkeys, known as exploratory monkeys, to explore new solutions. These monkeys will randomly move in the search space to discover potential solutions.

Step 5: **Exploitation Phase:** Select another subgroup of monkeys, known as exploitative monkeys. These monkeys will exploit the information provided by the leader and the exploratory monkeys to refine solutions in promising areas of the search space.

Step 6: **Update Leader:** Recalculate the fitness of the leader monkey based on the new solutions discovered during the exploration and exploitation phases. If a monkey with better fitness is found during this process, update the leader.

$$SM_{newpq} = SM_{pq} + G(0,1) * \left(GL_q - SM_{pq}\right) + G(0,1) * \left(SM_{tq} - LL_{kq}\right) \tag{4}$$

Where GL_q represents the local leader stage and LL_{kq} indicates the local leader stage.

Step 7: **Stopping Criterion & Termination:** Check if a stopping criterion is met, such as a maximum number of iterations, a convergence threshold, or a predetermined runtime. If the stopping criterion is met, end the algorithm and return the best solution found.

Just as spider monkeys explore their surroundings for various food sources, the algorithm explores different feature combinations to determine their efficacy in enhancing Afib detection accuracy. Through a process of exploitation, promising feature subsets are fine-tuned to improve performance. The algorithm incorporates a communication mechanism similar to the social interactions observed in spider monkey groups. This communication enables sharing of knowledge and solutions among different members of the population, fostering the discovery of optimal feature subsets. The fitness of each potential solution is evaluated based on its ability to effectively discriminate between Afib and normal heart rhythms. This is typically done using a machine learning classifier trained on the selected features.

4. 2 Golden eagle optimization (GEO) algorithm

The Golden Eagle Optimization (GEO) Algorithm takes its inspiration from the majestic hunting strategies of the golden eagle. Renowned for their exceptional visual acuity, strategic hunting tactics, and precise prey capture, these eagles serve as a model for the GEO algorithm's optimization approach. This algorithm harnesses these attributes to tackle intricate problems, such as feature selection for the detection of atrial fibrillation (Afib). The GEO algorithm closely mirrors the hunting conduct of golden eagles, employing a population of potential solutions in a dynamic manner. It incorporates mechanisms that are informed by the eagle's adept hunting prowess. Figure 4 represents the general steps involved in the Golden Eagle Optimization Algorithm [27]:

Much like the methodical surveying undertaken by golden eagles to pinpoint their prey, the GEO algorithm scrutinizes various feature subsets to identify those that yield the highest discriminatory potency in Afib detection. This approach mirrors the eagle's attentive assessment of its surroundings for potential targets. Similarly, as populations of golden eagles adapt to shifts in their environment, the GEO algorithm maintains a diverse collection of solutions that evolves across generations. This diversity assures a comprehensive exploration of feature combinations and augments the prospects of discovering optimal subsets. The algorithm introduces selective pressure, akin to the eagles' unwavering focus on securing the most suitable prey. This pressure underscores the significance of the most adept solutions, reinforcing their prominence in contributing to subsequent generations of solutions. This strategy aligns with the eagles' meticulous selection of their quarry.

In the empire of Afib detection, both the Spider Monkey Optimization (SMO) and Golden Eagle Optimization (GEO) algorithms contribute to the evolution of feature selection techniques. By mimicking the behaviors of spider monkeys and golden eagles, respectively, these algorithms offer novel avenues for navigating the intricate feature space landscape. This endeavor ultimately enhances the precision and efficiency of models employed in Afib detection. It's imperative, however, to acknowledge that while these algorithms exhibit promise, their application must be subject to rigorous validation and meticulous calibration to harmonize with the unique attributes of Afib datasets and the exigencies of detection requirements.

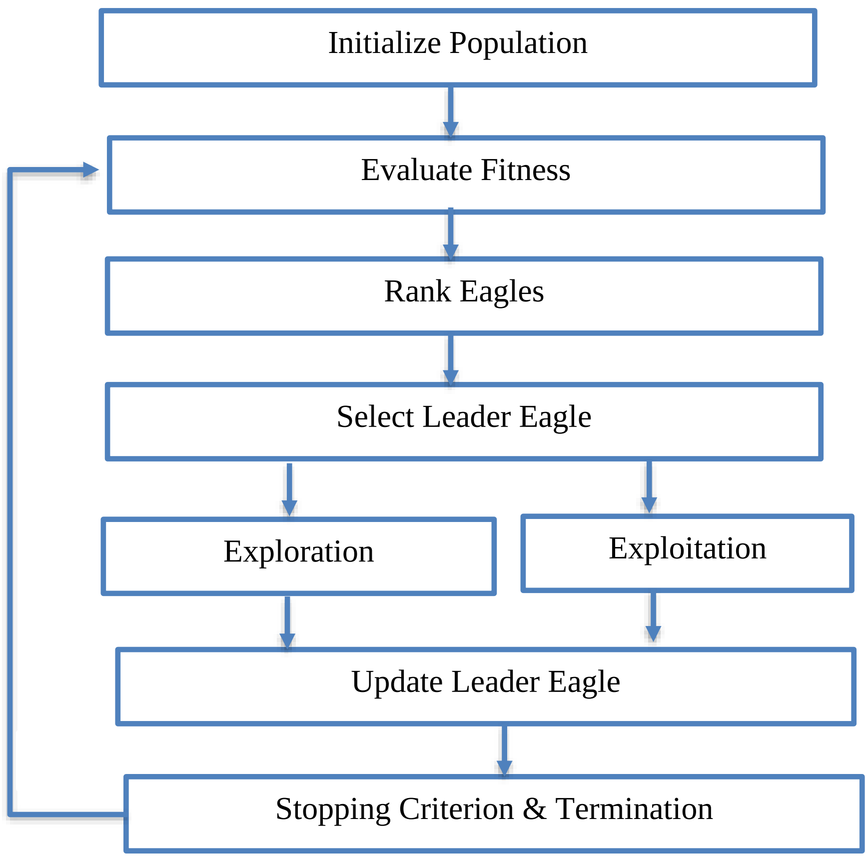

Figure 4. Steps of GEO algorithm.

After feature extraction, within the Afib category, there are a total of 400 epochs, and each epoch contains 250 samples. Within the NSR category, there are a total of 781 epochs and each epoch contains 128 samples. Table.3. presents an investigation into the

Average Statistical Metrics derived from the STFT features with SMO and GEO Feature Selection Algorithms. Table 3. reveals that the statistical parameters exhibit skewness and a flat kurtosis nature. Figure 5. represents the histogram difference analysis of STFT features with SMO algorithm for Afib and NSR classes. The Normal probability analysis of STFT features with SMO algorithm for Afib and NSR classes are represented by Figure 6. Figure 7. represents the histogram difference analysis of STFT features with GEO algorithm for Afib and NSR classes. The Normal probability analysis of STFT features with GEO algorithm for Afib and NSR classes are represented by Figure 8.

STFT Features with Spider Monkey Optimization (SMO) Algorithm							
Class	Mean	VAR	Skewness	Kurtosis	PCC	SamEn	P-value
AFib	0.143	0.0002	0.173	-1.142	0.996	5.481	0.00081
NSR	0.131	0.0004	0.361	-1.041	0.966	2.982	0.00010
STFT Features with Golden Eagle Optimization (GEO) Algorithm							
Class	Mean	VAR	Skewness	Kurtosis	PCC	SamEn	P-value
AFib	0.099	0.000003	0.166	-1.009	0.915	3.079	0.00022
NSR	0.781	0.00005	0.722	1.699	0.647	2.182	0.00030

Table 3. Average statistical measures for STFT features with SMO algorithm and STFT features with GEO Algorithm

Table 3 reveals that the statistical parameters display skewed distributions, with a flattened kurtosis nature. The Pearson Correlation coefficient demonstrates less correlation among intra-class features. Sample Entropy highlights less significant deviations between classes. P values indicates the highly of significant.

From figure 5, 6, 7 and 8 represents the less overlapping, less Outliers and less Nonlinearity of the classes. Compared to SMO and GEO algorithms, the GEO algorithms gives the better solutions.

Consequently, the selection of suitable classifiers is anticipated to enhance overall performance efficiency.

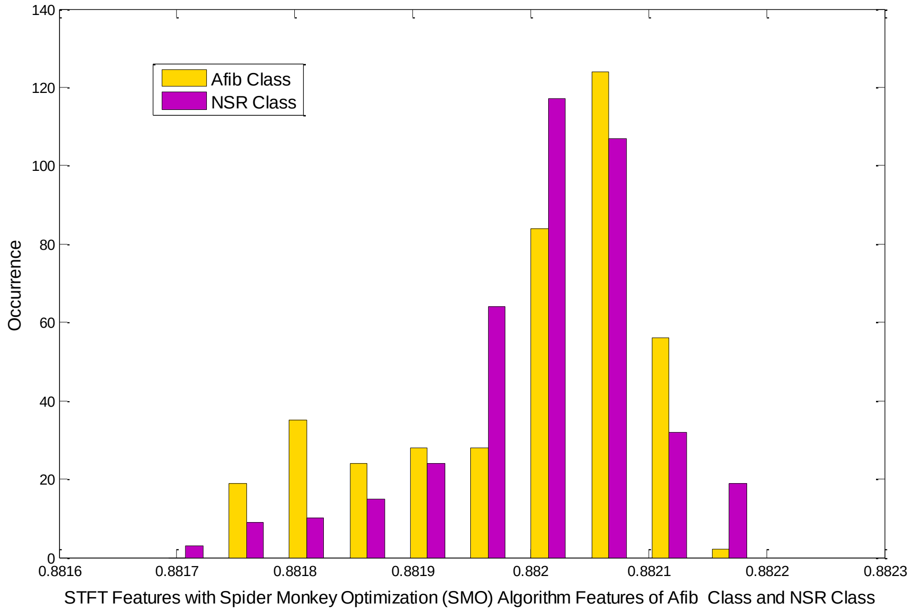

Figure 5. Histogram difference analysis STFT features with SMO features of Afib and NSR classes.

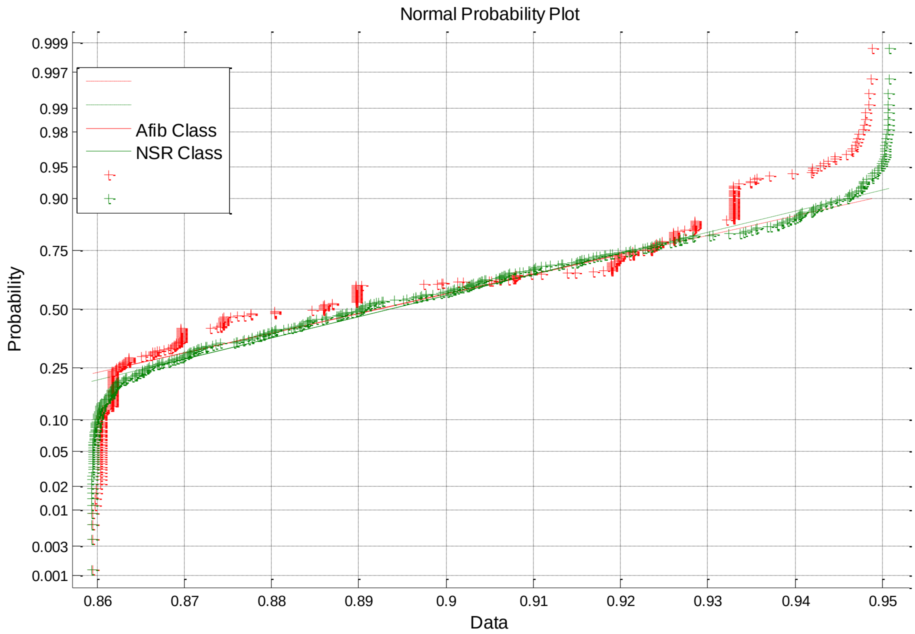

Figure 6. Normal probability analysis of STFT features with smo features of Afib and NSR classes.

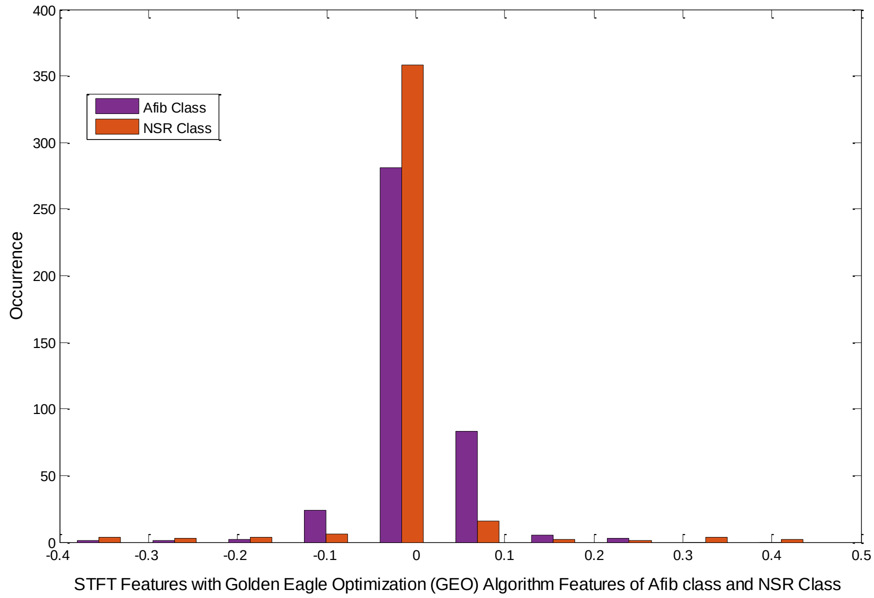

Figure 7. Histogram difference analysis STFT features with GEO features of Afib and NSR classes.

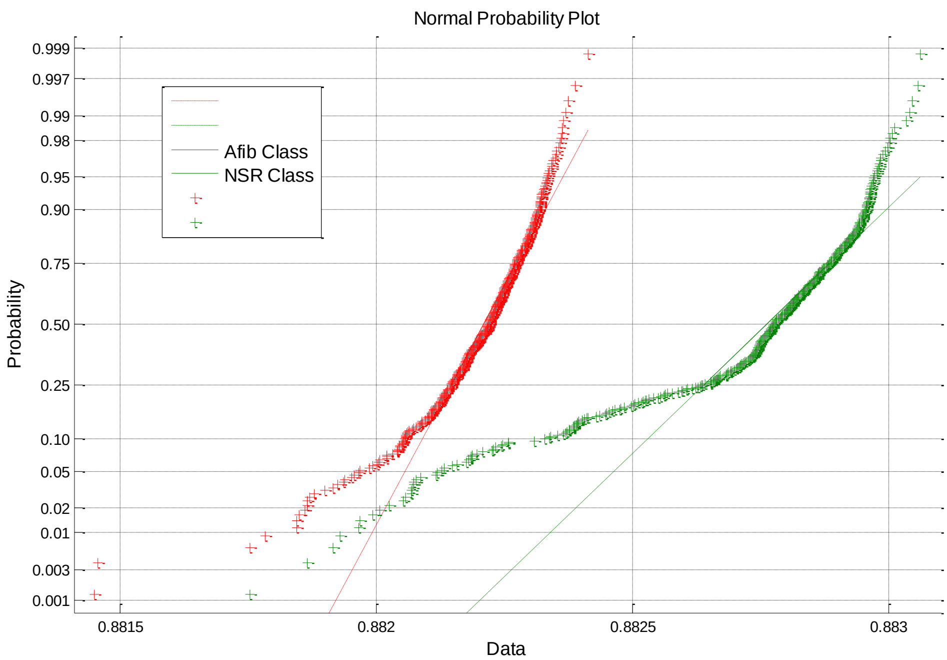

Figure 8. Normal probability analysis STFT features with geo features of Afib and NSR classes.

5. Classifications using ensemble classifiers

The features obtained through feature extraction, along with the subsequently reduced feature set, undergo analysis and comparison using ensemble classifiers. The detection of atrial fibrillation (Afib) holds paramount importance within the realm of cardiac health assessment. The precise identification of this irregular heart rhythm plays a pivotal role in enabling timely intervention and ultimately enhancing patient outcomes. To bolster the accuracy and reliability of Afib classification, the application of ensemble classifiers emerges as a powerful strategy. These ensemble classifiers represent a potent category of machine learning algorithms that harness the collective strengths of multiple individual models. In this proposal, we delve into three prominent ensemble classifiers: The Catboost Classifier, the XGboost Classifier, and the Adaboost Classifier.

5. 1 Catboost classifier

The Catboost Classifier, an advanced machine learning algorithm at the forefront of innovation, stands out as a valuable asset in the quest for precise detection of atrial fibrillation (Afib). Afib, characterized by irregular and often accelerated heart rhythms, necessitates accurate identification to facilitate effective medical intervention. Harnessing the distinct capabilities of the Catboost Classifier opens a pathway toward enhanced diagnostic outcomes. The Catboost Classifier distinguishes itself through its role as a resilient ensemble algorithm, meticulously crafted not only to adeptly manage categorical features but also to optimize the intricate process of gradient boosting. The general equation for Catboost can be represented as [28]:

$$Y_{pred} = \sum X + shrinkage \tag{5}$$

Where Y_{pred} represents the predicted output (class probability) for a given instance, X indicates the prediction of an individual base model (usually decision trees) and shrinkage represents the regularization term that controls the contribution of each base model. It exhibits a remarkable ability to seamlessly integrate categorical feature information, effectively mitigating the intricate preprocessing challenges frequently associated with such data. A standout feature within the Catboost algorithm is its introduction of the concept of ordered boosting. This innovative technique empowers the sequential training of models, strategically capitalizing on the complex interplay between features and the target variable. This intelligent approach allows the algorithm to harness the relationships between these factors, leading to more refined and accurate classification results.

5. 2 XGboost classifier

The XGboost Classifier stands out as a notable exemplar within the ensemble methods framework, firmly rooted in the foundational principles of gradient boosting. Its underlying architecture is characterized by an ensemble of decision trees, each systematically trained in succession. This coherent arrangement ensures that subsequent trees within the ensemble are dedicated to rectifying the misclassifications committed by their precursors. The XGboost algorithm has gained widespread recognition, largely attributable to its exceptional computational efficiency, along with its commendable versatility in accommodating an extensive range of data types. Additionally, the algorithm integrates crucial regularization mechanisms, strategically employed as safeguards to adeptly mitigate the perils associated with overfitting. Within the realm of atrial fibrillation detection, this robust classifier assumes particular importance, wielding its prowess to effectively contribute to accurate and reliable diagnosis. The equation for XGboost can be represented as [29]:

$$Y_{pred} = \sum X + \gamma * \Sigma \tag{6}$$

Where γ represents the learning rate, controlling the step size during optimization and Σ indicates the regularization terms applied to each tree to prevent overfitting.

5. 2 Adaboost classifier

The Adaboost (Adaptive Boosting) Classifier presents a distinctive approach designed to enhance the precision of its predictive outcomes. This ensemble technique embarks on an iterative journey, progressively refining the classification abilities of individual "weak learners." Instances that encountered misclassification in prior iterations are granted amplified importance through higher weights, thus directing the classifier's attention towards the intricate nuances posed by these challenging samples. The equation for Adaboost can be represented as [30]:

$$Y_{pred} = sign\left(\sum(\alpha * base\_model(x))\right) \tag{7}$$

Where $sign()$ indicates the function that maps positive values to +1 and negative values to -1 and α indicates the weight for the prediction of each base model. As the iterations unfold, succeeding "weak learners" are strategically crafted to rectify the previously identified misclassifications. This strategic orchestration ultimately leads to the formation of a potent final model, poised to tackle complex tasks such as the detection of atrial fibrillation.

6. Results and discussion

To conduct a comprehensive analysis of Afib classification, we examine various metrics. These metrics encompass Accuracy, Error Rate and Kappa Coefficient Measures. A 10-fold cross-validation approach is utilized, where in each iteration, one subset (representing 10% of the data) is used for testing, while the remaining nine subsets (90%) are used for training. This folding process is repeated 10 times, and subsequently, the average performance metrics across all the folds are computed and compared. These metrics are expressed through the following mathematical formulas [31]:

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} * 100 \tag{8}$$

$$Error\ Rate = \frac{FN + FP}{TN + TP + FN + FP} * 100 \tag{9}$$

$$Kappa\ Coefficient = \frac{accuracy - expected\ accuracy}{1 - expected\ accuracy} \tag{10}$$

The confusion matrices analysis on multiple ensemble classifiers utilizing SMO and GEO feature extraction methods for distinguishing between Afib and NSR cardiac detection represented by Table 4. From Table.4. STFT feature based GEO feature selection algorithm with Catboost classifier achieved the higher accuracy of 99%, 1% of error rate and 0.9689 Kappa Coefficient for detection of Afib category. Figure 9. indicates the graphical analysis of Multiple Ensemble Classifiers. Table 5 highlights the superior outcome achieved by the proposed approach when compared to prior studies.

Models	Classifiers	Confusion Matrices				Performance Metrics		
		TP	TN	FP	FN	Accuracy	Error Rate	Kappa Coefficient
STFT	Catboost	285	612	169	115	76	24	0.4815
	XGboost	248	594	187	152	71	29	0.3734
	Adaboost	238	528	253	162	64	35	0.2553
STFT with SMO	Catboost	357	704	77	43	90	10	0.7780
	XGboost	342	683	98	58	87	13	0.7121
	Adaboost	321	645	136	79	82	18	0.6066
	Catboost	**392**	**773**	**8**	**8**	**99**	**1**	**0.9689**

STFT with GEO	XGboost	360	732	49	40	93	7	0.8339
	Adaboost	338	714	67	62	89	10	0.7558

Table 4. The confusion matrices average analysis on multiple ensemble classifiers utilizing SMO and GEO feature extraction methods for Afib cardiac detection

S.No	**References**	**Models**	**Accuracy in %**
1	Attia et al. [2]	AFCODE	84
2	Bumgardner et al. [4]	Deep learning model	90.02
2	Li et al. [10]	Random forest and CNN	91.7
3	Wang et al. [11]	RNN with SVM	94.3
4	Maturo and Verde [20]	Integration of random forest and functional data analysis	Training accuracy :97.28 and testing accuracy: 93.64
5	**In this paper**	STFT feature based GEO feature selection algorithm with Catboost classifier	99

Table 5. Comparison of the proposed approach with prior studies

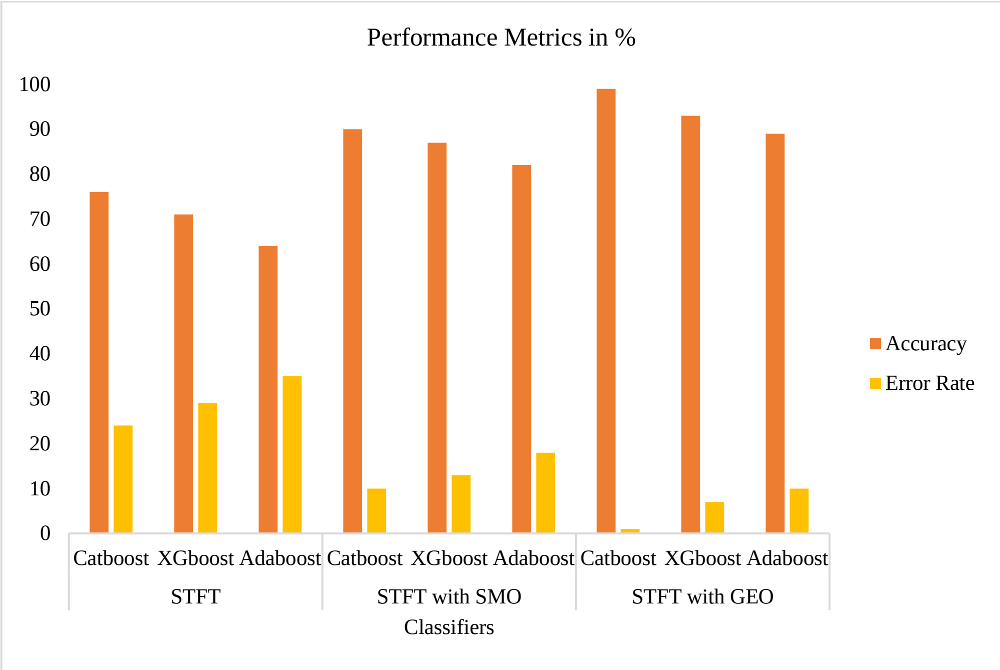

Figure 6. Normal probability analysis of STFT features with SMO features of Afib and NSR classes.

7. Conclusion

In this study, we introduce a novel approach for classifying Atrial Fibrillation (Afib) from ECG datas. When utilizing the Catboost Classifier in conjunction with the STFT-based GEO implementation, the results indicate an average perfect classification rate of approximately 99%, an error rate of 1%, and a kappa coefficient of 0.9689% for detection of Afib. Future plans involve integrating optimization techniques within post-classification processes and exploring a range of deep learning methods to enhance the precision of cardiovascular disease classification from ECG signals.

References

[1] S. Nattel, “New ideas about atrial fibrillation 50 years on”, Nature, Vol. 415, No. 6868, pp. 219-226, 2002.

[2] Z.I. Attia, P.A. Noseworthy, F. Lopez-Jimenez, S.J. Asirvatham, A.J. Deshmukh, B.J. Gersh and P.A. Friedman, “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.

[3] B.E. Moody, L.W. Lehman, I. Silva, A. Johnson and R.G. Mark, “AF classification from a short single lead ECG recording: the PhysioNet”, Computing in Cardiology Challenge 2017.

[4] C.L. Bumgardner, W.J. Tompkins and L. Zhang, “Atrial Fibrillation Detection via Consumer Wearable Devices and Machine Learning”, IEEE Access, Vol. 7, pp. 36582-36593, 2019.

[5] A.Y. Hannun, P. Rajpurkar, M. Haghpanahi, G.H. Tison, C. Bourn, M.P. Turakhia and A.Y. Ng, “Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network”, Nature Medicine, Vol. 25, No. (1), pp. 65-69, 2019.

[6] S. Kiranyaz, T. Ince and M. Gabbouj, “Real-time patient-specific ECG classification by 1-D convolutional neural networks”, IEEE Transactions on Biomedical Engineering, Vol. 63, No. (3), pp. 664-675, 2016.

[7] J. Smith, “A Novel Approach for Atrial Fibrillation Detection Using Deep Learning”, Journal of Biomedical Informatics, Vol. 94, pp. 103188, 2019.

[8] L. Chen, “Atrial Fibrillation Detection from Short Single-Lead ECG Records Using a Deep Learning Model”, Nature Communications, Vol. 11, No. 1, pp. 1-10, 2020.

[9] Y. Kim, “A Machine Learning Approach for Atrial Fibrillation Detection in Wearable ECG Devices”, IEEE Transactions on Biomedical Engineering, Vol. 68, No. 4, pp. 1014-1023, 2021.

[10] X. Li, X, “Atrial Fibrillation Detection Using Random Forest and Convolutional Neural Networks”, Computing in Cardiology, Vol. 45, pp. 1-4, 2018.

[11] H. Wang, “A Hybrid Model for Atrial Fibrillation Detection Based on Recurrent Neural Networks and Support Vector Machines”, Computing in Cardiology, Vol. 46, pp. 1-4, 2019.

[12] P. Rajpurkar, A.Y. Hannun, M. Haghpanahi, C. Bourn and A.Y. Ng, “Cardiologist-level arrhythmia detection with convolutional neural networks”, Computing in Cardiology (CinC), Vol. 44, 2017.

[13] S.P. Shashikumar, A.J. Shah, Q. Li, G.D. Clifford, and S. Nemati, “Atrial Fibrillation Detection from Short Single-Lead ECG Recordings Using Deep Learning”, IEEE Transactions on Biomedical Engineering, Vol. 67, No. 7, pp. 1961-1970, 2020.

[14] S. Asgari, A. Mehrnia, and Z.A. Sani, “Atrial Fibrillation Detection Using Wearable Smartwatch Data”, In 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 4095-4098, 2019.

[15] K.Y. Li, Y. Wang, C. Shi and Y. Li, "Automatic Detection of Atrial Fibrillation in ECGs Based on Deep Learning", IEEE Access, Vol. 8, pp. 195531-195540, 2020.

[16] G. Liu, Y. Li and X. Zhang, "Deep Learning for Atrial Fibrillation Detection in Mobile Health Monitoring", Sensors, Vol. 18, No. 7, pp. 2175, 2018.

[17] Z. Xiong, M.P. Nash, E. Cheng, and V.V. Fedorov, "Atrial Fibrillation Detection from ECG Signals Using Convolutional Neural Networks", Proceedings of the 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 3883-3886, 2018.

[18] J. Lee, B.A. Reyes, D.D. McManus and M. Maitin-Shepard, "Atrial Fibrillation Detection from Photoplethysmography Signals Using Machine Learning", Computing in Cardiology (CinC), pp. 1-4, 2019.

[19] Z. Ma, X. Cheng, J. Li and J. Liu, "ECG-Based Atrial Fibrillation Detection Using a Novel Algorithm with LSTM Recurrent Neural Networks", Frontiers in Physiology, Vol. 10, pp. 1558, 2019.

[20] F. Maturo and R. Verde, "Pooling random forest and functional data analysis for biomedical signals supervised classification: Theory and application to electrocardiogram data", Statistics in Medicine, Vol. 41, No. 12, pp. 2247-2275, 2022.

[21] F. Maturo, F and R. Verde, "Combining unsupervised and supervised learning techniques for enhancing the performance of functional data classifiers", Computational Statistics, pp. 1-32, 2022.

[22] F. Maturo and R. Verde, "Supervised classification of curves via a combined use of functional data analysis and tree-based methods", Computational Statistics, Vol. 38, No. 1, pp. 419-459, 2023.

[23] Kaggle Dataset: (https://www.kaggle.com/datasets/shayanfazeli/heartbeat), 2020.

[24] D. Griffin and J. Lim, "Signal estimation from modified short-time Fourier transform", IEEE Transactions on acoustics, speech, and signal processing, Vol. 32, No. 2, pp. 236-243, 1984.

[25] L. Durak and O. Arikan, "Short-time Fourier transform: two fundamental properties and an optimal implementation", IEEE Transactions on Signal Processing, Vol. 51, No. 5, pp. 1231-1242, 2003.

[26] H. Sharma, G. Hazrati and J.C. Bansal, "Spider monkey optimization algorithm", Evolutionary and swarm intelligence algorithms, pp. 43-59, 2019.

[27] A. Mohammadi-Balani, M.D. Nayeri, A. Azar, M. Taghizadeh-Yazdi, "Golden eagle optimizer: A nature-inspired metaheuristic algorithm", Computers & Industrial Engineering, Vol. 152, pp. 107050, 2021.

[28] B. Dhananjay and J. Sivaraman, "Analysis and classification of heart rate using CatBoost feature ranking model", Biomedical Signal Processing and Control, Vol. 68, pp. 102610, 2021.

[29] A.A. Rawi, M.K. Elbashir and A.M. Ahmed, "ECG heartbeat classification using CONVXGB model", Electronics, Vol. 11, No. 15, pp. 2280, 2022.

[30] M. Barstuğan and R. Ceylan, "The effect of dictionary learning on weight update of AdaBoost and ECG classification", Journal of King Saud University-Computer and Information Sciences, Vol. 32, No. 10, pp. 1149-1157, 2020.

[31] M.G. Shankar, C.G. Babu, H. Rajaguru, "Classification of cardiac diseases from ECG signals through bio inspired classifiers with Adam and R-Adam approaches for hyperparameters updation", Measurement, Vol. 194, pp. 111048, 2022.