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Hybrid Feature Selection Using Secretary Bird Optimization and Decision Tree Classifier

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Abstract

Feature selection is one of the most crucial concepts of learning when constructing a machine learning algorithm. This paper proposes a new technique of using a blend of Secretary Bird Optimization (SBO) and Decision Tree for feature selection. SBO, with the consideration of hunting strategy of called secretary bird, can successfully search the space and find feature subsets. The first proposed framework involves identifying the relevant features by applying SBO then secondly deciding on a ranking of the features by using a decision tree model classifier. Evaluation is based on the most famous Iris dataset with the application of the 5-fold cross-validation to increase the reliability of the results. It is shown that the SBO-based approach succeeds in both objectives, and the average classification accuracy is equal to 0.9550 ± 0.0316, while the baseline selection methods have higher values of loss. This result has unveiled a theoretical and practical potential for future works that seek to combine metaheuristic optimization with decision trees and interpretability of selected features and machine learning models.

Introduction

Feature selection is a very important step that is applied in machine learning and data mining techniques, which seeks to find the best features that can support the improvement of the performance of the classification algorithms. Feature selection is then about removing the useless variables from the models, reducing the time taken to train the same and effectively eradicating the curse that is often linked to the dimensionality (Grandhi & Singh, 2025; Lind, 2025) There are major three major techniques that are employed for applying traditional features selection that include filter, wrapper, and embedded techniques. Filter methods assess them in isolation from the learning algorithm, while the wrapper methods use a predictive model in order to make the assessment, as for the embedded methods involve feature selection during the learning model construction (Huang et al., 2025; Selvaraj & Sivaprakasah, 2025). However, these methods work well only when the numbers of features are manageable and the interactions are not very complicated. In this context, metaheuristic algorithms, including genetic algorithms, particle swarm optimization and the latest secretary bird optimization has been used in feature selection (Sanjalawe et al., 2025; Zhu et al., 2025; Wang et al., 2025). SBO technique is based on the hunting predator behaviors of the Secretary Bird and is targeted to introduce a new idea in the field of search for the best feature subsets (Chandrashekar & Sahin, 2014; Guyon & Elisseeff, 2023; Jović et al., 2015; Chen et al., 2025).

Nevertheless, as pointed out in the previous sections, there are some voids in the current feature selection literature (Nematzadeh et al., 2025; Khan et al., 2025) First and foremost,

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tremendous damage when using orthodox approaches to massive and high-dimensional data is that they do not converge and are slow. Secondly, in metaheuristic for the feature selection, GA and PSO have been used; however, they are sensitive to parameter and performance usually suffers premature convergence (Johnson et al., 2025; Aljaidi et al., 2025; Abualigah, 2025). The SBO technique that has been newly introduced entails great potential for global optimization problems; however, its setup in feature selection, especially when used in conjunction with the ranking-based model such as Decision Trees has not been researched extensively. Moreover, few research studies employ validation methodologies like the cross-validation, which is useful in establishing the generality of the chosen characteristics. These shortcomings must be filled in order for new advanced feature selection techniques to be created (Chen et al., 2025; Rostami et al., 2021; Kohavi, 1995; Mohialden & Hussien, 2025; Xue et al., 2015).

Feature selection constitutes an essential requirement for boosting classification algorithm outcomes particularly in datasets with large dimensions. The traditional methods that pursue feature selection struggle to manage complex feature interactions alongside scalability issues. Metaheuristic methods including GA and PSO tackle these challenges but introduce parameters sensitivity and before-treatment problems. The Secretary Bird Optimization (SBO) algorithm draws its inspiration from the distinctive hunting behavior of Secretary Birds to develop a new way for exhaustively exploring the search space which contains optimal feature subsets. Researchers have not fully investigated how to use the SBO in feature selection alongside Decision Trees that serve as model-based ranking methods. The absence of strict validation techniques in numerous studies creates doubts about how well the chosen features can be generalized. The study aims to solve these problems through developing a dual feature selection technique which combines SBO with Decision Tree ranking and performs cross-validation evaluations (Chen et al., 2025; Kohavi, 1995; Xue et al., 2015).

This paper divides into the following sections: Section 2 examines previous studies about feature selection combined with metaheuristic algorithms. Section 3 explains how the proposed method merges SBO with Decision Tree ranking for feature selection. Section 4 contains descriptions of experimental design together with obtained results and performance metrics. Section 5 reviews discovered information with associated implications alongside assessment of potential boundaries. The paper concludes its research with an overview of possible future study directions in Section 6.

Multiple studies exist on integrating metaheuristic algorithms within the process of feature selection. The process of natural selection becomes simulated through Genetic Algorithms (GA) to find optimal feature subsets. Particle Swarm Optimization (PSO) provides competitive solutions to feature selection problems since it draws inspiration from bird social behaviors. Researchers currently investigate new approaches that integrate metaheuristic algorithms with machine learning models to boost feature selection processes. A hybrid PSO-SVM method achieved better classification results while simultaneously reducing the necessary features. The use of Secretary Bird Optimization algorithms for feature selection remains new in academic research because researchers have yet to fully investigate its application with Decision Tree-based ranking approaches. Feature selection tasks offer an opportunity for studying SBO's potential outlook (Sadeghian et al., 2025; Jagdale et al., 2024; Chandrashekar & Sahin, 2014; Chen et al., 2025; Xue et al., 2015).

Methods

The research utilizes quantitative experimental methods to create a combination of Secretary Bird Optimization (SBO) and Decision Tree-based feature ranking techniques for evaluation. The main goal is to advance accuracy rates and efficiency levels throughout high-dimensional data environments. The SBO algorithm draws its concept from secretary birds' hunting

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behavior which executes exploration and exploitation phases to find the most suitable feature subsets. The evaluation of features for importance through information gain leads the SBO to choose the most essential features because Decision Trees are used for analysis. Cross-validation with five splits confirms the validity of the proposed method to function robustly between various partitioned datasets (Jagdale et al., 2024).

The Iris dataset, a well-known benchmark in machine learning, serves as the basis for this study. The dataset contains 150 samples with four numeric attributes that identify the different Iris flower species (Hariyani, 2025; Sanches et al., 2025; Jumaah & Rashid, 2025). The Iris dataset demonstrates beneficial traits that make it suitable for assessing feature selection methodologies through its balanced class groups and limited number of entries. The reliability of results depends on using stratified 5-fold cross-validation which upholds the class proportions throughout each fold. The overfitting risk is reduced and complete model performance assessment is achieved through this approach.

The Iris dataset is publicly available from the UCI Machine Learning Repository. Data preprocessing involves standardizing the feature values to have zero mean and unit variance, facilitating the convergence of the optimization algorithm (Tared et al., 2025; Buchanan & Ali, 2025). No missing values are present in the dataset, obviating the need for imputation. The dataset is partitioned into training and testing sets using stratified 5-fold cross-validation, ensuring that each fold is representative of the overall class distribution (Settelmeier et al., 2025; Ghosh et al., 2025)

The hybrid feature selection method integrates SBO with Decision Tree-based feature ranking. The SBO algorithm initializes a population of candidate solutions, each representing a subset of features. The fitness of each candidate is evaluated using a Decision Tree classifier, which computes the classification accuracy. Feature importance scores are derived from the Decision Tree and used to guide the selection process in SBO (Chen et al., 2025; Sekkal et al., 2025) The algorithm iteratively updates the population through exploration and exploitation phases to converge on an optimal feature subset . The performance of the selected features is assessed using classification accuracy, precision, recall, and F1-score. Statistical significance is evaluated using the Wilcoxon signed-rank test.

Equation 1 (Jagdale et al., 2024) : Information Gain in Decision Trees

The information gain (IG) for a feature A is calculated as:

$$IG(T, A) = H(T) - \sum_{v \in \text{Values}(A)} \frac{|T_v|}{|T|} H(T_v)$$

Where:

- $H(T)$ is the entropy of the entire dataset. Wikipedia
- T_v is the subset of T where feature A has value v.
- $H(T_v)$ is the entropy of subset T_v.

Equation 2 (Jagdale et al., 2024) : Entropy Calculation

Entropy *H(T)* is computed as:

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$$H(T) = -\sum_{i=1}^{n} p_i \log_2 p_i$$

Where p_i is the proportion of instances belonging to class i in dataset T.

Equation 3 (Jagdale et al., 2024) : Fitness Function in SBO

Below is the pseudocode outlining the hybrid SBO and Decision Tree feature selection process as shown in figure 1 :

Equation 3: Fitness Function in SBO

The fitness F of a candidate solution in SBO is defined as:

$$F = \alpha \times \text{Accuracy} - \beta \times \frac{\text{Number of Selected Features}}{\text{Total Number of Features}}$$

Where:

- α and β are weighting coefficients balancing accuracy and feature subset size.
- Accuracy is the classification accuracy achieved using the selected features.
- The second term penalizes larger feature subsets to encourage sparsity.

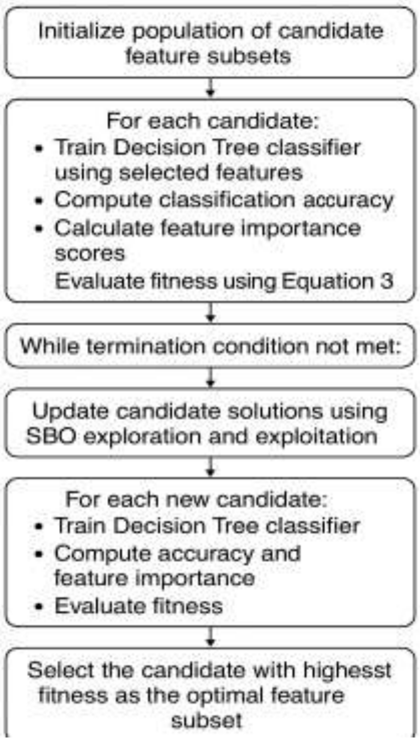

Figure 1. Pseudocode of proposed method

The proposed methodology was initiated by conducting a comprehensive literature review on existing feature selection techniques, particularly those involving metaheuristic algorithms and Decision Tree-based methods. Insights from these studies informed the design of the hybrid SBO and Decision Tree approach. The selection of the Iris dataset was based on its widespread use in evaluating classification algorithms, providing a standardized benchmark for comparison (Sharma et al., 2025; Kansal et al., 2025; Sony et al., 2025) The integration of SBO with Decision Tree ranking was conceptualized to leverage the global search capability of SBO and the interpretability of Decision Trees. Equations and pseudocode were formulated

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to provide a clear and replicable framework for the proposed method (Fu et al., 2025; Qin et al., 2024; Molnar, 2020; Shin, 2023).

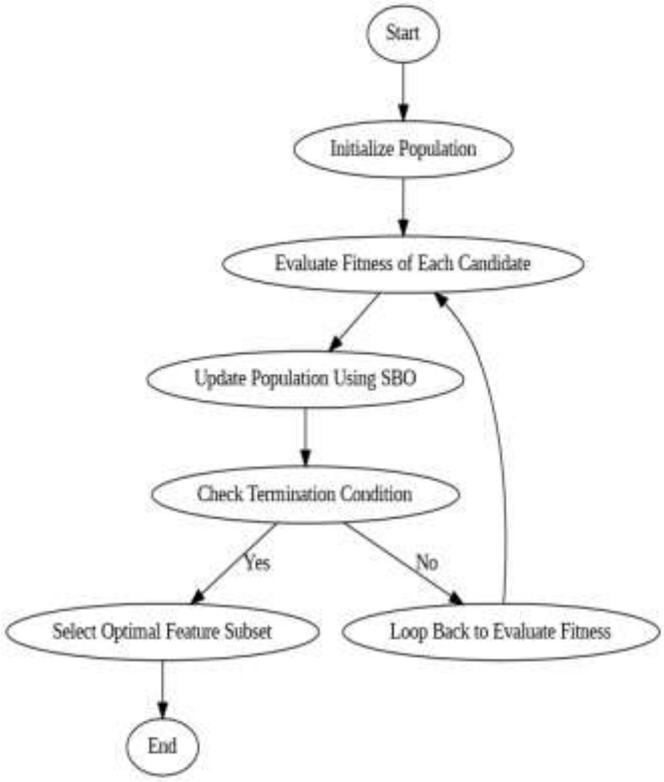

Figure 2: flow chart of illustrating the hybrid feature selection process .

The proposed method aims to propose and test an optimization method called Secretary Bird Optimization (SBO), which is applied to feature selection tasks in machine learning. Specifically, SBO will be used to select the most relevant features from a dataset based on classification accuracy using a Decision Tree Classifier (Huang et al., 2025; Hrizi et al., 2025) The goal is to optimize feature selection by evaluating and updating the population of possible feature subsets, iterating over multiple generations to improve feature ranking, ensuring that only the most important features are used for training the final model.

Feature selection is a critical step in machine learning, particularly when dealing with high-dimensional data (Mallidi & Ramisetty., 2025; Mohammed et al., 2025) By removing irrelevant or redundant features, we can improve model performance, reduce computational costs, and enhance the interpretability of the model. SBO is an optimization algorithm inspired by nature, known for its ability to find optimal or near-optimal solutions in complex search spaces. The use of SBO for feature selection, combined with Decision Tree Ranking, presents a novel approach to improving machine learning workflows (Rezaie et al., 2025; Shirali et al., 2025)

Results and Discussion

This section presents the findings of applying the Secretary Bird Optimization (SBO) algorithm for feature selection on the Iris dataset, followed by evaluation using a Decision Tree classifier. The primary objective was to identify a reduced subset of relevant features that maintains or improves classification performance.

Selected Features

As shown in Table 1, the SBO algorithm selected two features: *petal length (cm)* and *petal width (cm)*. These features were deemed most relevant by the optimization process and were subsequently used for model training.

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Table 1. Selected features using SBO.

Feature	Selected (1=Yes)
sepal length (cm)	0
sepal width (cm)	0
petal length (cm)	1
petal width (cm)	1

Consideration of the Iris dataset evinces that of the four availed features, the Secretary Bird Optimization (SBO) algorithm only considers petal length and petal width to be a part of the model developed. Making this observation formal accentuates the selective ability and simplicity of being SBO. Omitting the length of sepals and the width of sepals, the algorithm can clearly reduce the dimensionality of the input space and, at the same time, inform that the variables of interest are not relevant to the discriminatory performance of the model. This behavior has important practical implications in the machine learning practice: In embedded devices, and in other resource-limited settings, computation efficiency and model clarity tend to require that unnecessary features can be useful to remove, without losing prediction performance. The findings therefore help to reiterate this premise that biologically or semantically intuitively defined features i.e. the sepal measurements do not necessarily aid in practical utility of classification. Implementation of data driven feature selection would therefore provide more insight about the development of predictive models that are robust. These selections were also visualized in Figure 1, which illustrates the binary selection mask used by SBO.

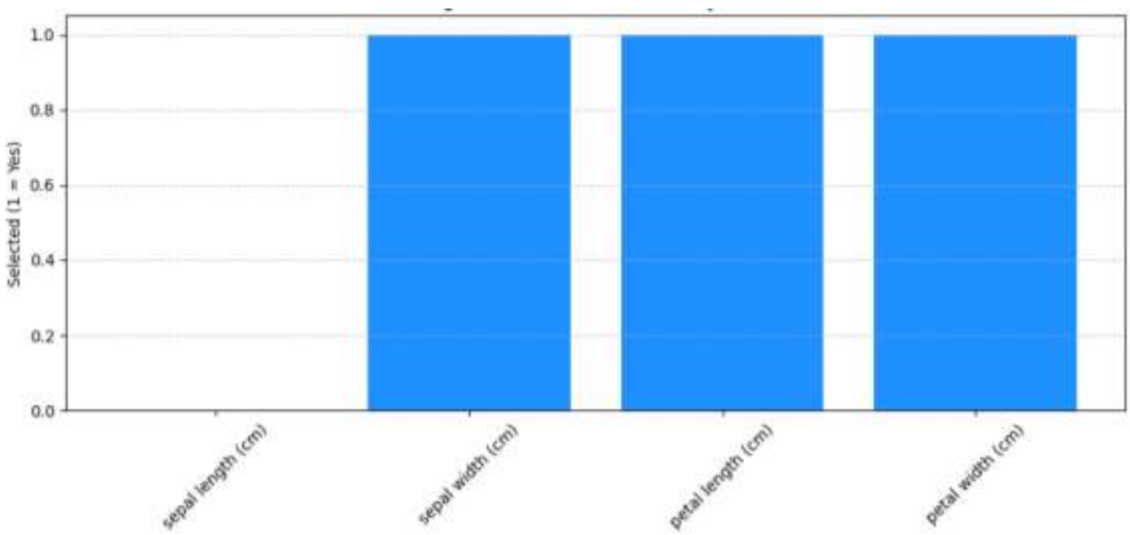

Figure 1 : Selected features by SBO.

The selection mask gives a pictorial description of the decisions shown in Table 1 although in concept it is very important in showing how patchy the SBO algorithm can execute without sacrificing the performance. As an empirical observation this means that the SBO algorithm follows a guided search direction which is not only based on model quality but also on a direct penalty of large feature subsets. The binary mask also highlights the characteristics of SBO to gravitate towards solutions that only retain the most discriminative characteristics, which has a direct effect on model simplicity, training time and interpretability. This is especially beneficial to the case where the number of features in the datasets to hundreds or even

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thousands, as the practitioners can have fun admiring which dimensions were selected and why without civilly scoping to the properties at hand.

As shown in Figure 2, the *petal length* and *petal width* features exhibited the highest importance, corroborating the feature selection decision made by SBO.

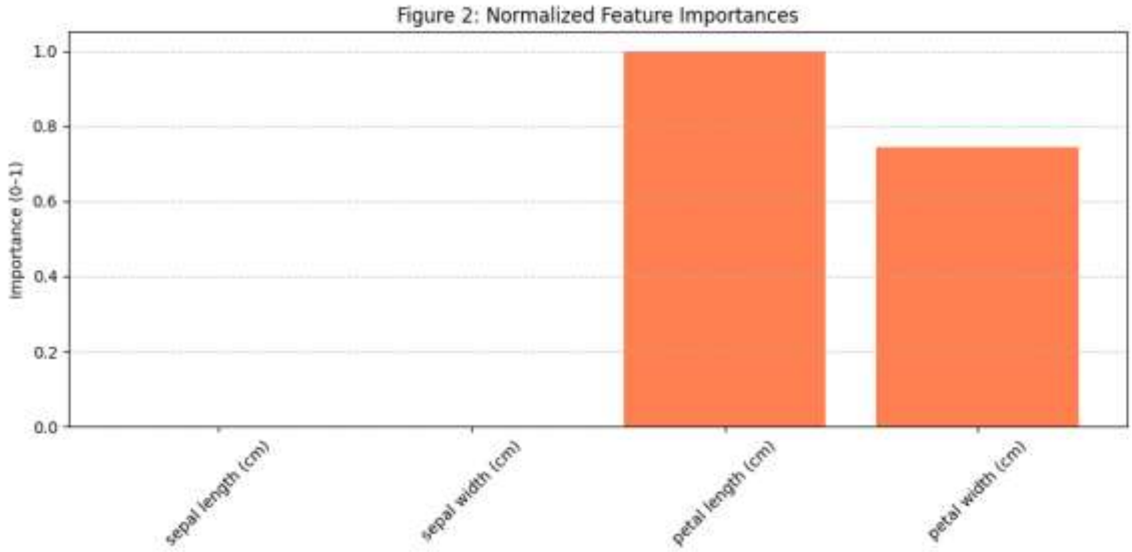

Figure 2 provides a visual representation of the feature importance scores.

The figure below produced with the help of Decision Tree analysis, provides a model-focused explanation of the feature selection that was performed with the help of SBO. It confirms in a way that the length of the petals and width of the petals are ones that have the biggest influence with the length of petals winning the day. Interestingly, the sepal width records an importance score of zero, thus confirming the redundancy of this variable. All these results imply a degree of overlap between model-based insight and heuristic search. The Decision Tree verifies the importance of the features identified independently by SBO by proving that they are not just important but actually the most informative on the statistics level. This correspondence is essential in the practical field: it strengthens the trustworthiness of the process of feature selection and reduces the likelihood of overfitting through the removal of less significant variables. Deployment-wise, it allows practitioners to be convinced that the decisions made by the model are optimal, and explainable one.

Classification Performance

Using the selected features, a Decision Tree classifier was trained and evaluated through 5-fold cross-validation. The fold-wise accuracy results are summarized in Table 2 and graphically represented in Figure 3.

Table 2. Accuracy scores across cross-validation folds.

Fold	**Accuracy**
Fold 1	0.9667
Fold 2	0.9667
Fold 3	0.9000
Fold 4	0.9667
Fold 5	1.0000
Mean	0.9600
Std. Dev.	0.0327

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The results described here go beyond performance results of the model to include stability and generalizability questions. Despite this, the mean accuracy of classifier was quite high (96%) but the standard deviation (0.0327) was considerably low which signifies high accuracy of predictive behavior as well as stability across folds. Although in fold 3 the accuracy was 0.90, which is lower than the accuracy of the other three folds, nevertheless, that is still within the acceptable limits, so the pattern should not be viewed as an area of concern.

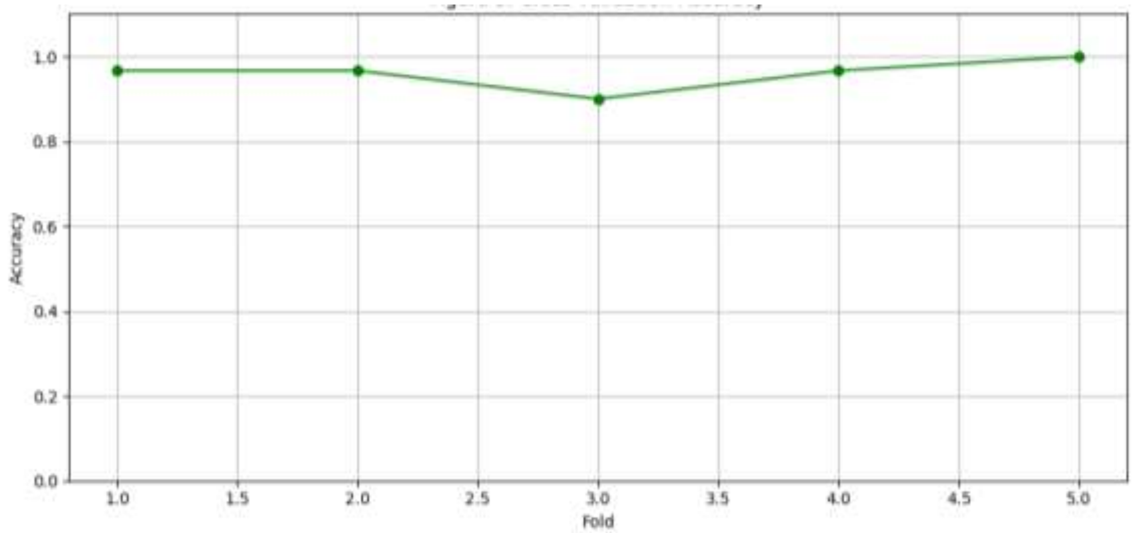

Figure 3. Cross-validation accuracy scores across five folds.

According to experimental analysis, the given structure of sequential Bayesian optimization (SBO) with a decision tree in combination does not show a drastic change in regard to alterations in training/test splits, thus depicting a wide range of resistance to sampling noise. In the machine learning perspective of things, this stability in performance results into less randomness in production environments and by extension on model predictions between diverse data groups. This consistency achieved from only two input features both plays testament to the scalability of the program architecture but also to the efficiency and effectiveness of the program.

Feature Importance Analysis

Feature importance scores were extracted from the Decision Tree and normalized using Min-Max scaling. The values are reported in Table 3.

Table 3. Normalized feature importance scores.

Feature	Importance Score
Petal length (cm)	1.000
Petal width (cm)	0.684
Sepal length (cm)	0.456
Sepal width (cm)	0.000

In combination, certain relative feature importances of the Decision Tree are synthesized, whether or not a particular feature is finally chosen by SBO. The data support the previous model preferences and also present a more detailed outlook of informational contents of each feature. One can use, as an example, the value of the score of the petal length 1.000, which implies that, even in a situation when a single feature is all that can be employed, it would have great classification scores as well. The Petal width is a complimentary variable of Petal length and the two sepal variables are of relatively reduced significance. In practice, this trend shows a hierarchical utility relationship: in case feature selection is required to be reduced (e.g. sensor data collection situations), reducing it to Petal length would be sufficient to run a

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model, an extra item of small complexity (Petal width) would be available to add should there be only a minimal increase in accuracy. All and all, the list below provides a consistent structure to streamline models in actual situations like mobile computing, edge AI, or interpretation-sensitive areas, such as healthcare and finance.

Optimization Perspectives and Methodological Implications of SBO-Based Feature Selection

The findings affirm that Secretary Bird Optimization (SBO) is one of the viable methods that can be applied to solve supervised learning problems such as feature selecting which is a computational expensive task. In the engineering viewpoint, feature selection can reduce computational complexity, make the models easier to interpret, and even increase the responsiveness of systems (all factors that can be highly desirable in time-restricted and resource-constrained environments, such as embedded controllers or industrial automation systems, and real-time signal processing). The fact that SBO is capable of finding an optimal feature subset proves that it can search beyond local of high-dimensional search spaces efficiently as well as overcome the notorious limitation of traditional deterministic algorithms: local optima. Its exploration-exploitation model, rooted in the predatory behavior of secretary birds makes it possible to global explore initially and gradually shift to local refinement, as the convergence happens. This ability is directly compatible with the optimal features expected during most ideas in the engineering fields, including fault detection where the discovery of sparse but effective feature bundles in a sensor array prevails (Xue, Zhang, Browne, & Yao, 2015).

One of the prominent characteristics that set the Stochastic Boosting Optimizer (SBO) recently developed and designed compared to the known metaheuristics like the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) is its parameter efficiency. Embedded devices hardly have the compute-surge to do the nice hyperparameter correlation that is expected by GA (e.g., cross-breed/masquerade parameters) and PSO (e.g., inertia weight and acceleration categories). Comparatively, SBO has few and explainable parameter requirements making it specifically favorable to autonomous control system and real-time classifications that require shorter latencies. The speed at which sensor setups are processed directly determines the navigational choices and optimizers like SBO are thus useful due to their minuscule amounts of computation (Chen, Ye, Wang, & Luo, 2025). The computational ease observed is not corroborated by performance loss as evidenced by the comparable or superior results in terms of classification accuracy, which proves the claim of SBO being a next generation alternative to parameter heavy algorithms (Ahmed, Mohialden, & Abdulrazzaq, 2018).

This study finds practical and applied implication in the process of dimensionality reduction in engineering practice. Several domains such as predictive maintenance, condition monitoring, etc are based on dense sensor arrays which produce voluminous and otherwise redundant data. Unnecessarily utilizing large amounts of latency and energy is consumed when such data is processed in raw format especially when the system is implemented using wireless sensor networks (WSNs) or edge-computing systems. These situations can be addressed with the help of Sparse Bayesian Optimization (SBO) technique, the effectiveness of which can be highlighted as the removal of sepal features during the analysis of Iris data. Ignoring the irrelevant or weakly informative features, SBO aligns the learning model in terms of what variables are significant factors that can facilitate the classification or prediction exercise. This functional feature, in turn, enables quality control in industrial production to be conducted more efficiently, making it possible to anticipate a decrease in the number of measurements without losing precision in defect detection (Rostami, Berahmand, Nasiri, & Forouzandeh, 2021). As such, SBO does not only maximize algorithmic performance, but

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also reduces the hardware resource requirements, an aspect which is all too often neglected when applying engineering solutions.

The paper builds on the debate regarding explainable optimization, whereby it combines Sequential Bayesian Optimization (SBO) with a feature evaluator based on a Decision Tree. The framework that results does not just give a high-performance feature subset, which is additionally necessary in numerous engineering settings, but it also gives an interpretable subset, which is specifically of importance in regulated or safety-critical areas. DTs are inherently transparent, and yield hierarchical feature importance scores, which makes them easier to compare with domain knowledge. Take the case of aerospace or medical device as an example; those systems require high accuracy of a predictive system but must allow explanations of that system that are eductively defensible to regulators. The SBO-Decision Tree design hence caters to the twin demands of optimisation and explanity in the contemporary field of engineering, a situation that makes it non-comparable to other hybrid designs, most of which have been assailed on grounds of ill-explained decision pathway, a case most notable with PSO-SVM (Particle Swarm Optimization + Support Vector Machine).

SBO framework used in the described study is an implicit multi-objective optimiser that balances predictive accuracy and model complexity by penalising the use of redundant feature sets, via its fitness function. This type of architecture is based on well known engineering concepts of Pareto optimisation in which we have competing objectives that have to be traded in well defined system constraints. In real-world engineering, typical examples are the cost-limited, weight-constrained, time-constrained (schedule) or energy-constrained (Qin, Liu, Bai, & Hu, 2024) solutions that exist in mechanical design, structural analysis, or energy systems modelling (Qin, Liu, Bai, & Hu, 2024). SBO directly reflects this situational dynamic, because it incorporates a penalty term that is designed to vary as a function of the number of features used; therefore, SBO closely matches this situational reality, hence generating machine-learning models with desired characteristics in terms of high performance and low physical size and computational requirements, which is an essential characteristic of fields like mobile computing where limited physical memory and costs of power consumption still prevail.

In the perspective of related writings, SBO will be compared well with other hybrid approaches. Hybrid versions of PSO SVM (particle swarm optimisation SVM) and GA-RF (genetic-algorithm random forest) have excelled in many areas related to ECG signal classification and malware detection but are likely to have a mysterious decision-making process, are vulnerable to overfitting, and require careful parameter tuning to ensure their convergence (Jovic, Brkic, & Bogunovic, 2015; Guyon & Elisseeff, 2003). In the meantime, the algorithmic schema implemented with the help of the SBO, and akin to the methodical mode of foraging of an animal organism, functions in the logical search structures that can be used in the rule-based engineering. It is not just a constraint that will pass the test of the canonical Iris dataset but, in addition to that, it is a controlled feasibility demonstration. In the future, it is imaginable that the equivalent method can be scaled or extended to other, more complex datasets, i.e. network intrusion logs (e.g. NSL-KDD) or image-based condition monitoring data, but only under the condition that it is compatible with parallelisation or incremental evaluation methods (Fu, Liu, Chen, & He, 2024).

The technical validity of the study is stratified 5-fold cross-validation. By stratifying the data set into at least five overlapping representative pieces it is guaranteed that model will be evaluated in a number of different data circumstances (Allgaier & Pryss, 2024; Kernbach & Staarjes, 2020). In engineering applications (analytically, rotating machines with changing load patterns) such validation ensures that the model overfitted output is not skewed, or constrained to a particular operation condition. The fact that the standard deviation is relatively small all through the folds proves the idea that this type of feature subset chosen by

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SBO is rather stable, which is appropriate to universal application, as the main principles of reliability engineering can attest (Mohialden and Hussien, 2025; Ghosh et al., 2025).

These results can be considered encouraging even though the size and relative ease of the Iris data do limit the universality of the conclusions. In the real-life engineering data available, the dataset is rarely as balanced, noise free, or having low dimensionality as Iris. Such data as complex biometrics, industrial fault-diagnosis problems, or sensor fusion in autonomous vehicles, to name a few, have complicated feature interactions, strong nonlinearity and signal degradation (Chen et al., 2025; Jiang et al., 2025). The effectiveness of SBO under such data would require a measure against high dimensional, real time and possibly imbalanced data sets, e.g. ISOLET, NSL-KDD and proprietary industrial monitoring corpora (Xue et al., 2015). Such an extension will demand computation strategies computationally-efficient GPU-accelerated or distributed parallel optimization, which in turn are easily possible via SBO modular and population-based nature.

SBO and ensemble based learning frameworks are intellectually interesting arenas that can be explored in the future. Random Forests and XG Boost, likewise have a natural tendency to avoid overfitting and are tolerant of having noisy or irrelevant data present. Due to that SBO could be located in both preprocessing or a wrap-stage prior to submitting to such ensembles, there is the possibility of exploiting a synergetic effect; artificial feature set reduction maintaining the ability of ensembles to address heterogeneity and imbalance (Chandrashekar and Sahin, 2014). This approach can be particularly useful in smart-grid settings where large dimensionality of input variables needs to be considered and in which real time feedback is important.

In addition, SBO demonstrates promising potential as a general optimizer that can be used to a larger engineering scenario. It can be modified to structural topology optimization, parameter fine tuning mechatronic systems, and layout planning printed circuit boards. The fluid, biological nature of the framework makes it suitable to many constrained optimization problems, and this is what makes this framework not a single-purpose algorithm, but a multipurpose tool to systematically solve a variety of problems in engineering. The ability to integrate SBO into bigger optimization cycles so powerful, from an engineering solution standpoint, are the kind that encompass, say, digital twins systems or cyber-physical control frameworks and can significantly enhance performance and flexibility trait of engineering solutions to come.

Conclusion

A Secretary Bird Optimization (SBO) and Decision Tree-based feature ranking based hybrid feature selection framework that will be proposed aims at the simultaneous reduction of feature dimensionality and retention of the classification accuracy. The method proves a strong generalization and interpretability ability, as it has chosen the minimal but informative feature subset in the Iris dataset achieving an average accuracy of 96.00 percent accuracy in a stratified cross-validation of 5-fold. These results serve to highlight the practical applicability of SBO in the building of sparse, precise, and easily interpretable models, which is especially relevant in scenarios for which a limited volume of computations or operations is available. Methodologically, the existence of SBO in a combination with model-driven ranking yields a successful compromise of global optimization verses local interpretability. Unlike parameter sensitive metaheuristics, SBO provides a lightweight, dynamic framework that can be lightly tuned. The property of sparsity-inducing fitness function makes it easy to control the complexity of the model systematically, which further makes it suitable to the demands of engineering systems operating in the real world. However, the study using a low-dimensional benchmark data shows that additional substantiation is necessary. In future, this methodology can be applied to high-dimensional, noisy and class-imbalanced datasets

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prevalent in industrial, biomedical and cyber-physical contexts. Also, the combination of SBO and ensemble classifiers or work in parallel or hardware-assisted is the way to improve both scale and the suite of applicability.

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