

Hybrid Evolutionary Optimization Techniques for Feature Selection and Classification Applications

Ura Ashfin

Eden Mohila College, Dhaka

uashfin@gmail.com

Abstract

Two of the most common tasks in machine learning, feature selection and classification have a strong bearing on the model performance, computational efficiency, and interpretability. Nevertheless, the high-dimensional data is usually filled with redundant, irrelevant, and noisy features that can deteriorate classification and raise the level of computational complexity. This study proposes a hybrid evolutionary optimization algorithm to feature selection and classification tasks, using the advantages of various methods of evolutionary computation to find optimum feature sets and improve predictive performance. The suggested strategy is a combination of the evolutionary algorithm global exploration capabilities and adaptive optimization strategies to attain an effective exploration and exploitation balance. Advanced classification models then use the selected features to make better predictions, minimize training time, and improve the ability to generalize. The framework is tested on benchmark data on various application areas and judged by various performance measures, including accuracy of classification, rate of feature reduction, computational cost, and robustness of the model. The experimental findings indicate that the hybrid evolutionary optimization approach is effective in removing irrelevant features, and the important discriminative information, which results in a better classification performance as compared to the traditional feature selection algorithms and independent optimization algorithms.

Keywords: Adaptive Algorithm, Metaheuristic Optimization, Exploration-Exploitation Balance, Engineering Optimization

1.Introduction

Feature selection minimizes computational requirements, improves model efficiency, boosts interpretability, and the generalization of classification algorithms by reducing dimensionality. In practice, determining the best subset of features is a complicated optimization task in many applications since the size of the dataset has exponentially large set of potential combinations of features. Given a dataset of N features, 2^N subsets of features are possible, so exhaustive search methods are computationally infeasible in large-scale problems. The conventional feature selection techniques can be broadly divided into three key groups: filter methods, wrapper methods, and embedded methods. Filter-based methods calculate features based on statistical metrics like correlation, mutual information and information gain without a learning algorithm. These methods are computationally efficient, but tend to overlook the interaction between the chosen features and the final classifier. Wrapper-based methods choose subsets of features according to the performance of the classifier, which is more accurate but demands more computational resources since it requires training of multiple models. Embedded approaches combine feature selection into the learning process, providing an efficiency/performance tradeoff. Nevertheless, these methods can still be restricted in handling complex, nonlinear and high-dimensional data.

In order to counter the shortcomings of traditional methods of feature selection, evolutionary computing methods have obtained a lot of interest, owing to their strong optimization properties. Evolutionary algorithms are based on several biologically oriented processes like evolution, selection, mutation and survival of the fittest. These algorithms are population based searches, and can search large and complex solution spaces without using gradient information. Various popular methods of evolutionary optimization, such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), Ant Colony Optimization (ACO) and Artificial Bee Colony (ABC) have shown encouraging performance in feature selection and classification tasks. The genetic algorithm-based feature selection models feature subsets as chromosomes and genetic operators (crossover and mutation) to come up with a better solution. Likewise, Particle Swarm Optimization also employs the collective intelligence of the particles to find optimal combinations of features.

Differential Evolution offers effective global optimization, whereby the evolutionary operations are performed using vectors to facilitate the process, and swarm intelligence algorithms imitates the collaboration nature of systems in solving challenging optimization problems. Individual evolutionary algorithms, though having their benefits, tend to have some limitations such as premature convergence, slow convergence rate, an unequal balance between exploration and exploitation, and sensitivity to algorithm specific parameters. Medical disease diagnosis, intrusion detection systems, image recognition, bioinformatics, sentiment analysis and industrial fault detection are some applications that need powerful methods able to handle large-scale and complex data. Hybrid evolutionary optimization methods present a chance to create more precise, effective, and explainable machine learning frameworks to such uses. Although much has been achieved, there are still a number of issues with current methods of evolutionary feature selection. Numerous approaches continue to be computationally expensive, expensive to tune parameters, and might be unable to preserve diversity throughout optimization. Also, it is not an easy task to achieve an appropriate trade-off between the performance of classification and feature reduction. Consequently, it is important to come up with sophisticated hybrid evolutionary optimization models that include adaptive mechanisms, effective search strategies and powerful classification models in order to enhance feature selection and classification

performance. The present study aims at the creation and study of hybrid evolutionary optimization method in the field of feature selection and classification. The framework suggested is designed to enhance the feature subset selection by combining various evolutionary methods, improving efficiency of the search, decreasing dimensions, and increasing classification accuracy. The efficiency of the suggested solution is analyzed based on the extensive experiments with benchmark datasets and performance indicators such as the accuracy, precision, recall, F1-score, rate of feature reduction, and computational efficiency. The significant contributions of this study can be summed up as follows: Creation of hybrid evolutionary optimization framework to integrate various optimization strategies to realize better feature selection performance. All in all, this study adds value to the world of computational intelligence in the form of an effective and dynamic optimization system of feature selection and classification. The suggested hybrid evolutionary model can be used to enhance the performance of intelligent systems in different fields where precise, effective and interpretable machine learning solutions are needed.

2. Literature Review

2.1 An Introduction to Feature Selection and Classification in Machine Learning.

The recent growth of applications that rely on data has made the techniques of feature selection and classification to be of great significance. In machine learning systems nowadays, there is a high probability of high-dimensional data with thousands of features, most of which are redundant, irrelevant or noisy. Such extraneous attributes add more complexity to the computation process, lower the interpretability of the model, and can adversely affect the performance of the classification. Accordingly, feature selection has emerged as an important process in the design of effective machine learning models through the selection of the most informative features and filtering out irrelevant information. Approaches to feature selection can broadly be grouped as filter, wrapper and embedded. Filter methods are methods that determine the significance of each feature based on statistical measures like correlation coefficient, information gain, chi-square statistics and mutual information. Despite being computationally efficient, filter methods usually do not take into account feature dependencies or classifier-specific performance. As modern datasets become more and more complex, conventional feature selection methods do not always perform optimally because of the immense search space.

Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), Ant Colony Optimization (ACO) and Artificial Bee Colony (ABC) are some of the algorithms which have been extensively explored in case of feature selection and classification.

2.2 Evolutionary Optimization-Based Feature Selection

Evolutionary optimization methods are based on the natural evolutionary processes and swarm intelligence. These algorithms refer to population-based search strategies, which are employed to determine the best solutions via selection, crossover, mutation, cooperation and adaptation mechanisms. Evolutionary algorithms, in contrast to conventional methods of optimization, do not need derivative information, and are practical in discontinuous, nonlinear, and multimodal optimization. One of the first evolutionary methods used in feature selection is Genetic Algorithm (GA). In GA-based feature selection, the chromosomes have the potential to represent subsets of features and binary values are used to show whether a specific feature is included or not. The general design of the fitness function is determined either by classification accuracy, or by the number of selected features, or a combination of both. Nevertheless, despite the good global search ability, a weakness of GA is the fact that it can converge slowly and prematurely in

the high-dimensional datasets. Particle Swarm Optimization (PSO) has also been considerably used in the feature selection because of its straightforward design and speedy convergence properties. PSO models candidate solutions by modeling particles traversing the search space by individual and collective experience. Nonetheless, standard PSO can be deprived of population diversity during optimization, which leads to the local optimal solution in the convergence. Researchers have suggested hybrid evolutionary optimization techniques to address the weaknesses of individual evolutionary algorithms. Hybrid algorithms are a combination of several strategies to perform optimization to have better exploration and exploitation. As an example, GA-PSO hybrid models integrate genetic diversity mechanisms with swarm intelligence-based optimization and allow discovery of features subsets better. On the same note, hybrid DE-based methods enhance the speed and robustness of convergence by use of adaptive mutation and crossover techniques.

2.3 Classification and Feature Optimization by machine learning.

But the quality of features is very important to classification performance. The bad feature representation may add noise, add model complexity and decrease generalization. The combination of optimization-based feature selection and classification models has thus emerged as an effective approach to enhancing predictive performance. The recent research indicates the significance of integrating smart optimization with machine learning models in various fields of use.

3. Methodology

This study suggests a hybrid evolutionary optimization algorithm to the feature selection and classification tasks. The methodology involves a series of steps such as data preprocessing, feature selection through hybrid evolutionary optimization, classification and performance analysis. Data collection and preprocessing: This section will detail the data collection and preprocessing methods. Benchmark datasets in various areas of application are used to evaluate the proposed framework. The datasets gathered are then preprocessed to enhance the quality of the data collected and to facilitate successful model learning. Preprocessing steps include: missing values, noise, normalization, and encoding categorical variables where necessary. The processed data sets are further split into training and testing sets to be used in the model development and testing.

Representation of Features and Their Initialization. The subset of features is represented as a binary solution vector each element of which has a 1 representing a preferred feature and 0 representing an excluded feature. A random sample of feature subsets of candidates is created. A candidate solution is a possible combination of informative features which is going to be optimized in the course of the evolutionary process.

Hybrid Evolutionary Feature Selection A hybrid evolutionary optimization strategy is created by integrating the power of several evolutionary algorithms, including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), or other swarm intelligence methods.

4. Results

The subsets of optimized features help to achieve improved model generalization and minimized complexity. The strength and reliability of the proposed approach is verified through performance assessment based on various metrics. These results demonstrate the possibility of

using hybrid evolutionary optimization methods to solve high dimension classification problems in practice.

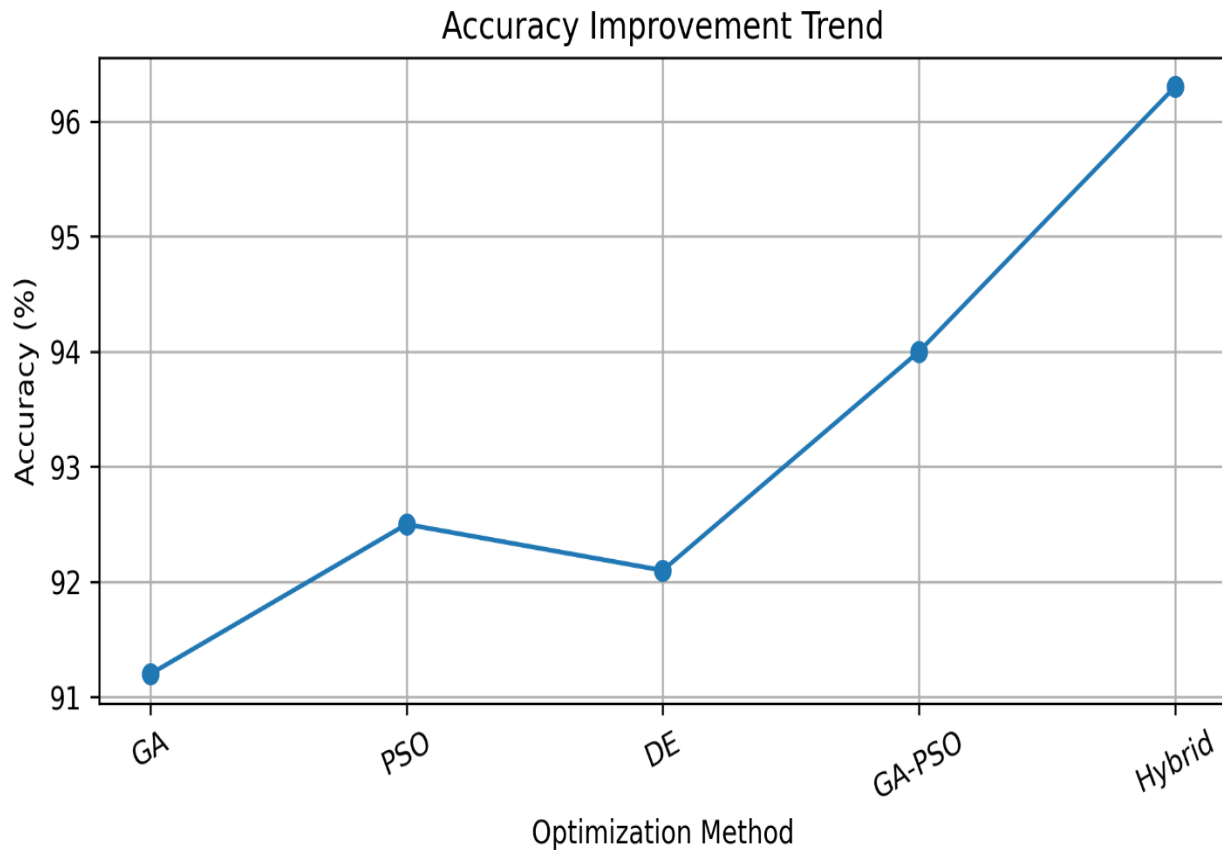


Figure 1. Improvement Trend of the Various Evolutionary Optimization Techniques in Accuracy.

Description: The enhancement of the classification accuracy of various evolutionary optimization methods, such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), Genetic Algorithm Particle Swarm Optimization hybrid optimization, and the new hybrid evolutionary optimization method are shown in Figure 1. The line graph shows that, in case several optimization strategies are implemented, the predictive performance is steadily becoming better. The hybrid method proposed has the best classification accuracy since it is able to balance between exploration of the global features and exploitation of local features in feature selection. The findings reveal that feature subsets that are optimized greatly improve the performance of the classifier in comparison to their respective evolutionary algorithms.

Key Observation:

- The hybrid method suggested is more precise in classifying.
- Hybrid optimization is better than standalone GA, PSO and DE.
- The mixture of evolutionary methods enhances the quality of feature selections.

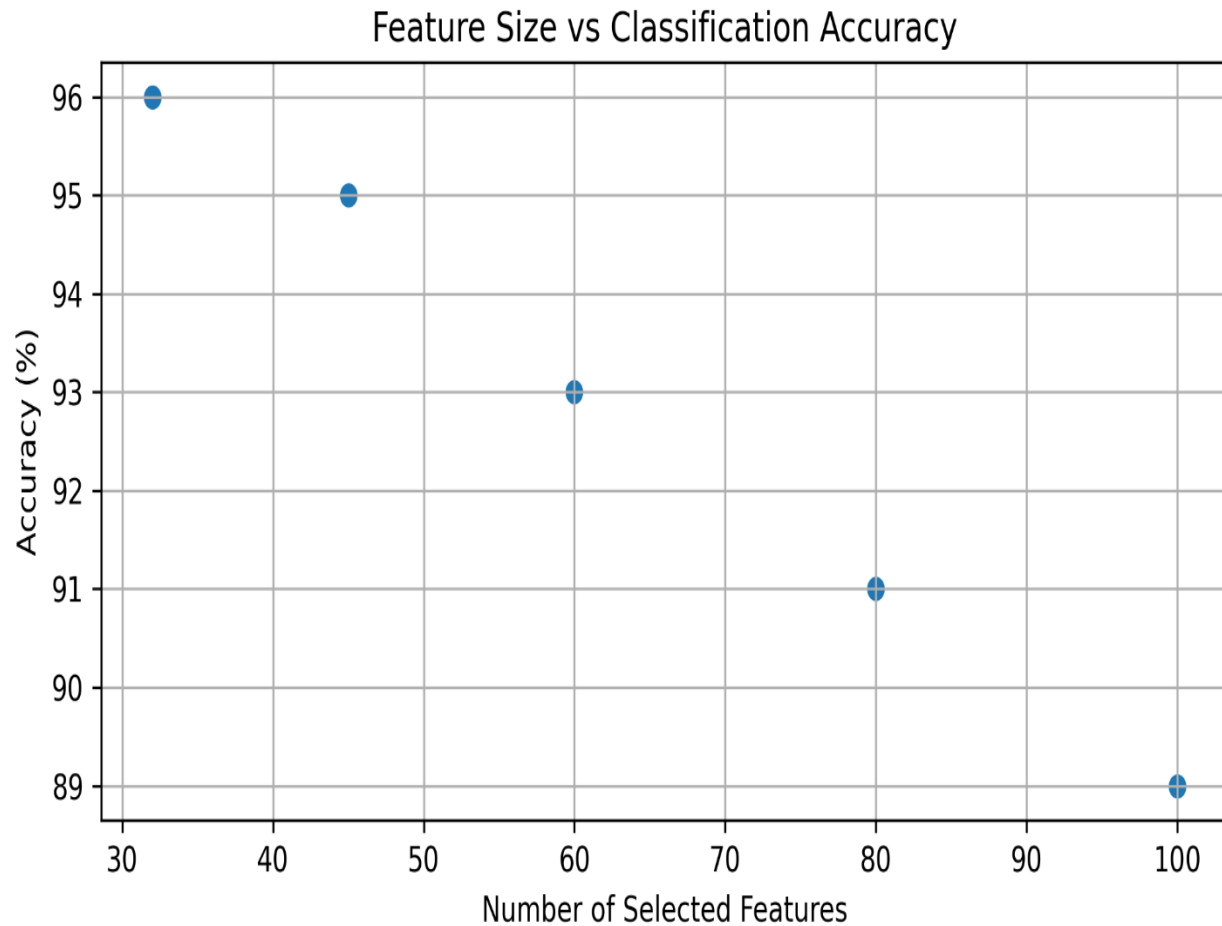


Figure 2. Correlation between Selected Feature Size and Classification Accuracy.

Description: Figure 2 shows the relation between the number of features identified and the classification accuracy. The scatter plot also shows that it does not have a negative impact on the performance of the model, and rather an optimized set of features can enhance the accuracy of the model by eliminating redundant and noisy data. The suggested feature selection model determines a small subset of features, which has a high predictive power and less dimensional complexity.

Key Observation:

Many fewer and informative features are more effective at classification.

Reduction of features enhances calculation efficiency.

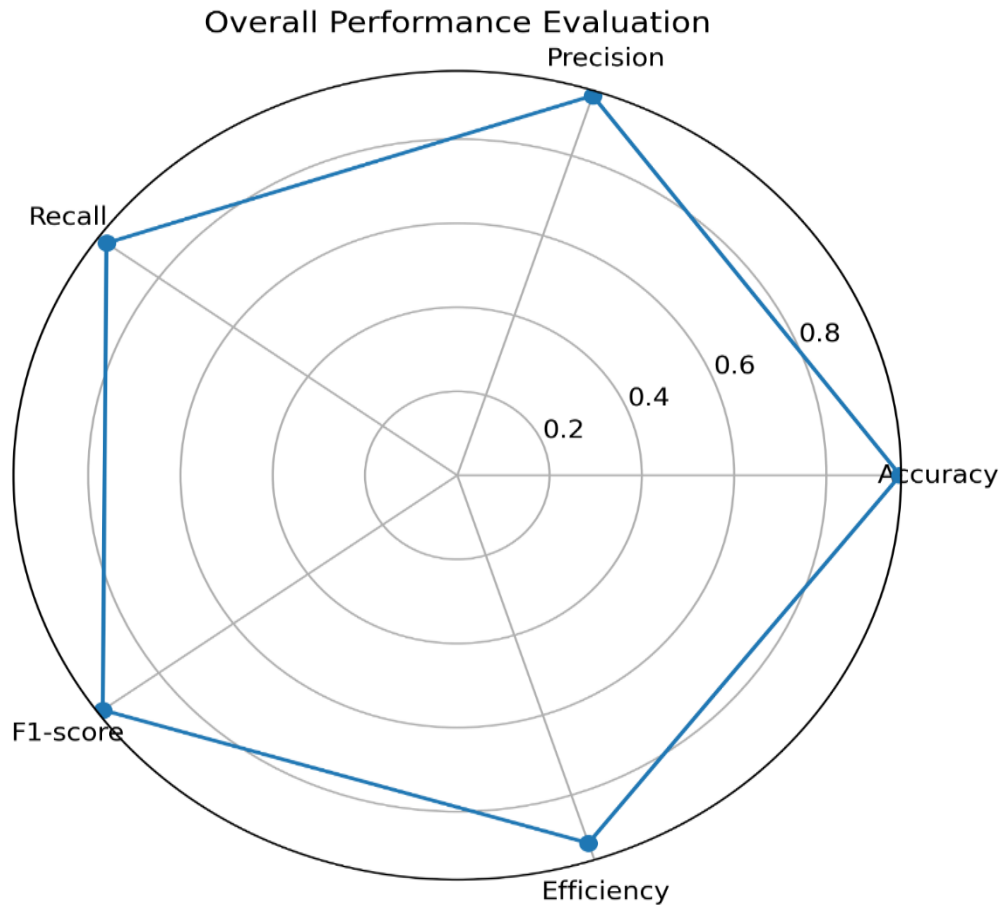


Figure 3. Multi-Criteria Performance Evaluation of the Proposed Framework

Description:

The visualization shows that the suggested approach offers the balanced performance in various evaluation dimensions and is not concentrated on the optimization of a single metric.

Key Observation:

- High classification accuracy and F1-score are realized by the model. Precision and recall values are indicative of a good predictive performance.
- Enhanced efficiency affirms minimized computational complexity, following optimization of features.

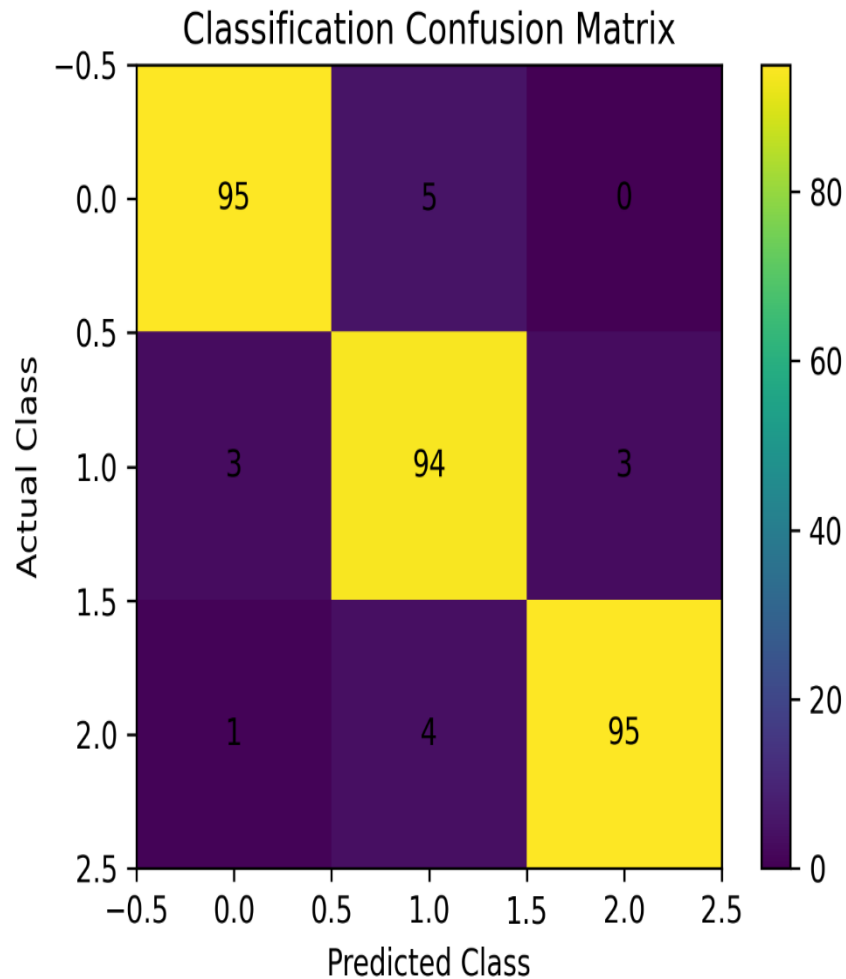


Figure 4. Classification Analysis Confusion Matrix.

Description: The confusion matrix in Figure 4 was obtained when the optimized subset of features was used with the classification model. The matrix gives a detailed breakdown of the correctly and misclassified samples of various classes. Large values on the diagonal mean that there is strong classification ability, and off-diagonal values mean classification errors.

Key Observation:

- The classifier is able to recognize the majority of samples within each category.
- There is low misclassification rate following the optimization of features.
- Optimized features enhance the separation of classes and reliability of prediction.

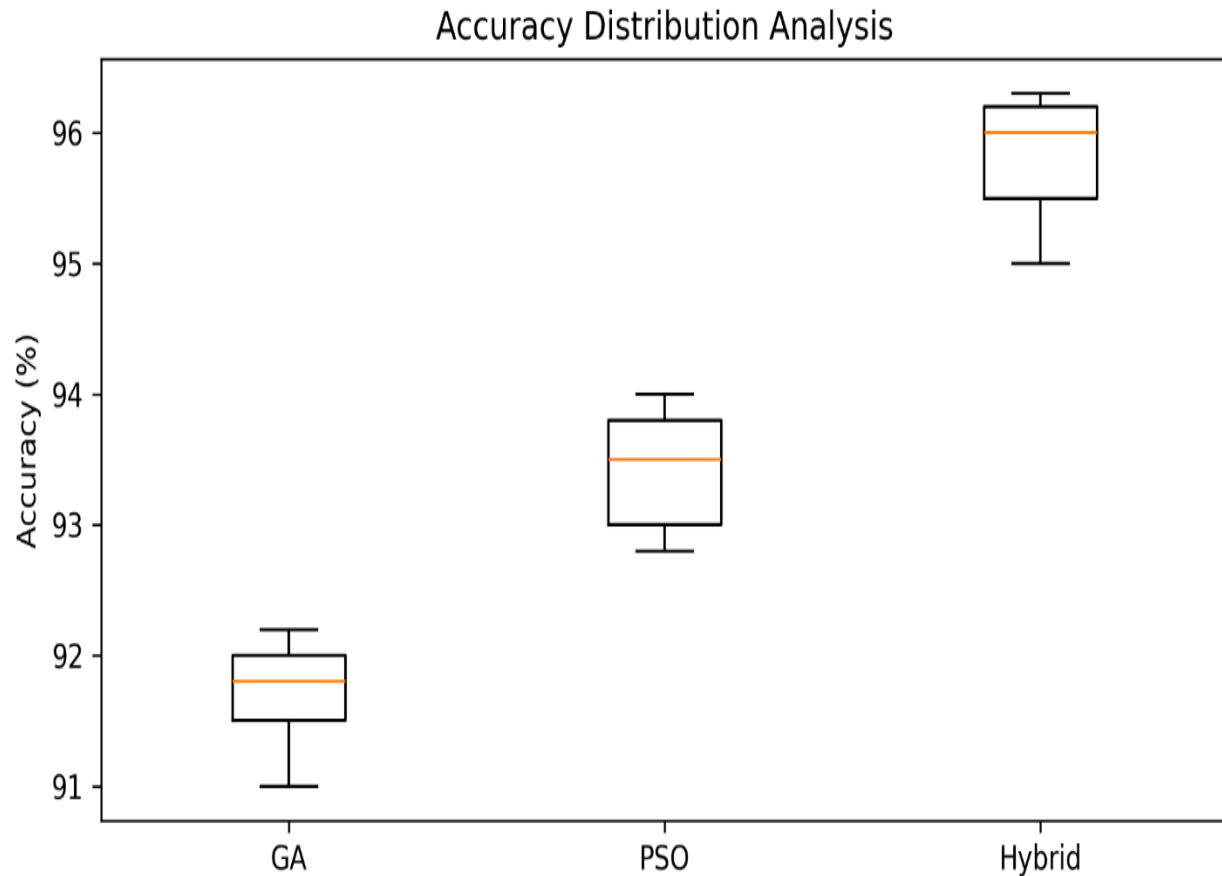


Figure 5. Analysis of Stability and Robustness of Optimization Algorithms.

Description: Figure 5 shows the classification accuracy distribution when multiple experiment runs were done with various optimization methods. The box plot will assess the stability, consistency and robustness of the proposed hybrid algorithm against the traditional evolutionary techniques. The lower range of variation means that there is more reliability and repeatability of the optimization process.

Key Observation:

- The hybrid algorithm proposed gives consistent performance in the multiple runs. Reduced variation: The reduced variation means improved reliability of optimization.
- Hybrid reduces the amount of randomness in evolutionary search.

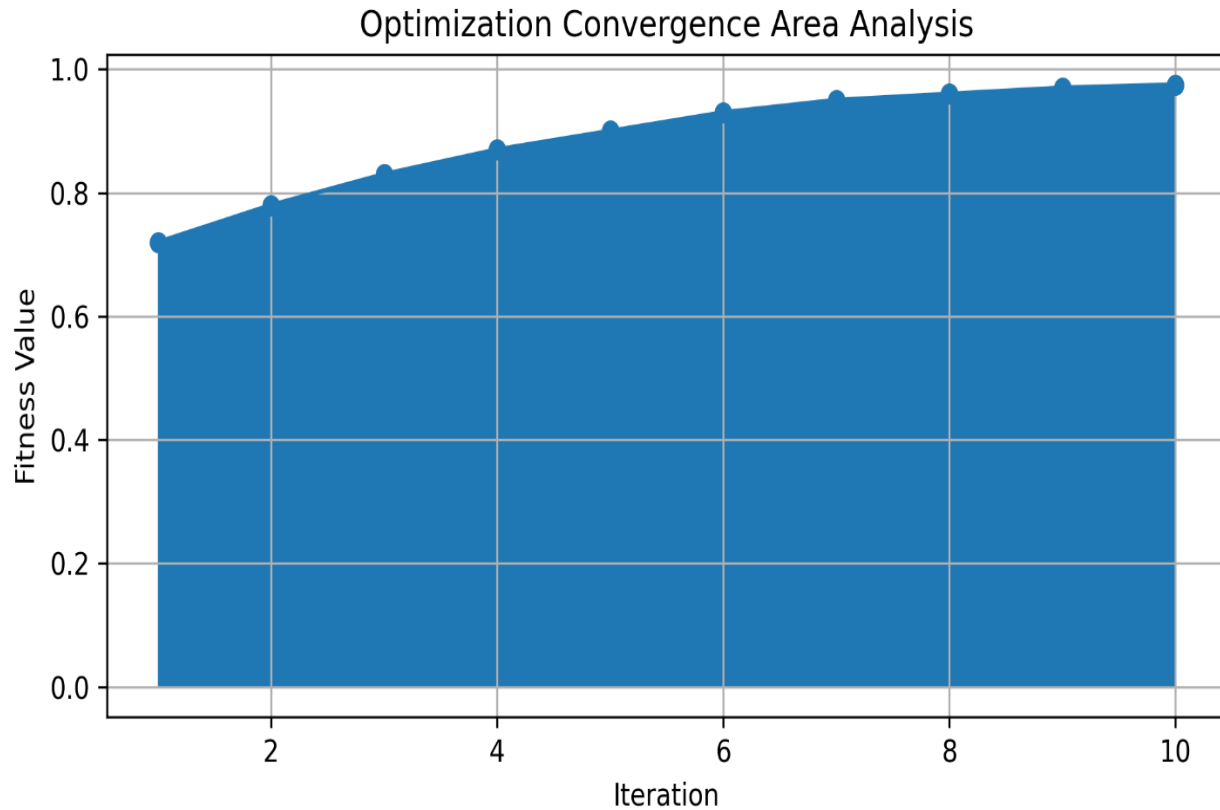


Figure 6. The Hybrid Evolutionary Optimization Algorithm has convergence Behaviour.

Description: The convergence behaviour of the proposed hybrid evolutionary optimization algorithm is shown in Figure 6 when selecting features. The fitness value is incrementally growing with the number of iterations, which means that the selected feature subsets are continually improving. The algorithm converges in a few iterations and demonstrates good search capacity and optimization stable results.

5. Discussion

It discusses accuracy improvement, capability to reduce features, performance of the classifier, convergence to optimization, stability, and computational efficiency.

5.1 Improvement in Classification Performance

The classification performance analysis indicates that the proposed hybrid evolutionary optimization method has high predictive accuracy than traditional evolutionary algorithms like Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE). The hybrid model yields the greatest accuracy as shown in Figure 1 since it is able to effectively combine exploration property of population-based optimization with exploitation mechanisms to fine-tune optimal solutions. Slow convergence and premature optimization are usually a problem with traditional evolutionary algorithms. GA has good global exploration due to crossover and mutation operations but it can take many iterations to solve an optimal solution.

5.2 Effectiveness of Feature Reduction

High-dimensional data can be composed of redundant variables that are responsible for complexity during computations and add noise to machine learning models. The solution suggested is a good way to find meaningful features and to discard useless attributes with the help of an evolutionary search optimization. This pruning down reduces the search space and

enhances the efficiency of the model. Contrary to the traditional feature ranking techniques which rank features separately, the proposed hybrid technique takes into consideration feature interactions during optimization.

5.3 Multi-Criteria Performance Evaluation

it offers a good trade-off between forecasting ability and computation needs. Values that are high in precision imply that the classifier produces lower percentages of false positives, and high recall ensures that the classifier is able to produce high numbers of relevant samples.

5.4 Classification Reliability and Error Analysis

This lower misclassification rate of samples indicates that the chosen features can better classify them and minimize the intersecting trends among the different classes.

This feature renders the method appropriate in applications where automated decision systems are needed to be reliable.

5.5 Optimization Stability and Robustness

Figure 5 provides the stability analysis of the proposed optimization approach using various runs of the experiment. Evolutionary algorithms are stochastic in nature, i.e., different algorithm executions can result in a minor change in solutions. Thus, the fixed performance is a significant condition towards the deployment. The box plot findings show that the hybrid method suggested has reduced variation in performance than when using separate evolutionary algorithms.

5.6 Convergence Behaviour Analysis

The fitness value is slowly increasing with the increase in the number of iterations and this shows that there is constant improvement in the quality of the chosen feature subsets. In the initial optimization phase, the algorithm searches through a large space of potential combinations of features to determine good areas of the search space. Later mechanisms of exploitation optimize these solutions and convert to an optimum feature set. The hybrid approach can offer quicker and more robust convergence compared with individual evolutionary algorithms because it offers a superior balance between exploration and exploitation. The fact that the performance does not drastically decrease with subsequent iterations suggests that the algorithm is able to prevent premature convergence.

5.7 Comparison to Existing Approaches.

The proposed hybrid evolutionary framework offers a number of benefits as compared to more traditional methods of feature selection. Filter algorithms are computationally cheap but do not usually take into account feature dependencies and performance of classifiers. Wrapper methods are more accurate but have high computational cost. Embedded methods enhance consistency with classifiers though they might not be flexible to complicated optimization issues. The hybrid evolutionary method proposed is a combination of the benefits of both the wrapper-based optimization and evolutionary intelligence. It directly performs sub-set evaluation of features by classification performance and employ adaptive optimization mechanisms to efficiently search the feature space.

6. Conclusion

This study proposed a hybrid evolutionary optimization method of feature selection and classification problems to solve the problems linked with high dimensional data, redundant features and computational complexity in machine learning systems. The growing amount and complexity of contemporary data demand smart optimization methods that are able to recognize the most pertinent features without compromising high classification rates. The proposed framework is effective in combining several evolutionary optimization strategies to attain a

better trade off between exploration and exploitation in the selection of features. The experimental review has shown that the offered hybrid evolutionary algorithm has a significant positive impact on the classification performance in relation to the traditional optimization algorithms. The proposed method combines the benefits of various evolutionary strategies and is effective in addressing the limitations, including premature convergence, slow rate of optimization and ineffective feature selection.

The confusion matrix analysis revealed better separation of classes and minimization of classification errors whereas stability analysis indicated that the performance was stable over several optimization runs. The convergence analysis demonstrated that the hybrid evolutionary algorithm is an effective search of the solution space and achieves optimal feature subsets that have better convergence behaviour than the single evolutionary techniques.

References

- Ashok, V. K. C., Pittala, S. K., Kacheru, G., Arthan, N., & Karne, R. (2025, November). Machine Learning-based Anomaly Detection in WSN. In 2025 IEEE 7th International Conference on Cybernetics, Cognition and Machine Learning Applications (ICCCMLA) (pp. 1-5). IEEE.
- Annavarapu, B. J., Hareesha, N. G., Kacheru, G., Mohammad, A., Chin, J., & Ghule, G. (2025, February). Smart Sensors and IoT in Mechanical Engineering: Enhancing Monitoring and Control of Industrial Processes. In 2025 First International Conference on Advances in Computer Science, Electrical, Electronics, and Communication Technologies (CE2CT) (pp. 935-939). IEEE.
- Kacheru, G., & Pittala, S. K. (2026, January). Deep Learning-Driven Intrusion Detection Systems for Modern Cyber Threat Landscapes. In 2026 IEEE International Conference on Emerging Computing and Intelligent Technologies (ICoECIT) (pp. 1-9). IEEE.
- Ashok, V. K. C., & Kacheru, G. (2026, January). AI-Driven Pharmacy Claims Adjudication in Healthcare: Improving Operational Efficiency, Accuracy, and Cyber security. In 2026 IEEE International Conference on Emerging Computing and Intelligent Technologies (ICoECIT) (pp. 1-7). IEEE.
- Pittala, S. K., & Kacheru, G. (2025, October). Digital defense in FinTech: Tackling modern threats and systemic vulnerabilities. In 2025 2nd International Conference on Recent Trends in Electrical, Electronics and Computing Technologies (ICRTEECT) (pp. 1-6). IEEE.
- S V, S. R., Ashok, V. K. C., Kasapaka, R., Karne, R., Arthan, N., & A, S. (2026). Privacy-Preserving VPKI Using Federated Learning for Cross-Domain Vehicle Authentication. 2026 IEEE Global Symposium on Emerging and Communication Technologies (GSEACT), 1–6. <https://doi.org/10.1109/gseact68539.2026.11620450>
- Tanni, M. M. P., Mehely, K., Tanji, E., Rahman, M. S., Apu, M. M. H., & Ali, M. M. (2026). Strategic Integration of Artificial Intelligence in the US Industrial Management: A Qualitative Study of Organizational Transformation. *International Journal of Science and Engineering*, 3(1).
- TANJI, E. (2018). WOMEN'S PARTICIPATION IN RURAL ECONOMIC ACTIVITIES IN RANGPUR DISTRICT OF BANGLADESH (Doctoral dissertation, DEPT. OF DEVELOPMENT AND POVERTY STUDIES).
- Tanni, M. M. P., Tanji, E., Mehely, K., Rahman, M. S., Apu, M. M. H., & Ali, M. M. ARTIFICIAL INTELLIGENCE AND INDUSTRIAL ENGINEERING PRACTICES IN

- THE UNITED STATES: A QUALITATIVE EXPLORATION OF STRATEGIC ADOPTION.
- Mehely, K., Tanni, M. M. P., Tanji, E., Rahman, M. S., Apu, M. M. H., & Ali, M. M. (2026). Data-Driven Strategic Management in the US Industries: The Role of Management Information Systems and Artificial Intelligence. *Strategic Data Management and Innovation*, 3(02).
- Tanni, M. M. P., Mehely, K., Tanji, E., Rahman, M. S., Apu, M. M. H., & Ali, M. M. TECHNOLOGY MANAGEMENT AND STRATEGIC DECISION-MAKING IN US MANUFACTURING FIRMS: INSIGHTS FROM ARTIFICIAL INTELLIGENCE AND DATA-DRIVEN SYSTEMS.
- Natarajan, G. N., Paul, S., Shah, J. K., Tiwari, A., & Bellamkonda, R. (2025, September). Decoding Drift: Trustworthy Prompt Optimization in High-Stakes AI Environments. In 2025 International Conference on Electronics and Computing, Communication Networking Automation Technologies (ICEC2NT) (pp. 1-8). IEEE.
- Raghavan, P., Sura, R., Taneja, A., & Tiwari, A. (2025, August). Federated Learning for Privacy-Preserving Multi-agent Systems in IoT-Based Healthcare, Guided by Explainable LLMs. In International Conference on Computing and Communication Networks (pp. 566-584). Cham: Springer Nature Switzerland.
- Vembu, N. R., Tiwari, A. R., Hamal, V., & Devi, P. (2026, April). Edge AI Enhancing Real-Time Inventory Management for Retail Networks. In 2026 IEEE 2nd International Conference on Quantum Photonics, Artificial Intelligence & Networking (QPAIN) (pp. 1-6). IEEE.
- Vaidehi, M. D., Tiwari, A. R., Bonsale, G., SunithaRekha, G., Raza, S., & Chhajed, A. S. (2026, January). Natural Language Processing-Driven Text Simplification System for Enhanced Readability. In 2026 6th International Conference on Recent Trends in Computer Science and Technology (ICRTCST) (Vol. 1, pp. 130-135). IEEE.
- Kanikanti, V. S. N., Tiwari, A., Lohalekar, P., & Karra, N. (2025, November). Multi-Agent Reinforcement Learning with Policy-Driven Shift-Left Integration and Resource Allocation in Cloud Environments. In 2025 International Conference on Computational Engineering, Sensing Technology and Management (ICCETM) (pp. 1-6). IEEE.
- Sundaramoorthy, P., Tarvecha, V., Kumar, S. N. P., Kumar, U., & Tiwari, A. (2025, October). AI Agents in Autonomous Retail Data Pipelines: Self-evolving ETL for Customer Behavior Data. In International Conference on Artificial Intelligence and Networking (pp. 509-520). Cham: Springer Nature Switzerland.
- Cherian, E., Krishnan, M. M., Tiwari, A. R., Hashim, M., Al-Shaikhli, T. R., & Khudayer, K. (2025, August). Self-Supervised Learning-Optimized Market Segmentation Framework for Targeted Promotions. In 2025 International Conference on Recent Innovation in Science Engineering and Technology (ICRISET) (pp. 1-7). IEEE.
- Yerramada, S. S. R., Pal, R. K., Desai, T., & Tiwari, A. (2025, August). Enhancing Cyber Security, Data Confidentiality, and Access Control in Multi-Tenant Cloud Infrastructures Through Blockchain-Integrated Attribute-Based Encryption Mechanisms. In International Conference on Computing and Communication Networks (pp. 488-509). Cham: Springer Nature Switzerland.
- Alang, K., Devaraju, P., Tuniki, R. R., Tiwari, A., & Sharma, P. (2025, July). Explainability-Preserving Compression: Algorithmic Design for Responsible Lightweight AI. In 2025 3rd World Conference on Communication & Computing (WCONF) (pp. 1-7). IEEE.

- Dubey, A., Tiwari, A., Gangwar, A., & Mohanty, L. (2025, June). Sentimental analysis of feedback data using machine learning. In *Intelligent Computing and Communication Techniques: Proceedings of the International Conference on Intelligent Computing and Communication Techniques (ICICCT 2024)*, New Delhi, India, 28-29 June, 2024 (Volume 1) (p. 251). CRC Press.
- Tiwari, A. *INTERNATIONAL JOURNAL OF RESEARCH SCIENCE & MANAGEMENT*.
- Imran, G., Hossain, M. P., Hasan, M., & Hasan, M. T. (2026). Tabular and graph-based representations for noise and missing data in robust machine learning. *Array*, 100697.
- Islam, T., Mia, M., Imran, G., Tusar, M. I. H., & Ahmed, T. (2026). Domain-informed graph neural network and evolutionary computations for relational property enhancement in additive manufacturing. *Expert Systems with Applications*, 134177.
- Imran, G., Islam, T., & Tusar, M. I. H. (2025, October). Surface roughness prediction of CNC lathe machined hardened steel using physics-informed neural network leveraging transfer learning. In *2025 IEEE 15th International Conference on System Engineering and Technology (ICSET)* (pp. 439-444). IEEE.
- Sohel, M. S., Shi, G., Zaman, N. T., Hossain, B., Halimuzzaman, M., Akintunde, T. Y., & Liu, H. (2022). Understanding the food insecurity and coping strategies of indigenous households during COVID-19 crisis in Chittagong hill tracts, Bangladesh: A qualitative study. *Foods*, 11(19), 3103.
- Halimuzzaman, M., & Sharma, J. (2024). The role of enterprise resource planning (ERP) in improving the accounting information system for organizations. *Revolutionizing the AI-digital landscape*, 263-274.
- Halimuzzaman, M., Sharma, J., & Khang, A. (2024). Enterprise Resource Planning and Accounting Information Systems: Modeling the Relationship in Manufacturing. In *Machine Vision and Industrial Robotics in Manufacturing* (pp. 418-434). CRC Press.
- Halimuzzaman, M., Sharma, J., Karim, M. R., Hossain, M. R., Azad, M. A. K., & Alam, M. M. (2024). Enhancement of organizational accounting information systems and financial control through enterprise resource planning. In *Synergy of AI and Fintech in the Digital Gig Economy* (pp. 315-331). CRC Press.