

# Network-Guided Particle Swarm Optimization for Feature Selection in High-Dimensional Microarray Data

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## Abstract

Feature selection is a critical task in high-dimensional microarray data classification, where the number of features significantly exceeds the number of samples. Traditional evolutionary feature selection methods often suffer from redundancy and instability due to the lack of structural information among features. In this work, we propose a Network-Guided Particle Swarm Optimization (NetG-PSO) approach that incorporates feature dependency information through a **distance-correlation**-based feature network. The proposed method leverages network-aware initialization and velocity control to guide the swarm toward compact and informative feature subsets. Experiments conducted on the colon cancer microarray dataset demonstrate that NetG-PSO consistently reduces the number of selected features while maintaining competitive or improved classification accuracy compared to Binary PSO, Differential Evolution-based feature selection, and a network-agnostic PSO variant. Furthermore, a post-selection pruning strategy using Random Forest feature importance yields a compact gene signature of 20 features with an accuracy of 84.21% (reported for dCor,  $\delta = 0.3$ ). These results confirm the effectiveness of integrating distance-correlation network structure into swarm-based feature selection.

**Keywords:** Feature Selection, Particle Swarm Optimization, Feature Network, Microarray Data, Evolutionary Computation

## 1 Introduction

High-dimensional datasets are common in bioinformatics, particularly in microarray gene expression analysis, where thousands of genes are measured for a limited number of samples. This high feature-to-sample ratio often leads to overfitting, increased computational cost, and reduced model interpretability. Feature selection aims to identify a small subset of informative features that improves classification performance while reducing redundancy.

Evolutionary algorithms such as Genetic Algorithms, Particle Swarm Optimization (PSO) [6, 4], and Differential Evolution (DE) [7] have been widely used for feature selection due to their ability to perform global search in large spaces. However, most existing approaches treat features as independent entities and ignore inherent relationships among them. In biological data, genes often interact and form functional groups, suggesting that exploiting feature dependencies may improve selection quality.

To address this limitation, we propose a Network-Guided Particle Swarm Optimization (NetG-PSO) framework that integrates feature interaction information through a distance-correlation-based network. By embedding network structure into swarm initialization and velocity updates, the proposed method promotes the selection of coherent and non-redundant feature subsets. A comprehensive overview of feature selection techniques can be found in [5].

## 2 Dataset Description

The proposed approach is evaluated on the colon cancer microarray dataset [2], a widely used benchmark in feature selection research. The dataset consists of gene expression profiles from colon tissue samples, containing a small number of samples and a large number of gene features. Prior to feature selection, the data are normalized using z-score normalization to ensure consistent feature scaling.

## 3 Proposed Methodology

### 3.1 Feature Network Construction

A feature network is constructed to capture dependencies among features. Each feature is represented as a node, and weighted edges are established between pairs of features whose **distance correlation** exceeds a predefined threshold. Distance correlation captures both linear and nonlinear dependencies between variables and is therefore preferable to Pearson correlation for detecting complex relationships in gene expression data [8]. The resulting network encodes feature relationships and serves as prior knowledge for the optimization process. Feature relationships are particularly important in biological data, where genes often interact in functional groups [1].

For our experiments we use distance correlation with a threshold  $\delta = 0.3$  (notation:  $\text{dCor-}\delta = 0.3$ ) for network construction. We report network statistics and downstream feature-selection performance for this choice; a discussion of threshold sensitivity and runtime impact appears in the Results section.

**Computational optimization of distance-correlation networks.** Computing pairwise distance correlation for high-dimensional microarray data incurs a quadratic computational cost with respect to the number of features. To mitigate this overhead while preserving network fidelity, we introduce a Pearson-correlation-based prefilter that restricts distance-correlation computation to candidate feature pairs with sufficiently strong linear association or local neighborhood relevance. Specifically, we retain pairs exceeding a Pearson threshold of 0.30 or belonging to the top- $k$  ( $k = 25$ ) strongest Pearson neighbors per feature, and subsequently compute distance correlation only on this reduced candidate set. Importantly, this prefilter is used solely as a computational accelerator; all retained edges are still weighted by distance correlation, ensuring that nonlinear dependencies are preserved. On the colon microarray dataset, we observe that the feature network remains relatively dense even under conservative prefiltering, reflecting the intrinsically high correlation structure of gene expression data. Empirically, this optimization reduces redundant computations without degrading classification accuracy or feature-selection behavior, yielding comparable performance with reduced runtime.

### 3.2 Network-Guided Particle Swarm Optimization

In the proposed NetG-PSO framework, each particle encodes the feature subset as a real-valued position vector. A sigmoid transfer function maps particle positions to binary feature selection decisions. Unlike standard PSO, network information is incorporated into both the initialization and velocity update mechanisms. Features with higher network centrality are more likely to be selected during initialization, while velocity updates are adjusted to favor features belonging to highly connected network regions.

### 3.3 Fitness Function

The fitness of a particle is defined as a weighted combination of classification accuracy and feature subset size:

$$Fitness = \alpha \cdot Accuracy - (1 - \alpha) \cdot \frac{|S|}{D} \quad (1)$$

where  $|S|$  is the number of selected features,  $D$  is the total number of features, and  $\alpha$  controls the trade-off between accuracy and sparsity.

### 3.4 Post-Selection Pruning

To further enhance interpretability, a post-selection pruning step is applied using Random Forest feature importance [3]. The initially selected feature pool is ranked by importance, and only the top- $k$  features are retained for final evaluation.

## 4 Experimental Setup

The proposed method is compared against Binary PSO (BPSO), Differential Evolution-based Feature Selection (DE-FS), a network-agnostic PSO variant, and a no-feature-selection baseline. All methods are evaluated using the same training-testing splits and classifier configuration. Performance is measured using classification accuracy, precision, recall, F1-score, and the number of selected features. Each experiment is repeated multiple times with different random seeds to assess stability.

## 5 Results and Discussion

### 5.1 Comparison of Feature Counts

Figure 1 compares the average number of selected features across methods. NetG-PSO selects substantially fewer features than BPSO and DE-FS, demonstrating the effectiveness of network guidance in reducing redundancy.

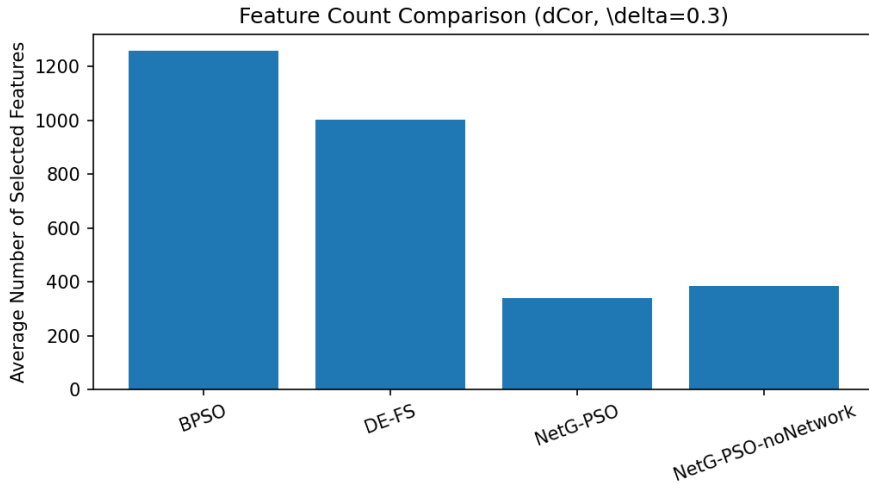


Figure 1: Average number of selected features by different methods (distance correlation,  $\delta = 0.3$ ).

## 5.2 Classification Accuracy Comparison

Figure 2 presents the distribution of test accuracy for all methods. NetG-PSO achieves competitive accuracy with improved stability compared to baseline approaches.

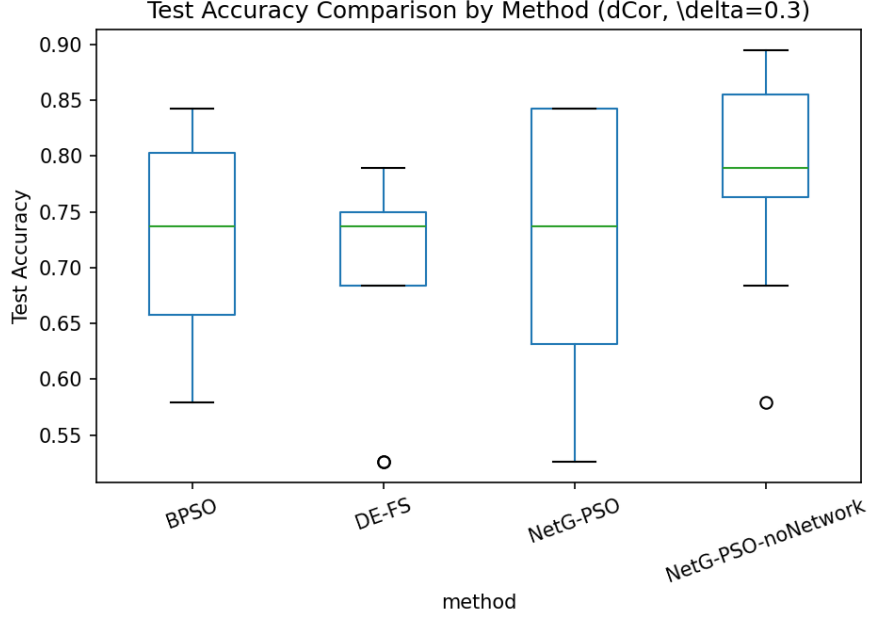


Figure 2: Test accuracy comparison across methods (distance correlation,  $\delta = 0.3$ ).

## 5.3 Accuracy vs Feature Count

The trade-off between accuracy and feature subset size is illustrated in Figure 3. NetG-PSO achieves higher accuracy with significantly fewer features.

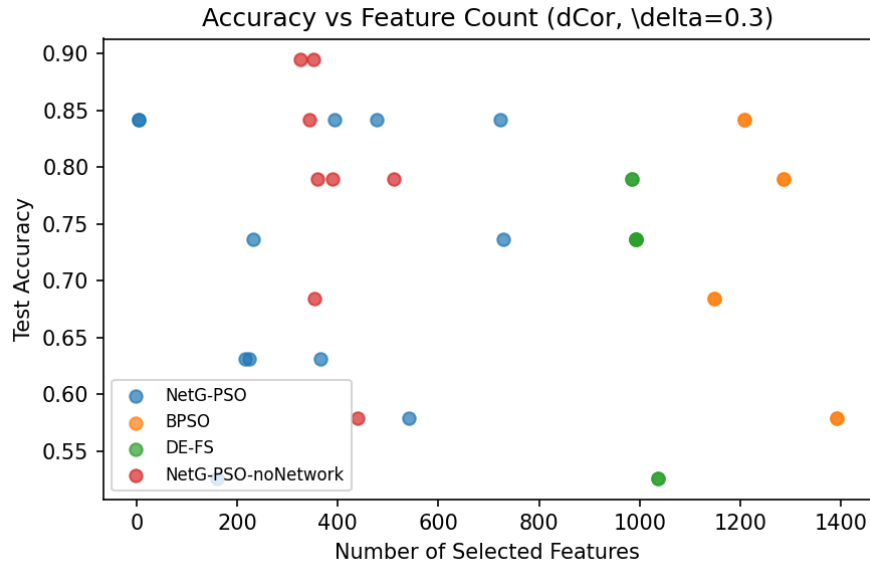


Figure 3: Accuracy versus number of selected features (distance correlation,  $\delta = 0.3$ ).

**Distance-correlation sensitivity.** We experimented with various distance correlation thresholds and observed that network density and downstream selected-set sizes are sensitive to the chosen threshold. Higher thresholds can fragment the network and produce very compact feature pools in some runs, while lower thresholds yield denser networks. Distance correlation is computationally more expensive than Pearson correlation; computing pairwise distance correlations increases CPU time for the same dataset size (our  $\text{dCor-}\delta = 0.3$  NetG-PSO runs required approximately 50–60 seconds per run, compared with roughly 30 seconds for Pearson-based networks). Despite this sensitivity and runtime overhead, NetG-PSO preserves competitive accuracy and, combined with post-selection pruning, yields compact and interpretable signatures.

Table 1: Effect of distance-correlation threshold  $\delta$  on network density and NetG-PSO performance.

$\delta$	edges	mean_sel	std_sel	mean_acc	std_acc
0.15	1997321	201.7	191.3	0.561	0.219
0.20	1948865	206.3	188.3	0.737	0.053
0.25	1841259	335.7	205.7	0.667	0.132
0.30	1697205	370.7	59.6	0.667	0.080
0.35	1513746	279.0	94.9	0.702	0.080

**Delta-sweep summary.** Table 1 reports the effect of the distance-correlation threshold  $\delta$  on network density and downstream NetG-PSO performance. Lower thresholds produce denser networks but exhibit higher variability in the number of selected features across runs. In our sweep,  $\delta = 0.20$  achieved the highest mean test accuracy but with substantial variance in selected feature counts, whereas  $\delta = 0.30$  provided more stable feature-set sizes with only a marginal reduction in mean accuracy. Based on this trade-off, we report  $\text{dCor-}\delta = 0.3$  as our primary configuration to favor reproducibility and robustness.

## 5.4 Post-Pruning Analysis

After Random Forest-based pruning, NetG-PSO achieves a classification accuracy of 84.21% using only 20 features, highlighting the potential for highly compact and interpretable gene signatures.

## 6 Conclusion

This work presents a Network-Guided Particle Swarm Optimization approach for feature selection in high-dimensional microarray data. By incorporating feature dependency information through a distance-correlation-based network ( $\text{dCor-}\delta = 0.3$ ), the proposed method effectively reduces feature redundancy while maintaining competitive classification accuracy. Experimental results demonstrate that NetG-PSO outperforms traditional evolutionary feature selection methods and yields compact feature subsets after post-selection pruning. We further show that careful computational optimization enables the practical use of distance correlation at scale without compromising performance. Future work may explore extending the proposed framework to additional biological datasets and multi-objective optimization settings.

## References

- [1] Constantin F Aliferis et al. Machine learning models for microarray data. *Methods in Microarray Data Analysis*, pages 87–102, 2003.

- [2] Uri Alon, Niv Barkai, Daniel A Notterman, K Gish, S Ybarra, D Mack, and AJ Levine. Gene expression profiles of colon cancer. *Proceedings of the National Academy of Sciences*, 96(12):6745–6750, 1999.
- [3] Leo Breiman. Random forests. *Machine Learning*, 45(1):5–32, 2001.
- [4] Russell Eberhart and Yuhui Shi. Particle swarm optimization: Developments, applications and resources. *Proceedings of the 2001 Congress on Evolutionary Computation*, 1:81–86, 2001.
- [5] Isabelle Guyon and André Elisseeff. An introduction to variable and feature selection. *Journal of Machine Learning Research*, 3:1157–1182, 2003.
- [6] James Kennedy and Russell Eberhart. Particle swarm optimization. *Proceedings of ICNN'95 - International Conference on Neural Networks*, 4:1942–1948, 1995.
- [7] Rainer Storn and Kenneth Price. Differential evolution – a simple and efficient heuristic for global optimization over continuous spaces. *Journal of Global Optimization*, 11(4):341–359, 1997.
- [8] Gabor J Székely, Maria L Rizzo, and Nail K Bakirov. Measuring and testing dependence by correlation of distances. *The Annals of Statistics*, 35(6):2769–2794, 2007.