Integration of PSO-based advanced supervised learning techniques for classification data mining to predict heart failure

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ABSTRACT

Heart failure (HF) is a global health threat, requiring urgent research in its classification. This study proposes a novel approach for HF classification by integrating advanced supervised learning (ASL) and particle swarm optimization (PSO). ASL techniques like bagging and AdaBoost are employed within the PSO+ASL optimization model to enhance prediction accuracy. PSO optimizes model weights and bias, while ASL addresses overfitting or underfitting issues. Split validation and cross-validation (70:30, 80:20, 90:10 with k-fold=10) are used for further optimization. The testing phase involves 12 classifiers in five groups: decision tree models (DTM), support vector machines (SVM), Naïve Bayes classifiers models (NBCM), logistic regression models (LRM), and lazy model (LM). Evaluating the proposed approach with an HF patient dataset from https://www.kaggle.com, results are compared against the standard model, PSO optimization, and PSO+ASL. Experimental findings demonstrate the superiority of the proposed approach, achieving higher accuracy in HF prediction. The PSO+ASL optimization model with the k-nearest neighbor (k-NN) method exhibits the best classification performance. It consistently achieves the highest accuracy across all tests on dataset composition ratios, with 100% accuracy, f-measure, sensitivity, specificity values, and area under cover (AUC) of 1. The proposed approach serves as a reliable tool for early detection and prevention of HF.

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1. INTRODUCTION

Heart failure (HF) is a medical condition that is characterized by a complex set of symptoms rather than a specific disease [1]. It occurs when the ventricle struggles to fill or empty with blood, making it challenging for the heart to meet the body's circulation needs. Common symptoms include shortness of breath, swollen ankles, and fatigue, while signs such as high jugular venous pressure, pulmonary crackles, and peripheral edema may also be present, indicating structural and/or functional cardiac or non-cardiac abnormalities [2], [3]. In Indonesia, heart disease is the leading cause of death, and HF represents a significant portion of these cases [4]. Approximately 5% of the country's population is estimated to suffer from HF [5]. Furthermore, the fatality rate is significant, with up to 17.2% of all HF patients dying during their initial hospitalization, regardless of a history of heart attacks. Additionally, 11.3% of patients died within a year of starting treatment, while another 17% required repeated hospitalizations due to worsening

HF. These patients are typically hospitalized at least once a year after diagnosis, with an average age of 58. Data from the Basic Health Research Data (Riskesdas) for 2013 and 2018 show an increasing trend in heart disease, rising from 0.5% in 2013 to 1.5% in 2018. Heart disease, including HF, is associated with significant healthcare costs, with IDR 7.7 trillion spent on it in 2021, according to data from the Social Security Administering Body for Health (BPJS). These statistics emphasize the importance of early detection and treatment of HF. Traditional diagnosis of HF relies on the patient’s medical history, physical tests, and the doctor’s examination of related symptoms [3], [6]. Angiographic techniques are one of the most reliable conventional methods for diagnosing HF [7]. However, this method requires specialized expertise and comes with a high cost and potential side effects [8].

While there have been efforts to achieve high predictive performance and identify relevant risk factors associated with HF, the emergence of artificial intelligence (AI) tools and machine learning (ML) algorithms [9], [10] in recent years has provided powerful diagnostic aids [11]. These tools can extract knowledge from large amounts of data, which may be difficult or impossible for humans to achieve [12], [13]. By employing ML-based decision-making approaches, doctors can detect the risk of HF and provide necessary treatments and recommendations to manage these risks [14]. Early detection and treatment using ML techniques have the potential to significantly improve patient survival rates. Consequently, several studies have utilized ML for the diagnosis [15]–[19] and prediction of HF, such as determining the likelihood of a patient having a disease history that may cause HF, such as hypertension, diabetes, or hyperlipidemia [20]–[23]. Various classification algorithms, including decision trees [24]–[26], support vector machines (SVM) [27], Naïve Bayes [28], and neural networks [29] have been used for HF prediction. Despite these efforts, accurately predicting HF remains a significant challenge. Comparison and benchmarking results of ML classifiers have shown no significant differences in performance [30], and no single classifier has proven to be the best for all datasets.

Our study aims to address the existing gap in accurately predicting heart failure using machine learning techniques. Despite various efforts, no single classifier has proven to be the best for all datasets. In this research, we present a novel approach that incorporates advanced supervised learning (ASL) [29]–[31] and particle swarm optimization (PSO) [32], [33] techniques to optimize classification results. Moreover, we employed split and cross-validation techniques with varying composition ratios of 70:30, 80:20, and 90:10, using k-fold=10, and tested twelve classifiers sorted into five groups: decision tree models (DTM), SVM, Naïve Bayes classifier models (NBCM), logistic regression models (LRM), and lazy models (LM). The selection of these classifiers was based on several considerations. Firstly, previous studies have shown that various classification algorithms, such as decision trees [22]–[24], SVM [25], Naïve Bayes [26], and neural networks [27], have been used for HF prediction. These algorithms have demonstrated their effectiveness in handling complex datasets and have been widely employed in HF research. Secondly, the rationale behind choosing multiple classifiers lies in the understanding that no single classifier has proven to be the best for all datasets or consistently outperforms others. Comparison and benchmarking results of ML classifiers have shown no significant differences in performance [28]. Therefore, by employing a diverse set of classifiers, the paper aims to explore the strengths and weaknesses of each algorithm and identify the most suitable classifiers for HF classification. By evaluating the PSO and ASL algorithms on 12 classifiers grouped into five categories, this study aims to assess the strengths and weaknesses of each classifier and determine the most appropriate one for HF classification. This research makes a significant contribution by offering a more precise approach to diagnosing heart failure, leading to early detection and improved patient outcomes. Furthermore, our findings can guide future research endeavors aimed at enhancing the diagnosis and treatment of heart failure. The integration of AI and ML techniques [31], [32] in healthcare holds great promise for enhancing patient well-being and reducing healthcare expenses.

2. METHOD

The primary objective of this study is to enhance the classification performance of 12 classifiers through the integration of ASL and PSO techniques. A comprehensive evaluation of classifier performance was conducted using a combination of split tests and cross-validation. The training and test data were partitioned into different ratios, namely 70:30, 80:20, and 90:10, with a k-fold value of 10. To assess the effectiveness of the proposed model, data from HF patients were employed. By subjecting the classifiers to this dataset, the study aimed to improve their classification performance.

2.1. Data preparation and processing

For this study, a dataset comprising five distinct datasets from various sources was obtained from Kaggle (https://www.kaggle.com). These datasets include Cleveland (303 observations), Hungary (294 observations), Switzerland (123 observations), Long Beach VA (200 observations), and a Stalog (liver) dataset (270 observations). The combined dataset consists of a total of 918 observations and encompasses twelve variables, with eleven variables serving as inputs and one variable acting as the output (label). Each variable's subset was tailored according to the specific requirements of the study. The subsequent section provides a comprehensive description of the variables utilized in the HF study.

The study utilized a sample dataset (complete data can be accessed at https://shorturl.at/klvS2), as presented in Table 1, consisting of various parameters related to patients. These parameters include the age of the patient in years, the sex of the patient (M for male and F for female), the type of chest pain experienced (TA for typical angina, ATA for atypical angina, NAP for non-anginal pain, and ASY for asymptomatic), the resting blood pressure (RestingBP) in mm Hg, the serum cholesterol level in mm/dl, the fasting blood sugar (FastingBS) (1 if FastingBS > 120 mg/dl, 0 otherwise), the results of the resting electrocardiogram (RestingECG) (normal, ST for ST-T wave abnormality, and LVH for probable or definite left ventricular hypertrophy), the maximum heart rate achieved (MaxHR) (numeric value between 60 and 202), the presence of exercise-induced angina (Y for yes and N for no), the oldpeak value measured in depression, the slope of the peak exercise ST segment (up for upsloping, flat for flat, and down for downsloping), and the output class indicating the presence of heart disease (1 for HF and 0 for normal).

The table represents data for predicting heart failure. It includes information about patients' age, gender, chest pain type, resting blood pressure (RestingBP), cholesterol levels, fasting blood sugar (FastingBS), the results of the resting electrocardiogram (restingECG), the maximum heart rate achieved (MaxHR), exercise-induced angina, ST depression at exercise, ST slope, and heart disease condition. The data consists of 918 patients, where each row represents one patient's information. This data can be used to build a predictive model that will help identify the risk factors associated with heart failure. Through analyzing this data, researchers can gain insights into patterns or correlations between the different variables that may contribute to the onset of heart failure. Ultimately, this data has tremendous potential to inform clinical decisions and improve patient outcomes.

2.2. Proposed model architecture

The proposed model architecture aims to enhance the accuracy of predicting HF by leveraging advanced ML techniques, such as PSO-based algorithms and supervised learning algorithms. Through the selection of pertinent features and optimization of model parameters, this approach enables more precise predictions, which can be instrumental for healthcare professionals in making informed decisions regarding patient care. To ensure the robustness of the proposed approach, a combination of split validation and cross-validation was implemented, utilizing different composition ratios of 70:30, 80:20, and 90:10, with a k-fold value of 10. To evaluate the effectiveness of the model, twelve classifiers were employed and grouped into five categories, namely DTM, SVM, NBCM, LRM, and LM.

The confusion matrix and area under the receiver operating characteristic curve (AUC) are utilized for model evaluation in the classification task due to their ability to comprehensively assess the performance of the classification model [33], [34]. The confusion matrix allows for a detailed analysis of the model's predictions compared to the actual labels, enabling an evaluation of its accuracy in classifying instances into different classes. Additionally, the selection of AUC serves to measure the overall performance of the classifier [35]. AUC represents the classifier's capacity to distinguish between positive and negative examples at various classification thresholds. It provides a concise summary of the classifier's performance in a single value, making it particularly valuable when adjusting the classification threshold based on specific applications or domains [36].

Table 1. Dataset

No	Age	Sex	Chest pain type	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR	Exercise angina	Oldpeak	ST_slope	Heart disease
1	40	M	ATA	140	289	0	Normal	172	N	0	Up	Normal
2	49	F	NAP	160	180	0	Normal	156	N	1	Flat	HF
3	37	M	ATA	130	283	0	ST	98	N	0	Up	Normal
4	48	F	ASY	138	214	0	Normal	108	Y	1.5	Flat	HF
5	54	M	NAP	150	195	0	Normal	122	N	0	Up	Normal
6	39	M	NAP	120	339	0	Normal	170	N	0	Up	Normal
7	45	F	ATA	130	237	0	Normal	170	N	0	Up	Normal
8	54	M	ATA	110	208	0	Normal	142	N	0	Up	Normal
.	.	.	…	…	…	…	…	…	…	…	…	…
914	45	M	TA	110	264	0	Normal	132	N	1.2	Flat	HF
915	68	M	ASY	144	193	1	Normal	141	N	3.4	Flat	HF
916	57	M	ASY	130	131	0	Normal	115	Y	1.2	Flat	HF
917	57	F	ATA	130	236	0	LVH	174	N	0	Flat	HF
918	38	M	NAP	138	175	0	Normal	173	N	0	Up	Normal

2.3. Model training and evaluation

The implementation of ASL and PSO techniques for data mining classification in predicting HF involves several key steps. These steps, including data preparation, model selection, hyperparameter optimization, training, evaluation, and reporting, are crucial for constructing a precise and reliable classification model for HF prediction. It is worth noting that during the training phase, each model utilizes k-fold=10, a cross-validation technique. This ensures robustness and generalizability of the models. Figure 1 provides a visual representation of these steps, highlighting their significance in the overall process.

Furthermore, Table 2 provides a visual representation of the optimization technique utilized in the study, which is a combination of PSO and ASL. The pseudocode depicted in Table 2 outlines the step-by-step process of this combined optimization approach. This figure serves as a valuable reference point for understanding the methodology employed in the study and showcases the integration of PSO and ASL in the optimization process.

The following is an explanation of the psedeucode from PSO and ASL where the ASL algorithm takes as input the training data T, the number of base classifiers B, the subspace size S, the learning rate alpha, and the number of iterations T. It aims to create an ensemble classifier model. The algorithm starts by initializing the base classifiers and their corresponding weights. For each base classifier, a random subspace of features is selected. The base classifier is trained using a subset of the training data with the selected features. The weight for each base classifier is calculated based on its classification error on a validation set. Next, the base classifiers are combined using weighted majority voting. For each test instance in the training data, the ensemble output vector Y is initialized to zero. Each base classifier classifies the test instance, and the weighted output is added to the ensemble output. The ensemble output vector is then normalized to obtain a probability distribution. The weights for the base classifiers are updated based on the error rate on this instance. The algorithm repeats this process for a specified number of iterations. Finally, the ensemble classifier model is returned. These algorithms will be compared with a standard classification model consisting of 11 classifiers.

In simple terms, Table 2 is explained PSO and ASL algorithms can greatly improve the performance of classification in predicting heart failure. PSO algorithm can be used to select optimal features subset from the predict heart failure dataset, while ASL combines bagging and boosting techniques to form a more reliable ensemble classifier with diverse basis classifiers. The output from the ensemble classifier can then be used as input for the PSO algorithm to optimize the parameters in the classification model. By using these two algorithms together, the quality of the output from each basis classifier can be improved, and the most important features can be selected to form the feature subspace, resulting in a more accurate and reliable classification model for predicting heart failure.

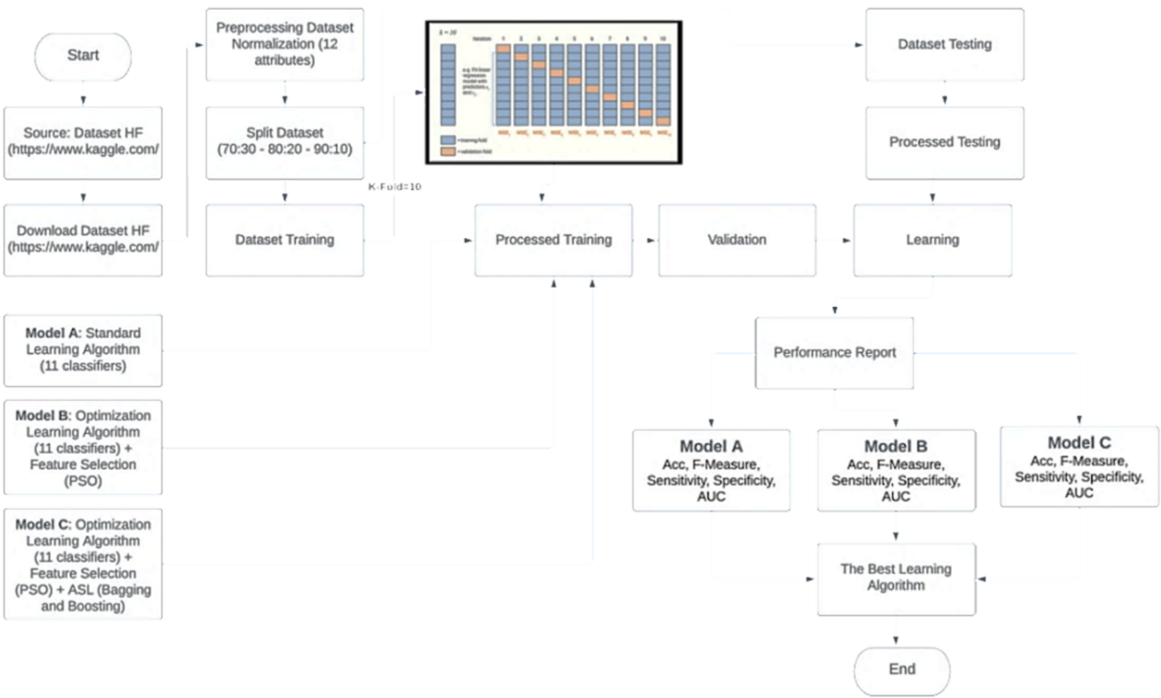

Figure 1. Proposed model

Table 2. Pseudocode combination algorithms

Algorithm 1. PSO	Algorithm 2. ASL (bagging + boosting)

initialize population of particles
for each particle in population do:
  initialize particle position and velocity
  evaluate particle fitness
  update personal best position and fitness
end for
 	
initialize global best position and fitness
repeat until termination condition is met do:
  for each particle in population do:
    update particle velocity based on current and previous positions
    update particle position
    evaluate particle fitness
    if particle has better fitness than personal best then:
      update personal best position and fitness
    end if
    if particle has better fitness than global best then:
      update global best position and fitness
    end if
  end for
end repeat
	input: training data T, number of base classifiers B, subspace size S, learning rate alpha, number of iterations T
	output: ensemble classifier model
	for t = 1 to T do:
	  // Initialize base classifiers and weights
	  for b = 1 to B do:
	    // Randomly select subspace of features
	    select S features at random
	    // Train base classifier on subspace of features
	    train base classifier using subset of T with selected features
	    // Calculate weight for each base classifier
	    calculate weight for base classifier based on classification error on validation set
	  end for
	  // Combine base classifiers using weighted majority voting
	  for each test instance in T do:
	    initialize ensemble output vector Y to zero
	    for b = 1 to B do:
	      // Classify instance using base classifier and add to ensemble output
	      classify test instance using base classifier b and add weighted output to Y
	    end for
	    // Normalize output vector to get probability distribution
	    normalize Y
	    // Update weights for base classifiers based on error rate on this instance
	    update weight for each base classifier based on error rate on this instance
	  end for
	end for
	
	// Return ensemble classifier model
	return ensemble model

In addition to developing an accurate and robust model, it is also essential to evaluate the model's accuracy in predicting HF. This is carried out through the confusion matrix and the receiver operating characteristics (ROC)/area under cover (AUC) curve. The ROC curve was created based on the values calculated from the confusion matrix, which compares the false positive rates (FPR) and the true positive rates (TPR). Where:

a) $FPR = False\ Positive / (False\ Positive + True\ Negative)$;

b) $TPR = True\ Positive / (True\ Positive + False\ Negative)$;

Subsequently, BAD, if the resulting curve is close to the baseline line or the line that crosses from point 0.0. and GOOD, if the curve is close to 0.1 points.

3. RESULT AND DISCUSSION.

This section presents the experiments conducted and the results obtained for 12 standard model classifiers, PSO optimization, and PSO+ASL optimization. The aim is to compare and explore which model produced the best results for the HF classification. To evaluate these models, a combination of split and cross-validation was used with different compositions of 70:30, 80:20, and 90:10, of which k-fold=10. The model performance was evaluated using various metrics such as accuracy, f-size, sensitivity, specificity, and AUC. The evaluation steps for each model are summarized in Table 3, and the AUC values for each model are presented in Table 4.

Across all 12 classifiers listed in Table 3, there was a noticeable improvement in performance for both PSO and PSO+ASL optimization models. Compared to the standard model, these optimization models showed an increase in accuracy ranging from 1% to 35%. Notably, k-NN showed a significant improvement in accuracy for all dataset ratios, with an increase of 27.99%. The AUC values for classifier models, as summarized in Table 4, also showed improvement ranging from 0.0204 to 0.077 compared to the standard model. In this case, k-NN achieved a "very good classification" with an AUC value of 1 for all dataset ratio compositions.

From the Table 5, it can be observed that the combination of PSO and ASL yields better results in improving classification accuracy for some classifiers compared to using only PSO. In the 70:30 dataset split, significant improvements were observed for several classifiers such as decision tree, random forest, gradient boosted tree, and Naïve Bayes (Kernel) when using PSO+ASL, while SVM (LibSVM) and k-NN did not show any significant changes. In the 80:20 dataset split, PSO+ASL provided better accuracy improvements than using only PSO in all classifiers, with the most significant increase seen in random tree and k-NN. However, the results were less consistent in the 90:10 dataset split, with some classifiers showing improvements with PSO+ASL, such as SVM, Naïve Bayes (Kernel), and LR (SVM), while others such as decision tree, gradient boosted tree, and random tree showed a decrease in accuracy. Overall, the use of PSO+ASL algorithms can improve classification performance for some classifier types and dataset splits, but the appropriate algorithm should be chosen depending on the characteristics of the dataset used for predicting heart failure. The information provided in Table 5 can be effectively represented and understood through the graphical representation presented in Figure 2.

The results obtained from grouping the classifiers, as depicted in Figure 3, reveal that the LM classifier achieved the highest average accuracy value of 100%. This corresponds to an average increase of 31.9%, 25.1%, and 26.97% for the 70:30, 80:20, and 90:10 ratios, respectively, when compared to the standard model. For more detailed information regarding the average accuracy value per group, please refer to Table 6.

Table 3. Evaluation for each classifier model (accuracy (%))

Classifiers		70:30			80:20			90:10		
		Standard	PSO	PSO+ASL	Standard	PSO	PSO+ASL	Standard	PSO	PSO+ASL
DTM	Decision tree	87.25	88.34	88.81	85.55	87.33	87.34	85.59	86.43	87.40
	Random forest	85.07	87.72	87.25	86.1	87.87	87.73	84.86	87.05	86.43
	Gradient boosted tree	84.45	87.42	100	86.38	88.69	100	86.08	87.77	100
	Random tree	70.44	82.10	92.53	74.55	82.56	91.96	79.17	81.49	91.65
SVM	SVM	86.94	87.87	87.87	85.83	86.77	87.60	85.47	87.05	87.29
	SVM (LibSVM)	72.63	81.65	83.36	72.21	85.83	81.88	72.41	79.66	85.59
	SVM (linear)	87.1	88.49	87.71	85.68	87.32	87.60	85.59	86.91	87.29
NBCM	Naïve Bayes	86.47	88.01	88.80	86.93	88.01	88.01	86.45	87.77	88.62
	Naïve Bayes (Kernel)	84.91	89.24	90.98	85.01	87.05	90.05	85.1	87.54	89.35
LRM	LR	86.47	88.80	88.34	86.51	87.21	87.74	86.2	87.30	87.53
	LR (SVM)	85.85	88.02	88.49	84.74	87.74	87.60	84.98	87.05	87.29
Lazy	K-NN	68.1	100	100	66.86	83.92	100	64.99	83.92	100

Table 4. Evaluation for each classifier model (AUC)

Classifiers		70:30			80:20			90:10		
		Standard	PSO	PSO+ASL	Standard	PSO	PSO+ASL	Standard	PSO	PSO+ASL
DTM	Decision tree	0.863	0.8830	0.9180	0.847	0.8690	0.9140	0.843	0.8490	0.9060
	Random forest	0.896	0.9080	0.9240	0.908	0.9130	0.9230	0.908	0.9150	0.9220
	Gradient Boosted tree	0.922	0.9240	1	0.93	0.9260	1	0.927	0.9240	1
	Random tree	0.702	0.8180	0.9480	0.735	0.8360	0.9450	0.804	0.8250	0.9350
SVM	SVM	0.928	0.9290	0.9330	0.925	0.9250	0.9240	0.923	0.9180	0.9180
	SVM (LibSVM)	0.784	0.8960	0.8460	0.774	0.9120	0.8370	0.778	0.8540	0.8500
	SVM (linear)	0.923	0.9340	0.9320	0.921	0.9240	0.9240	0.922	0.9170	0.9180
NBCM	Naïve Bayes	0.913	0.9260	0.9450	0.919	0.9250	0.9280	0.917	0.9230	0.9260
	Naïve Bayes (Kernel)	0.898	0.9450	0.9700	0.905	0.9220	0.9620	0.907	0.9120	0.9520
LRM	LR	0.931	0.9360	0.9260	0.927	0.9290	0.9120	0.926	0.9260	0.9030
	LR (SVM)	0.932	0.9330	0.8900	0.925	0.9250	0.8830	0.924	0.9220	0.8710
LM	K-NN	0.5	0.5000	1	0.5	0.5000	1	0.5	0.5000	1

Table 5. The improved average accuracy of each classifier

Classifiers		70:30		80:20		90:10	
		PSO	PSO+ASL	PSO	PSO+ASL	PSO	PSO+ASL
DTM	Decision tree	1.09	1.56	1.78	1.79	0.84	1.81
	Random forest	2.65	2.18	1.77	1.63	2.19	1.57
	Gradient boosted tree	2.97	15.55	2.31	13.62	1.69	13.92
	Random tree	11.66	22.09	8.01	17.41	2.32	12.48
SVM	SVM	0.93	0.93	0.94	1.77	1.58	1.82
	SVM (LibSVM)	9.02	10.73	13.62	9.67	7.25	13.18
	SVM (linear)	1.39	0.61	1.64	1.92	1.32	1.70
NBCM	Naïve Bayes	1.54	2.33	1.08	1.08	1.32	2.17
	Naïve Bayes (Kernel)	4.33	6.07	2.04	5.04	2.44	4.25
LRM	LR	2.33	1.87	0.70	1.23	1.10	1.33
	LR (SVM)	2.17	2.64	3.00	2.86	2.07	2.31
LM	K-NN	31.90	31.90	17.06	33.14	18.93	35.01

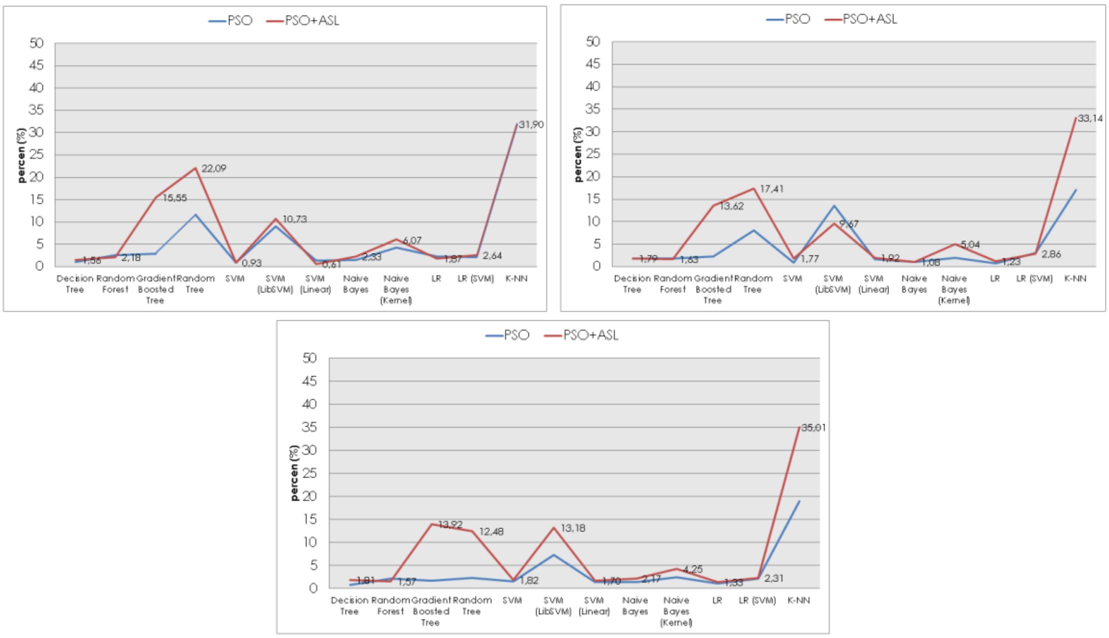

Figure 2. The graph improved the average accuracy of each classifier (70:30, 80:20, 90:10)

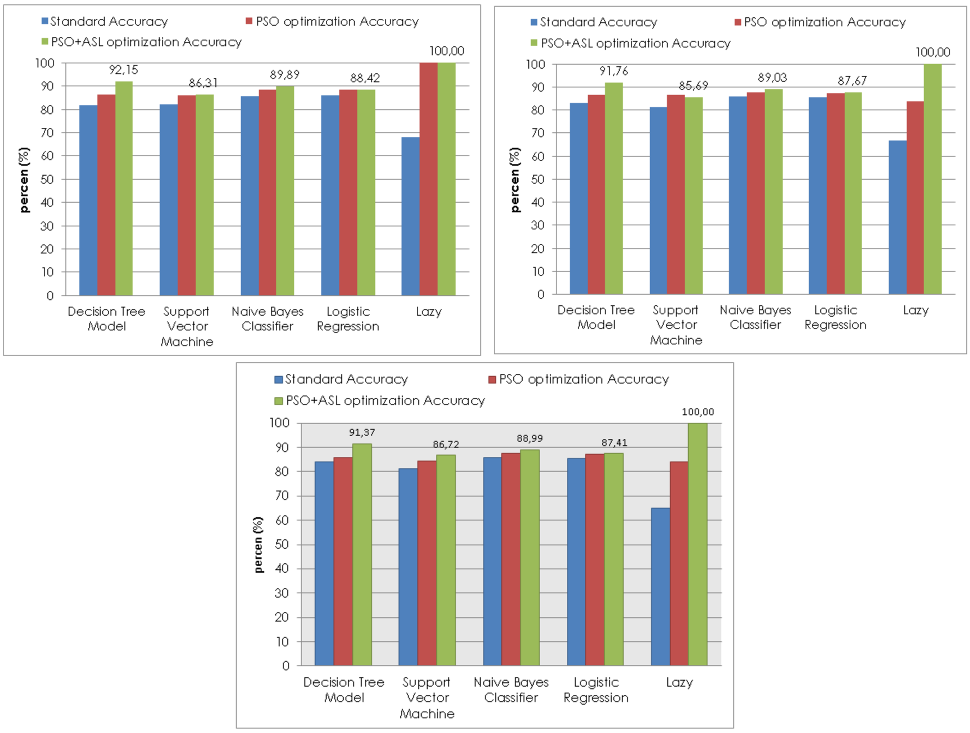

Figure 3. The graph of the average value of accuracy by group (70:30, 80:20, 90:10)

Table 6. The results of the average value of accuracy by group

Classifiers	70:30			80:20			90:10		
	Standard	PSO	PSO+ASL	Standard	PSO	PSO+ASL	Standard	PSO	PSO+ASL
DTM	81.80	86.40	92.15	83.15	86.61	91.76	83.93	85.69	91.37
SVMM	82.22	86.00	86.31	81.24	86.64	85.69	81.16	84.54	86.72
NBCM	85.69	88.63	89.89	85.97	87.53	89.03	85.78	87.66	88.99
LRM	86.16	88.41	88.42	85.63	87.48	87.67	85.59	87.18	87.41
LM	68.10	100	100	66.86	83.92	100	64.99	83.92	100

The combination of PSO and ASL in the HF disease classification study demonstrated that the k-NN method outperformed all other classifiers across all dataset ratio compositions (70:30, 80:20, and 90:10 with k-fold=10). The analysis results are visually represented by the performance vector in Figure 4. Specifically, the true positive (TP) value, representing the number of true positives, is 287, indicating accurate prediction of HF disease classification. The false positive (FP) value, which represents the number of false positives, is 0, indicating no instances of negative data being incorrectly classified as positive data (70:30 ratio). Similarly, for dataset ratios of 80:20 and 90:10, the true positive values are 328 and 369, respectively, indicating correct classification of positive data for HF disease. In both cases, the false positive value remains at 0, indicating accurate prediction of negative data.

PerformanceVector

```
PerformanceVector:
accuracy: 100.00%
ConfusionMatrix:
True:   Normal  HF
Normal: 287     0
HF:     0       356
AUC: 1.000 (positive class: HF)
f_measure: 100.00% (positive class: HF)
ConfusionMatrix:
True:   Normal  HF
Normal: 287     0
HF:     0       356
sensitivity: 100.00% (positive class: HF)
ConfusionMatrix:
True:   Normal  HF
Normal: 287     0
HF:     0       356
specificity: 100.00% (positive class: HF)
ConfusionMatrix:
True:   Normal  HF
Normal: 287     0
HF:     0       356
```

PerformanceVector

```
PerformanceVector:
accuracy: 100.00%
ConfusionMatrix:
True:   Normal  HF
Normal: 328     0
HF:     0       406
AUC: 1.000 (positive class: HF)
f_measure: 100.00% (positive class: HF)
ConfusionMatrix:
True:   Normal  HF
Normal: 328     0
HF:     0       406
sensitivity: 100.00% (positive class: HF)
ConfusionMatrix:
True:   Normal  HF
Normal: 328     0
HF:     0       406
specificity: 100.00% (positive class: HF)
ConfusionMatrix:
True:   Normal  HF
Normal: 328     0
HF:     0       406
```

PerformanceVector

```
PerformanceVector:
accuracy: 100.00%
ConfusionMatrix:
True:   Normal  HF
Normal: 369     0
HF:     0       457
AUC: 1.000 (positive class: HF)
f_measure: 100.00% (positive class: HF)
ConfusionMatrix:
True:   Normal  HF
Normal: 369     0
HF:     0       457
sensitivity: 100.00% (positive class: HF)
ConfusionMatrix:
True:   Normal  HF
Normal: 369     0
HF:     0       457
specificity: 100.00% (positive class: HF)
ConfusionMatrix:
True:   Normal  HF
Normal: 369     0
HF:     0       457
```

Figure 4. Performance results of the KNN algorithm (70:30, 80:20, and 90:10)

4. CONCLUSION

The study on the integration of ASL and PSO techniques for classification data mining to predict HF has yielded promising results. The primary goal of the study was to enhance the accuracy of traditional ML algorithms in classifying HF patients based on various clinical characteristics. To achieve this, twelve classifiers were employed and categorized into five groups: DTM, SVM, NBCM, LRM, and LM. The parameters of these algorithms were optimized using ASL and PSO techniques, while a combination of split validation and cross-validation with composition ratios of 70:30, 80:20, and 90:10, along with a k-fold value of 10, was utilized. The results indicated that ASL and PSO techniques outperformed the conventional ML algorithms in terms of accuracy and AUC. However, it is important to note that the study had certain limitations, such as a small sample size and the absence of external validation, which warrant further investigation to assess the effectiveness of ASL and PSO techniques in a broader patient population. In conclusion, this research demonstrates that the utilization of PSO-based ASL techniques for classification data mining holds significant implications for clinical practice and improved patient outcomes in predicting HF.

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