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PSO-ML: Heartbeat Classifier Using Particle Swarm Optimization And Machine Learning Techniques

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Abstract
Electrocardiogram analysis is not only helpful but also inevitable in the detection of abnormal heartbeat and different cardiac disorders. Cardiologists, doctors, and consultants worldwide have raised cardiovascular disease concerns. However, the existing systems create problems like delayed diagnosis, high misdiagnosis rate, and even no findings. However, an early diagnosis is a prerequisite to ensuring an early treatment. Therefore, to reduce the misdiagnosis rate of heart disease, we have introduced four hybrid models in this study, combining optimization and machine learning algorithms. The dataset used for in study was accessed from the MIT-BIH arrhythmia database. This study will be concluded with detailed results obtained from testing different machine learning algorithms with PSO, which will help the cardiologists diagnose very easily than the existing systems. Additionally, this paper introduced a new hybrid type of model, which included an optimization algorithm named particle swarm optimization combined with supervised machine learning algorithms like support vector machine, extra tree classifier, gradient boosting algorithm, and XGBoost. Categorically, the ECG dataset is classified into five major sects in our study to provide a general evaluation of the heart's condition and an essential and dependable reference for the doctor's future diagnosis. Our classifier achieved an average accuracy of 95%, 98%, 97% and 98%, an average precision of 77%, 93%, 92% and 96%, an average recall of 93%, 87%, 83% and 86%, and an average f1-score of 83%, 89%, 87% and 90%. This model will help the manufacturing organizations to renovate the existing system and ensure timely treatment.
Keywords: *ECG, Heartbeat, MIT-BIH, Particle Swarm Optimization, Machine Learning*

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I. Introduction

According to the recent World Health Statistics 2019 [1] report, heart disease has been one of the leading causes of death globally during the last two decades and has been responsible for 16% of all causes of death. This incurs a colossal loss and severely contributes to a lower life expectancy in want of the proper detection. Analyzing electrocardiographic signals in the medical sector is constructive for detecting and recognizing various cardiac disorders because it provides cardiologists with the necessary information on heart rhythm and functions.

Nowadays, various diagnostic procedures, such as an electrocardiogram (ECG), ultrasonic cardiogram, X-ray, and magnetic resonance imaging (MRI), play a vital role in diagnosing cardiac diseases. The ECG, in particular, plays an essential role in these measurements, given its low cost and ease of use. However, ECG signals are most often used to quickly predict any human's prior health status. The heart's normal rhythm is commonly called normal sinus rhythm (NSR). Variations in the time duration of these waves and segments from the NSR parameters indicate a pathological condition called arrhythmia, classified into several types: tachycardia, bradycardia, premature ventricular contractions, and ventricular fibrillation, atrial flutter, sick sinus syndrome, and heart blocks. A heartbeat varies across individuals and within individuals depending on various conditions. In conventional ECG diagnosis methods, physicians try to find whether the ECG signal is different from the normal sinus rhythm in terms of the morphology of each component, time intervals, and heart rate. Researchers have been trying to introduce automated arrhythmia monitoring systems to assist cardiologists in detecting the signs of arrhythmia at early stages, ensuring timely diagnosis. Among the several types of research to categorize ECG signals, Mathunjw et al. [3] transformed 1D ECG signal data into 2D segments, using a combination of recurrence plot (RP) and CNN to the classification of arrhythmia, and had a classification accuracy of95% for ventricular fibrillation (VF) and 98% for atrial fibrillation (AF), normal, premature atrial fibrillation, and premature ventricular fibrillation. Houssein et al. [4] introduced a technique proposed to optimize a meta-heuristic algorithm based on Manta Ray Foraging Optimization (MRFO) and SVM, achieving 98% accuracy and 97% sensitivity. Pirova et al. [5] investigated random forest, decision tree, and convolutional neural network methods in ECG data categorization, finding that the neural network outperformed the others witha 93.47% accuracy rate. Baloglu et al. [6] established an end-to-end deep learning method for diagnosing myocardial infarction using conventional 12-lead ECG data. They employed a deep CNN model that implemented of completed the ECG data learning process in a short amount of time (10 epochs). Furthermore, this strategy eliminates the bear to feature extracted from the original ECG data factually and uses features obtained by other machine learning algorithms.

Various supervised learning-based algorithms are also commonly employed. ECG to recognize classification or detection methods like support vector machine algorithms (SVM) have also been tested. Kohli et al. [7] examined three prominent SVM models, one vs. one, one vs. all, and other techniques fuzzy decision and determined and then one vs. one technique works better process due to differentiating cardiac arrhythmia and classifying them and mapping into the correctly classified. Jun et al. [8] proposed a deep 2D convolution approach for ECG data classification, converting each ECG beat into a 2D grey-scale picture method to identify given data. In this work, CNN architecture investigates the ECG classification technique splitting into two parts. In the meantime, they established an optimizing solution by the CNN classification model using approaches like this normalization, augmentation technique, and initialization, and the average accuracy rate reached 97%. This procedure used ECG images for the CNN architecture method to identify arrhythmia. A local switching fault exists in an artificial neural network (ANN). Paul et al. [9] used the SVM technique to identify ECG data and strive for optimum margin segmentation. The search space bounds define a convex set. As a result of data imbalance, the Support Vector Machine leads only 87% of the f1-score. The ECG signal was withered using the wavelet transformation, and thirteen statistical measurement characteristics were extracted from these withered signals by Saini et al. [10]. The classification validity of the decomposed ECG signals was raised by 31.25% to 87%.

This study has proposed a new hybrid model that combines both optimization and machine learning algorithms. We have used four machine learning models optimized with particle swarm optimization. The proposed PSO-XGBoost model provides 98% accuracy, and the precision is 100%.

II. Materials and Methods

Description of ECG dataset

This research uses the MIT-BIH arrhythmia dataset [15], [16], which is illustrious for measuring heart arrhythmia and may be used for fundamental cardiac analysis. The MIT-BIH dataset consists of ECG recordings from 47 different subjects recorded at the sampling rate of 360Hz. At least two cardiologists annotate each beat. We use annotations in this dataset to create five different beat categories by the Association for the Advancement of Medical Instrumentation (AAMI) EC57 standard [17]. Table 2.1 shows a summary of mappings between beat annotations in each category, and figure 2.1 shows the waveforms of ECG signals from all five types using different colors.

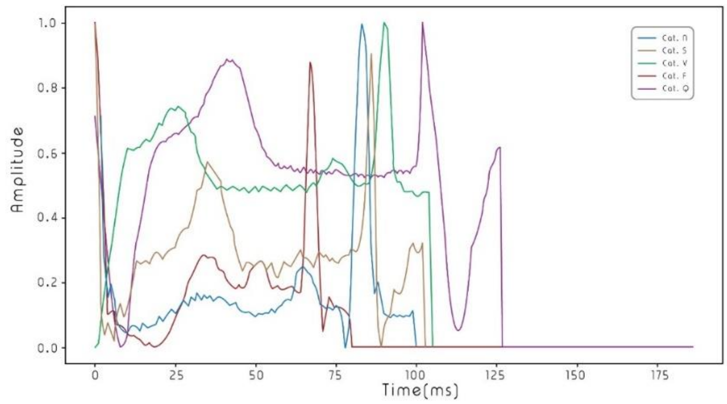

Figure-2.1: ECG signals from all five categories.

Table 2.1: Five different categories of ECS signals and their description by AAMI EC57

Class Name	Annotations
N	Normal beat
S	Supra-ventricular beat
V	Premature ventricular contraction
F	Fusion beat
Q	Unclassifiable beat

Splitting Dataset:
The dataset is divided into the training and test set in this stage using the percentage split method. In this case, 20% of the data is used as the test set and 80% as the training set.

Table 2.2: Splitting dataset

Partition	Dataset Size
Training set	87554
Test set	21892
Total	109446

The total dataset is classified into the following five basic categories and is separated from the 87554 data into the training set and 21892 as a test set.

Table 2.3: Class-wise summary of the dataset after spliting

Partition	N	S	V	F	Q	Total
Train	72471	2223	5788	641	6431	87554
Test	18118	556	1448	162	1608	1608
Total	90589	2779	7236	803	8039	109446

Machine Learning Algorithms:
The power of machine learning is in its ability to generalize by correctly classifying unseen data based on models built using training data. In this case, we have used the support vector machine, extra tree classifier, gradient boosting machine and extreme gradient boosting to build machine learning models for classification, using 80% of the data for training and 20% for testing the model.

Support Vector Machine (SVM):
The SVM is used to classify and analyze data in machine learning. In statistical learning-based frameworks, the SVMs are robust prediction methods. It is a fast and reliable algorithm with limited data to analyze.
The hyperplane equation is,

$$w^T \emptyset(x) + b = 0 \quad (1)$$

b = Intercept and bias term of the hyperplane equation. The distance of a hyperplane equation is written as [50],

$$d_H\big(\emptyset(x_0)\big) = \frac{|w^T(\emptyset(x_0)) + b|}{||w||_2} \quad (2)$$

For solving the non-linearity of the equation, the SVM is effective because it has a straightforward manner.

Extra Tree Classifier:
Extra Trees Algorithm (ETA) is the short form of Extremely Randomized Trees, which has computational efficiency strength. ETA works by creating many unpruned decision trees from the training dataset. For the prediction making in case of regression problems, ETA used average prediction of decision trees; but in the case of classification problems, ETA used majority voting of decision trees. The extra-Trees algorithm provides geometrically and a kernel characterization of a model; ETA also provides insight on how to adjust it in particular situations

Gradient Boosting Machine:
GBM is one of the most peerless techniques for working on the loss function, weak learners, and the additive model. It is tooled from decision tree models. The update equation for GBM is,

$$f_m(x) = f_{m-1}(x) + v.\gamma_m h_m\,; \;\; 0 < v \leq 1 \quad (3)$$

Where, v = learning rate, γ_m = compute multiplier and h_m = compute hessians. This model is used for the rank learning field. It can be used for classification or regression predictive problems. It is fit to secernate the loss function. It is an operative algorithm for competing on tabular structured datasets.

Extreme Gradient Boosting:
XGBoost is worked on the Newton-Raphson method. It is induced as a research project in an initial position. The initialize model with a constant value,

$$f_{(0)}(x) = arg\min_{\theta} \sum_{i=0}^{N} L\,(y_i, \theta)\,; \quad i = 1, \dots \dots \dots \dots \dots, n \quad (4)$$

Here, $L(y_i, f(x))$ = a differentiable loss function.

The updated model for XGBoost is,

$$f_{(M)}(x) = f_{m-1}(x) + f_m(x); \quad (m) = 1 \; to \; M \;\; \& \;\; f_m(x) = \alpha \emptyset_m(x) \tag{5}$$

The output is, $$f(x) = f_{(M)}(x) = \sum_{m=0}^{M} f_{(m)}$$ (6)

Where $M =$ weak learners and $\alpha =$ a learning rate.

It is an extra randomized parameter implemented on single distributed systems and out-of-core computation. It is a popular algorithm for winning the machine learning competition. This algorithm provides scalable, portable, and distributed gradient boosting data.

Hybrid PSO-MLA

Particle Swarm Optimization (PSO):

Particle swarm optimization (PSO) is a population-based stochastic optimization technique inspired by the social behavior of bird flocks and fish schools, etc. [20]. PSO is also a swarm intelligence algorithm studying computational systems inspired by collective intelligence. Collective intelligence occurs because of population or homogeneous cooperation in particle environments. The particle environment was assumed to have a specific size where each particle had a random starting position and located its position in a search space. Eachparticle in one space was assumed to have two characters; position and speed. If the position of each particle found its best position, then the information would be conveyed to other particles. Following that, particle location updates were carried out to provide output in the form of new particles. The particle position update attempts to find the output used in the test parameters.

Proposing the PSO-SVM:

The PSO-SVM model was suggested to forecast heart arrhythmia, and the PSO method was used to optimize the hyper-parameters of an initial SVM model. Three hyper-parameters were evaluated and tuned in the first SVM model: kernel, penalty factor (C), and class weight. The particles fly in the search space and exchange experiences to determine the ideal valuesof these parameters. They calculate particle fitness for each place using a fitness function, i.e., accuracy in equation 3.1. A matching accuracy value was generated for each value of hyper-parameters, and the best-suited model corresponds to the highest accuracy. The scheme of the development of the PSO- SVM model is established. Tuning the best parameter list given below:

Table 2.4: Best parameter of SVM as the results of tuning parameter using PSO.

Parameter	**Value**
Kernel	rbf
Penalty_factor	10
Class_weight	balanced

Proposing the PSO-ETC:

The PSO-SVM model was suggested in this part to forecast the heart arrhythmia of these systems. For this step, the PSO method was used to optimize the hyper-parameters of an initial SVM model. Six hyper-parameters were evaluated and tuned in the first SVM model: criterion, max samples, n_estimators, max depth, max features, and class weight. The particles fly in the search space and exchange experiences to determine the ideal values of these parameters. They calculate particle fitness for each place using a fitness function, i.e., accuracy in equation 3.1. A matching accuracy value was generated for each value of hyper-parameters, and the best-suited model corresponds to the highest accuracy. The scheme of the development of the PSO-SVM model is established. Tuning the best parameter list is given below:

Table 2.5: Best parameter of ETC as the results of tuning parameter using PSO.

Parameter	**Value**
criterion	entropy
max_samples	10
n_estimators	30
max_depth	20
max_features	auto
class_weight	balanced

Proposing the PSO-GBM:

The PSO-SVM model was suggested in this part to forecast the heart arrhythmia of these systems. For this step, the PSO method was used to optimize the hyper-parameters of an initial SVM model. Four hyper-parameters were evaluated and tuned in the first SVM model: learning rate, max depth, max features, and n_estimators. The particles fly in the search space and exchange experiences to determine the ideal values of these parameters. They calculate particle fitness for each place using a fitness function,i.e., accuracy in equation 7. A matching accuracy value was generated for each value of hyper-parameters, and the best-suited model corresponds to the highest accuracy. The scheme of the development of the PSO-SVM model is established. Tuning the best parameter list is shown in the following table2.6:

Table 2.6: Best parameter of GBM as the results of tuning parameter using PSO.

Parameter	Value
learning_rate	0.1
max_depth	8
max_features	sqrt
n_estimators	100

Proposing the PSO-XGBoost:

The PSO-XGBoost model was suggested in this part to forecast the heart arrhythmia of these systems. For this step, the PSO method was used to optimize the hyper-parameters of an initial XGBoost model. Two hyper-parameters were evaluated and tuned in the first XGBoost model: eta (η), and max tree depth(d). The particles fly in the search space and exchange experiences to determine the ideal values of theseparameters. They calculate particle fitness for each place using a fitness function. A matching accuracy value was generated for each value of hyper-parameters, and the best-suited model corresponds to the highest accuracy. The PSO-XGBoost model's development plan has been completed. Tuning the best parameter list given below:

Table 2.7: Best parameter of XGBoost as the results of tuning parameter using PSO.

Parameter	**Value**
eta	0.1
max_depth	12

III. Methodology:

Evaluation Metrics:

Accuracy is the number of correct predictions fractionated by the number of predictionscreated for a dataset. It can inform immediately if a model is trained correctly and by which method it may perform in general. Nevertheless, it does not give detailed information concerning its application tothe issue. Precision, called PPV, is a good measure to determine, whereas the high false positives cost. The recall is the model metric used to select the best model when a high cost linked with a false negative. Recall helps while the cost of the false negative is high. F1-score is requiredwhen the desire to seek symmetry between both precision and recall. It is a general measure of the accuracy of the model. It combines precision and recall. A good f1-score is explained by havinglow false positives and low false negatives. In the following equations, we have calculated the accuracy, precision, recall, and f1-score, respectively.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (7)$$

$$Precision = \frac{TP}{TP+FP} \quad (8)$$

$$Recall = \frac{TP}{TP+FN} \quad (9)$$

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision+Recall} \quad (10)$$

With TP being the computation of the samples of true positives, TN is the calculation of the samples of true negatives, FP is the counting of the samples of false positives, and FN is the enumeration of the samples of false negatives, from a confusion matrix. The sensitivity and specificity are two statistical measures of the binary classification test performance which are largely used in medicine. Sensitivity, known as true positive rate, measures the proportion of positives which are correctly identified. The specificity, known as true negative rate, measures theproportion of negatives which are correctly identified.

IV. Result and Discussion:

In order to train and test the dataset we have proposed four different hybrid models such as PSO-SVM, PSO-ETC, PSO-GBM and PSO-XGBoost which were used to validate and generalize in an independent dataset. Training set is used to learn about the dataset and to build the model, whereas testing set is an independent dataset used to assess the performance of the generated model as well as to obtain the desired performance characteristics such as accuracy.

Result on PSO-SVM & PSO-ETC:

The below table 4.1 and 4.2 shows the predictions on Accuracy, Precision, Recall and F1-Score of the hybrid models PSO-SVM and PSO-ETC. The accuracy of both of models are 95% and 98% respectively, precision is almost same but in case of recall the PSO-SVM predicts 95% where as PSO-ETC is exactly 100%.

Table 4.1: Classification report of PSO-SVM model

Classifier	Class	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
PSO-SVM	N	95	99	95	97
	S		48	85	62
	V		89	94	91
	F		34	92	49
	U		97	99	98

Table 4.2: Classification report of PSO-ETC model

Classifier	Class	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
PSO-ETC	N	98	98	100	99
	S		93	68	79
	V		98	88	93
	F		72	79	75
	U		100	100	98

Result on PSO-GBM & PSO-XGBoost:

The below table 4.3 and 4.4 shows the predictions on Accuracy, Precision, Recall and F1-Score of the hybrid models PSO-GBM and PSO-XGB. The accuracy of both of models are 97% and 98% respectively, precision of PSO-XGB is very accurate than the PSO-GBM but in case of recall both models show the same and F1-score is also same.

Table 4.3: Result on PSO-GBM

Classifier	Class	Accuracy	Precision	Recall	F1-Score
GBM	N	97%	0.98	1.00	**0.99**
	S		0.91	0.65	**0.76**
	V		0.96	0.88	**0.92**
	F		0.74	0.64	**0.69**
	U		**0.99**	**0.96**	**0.97**

Table 4.4: Result on PSO-XGBoost

Classifier	Class	Accuracy	Precision	Recall	F1-Score
XGBoost	N	98%	1.00	1.00	**0.99**
	S		0.96	0.69	**0.80**
	V		0.96	0.90	**0.93**
	F		0.91	0.73	**0.81**
	U		**0.99**	**0.97**	**0.98**

RESULT COMPARISON AMONG THE MODELS:

In order to detect and predict the occurrence of arrhythmia in ECG signals, we need to compare the effectiveness of all four proposed models. The produced results from our proposed models based on the PSO-SVM classifier with accuracy is 95%, PSO-ETC is 98%, PSO-GBM is 97%, and PSO-XGboost is 98% and we also have shown the precision, recall, and f1-score. The following table 4.5 shows the combined result withprecision, recall, F1 and accuracy metric for each category.

Table 4.5: Overall Comparison of results.

Classifier	Class	Precision	Recall	F1-Score
PSO-SVM	**N**	0.99	0.95	0.97
	S	0.48	0.85	0.62
	V	0.89	0.94	0.91
	F	0.34	0.92	0.49
	U	0.97	0.99	0.98
PSO-ETC	**N**	0.98	1.00	0.99
	S	0.95	0.69	0.80
	V	0.98	0.86	0.92
	F	0.70	0.82	0.76

	U	1.00	0.96	0.98
PSO-GBM	**N**	0.98	1.00	0.99
	S	0.93	0.64	0.76
	V	0.96	0.88	0.92
	F	0.77	0.66	0.71
	U	0.99	0.96	0.98
PSO-XGBoost	**N**	0.98	1.00	0.99
	S	0.96	0.69	0.80
	V	0.96	0.90	0.93
	F	0.91	0.73	0.81
	U	0.99	0.97	0.98

The overall accuracy of all four proposed models are presented using the following table 4.6-

Table 4.6: Overall result comparison on accuracy.

Classifier	Accuracy
PSO-SVM	**95%**
PSO-ETC	**98%**
PSO-GBM	**97%**
PSO-XGBoost	**98%**

Macro-average precision computes the average precision of each class. It is also known as macro-precision. Macro-precision score can be determined arithmetically by the mean of all the precision scores of the different classes.

Table 4.7: Overall result comparison on precision.

Classifier	Precision-macro average	Precision-weighted average
PSO-SVM	73%	**97%**
PSO-ETC	92%	**98%**
PSO-GBM	92%	**97%**
PSO-XGBoost	**96%**	**98%**

Table 4.8: Overall result comparison on recall.

Classifier	Recall-macro average	Recall-weighted average
PSO-SVM	93%	**95%**
PSO-ETC	87%	**98%**
PSO-GBM	83%	**97%**
PSO-XGBoost	**86%**	**98%**

Table 4.9: Overall result comparison on f1-score.

Classifier	F1-Score macro average	F1-Score weighted average
PSO-SVM	79%	**95%**
PSO-ETC	89%	**98%**
PSO-GBM	87%	**97%**
PSO-XGBoost	**90%**	**98%**

Graphical Representation of Result

The overall result getting from different algorithms is plotted using bar graph where X-axis represents the percentages of evaluation metrics measurement and Y-axis represents the models.

Graphical Representation of Result based on Accuracy

Figure 4.1: Classification accuracy obtained for different classifiers.

The above Figure 4.1 shows the comparison among different developed models. It shows that PSO-ETC and PSO-XGboost models has the utmost accuracy.

Graphical Representation of Result based on Precision

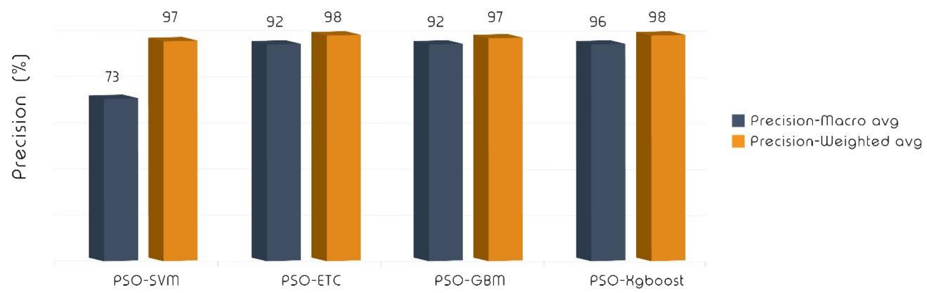

Figure 4.2: Classification precision obtained for different classifiers

Figure 4.2 shows the comparison among different model metrics on precision. It shows that a PSO-XGboost model has highest precision. Here macro average is the average of precision and the weighted average is just the weighted average of precision.

Graphical Representation of Result based on Recall

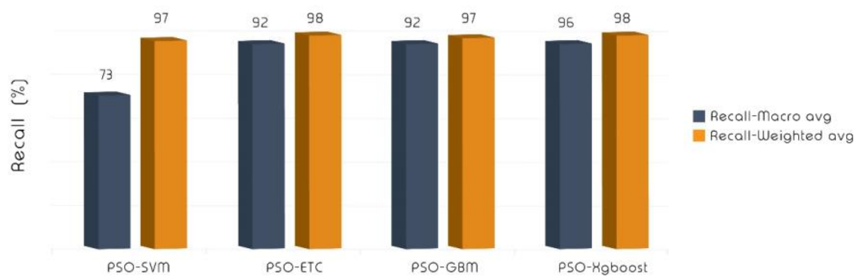

Figure 4.3: Classification recall obtained for different classifiers.

Figure 4.3 shows the comparison among different model metrics on recall score. It shows that PSO-XGboost model has the highestrecall value. In fact, out of the observations that are actually positive or yes, how many of them have been predicted by the algorithm.

Graphical Representation of Result based on F1-Score

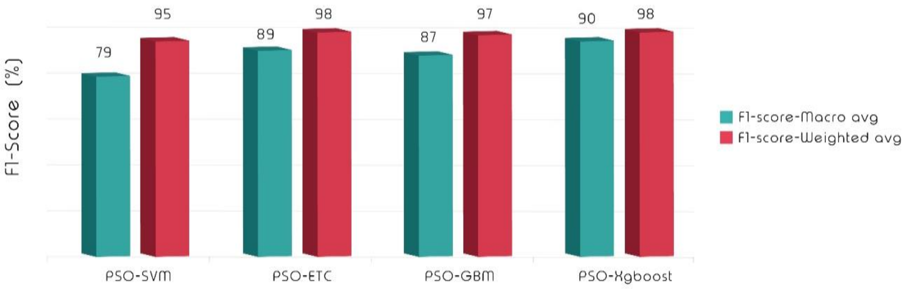

Figure 4.4: Classification f1-score obtained for different classifiers.

The above Figure 4.4 shows the comparison among different model metrics on f1-score. It shows that PSO-XGboost model has the highest f1-score. This f1-score metric is also known as f-score or f-measure, takes both precision and recall into consideration in order to calculate the performance of an algorithm.

V. Conclusion

In this paper, a new hybrid type of classifier is designed for the discrimination among five different principal types of ECG beats from MIT-BIH database. However, it is classified by using four different machine learning models trained by an improved evolutionary algorithm (EPSO). The newly developed hybrid type classifier can ensure the highest statistical performances because the PSO approach is proved to be a successful learning algorithm for improving the capability of the MLA to classify arrhythmia diseases with a few number of iterations. Consequently, the PSO-MLA based model can be considered as an effective tool to detect and classify the ECG signals which will inspire the developers and industries to patch. Our future study will involve a new metaheuristic algorithm with machine learning models in order to optimize the performances and accuracy.

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