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A Hybrid Swarm Intelligence Technique for Feature Selection in Support Vector Machine (SVM) Classifier using Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO)

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Abstract

Complex optimization issues have been successfully resolved by swarm intelligence algorithms like Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO). A preprocessing technique called feature selection chooses the most important attribute from datasets in order to minimize their dimensionality. In this research, the Support Vector Machine (SVM) classifier is trained using the features selected by both PSO and ACO. These optimization methods are assessed using performance criteria, including F1 score, accuracy and precision. Additionally, the execution time of both algorithms is measured. A hybrid approach combining PSO and ACO with SVM is explored to further improve feature selection and achieve better overall classification results. This hybrid methodology would maximize the strengths of both algorithms, providing a more robust solution for complex optimization problems. The findings demonstrate the effectiveness of swarm intelligence technique for feature selection, offering an efficient method to enhance model performance.

Categories: AI applications, Operating Systems (OS), Computational Science and Engineering
Keywords: artificial intelligence, feature selection, machine learning, support vector machine, swarm intelligence, classification performance, accuracy, precision, f1 score, execution time

Introduction

Swarm Intelligence (SI) is a subfield of artificial intelligence that takes inspiration from the collective actions of naturally occurring decentralized, self-organized systems. Individual agents in these systems operate according to simple rules, and despite their limited capabilities and lack of centralized management, their interactions cause complex intelligent group behavior to evolve [1]. The SI algorithms were developed in response to observations of both artificial and natural behaviors including ant foraging, fish schooling and bird flocking. A collection of population-based nature-inspired algorithms generate fast, reliable and low-cost solutions to complex problems [2]. The SI algorithms effectively explore vast solution spaces and resolve challenging issues in a variety of fields. SI-based algorithms are valued for their scalability, flexibility and capacity to identify the optimal solution in complex and dynamic environments. A hybrid technique combining the Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) algorithms with SVM has been proposed [3]. By minimizing dimensionality and concentrating on the most relevant data, feature selection is essential to enhancing the performance of SI models. SI techniques, particularly PSO and ACO, have demonstrated their effectiveness in solving complex optimization problems including feature selection.

Related work

Khourdifi et al. [4] proposed a hybrid approach that improves the quality of heart disease classification by filtering redundant information using the Fast Correlation-based Feature Selection method. They analyze data using a variety of classification algorithms including K-Nearest Neighbor, SVM, Naive Bayes, Random Forest, Multilayer Perception and an Artificial Neural Network optimized using PSO and ACO approaches.

Tan et al. [5] presented a hybrid strategy that uses a wrapper-based approach to combine two machine learning techniques, SVM and Genetic Algorithm (GA). They used the LIBSVM package and the WEKA data mining tool for analysis in order to assess the efficacy of their strategy. Five datasets from the UCI Machine Learning Repository, Iris, Diabetes, Breast Cancer, Heart Disease and Hepatitis were used in the trials. Among the noteworthy outcomes of the hybrid GA-SVM approach were an accuracy of 78.26% for the diabetes dataset and 84.07% for the heart disease dataset. The hepatitis dataset produced the maximum accuracy of 86.12% while the breast cancer dataset generated an accuracy of 76.20%.

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Parthiban et al. [6] proposed a machine learning approach that looked into the identification of cardiac disease in diabetic patients. Using the WEKA software, the study implemented the Naive Bayes and SVM algorithms. Of the 500 patients in the dataset obtained from the Chennai Research Institute, 142 had the illness and 358 did not. With an accuracy of 94.60%, the SVM algorithm performed the best, whereas the Naive Bayes approach only managed 74%.

Liu et al. [7] proposed an improved detection of cardiac illness that used a hybrid classification methodology that combines the ReliefF and Rough Set (RFRS) methods. The two primary parts of the suggested system are a classification system with an integrated classifier and a feature selection system that makes use of RFRS. The system reached a maximum classification accuracy of 92.59% by using a jackknife cross-validation approach.

Malav et al. [8] proposed an effective hybrid algorithmic approach to cardiac disease prediction with the goal of identifying and extracting hidden patterns associated with the condition. This approach uses an artificial neural network in conjunction with the K-means clustering technique. The accuracy of the suggested model is 97%.

Chaurasia et al. [9] proposed the application of data mining techniques for the identification of cardiac disease. They made use of the WEKA data mining tool, which comprises a set of machine learning analytical methods. The algorithms Naive Bayes, J48 and Bagging were used in this investigation. Out of the 76 attributes in the dataset which was taken from the UCI Machine Learning Repository, only 11 were chosen for prediction. The accuracy of the J48 method was 84.35%, whereas the accuracy of the Naive Bayes was 82.31%. Bagging achieved the highest accuracy of 85.03% outperforming both approaches. This outcome suggests that for this dataset, bagging offers better classification performance.

Vembandasamy et al. [10] proposed the Naive Bayes algorithm. Naive Bayes makes use of Bayes' theorem. As a result, Naive Bayes has a strong independence principle. One of Chennai's top diabetic research institutes provided the data. There are 500 patients in the data collection. As a tool, WEKA uses 70% of the Percentage Split to perform classification. The accuracy of Naive Bayes is 86.419%.

Materials And Methods

Dataset and attributes

The information was gathered from the Kaggle database. The Students Adaptability Level in Online Education Data Set is the database's name. Many different types of datasets from different disciplines are available in the Kaggle repository. This repository was created by Nishat Ahmed Samrin and Md. Aktaruzzaman Pramanik. The dataset provided for Effectiveness of Online Education, and its attributes are mentioned below in Table *1*. The dataset URL is provided in Kaggle [11].

Classification task

SVMs are often regarded as classifiers that achieve high accuracy across various tasks. They work by constructing a hyperplane with the maximum Euclidean distance or margin from the nearest training examples. Simply put, SVMs represent instances as points in space, which are mapped to a high-dimensional plane in which the instances of different classes are differentiated by the largest possible margin from the hyperplane [3]. In the same space, new instances are mapped, and their anticipated class is determined by which side of the hyperplane they fall on. Support vectors are a relatively small subset of the training data that determines the SVM hyperplane, and the remaining training data has no effect on the final classifier [12,13].

Feature selection

The datasets contain 14 features. It may contain irrelevant, unclear or noisy data involved in the dataset, which makes classification task more complex. Classification accuracy will be reduced, calculation time and expenses will increase if complete data are used which is of no use to us. Feature selection as a preprocessing step improves comprehension of outcomes, decreases size, removes unresolved data and raises learning accuracy. The hybrid approach is adopted to select a subset of discriminatory features prior to classification by eliminating attributes to get good performance with full consideration of feature correlation and redundancy. In this research, before selecting the features for this study, we first conduct a feature selection process.

Particle swarm optimization

The social behavior of a flock of birds attempting to reach an unknown location served as the model for the PSO algorithm. Each solution is represented in PSO as a particle, which is a bird in the flock. The social behavior that the population's birds develop helps them navigate their way to their destination. Each bird moves in a particular direction while flying and by interacting with each other, the birds are able to determine which bird is closest to the ideal location. As a result, each bird modifies its velocity based on its present position to go toward the bird in the best position. From its new local position, each bird investigates the search space, and this cycle is repeated until the flock reaches its target. Through social interaction and intelligence, this process enables the birds to learn from both their own experiences (local search) and those from other members of the flock (global search) [2].

To implement PSO, it is essential to define a search space consisting of particles and an objective function to be optimized. The algorithm operates by iteratively moving the particles toward the optimal solution. Each particle possesses the following properties.

Position: Represents the particle's coordinates within the defined search space.

· Velocity: Controls the particle's motion's magnitude and direction. The particle can change its position because the velocity is changed at each iteration. The motion of the particle is determined by own experience, its best position so far and the influence of neighboring particles.

· Neighborhood: Denotes a collection of particles that interact with a particular particle especially the one that most closely matches the criterion of fitness.

Each particle stores the following data at any given moment:

· Personal best position (pbest): The coordinates and matching value of the objective function at its optimal position are included in its pbest.

. Global best position (gbest): The location of the swarm's top-performing particle which stands for the best outcome thus far.

. Objective function value: To assess progress toward the solution, the fitness value of the current particle is compared to the ideal value at each iteration.

In PSO, each particle modifies its position and velocity according to two primary criteria: the swarm's overall best experience gbest and its own best experience pbest. Equations (1) and (2) define the conventional velocity and position update equations that are used to perform these changes. The performance of each particle is assessed at the conclusion of each iteration using a predetermined cost or fitness function. Particles can gradually converge toward the ideal solution thanks to this repeated process.

$$v_i[t+1] = w \cdot v_i[t] + c_1 r_1 (p_{i,\text{best}}[t] - p_i[t]) + c_2 r_2 (p_{g,\text{best}}[t] - p_i[t]) \qquad (1)$$

$$p_i[t+1] = p_i[t] + v_i[t+1] \qquad (2)$$

Where, ⊠=1,2,...,⊠, and N is the number of swarm population. $v_i[t]$ is the velocity vector at the t (⊠*h*) iteration, and $p_i[t]$ represents the current position of the ith particle. $p_{i,\text{best}}[t]$ is the previous best position of ith particle and $p_{g,\text{best}}[t]$ is the previous best position of whole particle. To control the pressure of local and global search, w has been used. ⊠1 and ⊠2 are positive acceleration coefficients, referred to as the cognitive parameter and social parameter, respectively. ⊠1 and ⊠2 are random number between 0 and 1 [14].

Ant colony optimization

Ant colonies' social behavior serves as an inspiration for ACO. Ants have been shown to be able to figure out the shortest path between their food source and their nest as a group [15]. Ants leave behind a chemical called a pheromone that aids other ants in determining the shortest path between their nests and food source, and help other ants make decisions by pointing them in the direction of the most effective paths. The Ant Colony Optimization approach reduces redundancy by choosing a subset of features with each ant choosing the features with the lowest resemblance to the previously chosen features. Therefore, if the majority of ants choose a feature it means that the feature has the least amount of resemblance to the other features. The features that receive the most pheromone will have a higher probability of being chosen by other ants in later iterations. The features that are chosen will have high pheromone values based on how similar the features are. The features' significance allows for the minimization of redundancy, which is determined by the features' similarity [16].

PSO-ACO+SVM hybrid algorithm

In this method of hybridization, PSO identifies the optimal subset of features that maximizes the classifier's accuracy [17]. The fitness function for PSO is defined to evaluate the accuracy of an SVM classifier (SVC) on the selected feature subset. The PSO optimizes the feature subset by minimizing the negative accuracy, aiming for high classification accuracy. Once PSO has identified the optimal feature subset, ACO is applied to the same subset of features to further refine or confirm the feature selection. The initial pheromone values for ACO are based on the PSO results, and the best feature set from PSO is used as the starting point. The algorithm iterates over the PSO-selected features, adjusting the pheromone levels to refine the feature subset and potentially improve the model's accuracy. After feature selection using PSO and ACO, an SVC is trained on the selected features. Accuracy, precision, F1 score and other performance metrics are calculated for both PSO- and ACO-selected feature subsets. The SVC's performance is evaluated on the test set to measure its generalization capability. Execution time is recorded for both PSO and ACO to compare the computational efficiency of the two algorithms.

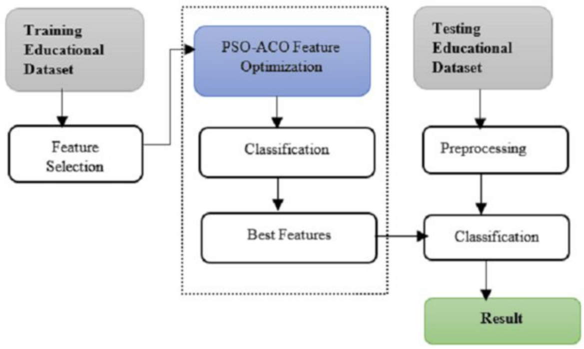

FIGURE 1: The Proposed Architecture

PSO, Particle Swarm Optimization; ACO, Ant Colony Optimization

Our SVM-based feature selection and classification approach, based on PSO-ACO, is included. Figure *1* depicts the proposed system's primary structure.

Results

The experiment was carried out using a laptop running Windows 10 with an Intel i5 8th Gen processor and 8 GB of RAM. Python was used for the coding. A total of 30% of the dataset was used for testing while 70% was used for training. As indicated in Table *1*, the dataset has 14 attributes in total, and we utilized a dataset containing 100 educational records obtained from Kaggle, titled "Students Adaptability Level in Online Education".

Sr. No.	Attribute	Description
1.	Gender	Boy, Girl
2.	Age	21–30
3.	Education Level	University, College, School
4.	Institution Level	Non-Government, Government
5.	IT Student	No, Yes
6.	Location	No, Yes
7.	Load-shedding	Low, High
8.	Financial Condition	Medium, Poor
9.	Internet Type	Wifi, Mobile Data
10.	Network Type	4G, 3G
11.	Class Duration	Time
12.	Self Lms	No, Yes
13.	Device	Tablet, Mobile
14.	Adaptivity Level	Moderate, Low

TABLE 1: Dataset Attributes

The use of machine learning algorithms for classification and prediction has been investigated in earlier works. However, these studies frequently ignore its optimization utilizing cutting-edge techniques and instead concentrate solely on the effects of particular machine learning algorithms. Additionally, few academics have tried to improve machine learning classification performance using hybrid optimization techniques. The majority of studies in the literature use optimization methods like ACO and PSO in conjunction with a particular machine learning algorithm, like Multilayer Perceptron (Artificial Neural Network), KNN, SVM, Decision Tree, Naive Bayes and Random Forest.

In this research, the Feature Selection method is applied as an initial step, i.e. preprocessing. All relevant features are selected from the original set of attributes, removes redundant and irrelevant data because it hampers the processing of data by taking more time to execute, check for class imbalance, noisy data, and imbalance datasets to enhance learning accuracy and improve the interpretability of results.

The second step, involves the PSO and ACO algorithms being employed to select the relevant features from the dataset. The optimal subset of features chosen through these feature selection methods enhances classification accuracy. The third step, involves applying the classification algorithm and measuring the classification accuracy to assess the performance of the feature selection methods.

This study's main goal is to employ a hybrid approach in which PSO, ACO and SVM are used for:

· Elimination of redundant and irrelevant features through feature selection techniques. The feature subsets selected by PSO and ACO are compared to determine whether they are identical or different, providing insights into the effectiveness of both algorithms.

· Optimization of classification performance using PSO where the results of PSO serve as the initial values for the ACO approach.

· Extraction of classification accuracy, Performance Metrics, Accuracy, precision, F1 score, and classification reports are generated for both the PSO and ACO feature selection methods and the SVC.

· Evaluate the effectiveness of the model in terms of execution time.

· Hybrid approach: The hybrid PSO-ACO model maximizes the strengths of both PSO and ACO. PSO provides an initial feature selection while ACO refines it by reinforcing the best selected features based on pheromone updates, leading to more robust feature selection for the SVC.

Based on Figure 2, the PSO-ACO+SVM model is shown to be a better solution for achieving higher accuracy.

During the experiment setup, we configured swarm size (num_particles) as 30, pheromone decay rate (evaporation_rate) as 0.5, and allowed the swarm library to control the inertia weight. The maximum number of iterations was set to 100. Additionally, the LabelEncoder from sklearn preprocessing was utilized to encode the target column into numerical values, as machine learning models like SVM require numerical inputs rather than categorical labels. This encoding step not only ensures compatibility but also accelerates processing.

The initial feature selection was performed using PSO, which identified the most relevant features based on classification accuracy. These selected features were further refined through ACO, reinforcing the feature subset and leading to improved classification performance. By enhancing PSO's global exploration capability and ACO's local optimization strength, the hybrid approach effectively enhanced search efficiency while avoiding premature convergence to suboptimal solutions. This synergy improved solution quality, convergence speed and adaptability making it superior to traditional algorithms for feature selection, classification and optimization tasks.

To evaluate performance, both PSO and ACO methods were assessed using key metrics such as classification accuracy, precision, F1-score in detailed classification reports. Accuracy measures the overall correctness of the model, precision measures the quality of positive predictions, i.e. how many predicted positives were actually correct and F1-score balances precision and recall into a single score.

We selected SVM as the classifier due to its exceptional performance with high-dimensional data. SVM finds the optimal hyperplane for separating data points in a higher-dimensional feature space, and its margin-based approach and kernel functions make it resistant to outliers and noise particularly when using a soft-margin classifier.

In comparison, other classifiers exhibit limitations in high-dimensional spaces. Random Forest and Decision Trees tend to struggle with overfitting if not properly tuned with Random Forest being more robust but requiring longer execution times. Decision Trees alone are highly sensitive and prone to instability. K-Nearest Neighbors experiences performance degradation due to the curse of dimensionality and is highly sensitive to noise, as it relies directly on distance calculations between neighbors [18]. Similarly, Naive Bayes assumes feature independence, which is rarely valid in high-dimensional spaces, leading to poor performance in noisy datasets.

Fine-tuning played a crucial role in optimizing our approach. We carefully adjusted PSO and ACO parameters, fine-tuned SVM hyperparameters and applied techniques to prevent overfitting, ensuring robust model performance. Furthermore, the computational time for both PSO and ACO implementations was recorded, demonstrating the efficiency of our hybrid approach. Although execution time may vary with problem complexity, the optimizations applied to both algorithms significantly enhanced the feature selection process, leading to efficient and effective model training and evaluation.

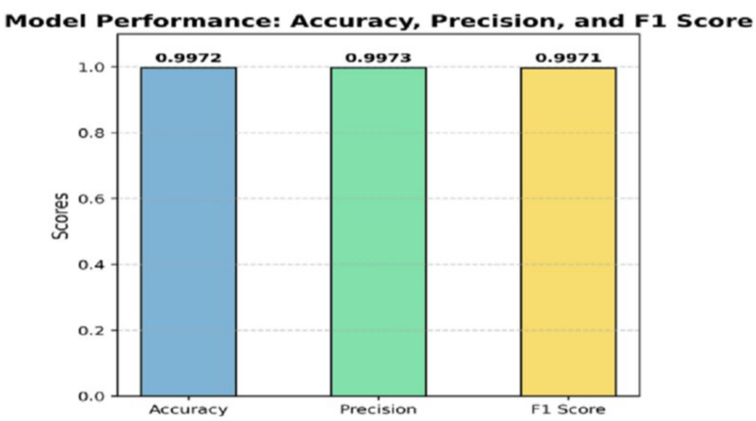

FIGURE 2: Model Performance

The experiment demonstrates the following:

Model performance:

Accuracy: 0.9972

Precision: 0.9973

F1 Score: 0.9971

Classification report:

	Precision	Recall	F1-Score	Support
0	0.96	1.00	0.98	26
1	1.00	0.75	0.86	4
3	1.00	1.00	1.00	332
Accuracy			1.00	362
Macro avg	0.99	0.92	0.95	362
Weighted avg	1.00	1.00	1.00	362

TABLE 2: Classification Report

Execution time:

PSO Execution Time: 94.26 seconds

ACO Execution Time: 0.05 seconds

Discussion

The hybrid model effectively balances global and local search capabilities. PSO enables efficient exploration by guiding particles based on personal and global best positions while ACO refines the selection process by reinforcing optimal feature paths based on pheromone updates. The combination results in an optimized feature subset, enhanced classification accuracy, and we can also refer to Table *2*. The performance of the hybrid approach suggests that multi-algorithm optimization strategies can significantly improve feature selection efficiency, leading to more robust and generalized models across diverse datasets.

Furthermore, the adaptability of this hybrid technique makes it a promising approach for applications requiring high-dimensional feature selection. The model's ability to refine selected features adaptively ensures its effectiveness in handling complex, real-world classification problems.

Conclusions

The hybrid approach of PSO and ACO combined with SVM classification, demonstrated a robust framework for classifying and selecting features with an accuracy of 99.72%. This approach focuses on the strengths of both PSO and ACO to optimize feature selection and enhance the performance using SVC. By combining PSO and ACO, the hybrid model maximizes the collective strengths of both algorithms, social behavior-driven exploration and global search capabilities, resulting in a more robust feature selection process. This led to improved classification results from the SVM, demonstrating the effectiveness of hybridizing optimization techniques for robustness of the hybrid model.

Overall, the PSO-ACO+SVM hybrid approach successfully demonstrates that by combining optimization techniques can lead to superior feature selection and classification outcomes, providing a promising direction for future research. The ability of this hybrid model to adaptively refine feature selection enhances its potential applicability across various domains requiring accurate classification in complex datasets.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Utkarsha B. Jiwane, Ravikant N. Jugele

Acquisition, analysis, or interpretation of data: Utkarsha B. Jiwane, Ravikant N. Jugele

Drafting of the manuscript: Utkarsha B. Jiwane, Ravikant N. Jugele

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

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