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# Particle Swarm Optimization for Parameter Tuning in Machine Learning Algorithms

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**Abstract:**

Heart disease is one of the leading causes of death. One area where machine learning can be used is in the prediction of heart disease. In the medical area, classification is one of the Machine Learning techniques employed because of its high accuracy. The utilization of features and dimensions in the dataset affects the accuracy of the classification algorithm.

In this paper using the PSO algorithm, we present an optimization strategy for tuning support vector machine (SVM) parameter values to classify a dataset of heart disease.

The test results show that the classification using SVM with PSO can improve accuracy better than the classification using SVM without PSO, namely the determination of the parameters randomly. Results show that heart disease data classification without PSO accuracy is 0.7711 in time heart disease dataset classification with PSO accuracy increased to 0.8159 after optimizing the main two parameters of SVM C and gamma.

**Key words:** Heart Disease, Support Vector Machines, Artificial Intelligence, Machine Learning, Particle Swarm Optimization.

**الملخص:**

أمراض القلب هي واحدة من الأسباب الرئيسية للوفاة. أحد المجالات التي يمكن فيها استخدام التعلم الآلي هو التنبؤ بأمراض القلب. في المجال الطبي، يعد التصنيف أحد تقنيات التعلم الآلي المستخدمة بسبب دقته العالية. يؤثر استخدام الميزات والأبعاد في مجموعة البيانات على دقة خوارزمية التصنيف .في هذه الورقة باستخدام خوارزميةPSO ، نقدم استراتيجية تحسين لضبط قيم معلمات آلة ناقلات الدعم (SVM) لتصنيف مجموعة بيانات عن أمراض القلب .تظهر نتائج الاختبار أن التصنيف باستخدام SVM مع PSO يمكن أن يحسن الدقة بشكل أفضل من التصنيف باستخدام SVM بدونPSO ، أي تحديد المعلمات بشكل عشوائي. تظهر النتائج أن تصنيف بيانات أمراض القلب بدون PSO دقة هو 0.7711 في الوقت المناسب تصنيف مجموعة بيانات أمراض القلب مع PSO زيادة دقة إلى 0.8159 بعد تحسين المعلمتين الرئيسيتين ل SVM C وgamma .

**الكلمات المفتاحية:** أمراض القلب، دعم ناقلات الآلات، الذكاء الاصطناعي، التعلم الآلي، تحسين سرب الجسيمات.

**پوختە:**

نەخۆشی دڵ یەکێکە لە هۆکارە سەرەکیەکانی مردن. بابەتێکە کە فێربوونی ئامێر دەتوانێت بەکاربهێنرێت لە پێشبینی نەخۆشی دڵدا. لە بواری پزیشکی، پۆلێنکردن یەکێکە لە تەکنیکەکانی فێربوونی ئامێر کە بە هۆی دروستی زۆرەوە بەکار دەهێنرێت. کەڵک وەرگرتن لە تایبەتمەندیەکان و ڕەهەندەکان لە داتاسێت دا کار دەکاتە سەر وردی لۆگاریتمی پۆلێنکردن .لەم توێژینەوەیەدا بە بەکارهێنانی لۆگاریتمیPSO ، ئێمە ستراتیجێکی باشترکردن بۆ بەهای پارامیتەری (SVM) پێشکەش دەکەین بۆ پۆلێنکردنی داتاسێتێک لە نەخۆشی دڵ. ئەنجامەکانی تاقیکردنەوەکان ئەوە نیشان دەدەن کە پۆلێنکردنەکە بە بەکارهێنانی SVM لەگەڵ PSO دەتوانێت چاکتر بێت لە پۆلێنکردنەکە بە بەکارهێنانی SVM بەبێPSO ، واتە دیاریکردنی پارامیتەرەکان بە شێوەیەکی هەڕەمەکی.


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ئەنجامەکان ئەوە نیشان دەدەن کە پۆلێنکردنی داتای نەخۆشی دڵ بە بێ (PSO) وردیەکەی ئەکاتە 0.7711 لە کاتی پۆلێنکردنی داتاکانی نەخۆشی دڵ لەگەڵ (PSO) وردی زیادی کردووە بۆ 0.8159 دوای باشترکردنی دوو پارامیتەرە سەرەکیەکەی (C و SVM Gamma).

**کلیلە وشە:** نەخۆشی دڵ، ئامێرەکانی بریکار زیرەکی دەستکرد، فێربوونی ئامێر.

## 1. Introduction

Machine learning algorithms give a statistical model for making predictions, classifications, and estimations. Researchers have more than three decades of learning techniques to forecast cardiac disease. [1]

Support Vector Machine (SVM) uses the SRM concept to determine the optimum hyperplane separating two classes in the input space. SVM also reduces common errors. SVM may be theoretically studied using computational learning theory. [2]

Particle Swarm Optimization (PSO) is inspired by social animal behavior. It's the trait of systems having dumb actors but intelligent collective behavior. This approach for stochastic search in a multidimensional space has been used to address complicated issues. The PSO is a great optimization method that can tackle difficult optimization issues, hence it's used in AI. PSO can search large multimodal and noncontinuous spaces to find the best solution near the optimal value. It's a random-solutions guide. SVMs have applications in medical, multimedia processing, security, and economics. [3]

## 2. Literature review

in [4] Their work employs a modified PSO-based algorithm to decrease the fitness of the Mean Squared Error (MSE). The outcome demonstrates that the suggested method is able to anticipate the tested classifier's future price with accuracy. In order to choose the best features from the available indicators that were produced from the technical analysis section, the study in stock market forecasting offered an algorithm based on SVM optimized by the PSO. This is done by using PSO algorithms to choose the best input features out of all the indications that are available, which led to the PSOSVM outperforming the individual SVM approach.

In [5] They categorized the PSO as having internal modification and external modification. The term "internal modification" describes changes made to PSO's fundamental parts. Numerous modifications have been created in order to enhance the convergence and the quality of PSO, including the addition of inertia weight, velocity clamping, constriction, and models, as well as various methods of identifying global and local maximum positions. The term "external modification" describes all changes made utilizing multiple swarms or strategies that cause the swarm to split.

In [6] Using FCBF identifies superfluous and redundant aspects used in this article (First Correlation-based feature selection). Later, SVM was improved using PSO and recursive FA (Firefly algorithm). Utilized is PRFA-SVM. Public datasets are used to implement the suggested method. Comparisons of classification accuracy show that the PRFA-SVM method is effective and durable.

In [7] their research produced an airborne fuel pump failure status extraction method by merging multiscale fuzzy entropy (FE) and support vector machines (PSO-SVM). Fuel pump vibration signals

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that are non-stationary and non-linear make fault diagnosis difficult. The PSO-SVM model is trained using training data, and the suggested method is validated using testing data. Finally, they collect the vibration data from the airborne fuel pump on their experimental platform and assess the proposed strategy. They show that the method can identify problems with airborne fuel pumps.

In [8] This study examines the detection and characterization of rice leaf diseases using K-means clustering, multi-class SVM, and PSO. Features are extracted through GLCM. SVM is used to categorise the sickness, and PSO is used to boost the detection's precision. According to the research, the anticipated method may accurately diagnose illnesses in 97.91 % of cases. KNN, FFNN, and SVM have accuracy rates of 77.96%, 85.6%, and 90.56%, respectively.

## 3. Methodology

### 3.1 Normalizing Dataset

Normalization is a common method of data preparation that transforms numerical scale to a standard scale. Not all machine learning datasets require normalization, however it is used when characteristics have wide ranges. It raises the efficiency and dependability of ML models. In this paper we use Min-Max normalization method.

### Min-Max Scaling

Also called scaling, this approach shifts and rescales the dataset's attribute values such they range between 0 and 1. [9]

Mathematically, we can calculate normalization with the below formula:

$$x_n = \frac{x_i - x_{Min}}{x_{Max} - x_{Min}} \tag{1}$$

Where:

- $X_n$= Value of Normalization
- $X_i$ = feature value
- X maximum = Maximum value of a feature
- X minimum = Minimum value of a feature

### 3.2 Support Vector Machine (SVM)

One of the greatest methods for categorizing data is the support vector machine (SVM), which was first introduced by Vapnik in 1995. It is founded on statistical machine learning theory and structural risk reduction (SLR).

In a typical linear classification task, the set of training data, (xi, yi), where i = 1, 2,..., m, and m is the number of given observations, where $xi \in R^n$ are feature vectors and $y_i \in (-1, +1)$ are label vectors. A binary classification problem can be posed as an optimization problem in the following way:


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$$Min: \frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^{m} \varepsilon_i \qquad (2)$$

Subjected to: $yi\ (w\ \times\ xi)\ +\ b\ \geq\ 1 - \xi i,$ (3

$$\xi i\ \geq\ 0, i\ =\ 1, \ldots, m,$$

Where:

w is the weight vector perpendicular to the hyperplane (normal plane)
$C$ is the regularization parameter
$\xi i$ the penalizing relaxation variables.
b is the position of the plane relative to the center of the coordinates. Equation (3) means

$$\begin{aligned} w\ \times\ \phi\ (x\ i)\ +\ b\ &\geq\ +1 \qquad if\ yi\ =\ +1, \\ & \qquad\qquad\qquad\qquad (4) \\ w\ \times\ \phi\ (x\ i)\ +\ b\ &\geq\ -1 \qquad if\ yi\ =\ -1. \end{aligned}$$

It is to be noted that the nonlinear classifier may be denoted in the input space as

$$f(x) = sign\left(\sum_{i=1}^{m} \alpha_i^* * y_i * K(x_i, y_i) + b^*\right) \qquad (5)$$

where $f(x)$ is the decision function and the bias $b^*$ is calculated by the Karush-Kuhn-Tucker (KKT) conditions; $K\ (x_i,\ y_i)$ is the kernel function that produces the inner product for this feature space. Separating two groups is one of the classification issues, as seen in Figure (1). The ideal separator hyperplane is found by measuring the hyperplane margin and locating its maximum point. The margin is the separation between the closest hyperplanes for each class. The closest patterns are support vectors. The goal of SVM learning is to locate this hyperplane. [10]

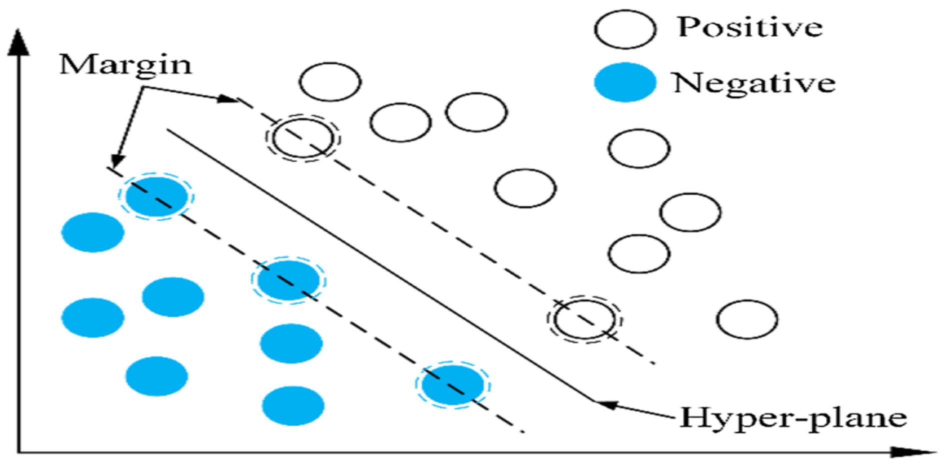


**Figure 1** Classification of two types using SVM. **[11]**

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### 3.3 Particle Swarm Optimization (PSO)

Kennedy and Eberhart developed PSO in 1995 based on a stochastic optimization technique known as a social simulation model [12]. PSO was developed for solving optimization problems using behavior of swarm [13]. Since its creation, Particle Swarm Optimization (PSO) research and applications have exploded, leading to several PSO algorithms that are now widely used to solve different kinds of optimization problems.

During the entire search process, the position and velocity of each particle can be updated according to Equations 6 and 7.

$$V_i(t+1) = wV_i(t) + C_1Rand(.)_1|pbest_it - X_i(t)| + C_2Rand(.)_2|gbest_it - X_i(t)| \quad (6)$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (7)$$

Where $Vi$ and $Xi$ are the velocity and position of the particles, respectively; $(\cdot)_1$ and $Rand(\cdot)_2$ are random numbers that are uniformly distributed between 0 and 1; *pbest* denotes the best position of each particle in space, and *gbest* represents the globally best position of all the particles. Acceleration coefficients $c1$ and $c2$ describe the 'trust' settings that mention the degree of confidence in the optimal solution found by an individual particle ($c1$ -cognitive parameter) and by the whole swarm ($c2$-social parameter). The term *w* in Equation 6 refers to the inertial weight that was presented to improve the convergence of the iteration procedure. This weight is a scaling factor utilized to control the search capabilities of the swarm, which scales the current velocity value that affects the updated velocity vector, Figure 2 shows the revised 2D particle location and velocity. First vector is preceding stage's momentum velocity. The second vector relates to iterated particle memory components. This particle's speed attracted it to the optimal solution point. So, the final vector is a swarm. This component attracts the best swarm particle.

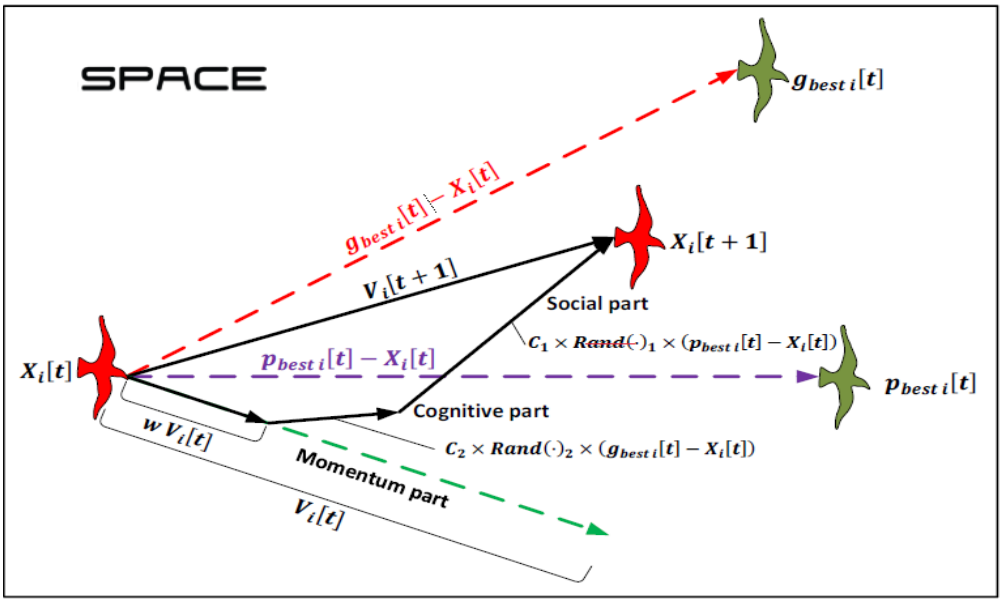


**Figure 2.** Pictorial view of particle behavior showing position and velocity update [14]


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### 3.4 Support Vector Machine with Particle Swarm Optimization (SVM-PSO)

SVM and PSO problem-solving steps are as follows:

- Initialize SVM parameters. SVM parameters must be initialized before use.
- Randomize initial particles. Parallel N particles create the SVM parameter.
- The aforementioned SVM parameters train training data. Fitness evaluates each particle. This study's fitness value is SVM classification accuracy.
- Update particle position and speed. PSO needs particle location and velocity. The SVM model is evaluated again to determine the best particles**. Step D's** best particle is used to retrain the training data and determine the fitness value.
- Update Pfit and POP (pbest). The first (first) iteration has produced the best particle so far (pbest).
- Check whether all iterations are done. If **step C** wasn't continued, go to **step H**.
- Each iteration has best particles. The best particle from all iterations is analyzed to establish its global ideal location (gbest).
- If **step G's** gbest value equals the predicted value, the optimum SVM parameter value has been found and step I is continued. If the gbest value doesn't satisfy the anticipated criteria, **step C** is repeated. [15]

### 3.5 Confusion Matrix

The performance of the classification models for a certain set of test data is evaluated using a matrix called the confusion matrix. The confusion matrix's rows reflect the values of the predicted class and its columns represent the values of the actual class, as illustrated in Table (1).
In the 2×2 confusion matrix, there is a true positive (TP), false positive (FP), true negative (TN) and false negative (FN). [16]

**Table (1).** Confusion Matrix.

| | | **Predicted Class** | | |
|---|---|---|---|---|
| | | **Positive** | **Negative** | |
| **Actual Class** | **Positive** | True Positive (TP) | False Negative (FN) **Type II Error** | **Sensitivity** $\frac{TP}{(TP+FN)}$ |
| | **Negative** | False Positive (FP) **Type I Error** | True Negative (TN) | **Specificity** $\frac{TN}{(TN+FP)}$ |
| | | **Precision** $\frac{TP}{(TP+FP)}$ | **Negative Predictive Value** $\frac{TN}{(TN+FN)}$ | **Accuracy** $\frac{TP+TN}{(TP+TN+FP+FN)}$ |

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### 3.6 Mean squared error (MSE)

The degree of inaccuracy in statistical models is gauged by the mean squared error, or MSE. Between the observed and projected values, it evaluates the average squared difference. The MSE is equal to 0 when a model is error-free. Its value grows when model error increases. [17]
Mathematically, the MSE formula represented as:

$$\boldsymbol{MSE = \frac{1}{n}\sum_{i=}^{n}\left(Y_i - Y_i^{\wedge}\right)^2} \qquad (\mathbf{8})$$

MSE = mean squared error
$n$ = number of data points
$Y_i$ = observed value
$Y_i^{\wedge}$ = predicted value

### 3.7 Area Under the Curve (AUC)

AUC used as a fitness function for PSO. It is used to measure the quality of the model prediction. AUC is calculated using 9 equation. [18]

$$AUC = \frac{TPR + TNR}{2} \qquad (9)$$

Where TRP is the true positive rate (Sensitivity) and is the true negative rate (Specificity).

## 4. Dataset Description

To evaluate the classification accuracy of the proposed method, the dataset used in this paper was obtained from Heart Centers in Sulaymaniyah, Erbil, and Duhok from 2021 patient files.

The heart disease data set contains 699 cases including 165 cases with the diagnosed "surgery is required" (class 1) and 504 cases without such diagnosis (class 2); each patient is described by 15 characteristics.(Gender, Age, Blood Group, Smoking, Drinker, Genetic, Blood Sugar, Chest Pain, Troponin, Creatinine Kinase (CK), Enjection fraction, S.electrolytes(sodium), Cholesterol, Triglycerides and CRP).

Each attributes of the datasets is measured using a different scale, and each attribute has a distinct range of potential values. All of the attributes are numerical values. A data pre-processing technique called normalization is used to normalize the range of independent characteristics (attributes of data)

## 5. The Proposed Methods

The major objective of the proposed method (SVM-PSO) is to choose the best optimal parameters gamma and C for SVM training in order to improve accuracy. Figure 3 displays the suggested method's algorithm and diagram.

The proposed technique was implemented and evaluated using the Python programming language and the machine learning toolkit scikit-learn library.


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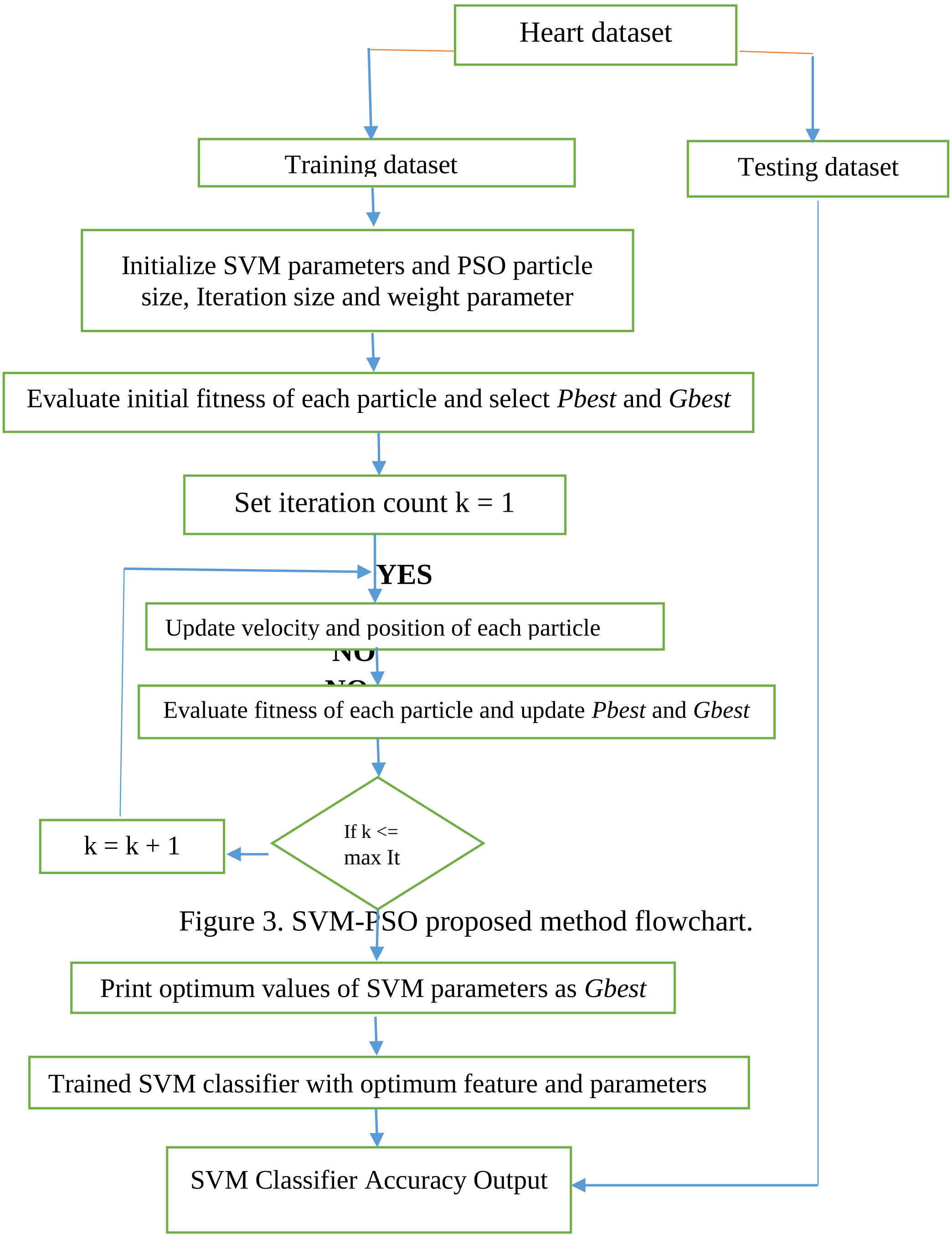


Figure 3. SVM-PSO proposed method flowchart.

## 6. Results and discussion

### 6.1 SVM Classification Without PSO

The SVM classification accuracy without using PSO. the default values specified by the Python s cikit-learn library package is used as initial values. As shown in **Table 2** the accuracy, AUC, and M SE are 0.7711, 0.802, 0.2288 respectively.

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**Table 2.** Performance comparison of SVM without PSO.

| Dataset | C | Gamma | Accuracy | AUC | MSE |
|---|---|---|---|---|---|
| Heart Disease | default | Auto | 0.7711 | 0.802 | 0.2288 |

The Confusion Matrix for Heart Disease dataset as shown in Figure **(4):** each (True Negative, False Negative, False Positive, True Positive) are (144,43,3,11) respectively.

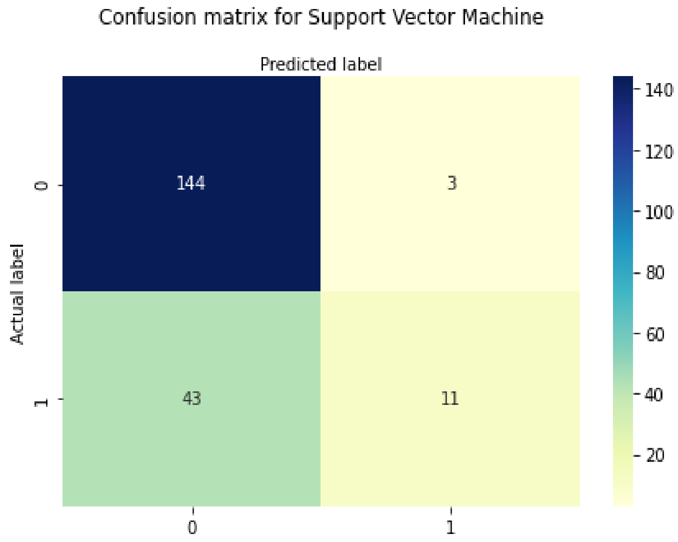
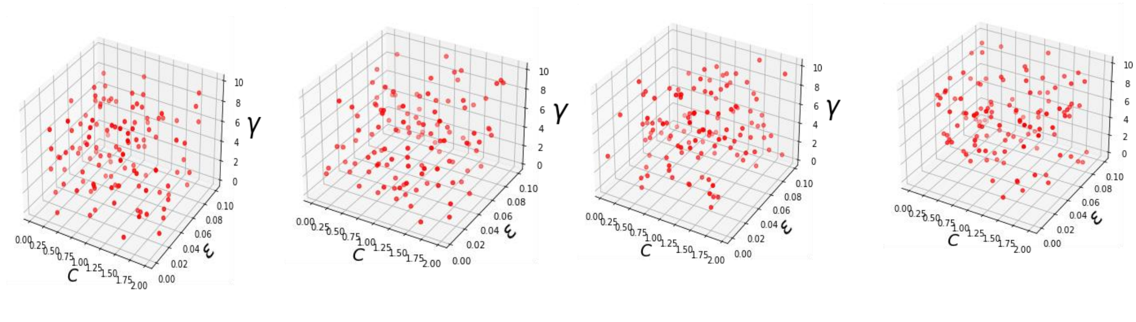



Figure **(4)** Confusion Matrix for SVM without PSO

### 6.2 SVM Classification with PSO (SVM-PSO)

To improve SVM classification accuracy, the kernel function parameter gamma and the regulariz ation parameter C. PSO are implemented as the first step for choosing optimal parameters and in the next step these parameters inserted as input parameters to calculate SVM classifier accuracy.

Figure 5 displays the location of the particle swarm during the initialization stage in the D-3 search spaces.



(a) (b) (c) (d)

Fig **(5):** (a) Dataset Scatter plot for weight=0.2; (b) Dataset Scatter plot for weight=0.4;

(c) Dataset Scatter plot for weight=0.6; (d) Dataset Scatter plot for weight=0.8;


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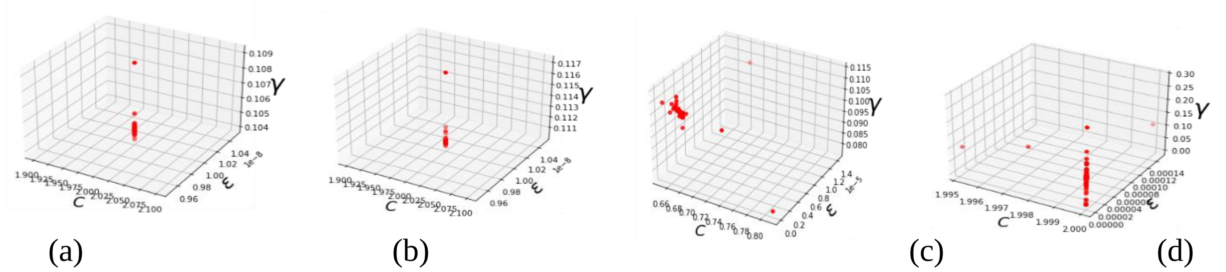
Figure 6 depicts the location of the particle swarm at the 100th iteration in the D-3 search spaces.



(a) (b) (c) (d)

Fig **(6):** (a) proper direction for weight=0.2; (b proper direction for weight=0.4;

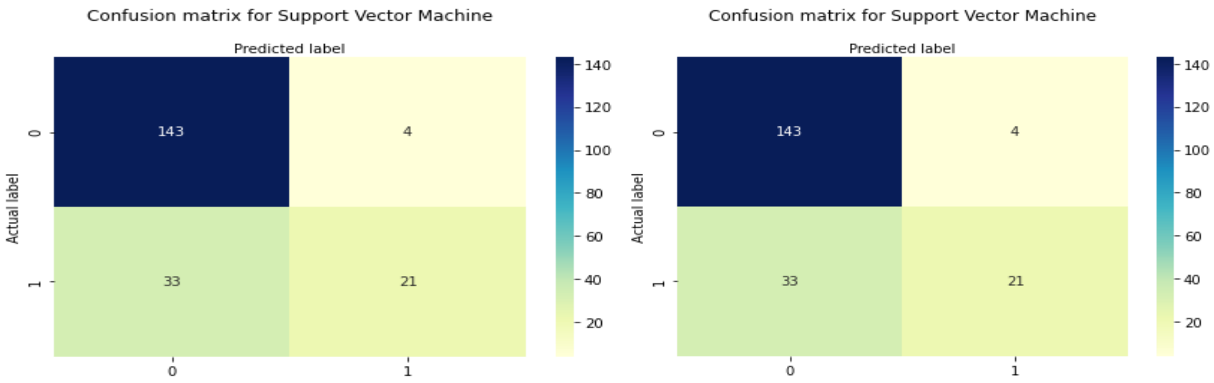
(c) proper direction for weight=0.6; (d) proper direction for weight=0.8;

In table 3 the results of the different PSO initialize parameter with optimal values of parameters of the SVM classifier are presented. The result shows increasing of accuracy values after using PSO for four different weights in comparison with SVM without using PSO.

**Table (3): Performance comparison of SVM with PSO.**

| Heart Disease Dataset | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| PSO Initialize Parameter | | | SVM-PSO Optimal Parameters | | | SVM with Optimal Parameters | | |
| Particles | Iteration | Weight | C | Gamma | MSE | Accuracy | AUC | MSE |
| 120 | 100 | 0.8 | 2 | 0.1047 | 0.0592 | 0.81592 | 0.815 | 0.1841 |
| 120 | 100 | 0.6 | 0.6758 | 0.108 | 0.0521 | 0.7562 | 0.817 | 0.2437 |
| 120 | 100 | 0.4 | 2 | 0.1108 | 0.0524 | 0.8159 | 0.814 | 0.183 |
| 120 | 100 | 0.2 | 2 | 0.1046 | 0.0592 | 0.8158 | 0.816 | 0.184 |

From Figure (7) we have four confusion matrices for each value of (w) comprising of (0.2, 0.4, 0.6, 0.8) respectively, as shown is:




**(a)** **(b)**

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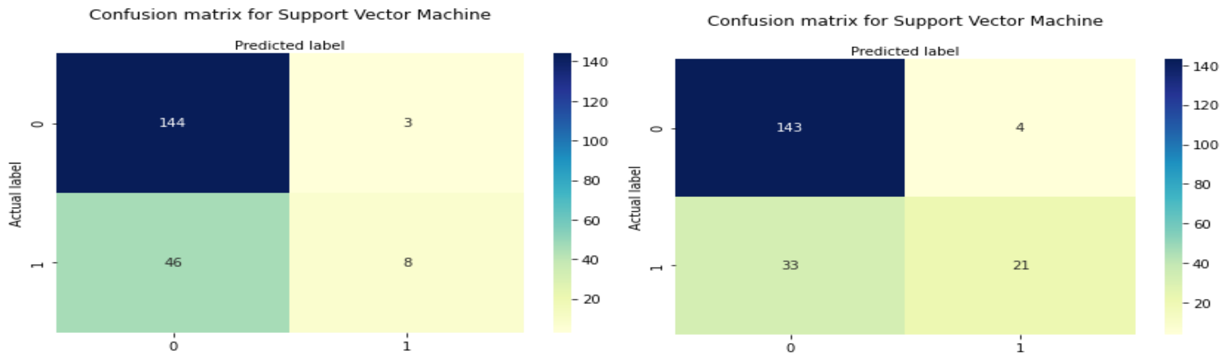
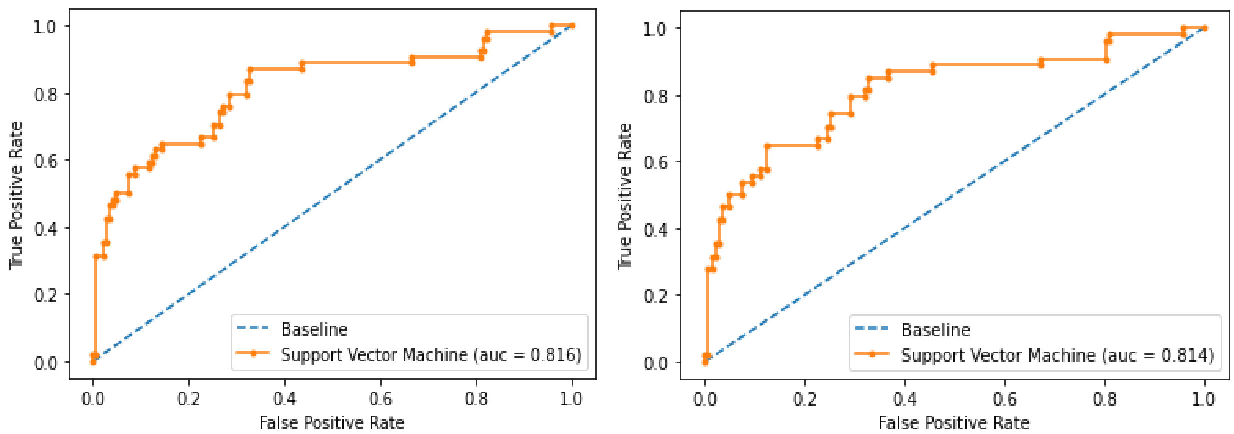


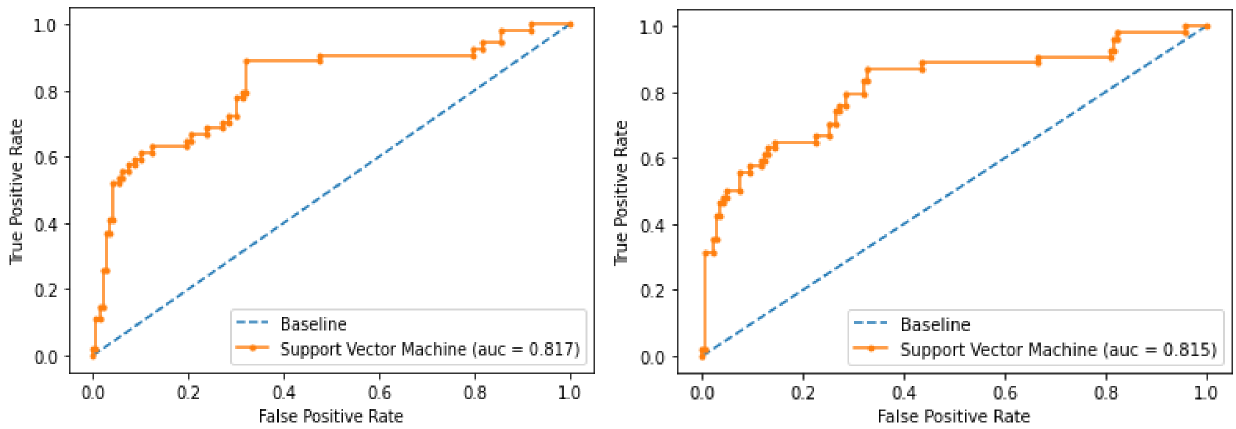

**(c)** **(d)**

**Figure (7):** Confusion Matrices for (a) w=0.2, (b) w=0.4, (c) w=0.6, (d) w=0.8

Figure 8 represents AUC rate and as shown for all different weights value the rate of true positive increases




**(a)** **(b)**




**(c)** **(d)**

**Figure (8).** (True Positive Rate and False Positive Rate) for (a) w=0.2,(b) w=0.4, (c) w=0.6, (d) w=0.8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**Conclusion:**

In order to determine the optimal parameter value for SVM, PSO optimization techniques are combined with SVM. in this research. Finding the optimal parameter value may be done pretty well using the SVM and PSO. Combining these two approaches results in a technique for determining the SVM parameter value that is more systematic than the trial-and-error approach.

The optimal value can be reached with this merging, but it takes more time to complete. The accuracy of SVM-based classification with PSO optimization has been improved more than SVM-based classification without parameter optimization, where the parameters are chosen at random. The data on heart disease can now be classified with an accuracy of 0.8159.

The classification accuracy depends also on quality of the data and we believe that this value increases with more accurate dataset. Since we implement our proposed algorithm on diabetes disease obtained from UCI repository and the SVM accuracy are increased for different C and gamma parameters to 0.95 approximately.

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