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Major: **Fundamental Computing**

An Opposition-Based Great Wall Construction Metaheuristic Algorithm with Gaussian Mutation for Feature Selection

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Dedication

من قال أنا لها ... نالها

وأنا لها وإن أبت رغماً عنها أتيت بها

الحمد لله حباً وشكراً وامتنانا على البدء والختام

(وَآخِرُ دَعْوَاهُمْ أَنِ الْحَمْدُ لِلَّهِ رَبِّ الْعَالَمِينَ)

الى من كلل العرق جبينه وعلمني أن النجاح لا يأتي إلا بالصبر والأصرار، الى النور الذي أنار دربي والسراج الذي لا ينطفي نوره بقلبي أبداً، من بذل الغالي والنفيس واستمديت منه قوتي واعتزازي بذاتي (أبي العزيز)

الى من جعل الله الجنة تحت أقدامها وسهلت لي الشدائد بدعائها، الى الانسانة العظيمة التي طالما تمنت أن تقر عينها برؤيتي في يوم كهذا، إلى ملهمتي (أمي الحبيبة)

الى الجندي المجهول الذي لطالما كان معطاء كريماً داعماً وسنداً و مساعد لي في كل خطوة اخطوها ...(أخي)

الى ضلعي الثابت وأمان أيامي، الى من شددت عضدي بهم فكانو لي ينابيع أرتوي منها، الى خيرة أيامي وصفوتها الى قرة عيني، (أخواتي و بنات اختي مرام و لُجين)

الى صاحبة الفضل العظيم, رفيقة قلبي, صديقة الرحلة و النجاح الى من وقفت بجانبي دائما (مجدة)

لكل من كان عوناً وسنداً في هذا الطريق ... للأصدقاء الأوفياء ورفقاء السنين وأصحاب الشدائد والأزمات ، إلى (صُحبتي الصالحة)

إلى ثمرتنا الصغيرة، نادينا (نـادي فضـاء), و إلى أرضٍ خُـلقت للسَـلام و ما رأت يـوما سـلاما، (فلسطين)

أهديكم هذا الإنجاز وثمرة نجاحي، ها أنا اليوم أتممت أول ثمراته بفضل من الله عز وجل ، فالحمد لله على ما وهبني ، وأن يعينني ويجعلني مباركة أينما كنت.

انفال باسيمان

Dedication

الحمد لله و الصلاة وسلام على نبي الله اما بعد
الى نفسي التي حاربت وجاهدت ورابطت طوال هاته السنين ولا يعلم حالها الا ...الله الحمد لله الذي وفقني لهذا الحمد لله
لوصولي آخر الطريق
إلى والديا الغاليان الى أمي التي رحلت ولم المح منها شيئا كم تمنيت ان تكوني اول من يحضر لهذا النجاح كم تمنيت ان
تكوني السند والعون لي طوال هاته السنين مشواري هذا وتخرجي هذا وكل مستقبلي لك يا اغلى الناس الى ابي ...الحبيب
الى الظلع الثابت اللهم ارحمهما واجعل مثواهما الجنة
الى أخواتي الحبيبات(أحلام وامال سعيدة) الى أخواني سندي في هاته الحياة الى بنات ...اختي يا اغلى من انجبت
الغالية (سلوى صفاء كوثر نجاح)
الى رفيقة الدرب ورفيقة الروح وصديقة مشواري هذا وأفضل هدايا الله (انفال)..
وإلى كل صديقاتي الحبيبات وإلى من ساندني ودعمني طوال مشواري الدراسي الى كل من وقف معي ولو بكلمة..
اهديكم هذا العمل...

مجدة حمادي

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Abstract

The feature selection problem involves selecting a subset of relevant features to enhance the performance of machine learning models, crucial for achieving model accuracy. Its complexity arises from the vast search space, necessitating the application of metaheuristic methods to efficiently identify optimal feature subsets. In this work, we employed a recently proposed metaheuristic algorithm named the Great Wall Construction Algorithm to address this challenge – a powerful optimizer with promising results. To enhance the algorithm's performance in terms of exploration, exploitation, and avoidance of local optima, we integrated opposition-based learning and Gaussian mutation techniques. The proposed algorithm underwent a comprehensive comparative analysis against ten influential state-of-the-art methodologies, encompassing seven contemporary algorithms and three classical counterparts. The evaluation covered 22 datasets of varying sizes, ranging from 9 to 856 features, and included the utilization of six distinct evaluation metrics related to accuracy, classification error rate, number of selected features, and completion time to facilitate comprehensive comparisons. The obtained numerical results underwent rigorous scrutiny through several non-parametric statistical tests, including the Friedman test, the post hoc Dunn's test, and the Wilcoxon signed ranks test. The resulting mean ranks and p-values unequivocally demonstrate the superior efficacy of the proposed algorithm in addressing the feature selection problem.

keywords

Feature Selection Problem (FS), Great Wall Construction Metaheuristic Algorithm(GWCMA), Opposition-Based Learning, Gaussian Mutation.

Résumé

Le problème de sélection des caractéristiques implique la sélection d'un sous-ensemble de caractéristiques pertinentes afin d'améliorer les performances des modèles d'apprentissage automatique, ce qui est crucial pour atteindre la précision du modèle. Sa complexité provient du vaste espace de recherche, ce qui nécessite l'application de méthodes méta-heuristiques pour identifier efficacement des sous-ensembles de caractéristiques optimaux. Dans ce travail, nous avons utilisé un algorithme métaheuristique récemment proposé appelé algorithme de construction de la Grande Muraille pour relever ce défi - un optimiseur puissant avec des résultats prometteurs. Pour améliorer les performances de l'algorithme en termes d'exploration, d'exploitation et d'évitement des optima locaux, nous avons intégré des techniques d'apprentissage basées sur l'opposition et de mutation gaussienne. L'algorithme proposé a fait l'objet d'une analyse comparative approfondie par rapport à dix méthodologies d'avant-garde influentes, englobant sept algorithmes contemporains et trois homologues classiques. L'évaluation a porté sur 22 ensembles de données de tailles variables, allant de 9 à 856 caractéristiques, et a inclus l'utilisation de six métriques d'évaluation distinctes liées à la précision, au taux d'erreur de classification, au nombre de caractéristiques sélectionnées et au temps d'exécution pour faciliter des comparaisons complètes. Les résultats numériques obtenus ont été soumis à un examen rigoureux au moyen de plusieurs tests statistiques non paramétriques, notamment le test de Friedman, le test post-hoc de Dunn et le test des rangs signés de Wilcoxon. Les rangs moyens et les valeurs de p résultantes démontrent sans équivoque l'efficacité supérieure de l'algorithme proposé pour résoudre le problème de sélection des caractéristiques.

Mots clés

Feature Selection Problem, Great Wall Construction Metaheuristic Algorithm, Opposition-Based Learning, Gaussian Mutation.

ملخص

تتضمن مشكلة اختيار الميزات تحديد مجموعة فرعية من الميزات ذات الصلة لتحسين أداء نماذج التعلم الآلي ، وهو أمر ضروري لتحقيق دقة النموذج. ينشأ تعقيده من مساحة البحث الشاسعة ، مما يستلزم تطبيق طرق ميتاهورية لتحديد مجموعات الميزات المثالية بكفاءة. في هذا العمل ، قمنا بتوظيف خوارزمية ميتاهورية المقترحة حديثًا والتي تسمى خوارزمية بناء سور الصين العظيم لمعالجة هذا التحدي وهي أداة تحسين قوية تحقق نتائج واعدة. لتحسين أداء الخوارزمية من حيث الاستكشاف والاستغلال وتجنب الحلول المحلية المثلى ، قمنا بدمج تقنيات التعلم القائم على المعارضة والطفرات الغاوسية. خضعت الخوارزمية المقترحة لتحليل مقارن شامل مقابل عشر مناهج مؤثرة في الفن ، تشمل سبع خوارزميات معاصرة وثلاث نظيرات كلاسيكية. شمل التقييم 22 مجموعة بيانات بأحجام مختلفة ، تتراوح من 9 إلى 856 ميزة ، وشمل استخدام ستة مقاييس تقييم مميزة متعلقة بالدقة ومعدل خطأ التصنيف وعدد الميزات المحددة ووقت الإكمال لتسهيل المقارنات الشاملة. خضعت النتائج العددية التي تم الحصول عليها لفحص دقيق من خلال عدة اختبارات إحصائية غير المعلمات ، بما في ذلك اختبار فريدمان ، واختبار دان التالي للاختبار ، واختبار رتب علامات ويلكوكسون الموقعة. تظهر الرتب المتوسطة والقيم الاحتمالية الناتجة بشكل لا لبس فيه الفعالية الفائقة للخوارزمية المقترحة في معالجة مشكلة اختيار الميزات.

الكلمات المفتاحية
مشكلة اختيار الميزات، خوارزمية بناء سور عظيم، خوارزمية ميتاهورية، تعلم قائم على المعارضة، طفرة غاوسية

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General Introduction

Context

Metaheuristic algorithms are optimization techniques that can be applied to a wide range of problems without needing to know the specific details of the problem. These algorithms are general-purpose and can be used to solve combinatorial optimization problems, such as feature selection, scheduling, routing, and more.Metaheuristics are iterative and stochastic in nature, meaning they use randomness to explore the search space and find solutions. They are typically inspired by natural phenomena or human behavior and aim to efficiently explore a large solution space to find near-optimal solutions.

Problematic

Feature selection is a critical step in machine learning and data analysis, as it involves choosing the most relevant and informative features from a dataset. However, this process can be challenging due to a variety of problems that can arise. One common issue is the curse of dimensionality, where the number of features in a dataset is so large, This can lead to overfitting and poor generalization performance. Another problem is the presence of irrelevant or redundant features, which can introduce noise and reduce the model's accuracy. Additionally, feature selection can be computationally expensive, especially when dealing with high-dimensional data. Despite these challenges, selecting the right set of features is essential for building accurate and interpretable machine learning models.

Contribution

Our thesis aims to make a valuable contribution by Employing a recently proposed Metaheuristic algorithm called Great Wall Construction algorithm. Initially, We make the proposed algorithm underwent a comprehensive comparative analysis against ten well-known metaheuristic algorithm , than applying it at 22 datasets of varying sizes. This comparative analysis aims to evaluate the performance and effectiveness of the proposed algorithm in addressing the feature selection problem.

Structure

This dissertation is organized into three chapters as follows:

In the first chapter, we provide an overview of the field of meta-heuristic algorithms, we start by defining the meaning of the meta-heuristic algorithms and discussing when to use this algorithm, we discovered it Classification and we present a real application of this meta-heuristic .

In the second chapter, we provide an overview of the field of feature selection, we cover the life cycle of fs problem and it importance. We explore the approaches and provide the mathematical formulation, we present some of the Applications and related work to feature selection.

In the third chapter, we represent the partical part of the proposed algorithm and techniques used. Next we introduced our meta-heuristic implementation and pseudo code. Finally, we delivers the results of the performance and effectiveness of solving continuous feature selection problem.

Chapter 1

Introduction to Metaheuristics

1.1 Introduction

Metaheuristic algorithms have gained significant attention in the field of optimization and problem-solving due to their ability to efficiently find near-optimal solutions to complex problems. These algorithms are inspired by natural phenomena or abstract mathematical concepts and are designed to explore the solution space in a heuristic manner, making them suitable for a wide range of optimization problems where traditional methods may struggle. Metaheuristic algorithms are characterized by their flexibility, adaptability, and robustness in handling various types of optimization problems, including combinatorial optimization, continuous optimization, and multi-objective optimization. They are often used when the problem is $\mathcal{NP}$-hard or when the search space is too large to be exhaustively explored.

In this chapter, we will delve into the fundamentals of metaheuristic algorithms, exploring their underlying principles, common classifications. We will also discuss the importance of these algorithms and highlight some of the key considerations when selecting and implementing them for solving real-world problems. By understanding the core concepts of metaheuristic algorithms, researchers and practitioners can leverage their power to tackle complex optimization challenges effectively.

1.2 Definition of Metaheuristics

The words of “meta” and ‘‘heuristic” are Greek where, “meta” is “higher level” or“beyond” and heuristics means ‘‘to find”, ‘‘to know”, ‘‘to guide an investigation” or ‘‘to discover”. Heuristics are methods to find good (near-) optimal solutions in a reasonable computational cost without guaranteeing feasibility or optimality[3]. In other words, A meta-heuristic is an iterative generation process which guides a subordinate heuristic by combining intelligently different concepts for exploring and exploiting the search spaces using learning strategies to structure information in order to find efficiently near-optimal solutions[4]. Notable examples of metaheuristics include genetic/evolutionary algorithms[5], tabu search[6], simulated annealing[7], and ant colony optimization[8], although many more exist.

1.3 When Using Metaheuristic

The factors to be taken into account when applying metaheuristics to optimization issues are covered in this section. A problem’s complexity might reveal information about how difficult it is, and it is crucial to take the size of the input instances into account. Precise methods can effectively address small instances of hard problems.Instance structure is particularly important since some large or medium-sized instances with particular topologies can be solved optimally with precise methods.

A key consideration when selecting an optimization algorithm is the amount of time needed to search for a solution to a problem. It is not a good idea to use metaheuristics to solve issues when there are efficient exact procedures available. Examples of such circumstances are optimization problems belonging to the $\mathcal{P}$-hard class. When precise algorithms are able to resolve target instances in a reasonable Metaheuristics are no longer needed when precise algorithms are able to solve target instances in a reasonable amount of time. For example, known polynomial-time precise algorithms can be used to effectively tackle graph problems such as determining the shortest path or least spanning tree.

Consequently, even if some researchers and engineers continue to use metaheuristics for polynomial optimization issues, they are rarely applied to simple optimization problems. Analyzing the problem's complexity is the first step in fixing a problem. If the issue can be reduced to a well-known or already resolved issue in the literature, it is advisable to investigate the most recent optimization techniques that have been applied to that issue.Similar approaches used to solve related issues should be taken into consideration if there are no direct solutions accessible.

1.4 Search Behavior

For every metaheuristic algorithm, exploration and exploitation represent the most important characteristics for attaining success when solving a particular optimization problem. Achieving the best of both exploration and exploitation simultaneously in a single algorithm is a complex task. Researchers have indeed explored various approaches to address this trade-off, and the choice of methods depends on the problem at hand and the characteristics of the algorithm being used.

1.4.1 Exploration

Exploration refers to the ability of a search algorithm to discover a diverse assortment of solutions, spread within different regions of the search space[9]. it is also called Diversification which means generating diverse solutions so as to explore the search space on the global scale. On the other hand, the diversification via randomization increases the diversity of the solutions while keeping the solutions from being trapped at local optima[10].

1.4.2 Exploitation

Exploitation phase emphasizes the idea of intensifying the search process over promising regions of the solution space with the aim of finding better solutions or improving the existing ones[9]. Exploitation is often viewed as an intensification phase which means focusing on the search in a local region by exploiting the information that a current good solution is found in this region[10].

1.4.3 Local Optima

A local optimum is an extrema (maximum or minimum) point of the objective function for a certain region of the input space[11]. More formally, for the minimization case x_{local} is a local minimum of the objective function $f(x)$ if:

$f(x) \geq f(x_{local})$ for all values of x in range $[x_{local} - \epsilon, x_{local} + \epsilon]$.

1.4.4 Global Optima

A global optimum is the maximum or minimum value the objective function can take in all the input space[11]. More formally, for the minimization case x_{global} is a global minimum of the objective function $f(x)$ if:

$f(x) > f(x_{global})$ for all values of x. In the image below, we can see an example of a local and a global maximum:

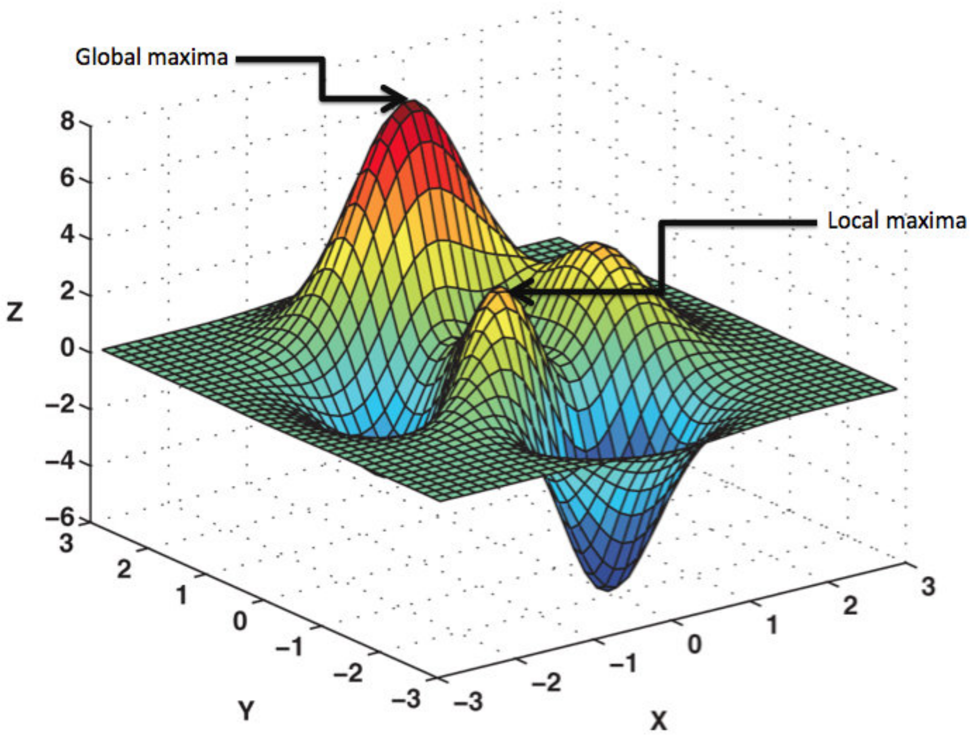


Figure 1.1: Global and local optima in a search space. [1]

1.5 Classification of Metaheurstic Algorithms

Different ways based on the selected characteristics have been proposed to classify metaheuristics as shown in Fig 1.2 .

This section briefly summarizes the most important classes including population-based against single point search, nature-inspired against non-nature inspired, memory usage against memory-less methods , deterministic against stochastic,Iterative against greedy ,Evolutionary algorithms , swarm intelligence based algorithms.

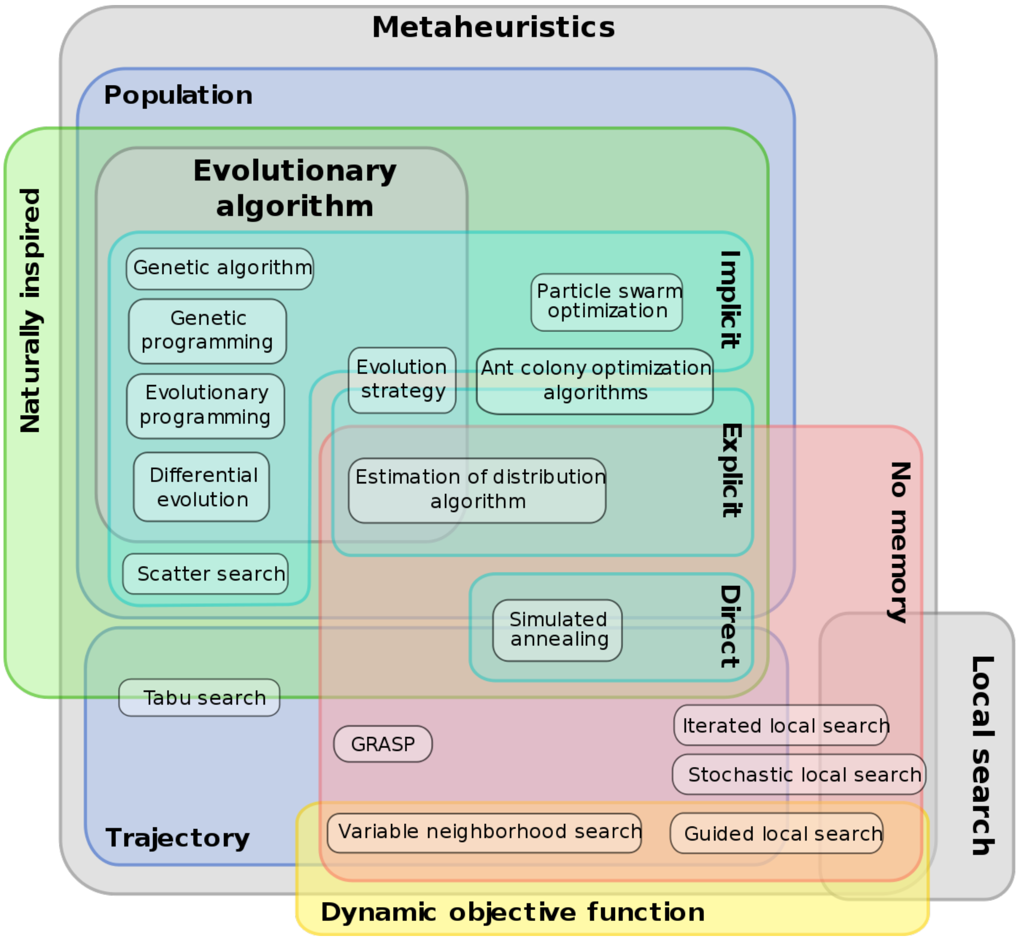


Figure 1.2: Metaheuristics Classifications. Source: [2]

1.5.1 Population-Based Search vs Single-Solution Based Search

Single-solution based algorithms (e.g., local search, simulated annealing) manipulate and transform a single solution during the search while in population-based algorithms (e.g., particle swarm, evolutionary algorithms) a whole population of solutions is evolved. These two families have complementary characteristics: single-solution based metaheuristics are exploitation oriented, they have the power to inten- sify the search in local regions. Population-based metaheuristics are exploration oriented, they allow a better diversification in the whole search space. In the next chapters of this book, we have mainly used this classification. In fact, the algorithms belonging to each family of metaheuristics share many search mechanisms[12].

1.5.2 Deterministic vs Stochastic

A deterministic metaheuristic solves an optimization problem by making deterministic decisions (e.g., local search, tabu search). In stochastic metaheuristics, some random rules are applied during the search (e.g., simulated annealing, evolutionary algorithms). In deterministic algorithms, using the same initial solution will lead to the same final solution, whereas in stochastic metaheuristics, different final solutions may be obtained from the same initial solution. This characteristic must be taken into account in the performance evaluation of metaheuristic algorithms[12].

1.5.3 Iterative vs Greedy

In iterative algorithms, we start with a complete solution (or population of solutions) and transform it at each iteration using some search operators. Greedy algorithms start from an empty solution, and at each step a decision variable of the problem is assigned until a complete solution is obtained. Most of the metaheuristics are iterative algorithms[12].

1.5.4 Evolutionary Algorithms

Evolutionary Algorithms (EAs) are stochastic search methods that mimic the natural biological evolution and/or the social behavior of species. Such algorithms have been developed to arrive at near-optimum solutions to large-scale optimization problems, for which traditional mathematical techniques may fail[13]. The most popular evolutionary techniques are Genetic Algorithm (GA)[5] this algorithm based on theory of Darwin for evolution. GAs have some operators to evaluate it is initial population generated randomly which are crossover, mutation and selection. the I Ching Algorithm (ICA)[14], for optimization problem-solving. The algorithm incorporates unique operators inspired by the principles of the I Ching, an ancient Chinese cultural system. In addition, the algorithm utilizes transformation methods such as the penalty method and the multiplier method. The Red Deer Algorithm(RDA)[15], takes inspiration from the behavior of male red deer during the mating season. Male red deer engage in competition to secure a large harem of females for mating purposes.The Quantum-inspired Evolutionary algorithm(QE)[16] is designed to handle continuous optimization problems while preserving the concept of superposition states. To achieve this, the algorithm incorporates a recursive sampling technique that progressively tightens the search space. By iteratively refining the search space.

1.5.5 Swarm-Intelligence-Based Algorithms

Swarm intelligence algorithms are nature-inspired algorithms developed based on organisms such as flocks of birds, ants, and fish[17]. These functions help algorithms in fitness functions in combination and numerical optimization problems from covering a wide range of search space, The Pity Beetle Algorithm (PBA)[18], developed by Kallioras is inspired by the gathering behavior and foraging strategies of Pityogenes chalcographus beetles, which have the ability to congregate on host trees and efficiently search for optimal nest sites and food sources using specific behaviors and communication patterns. The Sailfish Optimizer(SFO)[19], The algorithm you are referring to, which is inspired by a group of hunting sailfish, utilizes two types of populations: a sailfish population for intensification and a sardines population for diversification. is inspired by the behavior of sooty terns, a species of seabirds known for their remarkable navigation and foraging abilities. Sooty Tern Optimization Algorithm (STOA)[20], The algorithm mimics the foraging behavior of these birds to solve optimization problems. Chimp Optimization Algorithm (COA)khishe2020chimp a metaheuristic optimization algorithm inspired by the behavior and social structure of chimpanzees, one of the closest relatives of humans. The Archerfish Hunting Optimizer(AHO)[21], takes inspiration from the archerfish's ability to accurately target and shoot down insects by spitting water from its mouth. Dandelion Optimizer(DO)[22], is inspired by the characteristics and behavior of dandelion plants. Dandelions are known for their resilience, adaptability, and efficient dispersal of seeds. The DO algorithm aims to mimic these qualities in the optimization process.

Mountain Gazelle Optimizer(MGO)[23], is inspired by the behavior and characteristics of mountain gazelles. Mountain gazelles are known for their agility, speed, and efficient navigation through complex terrains. Golden eagle optimizer(GEO)[24], is a nature-inspired metaheuristic algorithm inspired by the hunting and foraging behavior of golden eagles. Golden eagles are known for their powerful flight, keen vision, and efficient hunting strategies. Beluga whale optimization(BWO)[25] ,is a inspired by the social behavior and foraging strategies of beluga whales. Beluga whales are known for their cooperative hunting. The Coati Optimization algorithm (COA)[14], is a nature-inspired metaheuristic algorithm that mimics the foraging behavior and social interaction of coatis. Coatis, also known as coatimundis, are small mammals found in the Americas and are known for their efficient foraging strategies and group coordination. Water strider algorithm(WSA)[26], is a metaheuristic optimization algorithm inspired by the behavior of water striders, a type of insect that can walk on the surface of water. The algorithm mimics the movement and foraging strategies of water striders to solve optimization problems. Mouth Brooding Fish (MBF)[27], is a nature-inspired optimization algorithm that draws inspiration from the behavior of mouth brooding fish species. Mouth brooding fish, also known as parental fish, exhibit a unique reproductive strategy where the female fish carries and incubates the fertilized eggs in her mouth until they hatch. is takes inspiration from the foraging behavior of nutcracker birds. Nutcracker optimizer(NOA)[28], Nutcracker birds are known for their unique feeding strategy, where they gather and store food for future consumption.

1.6 Applications of Metaheuristics

As fundamental research progress in a way that is somewhat defined by certain benchmark tests, a more positive development can be observed on the various applications of metaheuristic algorithms in real life applications.

In the area of **artificial intelligence**, various classical classification methods were found to be optimized using metaheuristic optimization techniques. It is observed that there were a lot of interest in optimization of neural networks using evolutionary algorithm. This group of works can be generally be termed as 'Neuroevolution'. In[29], multi objective evolutionary optimizations were applied to optimize ensemble of neural networks. Results tested on UCI datasets also showed increase classification rate as compared to single objective optimization. In[30], DE was applied to train neural networks with a specific case of missing data. The report states robustness and improvement despite missing data. This was reported and compared to standard backpropagation and PSO. This could reinforce the notion that certain algorithms works better for specific sets of problem, as demonstrated in the case of[30].

With the dominance of **Deep learning** in the last decade, it is an obvious area to apply metaheuristic methods. Gradient methods seemingly dominate the field of weight optimization in Deep learning such as Convolutional Neural Network CNN and deep belief network. However, in[31], a multi objective evolutionary algorithm was proposed to achieve better generalization deep learning neural networks considering the contradictory nature between the representation ability and the network connecting sparsity. [31] Is a good example of how evolutionary algorithms were used to optimize deep leaning networks, in this case to increase generalization.

Engineering controller designs are another application that has dominated application of metaheuristics. In[32] PSO were used to optimize integration of alkali fuel cell PID controls. Authors in[33] presented the feed forward controller plus feedback algorithm based on Prandtl-Ishlinskii hysteresis model and analyzed by PSO. The result was compared with traditional feed forward PID scheme. However, the parameterization can be improved by Prandtl-Ishlinskii hysteresis model to the PSO. Authors in[34] proposed a new Hybrid Jump PSO (HJPSO) to mutate the global best particles for regenerating new local and global best particle for next generation in tuning PI controller for the boiler turbine unit. In[35], researchers developed PSO analysis to obtain the optimal duty cycle to the Booster converter for sustaining output voltage regardless to power quantities produced by the solar panels. In[36], authors applied Leader Particle Swarm Optimization (LPSO) analysis in determining a global maximum power point tracking system for the Photovoltaic system that enabling LPSO produce hasty convergence within 0.5s under any shade conditions.

Robotics have also been applying metaheuristics specifically evolutionary algorithms. In fact, evolutionary robotics has been widely regarded as main area of research with multiple journals dedicated to this area of research. Evolutionary robotics generally divided into hardware and software optimization. In hardware optimization, the structure of the robots (height, width and other physical parameters) are often optimized using mathematical models for improvement. Authors in[37] reported an improvement when it is compared to GA for optimization of robot structure. This is another case of example in which certain problems are better optimized with certain algorithms. The software optimization are often in robotic controllers such as gait controls. This is demonstrated in[38] and[39]. The limitation of such application is 'reality gap' in which the mathematical model that was used for optimization is not accurate causing flaw when translated to real hardware. This issue has been constantly discussed with some reverting to optimization evaluation using real robotic hardware (hardware in loop). However, this method is time consuming. Often ahybrid of both are considered in considering the trade-off between reality Gap and training time. One significant area that was highly commercialized metaheuristic application is in the area of scheduling. Scheduling optimization may include worker schedule, exam schedule and even vessel scheduling can be optimized to reduce resources. In[40], yard crane scheduling was optimized to reduce resources using GA. In[41], diesel generator scheduling was reportedly optimized using GA. Flight scheduling was also considered to optimization in view of limited airport resources as demonstrated in[42]. This was perform using a combination of ant colony optimization demonstrating its efficiency in such problem domains.

1.7 Conclusion

In conclusion, metaheuristic algorithms have proven to be powerful and versatile tools in solving complex optimization problems in the real world. They offer efficient and effective solutions across a wide range of applications, including engineering, finance, logistics, and more. While there are various metaheuristic algorithms available, each with its own strengths and weaknesses, their ability to adapt and evolve makes them well-suited for tackling diverse and dynamic optimization challenges. By leveraging the strengths of metaheuristic algorithms and combining them with domain expertise, researchers and practitioners can harness their potential to drive innovation and improve decision-making in real-world scenarios. Metaheuristic algorithms are versatile optimization techniques that can be applied to a wide range of problems. They offer a flexible and efficient approach to finding high quality solutions in complex search spaces. By combining exploration and exploitation strategies, it can effectively balance the trade-off between global and local search. Overall, metaheuristic algorithms are a powerful tool for solving optimization problems in various domains.

Chapter 2

Introduction to Feature Selection

2.1 Introduction

Feature selection is a fundamental aspect of machine learning and data analysis that involves choosing a subset of relevant features from a dataset to build predictive models. The goal of feature selection is to improve model performance, reduce overfitting, increase interpretability, and enhance computational efficiency by eliminating irrelevant or redundant features.

In many real-world applications, datasets can contain a large number of features, some of which may not contribute significantly to the predictive power of the model. Including these irrelevant features can lead to increased complexity, longer training times, and reduced generalization performance. Feature selection helps address these issues by identifying and selecting the most informative features that are essential for making accurate predictions. There are various approaches to feature selection, each with its own strengths and limitations. Some common methods include filter methods, wrapper methods, embedded methods, and hybrid methods. Filter methods assess the relevance of features based on statistical measures such as correlation or mutual information. Wrapper methods evaluate feature subsets by training and evaluating models using different combinations of features. Embedded methods incorporate feature selection into the model training process, allowing the model to automatically select the most relevant features during training.

Feature selection is crucial in high-dimensional datasets where the number of features exceeds the number of observations. In such cases, feature selection helps prevent overfitting and improves the model's ability to generalize to unseen data. Additionally, feature selection can enhance the interpretability of the model by focusing on the most important predictors that drive the predictions.Choosing the right feature selection method depends on factors such as the dataset size, the number of features, the nature of the data, and the modeling task at hand. It is important to carefully consider these factors when selecting a feature selection technique to ensure that the resulting model is accurate, efficient, and interpretable.

Overall, feature selection is a critical step in the machine learning pipeline that can significantly impact the performance and effectiveness of predictive models. By selecting the most relevant features and eliminating noise and redundancy, we can build more robust and efficient models that provide valuable insights from complex datasets.

This chapter is an introduction to the feature selection. It is organized as follows, starting by overview about life cycle of machine learning, and definition of feature selection and its importance. We present approaches and mathematical formulation of FS Problems and explor the application of Feature Selection in Real World. Therefor we provides an overview of the current state-of-the-art meta-heuristic-based approaches designed to address the FS problem, shedding light on the latest advancements in this field.

Here is the life cycle of feature selection problem and we will focus on feature selection step because it is a very important, in this step the process of reducing data will be done (shown in Figure 2.1 bellow).

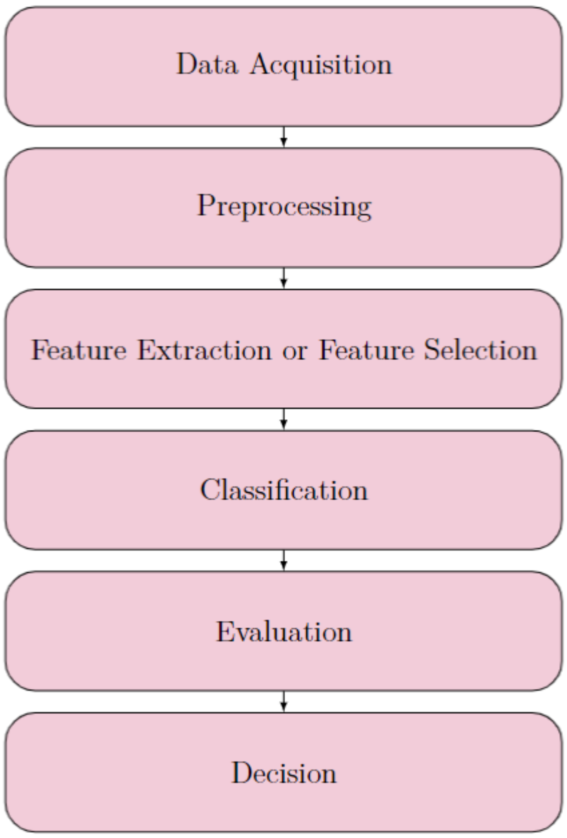


Figure 2.1: Components of pattern recognition

2.2 Definition of Feature Selection

Feature selection refers to the process of selecting a subset from the actual set of features or attributes from a given data set while ignoring the redundant or irrelevant features. The best feature subset (called the optimal) is measured based on an evaluation condition. However, discovering the optimal feature is generally intractable this is due to the fact that the increase in dimensionality increases the number of features as well. Numerous problems connected to feature selection are proved to be $\mathcal{NP}$-hard[43].

2.3 Importance of Feature Selection

Feature selection is the process of identifying and selecting a subset of the most relevant features (input variables) to include in the model. This technique can help improve the performance of a machine learning model by removing irrelevant or redundant features, which can reduce overfitting and improve generalization. There are several feature selection techniques, including forward selection, backward elimination, and principal component analysis (PCA). Forward selection involves starting with an empty set of features and gradually adding the most important ones, while backward elimination starts with all the features and removes the least important ones. PCA involves transforming the original features into a smaller set of uncorrelated features that explain the most variance in the data. In addition to feature selection techniques, feature importance methods are used to rank the importance of individual features in a model. These methods can be used to identify the features that have the strongest relationship with the target variable and can be particularly useful when dealing with large numbers of features. By using feature selection and feature importance methods, you can create new views of your data to explore with modelling algorithms and gain insights into the most important factors driving your model's predictions.

2.4 Approaches of Feature Selection

Feature selection approach can be classified into three main categories filter, wrapper, embedded:

2.4.1 Filter Approaches

The filter approach incorporates an independent measure for evaluating features subsets without involving a learning algorithm. This approach is efficient and fast to compute (computationally efficient). However, filter methods can miss features that are not useful by themselves but can be very useful when combined with others[38].

2.4.2 Wrapper Approaches

The wrapper approach to feature subset selection is based on using the classifier as a ”black box”. A search algorithm (such as hill climbing) is used to search for a ”good” subset and the classifier is used to find the error rate with a particular subset. However, the true error rate of the classifier with a given subset is hard to compute and an estimate obtained using cross-validation or bootstrap based methods[10]. A general algorithm for wrapper approaches is shown in Algorithm 1.

2.4.3 Embedded Approaches

This approach interacts with learning algorithm at a lower computational cost than the wrapper approach. It also captures feature dependencies. It considers not only relations

Algorithm 1: The Wrapper Algorithm.

```
Input: $D = \{X, L\}$: A training data set with $n$ number of features where $X = \{f_1, \ldots, f_N\}$
       and L labels.
Input: $X'$: Predefined initial feature subset $\{X' \subset X$ or $X' = \{\emptyset\}\}$
Input: 0: A stopping criterion.
Output: $X'_{opt}$: An optimal subset.
1  $X_{opt} = X'$;
2  $\varphi_{opt} = E(X', A)$ ; //evaluate $X'$ by using algorithm A
3  repeat
4      $X_g = generate(X)$; //Subset generation for evalution
5      $\varphi = E(X_g, A)$; //$X_g$ current subset evaluation by A
6      if $(\varphi > \varphi_{opt})$ then
7          $\varphi_{opt} = \varphi$;
8          $X'_{opt} = X_g$;
9      end
10 until ($\emptyset$ is reached);
11 return $X'_{opt}$ ;
```

between one input features and the output feature, but also searches locally for features that allow better local discrimination. It uses the independent criteria to decide the optimal subsets for a known cardinality. And then, the learning algorithm is used to select the final optimal subset among the optimal subsets across different cardinality[38].

2.5 Mathematical Formulation of FS Problems

The feature selection problem is about selecting a subset of features from a larger set while aiming to achieve a certain optimization goal, such as improving model performance or reducing complexity. The mathematical formulation can vary based on the specific objective and constraints of the problem. In the following, we give a mathematical formulation for the FS problem.In the FS problem, we assume a dataset with N instances and D features: $X = \{\mathbf{x}_1, \ldots, \mathbf{x}_N\}$, where $\mathbf{x}_i$, is a D-dimensional feature vector, and a response variable y. The goal is to select a subset of features from the original D features that maximizes or minimizes a certain objective function. The objective function can be defined based on various criteria, such as model performance (e.g., accuracy, F1-score), model complexity (e.g., number of selected features), or other domain-specific considerations. The general FS problem, used in this work, is mathematically formulated using Equations 2.1, 2.2 and 2.3.

Minimize:

$$\alpha \times \text{CER} + (1 - \alpha) \times \frac{|R|}{|D|} \tag{2.1}$$

where CER represents the classification error rate computed using Equation 3.20, α is a random number sampled from the uniform distribution, $|R|$ denotes the number of selected features, and $|D|$ refers to the total number of features.

Subject to:

$$\sum_{j=1}^{D} x_{i,j} \leq K \ , \ i \in \{1, \ldots, N\} \tag{2.2}$$

where K is the maximum number of selected features (if there are constraints on limiting the number of selected features).

With:

$$x_{i,j} \in \{0, 1\} \ , \ i \in \{1, \ldots, N\} \ , \ j \in \{1, \ldots, D\} \tag{2.3}$$

where $x_{i,j}$ is a binary decision variable that represents whether feature j is selected for instance i. If $x_{i,j} = 1$, the feature is selected; if $x_{i,j} = 0$, the feature is not selected.

2.6 Application of Feature Selection in Real World

During data collection, many problems are often encountered such as a high dependency of features, too many features, or redundant and irrelevant features. To deal with the mentioned problem, feature selection provides a tool to select a feature subset or feature to learn algorithms effectively. Therefore, in the literature, the applications of feature selection are used frequently in many research areas.

2.6.1 Text Categorization

The massive volume of online text data on the Internet such as emails, social sites, and libraries is increasing. Therefore, automatic text categorization and clustering are important tasks. A major problem with text classification or clustering is the high dimensionality of the document features. A moderate size text document may have hundreds of thousands of features. Therefore, feature selection (dimension reduction) is highly enviable for the efficient use of mining algorithms. In the literature, many applications of feature selection techniques are effectively used in the area of text mining. Feature selections using the information Gain Ratio (GR) is used for lyrics and poems for text data classification. Many feature selection techniques are used for feature reduction, then evaluated and compared to the classification problem[38].

2.6.2 Remote Sensing

Feature selection is one of the important tasks in the remote sensing image classification. The challenges and various issues in feature selection and hyper spectral remote sensing image analysis is explained. Pre-processing techniques have been proposed for hyper spectral images in which feature extraction and feature selection have been emphasized as important components in hyper spectral image classification. Feature selection guided by evolutionary algorithms has been proposed, and use a self-adaptive differential evolution for feature subset generation. Generated feature subsets are evaluated by the wrapper method with the help of fuzzy k-nearest neighbor classifier. Shijin Li, Hao Wu, Dingsheng, and Wan Jiali Zhu have developed a hybrid approach for feature selection using support vector machine and genetic algorithm. They have used the wrapper method to select the optimal number of features in order to obtain better accuracy, a novel technique has been proposed to select a subset of bands from a hyper spectral image to improve the performance of the classification. It utilizes spatial and spectral information simultaneously to improve the discrimination capability of the classifier[38].

2.6.3 Intrusion Detection

In this modern age, information sharing, distribution, or communication is widely done by network-based computer systems. Therefore, the security of the system is an important issue protecting communication networks from intrusion by enemies and criminals. One of the ways to protect communication networks (computer systems) is intrusion detection. Feature selection plays an important role to classifying system activity as legitimate or an intrusion, data mining techniques and feature selection techniques are used for intrusion detection[38].

2.6.4 Genomic Analysis

A large quantity of genomic and proteomic data is produced by microarray and mass spectrometry technology for understanding of function of an organism, and the behavior, dynamics, and characteristics of diseases. Tens of thousands of genes are measured in a typical microarray assay and mass spectrometry proteomic profile. Special data analysis is demanded because of the high dimensionality of the microarray data. One of the common ways to handle high dimensionality is identification of the most relevant features in the data. Therefore, in the literature, feature selection has been done successfully on full microarray data. The Filter, Wrapper, and Embedded methods have been used for feature selection and dimensionality reduction. The techniques covered by them are the most effective for proteomics data and genomic analysis. Comparative studies of 8 feature selection for classification task and their combinations have been done based on gene expression data. It is also shown that classification accuracy can be significantly boosted by a small number of genes by using a feature selection method[38].

2.6.5 Image Retrieval

Recently, the amount of image collections from military and civilian equipment has increased. To access the images or make use of the information, images should be organized in a way that allows effective browsing, retrieving, and searching. As stated, content-based image retrieval is scalable for the large size of images, but it is also cursed by high dimensionality. Therefore, feature selection is an important task for effective browsing, searching, and retrieval, content-based image retrieval is proposed that annotates images by their own colors, textures, and shape[38].

2.7 Related Work

Several survey papers have been published to investigate and review studies addressing the FS problem[44, 45]. In this section, we present a comprehensive overview of metaheuristic-based FS methodologies that have been published recently. Our emphasis lies in elucidating the introduced algorithms, the transfer functions, the classifier and the metrics employed for evaluating their efficacy, and the diverse advantages and disadvantages of each approach. By illuminating these facets, we aim to provide a good understanding of the evolving landscape of FS techniques and their practical implementation across a spectrum of datasets. In the comprehensive landscape of FS algorithms, a multitude of innovative approaches have been explored to address the challenges posed by high-dimensional datasets. The algorithms will be categorized into two approaches for FS, specifically binary and hybrid metaheuristic methods.

The algorithm outlined in[46] employs the binary bat algorithm for FS problem resolution, incorporating S and V shape transfer functions. It utilizes the support vector machine classifier, yielding an accuracy of 98.25%. While excelling with large datasets, this algorithm experiences a slower convergence time. In[47], the binary grasshopper optimization algorithm is utilized to address the FS problem, integrating S and V shape transfer functions. It incorporates the k-nearest neighbours classifier, achieving an accuracy of 97.9%. This algorithm boasts a swift convergence time and effective FS, but its performance is constrained in high-dimensional datasets. The algorithm in[48] employs the binary grey wolf optimizer for FS problem-solving, utilizing S and V shape transfer functions with the k-nearest neighbours classifier, resulting in an accuracy of 84.20%. While demonstrating rapid convergence and effective FS, it may become entangled in local optimums. In[49], the binary firefly algorithm is applied for FS, incorporating an aggregation function and k-nearest neighbours, naive Bayes, and linear discriminant analysis classifiers, achieving an accuracy of 97.78%. This algorithm exhibits fast convergence and robust FS, but it may face challenges with local optimums. Furthermore, [50] utilizes binary particle swarm optimization for FS, incorporating the sigmoid transfer function and the decision tree classifier, achieving an accuracy of 98.17%. While excelling with small datasets, it encounters limitations with larger datasets and potential entrapment in local optimums. The algorithm in[51] employs S-shaped and V-shaped gaining–sharing knowledge-based algorithms for FS problem-solving, utilizing S and V shape transfer functions. It integrates the k-nearest neighbours classifier, resulting in an accuracy of

99.6%. This algorithm performs well with high-dimensional datasets and adaptive parameter tuning, although additional parameter tuning may be necessary. In[52], the binary sine-cosine algorithm is utilized for FS problem resolution, employing S and V shape transfer functions with the k-nearest neighbours classifier, achieving an accuracy of 98.23%. It proves efficient for high-dimensional problems but may require fine-tuning. The algorithm in[53] uses the binary Giza pyramids construction algorithm for FS, incorporating S and V shape transfer functions with the k-nearest neighbours classifier, achieving an accuracy of 98.75%. This algorithm demonstrates swift convergence and strong performance with large datasets, yet it may not be suitable for smaller datasets. For[54], the binary ant lion algorithm is employed for FS problem-solving, using S and V shape transfer functions with the k-nearest neighbours classifier, resulting in an accuracy of 96.37%. While effectively handling high dimensionality or non-linearity, it may suffer from slow convergence and potential entrapment in local optimums, requiring significant computational resources for optimal performance. The work described in[55] applies the binary salp swarm algorithm for FS, utilizing S and V shape transfer functions with the k-nearest neighbours classifier, achieving an accuracy of 95.26%. While adept at addressing problems with complex search spaces or multiple objectives, this algorithm can be sensitive to parameter choices and may demand substantial computational resources for optimal performance. The algorithm outlined in[56] utilizes the binary cuckoo search algorithm for FS problem resolution, employing the sigmoid transfer function. It incorporates the optimum-path forest classifier, achieving an accuracy of 97.33%. While effectively managing problems with multimodal search spaces or noisy objective functions, it may be sensitive to parameter choices and susceptible to local optimums. Finally, the binary equilibrium optimizer in[57] is employed for FS problem-solving, utilizing S and V shape transfer functions with the k-nearest neighbours classifier, achieving an accuracy of 97.01%. This algorithm has demonstrated effectiveness in finding global optimums, performing well with a relatively small population size. However, it may be sensitive to parameter choices and could require a larger population size for optimal performance.

On the other hand, the algorithm introduced in[58] employs the binary chaotic bat algorithm to address the FS problem, utilizing V shape transfer functions. It incorporates random forest and k-nearest neighbours classifiers, achieving an accuracy of 96.97%. This algorithm adeptly manages challenges posed by intricate search spaces or multiple objectives. The integration of chaotic dynamics enhances its search capacity, preventing entrapment in local optimums. Nonetheless, sensitivity to the choice of chaotic function and a potential necessity for a sizable population size for optimal performance are noteworthy considerations. In[59], a similar approach is taken with the utilization of the binary chaotic dragonfly algorithm, incorporating chaotic transfer functions and the k-nearest neighbours classifier, resulting in an accuracy of 96.72%. While effectively handling complex search spaces or multiple objectives, this algorithm also displays sensitivity to the chosen chaotic function. The binary chaotic vortex algorithm, detailed in[60], leverages chaotic transfer functions and the k-nearest neighbours classifier, achieving an accuracy of 97.45%. Performance relies heavily on parameter settings, such as population size and maximum iteration number, necessitating careful tuning. However, computational expenses may arise, particularly for large datasets, due to multiple fitness function evaluations. In[46], the binary chaotic black hole algorithm integrates chaotic transfer functions and the k-nearest neighbours classifier, boasting an accuracy of 98.33%. Although promising for FS, its performance is contingent on parameter settings and specific applications. The binary chaotic moth–flame optimization algorithm, outlined in[61], applies chaotic transfer functions and the k-nearest neighbours classifier, yielding an accuracy of 96.62%. While effective in handling complex search spaces or multiple objectives, sensitivity to the chaotic function, potential slow convergence, and susceptibility to local optimums are potential drawbacks. The work in[62] introduces the fractional chaotic order marine predator algorithm, utilizing the k-nearest neighbours classifier with an accuracy of 97.13%. This promising FS method incorporates fractional calculus to enhance exploration and exploitation abilities, but computational expenses and potential reliance on a large population size are considerations. The island-based genetic algorithm in[63] employs support vector machine, k-nearest neighbours, decision tree, and multilayer perceptron classifiers, achieving an accuracy of 93.51%. Combining global and local search techniques enhances its search capability, but computational expenses are a concern. The optimizer described in[64] introduces the quantum whale optimization algorithm, utilizing the k-nearest neighbours, linear discriminant classifier, support vector machine, and decision tree classifiers, achieving an accuracy of 98.75%. Quantum-inspired operators enhance its search capability, but sensitivity to parameters and potential need for a large number of iterations are noted. Lastly, the approach in[65] combines the technique for order of preference by similarity to ideal solution with the binary JAYA algorithm, incorporating time-varying transfer functions. Using the Gaussian Naïve Bayes classifier, it attains an accuracy of 98.08%. While a hybrid algorithm effectively handling multiple objectives, it may require a substantial number of iterations and pose computational expenses for large-scale problems. This survey of diverse FS algorithms highlights their unique strengths and limitations, offering a rich spectrum of choices for researchers addressing the complexities of FS in various domains.

In the realm of FS, it is essential to recognize that achieving perfection remains elusive. Despite the proposal of numerous commendable solutions and their exceptional performance, the field continually calls for enhancements. This reality aligns with the principle articulated in the No-Free-Lunch theorem[66], emphasizing that no universally superior solution exists. Therefore, the door remains open for the exploration and development of new algorithms and solutions to address the ever-evolving challenges of the FS problem. In this vein, several promising avenues for further investigation emerge, including the exploration of algorithms such as the remora optimization algorithm[67] and the dynamic Harris Hawks optimization with a mutation mechanism[68]. These avenues promise to contribute valuable insights and advancements to the ongoing quest for optimizing FS methodologies.

2.8 Conclusion

In conclusion, feature selection is a crucial step in the machine learning process that involves selecting the most relevant and informative features from the dataset. By selecting the right features, we can improve model performance, reduce overfitting, and enhance interpretability. There are various techniques available for feature selection, including filter methods, wrapper methods, and embedded methods. It is essential to carefully consider the characteristics of the dataset and the specific goals of the model when choosing a feature selection method. Overall, feature selection plays a significant role in optimizing model performance and enhancing the efficiency of machine learning algorithms.

Chapter 3

An Opposition-Based Great Wall Construction Metaheuristic Algorithm with Gaussian Mutation

3.1 Introduction

the era of big data and complex datasets, Machine Learning (ML) has emerged as a powerful tool for extracting valuable insights and making data-driven decisions[69, 70, 71, 72]. However, with the ever-increasing dimensionality of data, the curse of dimensionality has become a significant challenge in developing accurate and efficient predictive models[73]. This is where the crucial role of Feature Selection (FS) comes into play. FS, also known as attribute selection or variable selection, is the process of identifying and choosing the most relevant and informative subset of features from a vast pool of input variables[74, 44]. The primary objective is to enhance the performance of ML algorithms by eliminating irrelevant, redundant, or noisy features that might negatively impact model accuracy, increase computational costs, and/or reduce interpretability.

The importance of FS lies in its ability to not only improve predictive model performance but also enhance the efficiency and generalization of ML algorithms[75, 76, 77]. By selecting a subset of the most discriminative features, FS not only reduces the risk of overfitting but also mitigates the computational burden associated with processing large volumes of data. Moreover, in many real-world applications, interpreting the model's decision-making process is crucial to gain trust and acceptance. By selecting a concise set of meaningful features, FS facilitates model interpretability, enabling domain experts and non-technical users to comprehend the factors influencing the model's predictions. This emphasizes the significance of FS in ML. Whether it is in the realm of predictive modelling, classification, regression, or any other ML task, FS serves as a critical preprocessing step to unlock the full potential of ML algorithms. Through careful selection of relevant features, data scientists can build more accurate, efficient, and interpretable models, paving the way for actionable insights and informed decision-making.

The FS problem, known to be $\mathcal{NP}$-hard, is increasingly tackled using Metaheuristic Algorithms (MAs)[45, 78, 44] instead of exact methods due to several compelling reasons. One key factor is the exponential increase in the number of possible feature subsets with the growing dimensionality of data. Exact methods typically suffer from combinatorial explosion, making them computationally infeasible for large-scale datasets. By contrast, MAs excel at efficiently exploring complex search spaces, providing near-optimal solutions within a reasonable time frame. Their ability to strike a balance between exploration and exploitation[79, 9, 80] allows them to effectively navigate through vast feature subsets and discover promising combinations that yield improved model performance. Moreover, MAs are inherently adaptive, making them suitable for a wide range of optimization problems, including FS, without relying on domain-specific knowledge. As a result, the use of MAs has become a preferred approach in addressing the FS problem, offering researchers a practical and scalable solution to enhance the accuracy, efficiency, and interpretability of ML models.

The pivotal role of FS in the ML process is evident in the seven-step framework, playing a crucial part in refining prediction accuracy. Thus, numerous scholars have dedicated extensive efforts to this phase, as evidenced by various research works. For instance, the study referenced in[81] addresses cancer classification, employing the kernel Shapley value rooted in cooperative game theory for feature extraction from high-dimensional gene expression data. Another notable work, referenced as[82], focuses on cancer prediction and combines spider monkey optimization with cuckoo search algorithm for hybridized feature selection. Additionally, [83] and[84] contribute valuable insights into FS across diverse ML classification tasks.

In the context of our research, we have harnessed the power of a cutting-edge metaheuristic algorithm, known as the Great Wall Construction Algorithm[85], to address the $\mathcal{NP}$-hard FS problem. This algorithm has garnered considerable attention for its exceptional performance across a wide spectrum of challenges, including both constrained and unconstrained benchmark problems. To further bolster its capabilities, we have taken the initiative to augment the fundamental version of this algorithm by introducing several key enhancements. These additions are strategically designed to amplify its prowess in exploring solution spaces, exploiting promising regions, and adeptly steering clear of local optimums, all of which are critical attributes for effective problem-solving. The enhanced algorithm underwent a comprehensive evaluation by being juxtaposed with ten influential metaheuristic algorithms commonly employed in solving feature selection problems. This comparative study encompassed key metrics such as classification accuracy and fitness value. The results unequivocally demonstrate the superior performance of the proposed enhanced algorithm, surpassing the effectiveness of the other metaheuristics across these evaluative criteria. The following three points summarize the main improvements added to the Great Wall Construction Algorithm:

- We employed an efficient opposition-based learning technique[86] to enrich our approach. This technique enhanced exploration and diversification through the generation of opposite or complementary solutions, facilitated escape from local optimums by offering alternative starting points or directions in the search space, and expedited convergence, enhancing the speed of our metaheuristic algorithm.

- We incorporated Gaussian mutation[87] into our approach to bolster local search capabilities and prevent entrapment in local optimums.

- We used the step function to discretize continuous values into a binary range, as it offers a straightforward and easily implementable method.

The chapter is structured into five distinct sections, each contributing to a comprehensive understanding of our research. In Section 3.2, we delve into the fundamental concepts and methodologies underpinning the development of our solution, establishing the theoretical groundwork for our approach. Section 3.3 is dedicated to presenting our proposed solution in detail, elucidating the various steps involved and discussing their significance in tackling the FS problem. The experimental aspect is addressed in Section 3.4, where we present the results of our empirical study and conduct a comparative investigation to evaluate the performance of our solution. Finally, in Section 3.5, we conclude by summarizing our primary contributions and offering insights into potential future directions for this research.

3.2 Background

In this section, we introduce the various concepts employed in the proposed methodology for addressing the FS problem. First, in Sections 3.2.1, 3.2.2, and 3.2.3, we explain the working principles of the concepts related to MAs. Then, in Sections 3.2.4 and 3.2.5, we describe the ML algorithm and metrics used to evaluate the performance.

3.2.1 Great Wall Construction Algorithm

The Great Wall Construction Algorithm (GWCA) represents a novel metaheuristic optimizer introduced by Ziyu Guan and his colleagues[85]. Its draws inspiration from the historical competition and elimination mechanisms observed among workers during the construction of the ancient Great Wall. The GWCA optimizer incorporates these principles into its optimization strategy. Besides, the algorithm prioritizes performance-driven methodologies over metaphorical aspects, leveraging the competitive spirit of the workforce that contributed to the Great Wall's construction. With this unique approach, the GWCA algorithm aims to efficiently tackle complex optimization problems while emulating the effectiveness and resource management exhibited during the historical construction process. Table 3.1 summarizes the parameters utilized in the definition of the GWCA algorithm. In the following sections, we describe the phases of the GWCA optimizer.

3.2.1.1 Initialization

Equation 3.1 is employed to initialize the individuals in the first population, where the parameter λ governs the growth rate of the logistic map (set to 4), and the parameter α is a uniformly distributed random number within the range $[0, 1]$ (excluding the values 0.25, 0.5, 0.75, and 1).

Table 3.1: The parameters used in the GWCA.

Parameter	**Signification**
N	The population size
D	The dimensionality of the search space
LB	A D-dimensional vector representing the lower boundaries of the search space
UB	A D-dimensional vector representing the upper boundaries of the search space
$T_{\max}$	The maximum number of iterations
t	The current iteration
$X_{i,j}^{(t)}$	The component j of the individual i at iteration t
M_i	The memory of an agent i used to save its best location found so far
$X_{\mathrm{b},j}^{(t)}$	The component j of the best solution at iteration t
$X_{\mathrm{n}\langle i\rangle,j}^{(t)}$	The jth component of the nearest individual to agent i at iteration t
$f(.)$	The objective function to be minimized
$\alpha_1, \ldots, \alpha_5$	Uniformly distributed random numbers within the range $[0, 1]$
T	The force produced by the tool (thrust)
m	The weight of the rock
g	The gravitational acceleration
θ	The angle between the worker's position on the slope and the horizon (random within the range $[0, 80]$)
$\mathbb{G}(t, P, Q)$	The gamma distribution's probability density function – P controls the shape of the distribution ($P > 0$), and Q scales the distribution ($Q > 0$)
$C_{\min}$ and $C_{\max}$	Two constant numbers controlling the step size

$$X_{i,j}^{(0)} = \varphi_{i,j} \times (\mathrm{UB}_j - \mathrm{LB}_j) + \mathrm{LB}_j \tag{3.1}$$

$$\varphi_{i,j} = \begin{cases} \alpha & , \quad i = 1 \\ \lambda \varphi_{i-1,j}\left(1 - \varphi_{i-1,j}\right) & , \quad 1 < i \leq N \end{cases}$$

$$i \in \{1, \ldots, N\} \text{ and } j \in \{1, \ldots, D\}$$

3.2.1.2 Exploitation

Equation 3.2 is employed to exploit the search space during the swarming process, where the parameter k is a uniformly distributed random number sampled from a uniform distribution over the set $\{0, 1\}$, and the parameter ϵ is an infinitely small number set to 2.22E-16.

$$X_{i,j}^{(t+1)} = \alpha_1 \times \upsilon \times X_{i,j}^{(t)} + R_{i,j}^{(t)} + X_{\mathrm{b},j}^{(t)} \tag{3.2}$$

$$\upsilon = \left(\frac{T \times \mathrm{TL}}{m} - g \times \frac{H(t)}{\sin(\theta)}\right) \times C(t) \times \mathbb{G}(t, P, Q)$$

$$H(t) = 1 - \frac{t}{T_{\max}}$$

$$C(t) = \log\left((C_{\max} - C_{\min}) \times \frac{T_{\max} - t}{T_{\max}} + C_{\min}\right)$$

$$R_{i,j}^{(t)} = (-1)^k \times \alpha_2 \times \left(X_{\mathrm{b},j}^{(t)} - X_{i,j}^{(t)}\right)$$

$$\mathrm{TL} = 1 - \frac{t}{T_{\max}} + \epsilon$$

3.2.1.3 Exploration

Equation 3.3 is employed to explore the search space during the swarming process, where the parameter ϵ is an infinitely small number set to 2.22E-16.

$$X_{i,j}^{(t+1)} = X_{i,j}^{(t)} + \alpha_3 \times T_1 + \alpha_4 \times \upsilon \times \mathrm{sign}\left(T_2\right) \times T_3 \tag{3.3}$$

$$T_1 = X_{\mathrm{b},j}^{(t)} - X_{i,j}^{(t)}$$

$$T_2 = f\left(X_{\mathrm{n}\langle i\rangle}^{(t)}\right) - f\left(X_{i}^{(t)}\right)$$

$$T_3 = X_{\mathrm{n}\langle i\rangle,j}^{(t)} - X_{i,j}^{(t)}$$

$$\upsilon = m \times g \times \frac{H\left(t\right)}{\sin\left(\theta\right)} \times C\left(t\right) \times \mathbb{G}\left(t, P, Q\right)$$

$$H\left(t\right) = 1 - \frac{t}{T_{\max}} + \epsilon$$

$$C\left(t\right) = \log\left(\left(C_{\max} - C_{\min}\right) \times \frac{T_{\max} - t}{T_{\max}} + C_{\min}\right)$$

$$\mathrm{sign}\left(x\right) = \begin{cases} -1 & , \quad x < 0 \\ 0 & , \quad x = 0 \\ 1 & , \quad x > 0 \end{cases}$$

3.2.1.4 Balance between Exploitation and Exploration

Equation 3.4 is employed to bias the search towards better solutions, promoting convergence towards the optimal or near-optimal solutions in the search space, and overcome the issue of getting trapped in local optimums during the optimization process.

$$X_{i,j}^{(t+1)} = X_{i,j}^{(t)} + 2 \times \alpha_5 \times T_1 + T_2 \times \mathbb{G}\left(t, P, Q\right) \tag{3.4}$$

$$T_1 = X_{\mathrm{b},j}^{(t)} - X_{i,j}^{(t)}$$

$$T_2 = M_{i,j} - X_{i,j}^{(t)}$$

3.2.1.5 Selection

Algorithm 2 is used to determine which individuals from the current population are more likely to be chosen to appear in the next generation (i.e., eliminate the worst solutions). The worst solution are replaced with new ones generated using Equation 3.5. It is worth mentioning that the coefficients $r_1, \ldots, r_D$ are uniformly distributed random numbers within the range $[0, 1]$.

$$X = [r_1 \times T_1, \ldots, r_D \times T_D] \tag{3.5}$$

$$\begin{cases} T_1 = (\mathrm{UB}_1 - \mathrm{LB}_1) + \mathrm{LB}_1 \\ \vdots \\ T_D = (\mathrm{UB}_D - \mathrm{LB}_D) + \mathrm{LB}_D \end{cases}$$

Algorithm 2: The selection mechanism.

```
   Input: $\rho$: The percentage of individuals to be eliminated.
   Input: $P = \{X_1, \ldots, X_N\}$: The population of individuals.
   Output: $P = \{X_1, \ldots, X_N\}$: The updated population of individuals.
1  $k \leftarrow 1$;
2  while $k \leq \lceil \rho \times N \rceil$ do
3      $P \leftarrow P - \left\{ \underset{i \in \{1,\ldots,|P|\}}{\operatorname{argmax}} \{f(X_i)\} \right\}$;
4      $k \leftarrow k + 1$;
5  end
6  while $|P| < N$ do
7      Generate a candidate solution $X$ using Equation 3.5;
8      $P \leftarrow P \cup \{X\}$;
9  end
```

3.2.1.6 GWCA's Pseudocode and Time Complexity

This section provides a comprehensive overview of the GWCA, focusing on both its pseudocode representation and its time complexity. The time complexity of a function evaluation is $O(D)$, and the time complexity of the swarming behaviour is $O(T_{\max} \times N \times D)$. Since the function evaluation step is included into the swarming loops, it means that the time complexity of the GWCA is $O(n^4)$. The pseudocode depicted in Algorithm 3 describes the different steps of the GWCA.

Algorithm 3: Pseudocode of the GWCA.

```
Input: Initialize the parameters of the GWCA.
Input: $P = \{X_1, \dots, X_N\}$: The population of individuals.
Input: $M = \{M_1, \dots, M_N\}$: The memory of individuals.
Output: $X^*$: The best solution.
1  for $i \leftarrow 1$ to $N$ do
2      for $j \leftarrow 1$ to $D$ do
3          $X_{i,j}^{(0)}$ is initialized using Equation 3.1;
4          $M_{i,j} \leftarrow X_{i,j}$;
5      end
6  end
7  for $t \leftarrow 1$ to $T_{\max}$ do
8      for $i \leftarrow 1$ to $N$ do
9          Generate a random integer number $I \in \{1, 2, 3\}$;
10         if $I = 1$ then
11             for $j \leftarrow 1$ to $D$ do
12                 $X_{i,j}^{(t)}$ is updated using Equation 3.2;
13             end
14         else if $I = 2$ then
15             for $j \leftarrow 1$ to $D$ do
16                 $X_{i,j}^{(t)}$ is updated using Equation 3.3;
17             end
18         else
19             for $j \leftarrow 1$ to $D$ do
20                 $X_{i,j}^{(t)}$ is updated using Equation 3.4;
21             end
22         for $j \leftarrow 1$ to $D$ do
23             $X_{i,j}^{(t)}$ is updated using Algorithm 4;
24         end
25         $M_i$ is updated using Algorithm 5;
26     end
27     Replace undesired individuals using Algorithm 2;
28 end
29 $X^* \leftarrow \underset{i \in \{1,\dots,N\}}{\operatorname{argmin}} \left\{ f\left(X_i^{(t)}\right) \right\}$;
```

Algorithm 4: The boundary checker.

```
Input: $X_{i,j}^{(t)}$: The solution to be checked.
Input: LB: The vector of lower boundaries.
Input: UB: The vector of upper boundaries.
Output: $X_{i,j}^{(t)}$: The checked solution.
1  if $X_{i,j}^{(t)} < LB_j$ then
2      $X_{i,j}^{(t)} \leftarrow \mathrm{LB}_j$;
3  end
4  if $X_{i,j}^{(t)} > UB_j$ then
5      $X_{i,j}^{(t)} \leftarrow \mathrm{UB}_j$
6  end
```

Algorithm 5: The memory updating process.

```
Input: $X_i^{(t)}$: The current solution.
Input: $M_i$: The memory to be updated.
Output: $M_i$: The updated memory.
1 if $\left(f\left(X_i^{(t)}\right) < f(M_i)\right)$ then
2     for $j \leftarrow 1$ to $D$ do
3         $M_{i,j} \leftarrow X_{i,j}^{(t)}$;
4     end
5 end
```

3.2.2 Opposition-Based Learning

Opposition-Based Learning (OBL)[88] stands as an emerging notion within the field of MAs, drawing inspiration from the contrasting dynamics observed among different entities. The inception of the opposition concept in 2005 marked a significant milestone, garnering substantial attention from researchers over the subsequent decade. Diverse algorithms in the field of soft computing, including optimization techniques, reinforcement learning, artificial neural networks, and fuzzy systems, have embraced the principles of OBL to enhance and elevate their operational efficiency. At the core of OBL lies the foundational idea of concurrently examining the current solution and its contrasting counterpart to achieve efficient problem-solving[89]. In simpler terms, when an optimization algorithm aims to discover the best possible outcome for an objective function, the incorporation of both a candidate solution and its opposite can be proven advantageous, thereby augmenting the algorithm's overall effectiveness.Starting from January 2005, over 400 academic works have been disseminated pertaining to the concept of OBL[88]. These research contributions have found their home within various platforms including conferences, journals, and books, all situated within the domains of soft computing. Within this compilation, approximately 60% manifest as journal papers, 38% materialize as conference papers, while the remaining 2% comprise books or theses.

Definition 3.1 *Let $X = (x_1, \ldots, x_D)$ be a candidate solution in the search space, where $x_j \in (LB_j, UB_j)$ and $j \in \{1, \ldots, D\}$. The opposite candidate solution of X is denoted by $\breve{X}$ and is computed by Equation 3.6 [89].*

$$\breve{X} = LB + UB - X \tag{3.6}$$

Since the introduction of the initial OBL concept, a series of works have emerged. In this context, we delve into a straightforward yet highly efficient OBL approach, as detailed in the publication[86]. This technique serves as a cornerstone within our proposed algorithm, specifically designed to address the FS problem. In the following section, we describe the working principle of the OBL technique described in[86]. This approach employs a pair of algorithms, namely Algorithms 6 and 7, to calculate contrasting solutions. The goal is to minimize the waste of function evaluations. The choice between these algorithms depends on the diversity of the current population. When the diversity, computed using Equation 3.7, surpasses a predefined threshold, Algorithm 6 is executed. Conversely, if it falls below the threshold, Algorithm 7 is employed. On the one hand, Algorithm 6 has demonstrated its ability to accelerate the convergence speed of MAs by fully leveraging opposing information. On the other hand, Algorithm 7 has been shown to enhance the diversity of MAs by partially incorporating opposing information. Table 3.2 summarizes the parameters utilized in the definition of Algorithms 6 and 7, and Equations 3.7 to 3.15.

Table 3.2: The parameters used in Algorithms 6 and 7.

Parameter	**Signification**
N	The population size
D	The dimensionality of the search space
LB	A D-dimensional vector representing the lower boundaries of the search space
UB	A D-dimensional vector representing the upper boundaries of the search space
$X_{i,j}$	The component j of the candidate solution i
$\breve{X}_{i,j}$	The component j of the opposite candidate solution i
$\mathbb{B}(\alpha, \beta)$	The beta function – the values of α and β determine the shape of the beta function's graph ($\alpha > 0$, $\beta > 0$)
$\mathbb{N}(0, 0.5)$	The Gaussian distribution of mean 0 and standard deviation 0.5

$$\text{normDiv} = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{D}\sqrt{\frac{1}{D}\left(\frac{X_{i,j}-\bar{X}_j}{\text{UB}_j-\text{LB}_j}\right)^2} \tag{3.7}$$

$$\bar{X} = \frac{1}{N}\left(X_1 + \ldots + X_N\right)$$

$$\breve{X}_{i,j} = \mathbb{B}(\alpha,\beta) \times (\text{UB}_j - \text{LB}_j) + \text{LB}_j \tag{3.8}$$

$$i \in \{1,\ldots,N\} \text{ and } j \in \{1,\ldots,D\}$$

$$\mathbb{B}(\alpha,\beta) = \int_0^1 t^{\alpha-1}\left(1-t\right)^{\beta-1} dt$$

$$\alpha = \begin{cases} \text{spread} \times \text{peak} & , \text{ mode} < 0.5 \\ \text{spread} & , \text{ otherwise} \end{cases} \tag{3.9}$$

$$\beta = \begin{cases} \text{spread} & , \text{ mode} < 0.5 \\ \text{spread} \times \text{peak} & , \text{ otherwise} \end{cases} \tag{3.10}$$

$$\text{spread} = \left(\frac{1}{\sqrt{\text{normDiv}}}\right)^{1+\mathbb{N}(0,0.5)} \tag{3.11}$$

$$\text{peak} = \begin{cases} \frac{(\text{spread}-2)\times\text{mode}+1}{\text{spread}\times(1-\text{mode})} & , \quad \text{mode} < 0.5 \\ \frac{2-\text{spread}}{\text{spread}} + \frac{\text{spread}-1}{\text{spread}\times\text{mode}} & , \quad \text{otherwise} \end{cases} \tag{3.12}$$

$$\text{mode} = \frac{\text{UB}_j - X_{i,j}}{\text{UB}_j - \text{LB}_j} \tag{3.13}$$

$$\text{spread} = 0.1 \times \sqrt{\text{normDiv}} + 0.9 \tag{3.14}$$

$$\text{mode} = \frac{X_{i,j} - \text{LB}_j}{\text{UB}_j - \text{LB}_j} \tag{3.15}$$

3.2.3 Gaussian Mutation

The Gaussian Mutation (GM)[87] operator introduces random perturbations to the current solution by sampling from a Gaussian distribution. The GM is commonly utilized to make slight adjustments to the values of the solution variables. Algorithm 9 depicts the pseudocode of the GM operator.

Two parameters govern the extent of mutation: the mutation rate (γ) and the mutation strength (δ). The former determines the probability of mutation for each solution variable (i.e., increasing the mutation rate raises the chances of mutation taking place); while the latter determines the magnitude of perturbations applied to the solution variables (i.e., higher mutation strength results in more significant variations across the search space). The normal distribution is referred to as $\mathbb{N}(\mu, \sigma)$, where μ and σ are its mean and its standard deviation, respectively.

3.2.4 K-Nearest Neighbors

The K-Nearest Neighbors (KNN)[90] is a simple yet effective ML algorithm used for classification and regression tasks. The working principle of KNN revolves around the idea of proximity-based prediction. Given a new data point, the algorithm identifies its k closest neighbours within the training dataset based on a chosen distance metric, often Euclidean distance. The value of k, the number of neighbours, is a crucial parameter that influences the algorithm's performance and generalization. Smaller k values result in more flexible, potentially noisy predictions, while larger k values lead to smoother but potentially oversimplified predictions. KNN is easy to understand and implement, making it a valuable tool for various tasks, but its efficiency can decrease with larger datasets due to the need to calculate distances for each query point.

Algorithm 6: The first OBL technique.

```
   Input: $P = \{X_1, \dots, X_N\}$: The population of individuals.
   Input: LB: Lower boundaries of the search space.
   Input: UB: Upper boundaries of the search space.
   Input: $N$: The population size.
   Input: $D$: The dimensionality of the search space.
   Input: $f(.)$: The objective function to be minimized.
   Output: $P = \{X_1, \dots, X_N\}$: The population of individuals.
1  Define a zero matrix $A = (a_{ij})_{1 \le i \le N, 1 \le j \le D}$;
2  for $i \leftarrow 1$ to $N$ do
3      for $j \leftarrow 1$ to $D$ do
4          $a_{ij} \leftarrow X_{i,j}$;
5      end
6  end
7  Compute the covariance matrix $C$ of $A$;
8  Compute the matrix $V$ whose columns are the eigenvectors of $C$;
9  $U \leftarrow \emptyset$;
10 Compute normDiv using Equation 3.7;
11 for $i \leftarrow 1$ to $N$ do
12     for $j \leftarrow 1$ to $D$ do
13         if $rand(0,1) \le 0.5$ then
14             Compute mode using Equation 3.13;
15             Compute spread using Equation 3.11;
16         end
17         else
18             Compute mode using Equation 3.15;
19             Compute spread using Equation 3.14;
20         end
21         Compute peak using Equation 3.12;
22         Compute $\alpha$ using Equation 3.9;
23         Compute $\beta$ using Equation 3.10;
24         Compute $\breve{X}_{i,j}$ using Equation 3.8;
25     end
26     $X'_i \leftarrow \left(V^T \times X_i^T\right)^T$;
27     $\breve{X}'_i \leftarrow \left(V^T \times \breve{X}_i^T\right)^T$;
28     Compute $U_1$ using Algorithm 8 ($X'_i$, $\breve{X}'_i$, $C_r = 0.1$);
29     Compute $U_2$ using Algorithm 8 ($X'_i$, $\breve{X}'_i$, $C_r = 0.9$);
30     $\left(V \times U_1^T\right)^T$ is updated using Algorithm 4;
31     $\left(V \times U_2^T\right)^T$ is updated using Algorithm 4;
32     $U \leftarrow U \cup \left\{\left(V \times U_1^T\right)^T, \left(V \times U_2^T\right)^T\right\}$;
33 end
34 $U \leftarrow U \cup P$;
35 $P \leftarrow \emptyset$;
36 while $|P| < N$ do
37     $B \leftarrow \left\{\underset{i \in \{1,\dots,|U|\}}{\text{argmin}} \{f(U_i)\}\right\}$;
38     $U \leftarrow U - \{B\}$;
39     $P \leftarrow P \cup \{B\}$;
40 end
```

Algorithm 7: The second OBL technique..

```
Input: $P = \{X_1, \dots, X_N\}$: The population of individuals.
Input: LB: Lower boundaries of the search space.
Input: UB: Upper boundaries of the search space.
Input: $N$: The population size.
Input: $D$: The dimensionality of the search space.
Input: $f(.)$: The objective function to be minimized.
Output: $P = \{X_1, \dots, X_N\}$: The population of individuals.
Define a zero matrix $A = (a_{ij})_{1 \le i \le N, 1 \le j \le D}$;
for $i \leftarrow 1$ to $N$ do
    for $j \leftarrow 1$ to $D$ do
        $a_{ij} \leftarrow X_{i,j}$;
    end
end
Compute the covariance matrix $C$ of $A$;
Compute the matrix $V$ whose columns are the eigenvectors of $C$;
Compute the median $m$ of the series: $f(X_1), \dots, f(X_N)$;
$U \leftarrow \emptyset$;
Compute normDiv using Equation 3.7;
for $i \leftarrow$ to $N$ do
    if $f(X_i) \ge m$ then
        for $j \leftarrow 1$ to $D$ do
            if $rand(0,1) \le 0.5$ then
                Compute mode using Equation 3.13;
                Compute spread using Equation 3.11;
            end
            else
                Compute mode using Equation 3.15;
                Compute spread using Equation 3.14;
            end
            Compute peak using Equation 3.12;
            Compute $\alpha$ using Equation 3.9;
            Compute $\beta$ using Equation 3.10;
            Compute $\breve{X}_{i,j}$ using Equation 3.8;
        end
        $X'_i \leftarrow \left(V^T \times X_i^T\right)^T$;
        $\breve{X}'_i \leftarrow \left(V^T \times \breve{X}_i^T\right)^T$;
        Compute $U_1$ using Algorithm 8 ($X'_i$, $\breve{X}'_i$, $C_r = 0.1$);
        Compute $U_2$ using Algorithm 8 ($X'_i$, $\breve{X}'_i$, $C_r = 0.9$);
        $U_1 \leftarrow \left(V \times U_1^T\right)^T$;
        $U_2 \leftarrow \left(V \times U_2^T\right)^T$;
        $U_1$ is updated using Algorithm 4;
        $U_2$ is updated using Algorithm 4;
        $U \leftarrow U \cup \left\{\text{argmin}\{f(U_1), f(U_2), f(X_i)\}\right\}$;
    end
    else
        $U \leftarrow U \cup \{X_i\}$;
    end
end
$P \leftarrow U$;
```

Algorithm 8: The multiple exponential recombination algorithm.

```
Input: $X_1$: The first parent solution.
Input: $X_2$: The second parent solution.
Input: $D$: The dimensionality of the search space.
Input: $C_r$: Mutation probability.
Input: $T$: Length of exchanged segments ($T = 2$).
Output: $X_3$: The offspring solution.
$E_m \leftarrow T \times C_r$;
$E_s \leftarrow T \times (1 - C_r)$;
Generate a random integer number $n \in \{1, \dots, D\}$;
$k \leftarrow 1$;
flag $\leftarrow 1$;
while $k \leq D$ do
    if $flag = 1$ then
        while $k \leq D$ and $rand(0,1) \leq \frac{E_m}{E_m+1}$ do
            $j \leftarrow 0$;
            if $n \leq D$ then
                $j \leftarrow n$;
            end
            else
                $j \leftarrow n - D$;
            end
            $X_{3,j} \leftarrow X_{2,j}$;
            $k \leftarrow k + 1$;
            $n \leftarrow n + 1$;
        end
        flag $\leftarrow 0$;
    end
    else
        while $k \leq D$ and $rand(0,1) \leq \frac{E_s}{E_s+1}$ do
            $j \leftarrow 0$;
            if $n \leq D$ then
                $j \leftarrow n$;
            end
            else
                $j \leftarrow n - D$;
            end
            $X_{3,j} \leftarrow X_{1,j}$;
            $k \leftarrow k + 1$;
            $n \leftarrow n + 1$;
        end
        flag $\leftarrow 1$;
    end
end
```

Algorithm 9: The Gaussian mutation process.

```
Input: $X_i$: The solution to be mutated.
Input: $\gamma$: The mutation rate.
Input: $\delta$: The mutation strength.
Input: $\mu$: The Gaussian distribution's mean.
Input: $\sigma$: The Gaussian distribution's standard deviation.
Output: $X_i$: The mutated solution.
1 for $j \leftarrow 1$ to $D$ do
2     if $(rand(0,1) < \gamma)$ then
3         $X_{i,j} \leftarrow X_{i,j} + \mathbb{N}(\mu, \sigma) \times \delta$;
4         $X_{i,j}$ is updated using Algorithm 4;
5     end
6 end
```

3.2.5 Evaluation Metrics

In classification tasks in ML, various evaluation metrics are used to assess the performance of model's predictions[91]. These metrics provide insights into how well the model is classifying different classes and help quantify its strengths and weaknesses. These metrics provide a comprehensive view of a classifier's performance from different angles. The choice of metric depends on the specific characteristics of the problem, the class distribution, and the goals of the application. It is often recommended to consider multiple metrics to get a well-rounded assessment of a model's performance. Some common evaluation metrics for classification tasks are given in the following sections.

3.2.5.1 Confusion Matrix

A confusion matrix provides a detailed breakdown of True Positives (TP) – the model identifies a positive case correctly, True Negatives (TN) – the model correctly identifies a negative case, False Positives (FP) – the model predicts a positive outcome when it should have predicted a negative outcome, and False Negatives (FN) – the model fails to predict a positive outcome when it should have, which are essential for calculating the subsequent metrics.

3.2.5.2 Accuracy

Accuracy is the ratio of correctly predicted instances to the total number of instances in the dataset. While easy to understand, accuracy might not be suitable for imbalanced datasets where one class dominates the others. Its mathematical expression is given by Equation 3.16.

$$\text{accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{3.16}$$

3.2.5.3 Precision

Precision measures the ratio of correctly predicted positive observations to the total predicted positives. It focuses on the correctness of positive predictions and helps in scenarios where false positives are costly. Its mathematical representation is defined by Equation 3.17.

$$\text{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{3.17}$$

3.2.5.4 Recall

Recall calculates the ratio of correctly predicted positive observations to the actual positives. It is useful when the emphasis is on minimizing false negatives. Equation 3.18 provides its mathematical formulation.

$$\text{recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3.18}$$

3.2.5.5 F1-Score

The F1-score is the harmonic mean of precision and recall. It provides a balance between precision and recall, which can be valuable when you need to consider both false positives and false negatives. Its mathematical formula is expressed in Equation 3.19.

$$\text{F1-score} = \frac{2 \times (\text{precision} \times \text{recall})}{\text{precision} + \text{recall}} \tag{3.19}$$

3.2.5.6 Classification Error Rate

The classification error rate in ML is a fundamental performance metric that quantifies the proportion of incorrectly classified instances in a dataset, comparing the number of misclassified data points to the total number of instances. It serves as a straightforward indicator of a classification model's accuracy, with lower error rates indicating better performance and higher rates reflecting lower accuracy. However, the classification error rate has limitations, such as not distinguishing between different types of errors (e.g., false positives and false negatives) and not accounting for class imbalances. As a result, it is often used in combination with other metrics to provide a more comprehensive assessment of a model's classification capabilities. Equation 3.20 gives its mathematical expression.

$$\text{CER} = \frac{\text{FP} + \text{FN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{3.20}$$

3.3 Proposed Algorithm

In this section, we present and elucidate the algorithm that embodies our proposed methodology for addressing the FS problem. Algorithm 10 provides a comprehensive overview of the distinct steps involved in its formulation. This algorithm serves as a vital roadmap for understanding the intricacies of our method and its practical implementation. Through the following discussion, we aim to provide a clear and detailed account of our approach, allowing for a deeper insight into the methodology's inner workings.

In our algorithm, we have employed the transfer function defined by Equation 3.21 to facilitate the mapping of candidate solutions from a continuous space to a binary space. This transfer function is called the step transfer function, and it plays a pivotal role in transforming the real-valued outputs into binary decisions, allowing us to effectively navigate the discrete nature of the FS problem and make meaningful decisions based on the continuous input data.

$$Y_{i,j}^{(t)} = \begin{cases} 0 & , \text{ if } X_{i,j}^{(t)} \leq 0.5 \\ 1 & , \text{ otherwise} \end{cases} \tag{3.21}$$

The various stages of the proposed algorithm can be elucidated as follows:

- Initially, the algorithm commences by initializing and inputting the values of controlling parameters, which are detailed in Table 3.4.
- Lines 1 to 6 of the algorithm involve the initialization of the initial population of candidate solutions through the utilization of chaotic maps. This approach aims to promote diversity within the population, facilitating exploration across a broad spectrum of values and potentially covering diverse regions within the solution space.
- Between lines 7 and 37, the algorithm carries out the swarming process in an interactive manner. The cessation of this process can be determined by various stopping criteria, such as a predefined maximum number of generations, a set maximum for function evaluations, or a threshold for objective function values, among other possibilities.
- Within the algorithmic framework, specifically in lines 8 to 11, the execution of either Algorithm 6 or 7 is determined based on the population diversity's value. Algorithm 6 is designed to expedite the convergence speed of the proposed algorithm by fully exploiting opposing information, while Algorithm 7 aims to amplify the diversity of the algorithm by selectively incorporating opposing information. Subsequently, in the span of lines 12 to 34, the swarming behavior of the GWCA

is considered, orchestrating movement within the search space. It is worth pointing out that the transition between the preceding phases is conducted randomly, contributing an element of stochasticity to the algorithmic process.

- In line 35, Gaussian mutation is executed to enhance the diversity of solutions and avoid getting trapped in local optimums.
- It is worth highlighting that lines 10, 30, 33, and 36 are used to save the best solution encountered by the various agents during the swarming process. This process plays a crucial role in guiding the algorithm toward better solutions over successive iterations.
- Finally, at line 38, the best solution found so far is returned, representing the set of selected features.

We scrutinize the time complexity of the proposed algorithm (Algorithm 10), observing that Algorithm 2 has a time complexity of $O(n)$, Algorithm 4 has a time complexity of $O(1)$, Algorithm 5 has a time complexity of $O(n)$, Algorithm 9 has a time complexity of $O(n)$, and Algorithm 11 has a time complexity of $O(n^4)$. Based on the elementary time complexities discussed earlier, we conclude that the time complexity of the improved version of the GWCA is $O(n^5)$.

3.4 Experimental Study and Discussion

Within this section, our focus centers on the rigorous evaluation of the proposed algorithm's efficacy in addressing the FS problem. Section 3.4.1 lays the foundation by providing a comprehensive overview of both the datasets employed in our comparative study and the parameter settings configured for optimal performance of our proposed optimizer. Subsequently, Section 3.4.2 meticulously delineates the diverse algorithms included in the comparative study, shedding light on their respective parameter configurations. The culmination of this evaluation is encapsulated in Section 3.4.3, where a detailed presentation of the comparative study unfolds. This section systematically delves into the selected criteria, offering a nuanced exploration of the obtained numerical results.

3.4.1 Used Datasets and Parameters Setting

Table 3.3 provides a comprehensive overview of the key characteristics of the 22 datasets employed in our comparative study. Access to the datasets can be obtained through the link `https://archive.ics.uci.edu/datasets`. The datasets are categorized into three groups – small, medium, and large – based on the number of features, with datasets

Algorithm 10: Pseudocode of the proposed algorithm.

```
   Input: $P = \{X_1, \dots, X_N\}$: The population of individuals.
   Input: $M = \{M_1, \dots, M_N\}$: The memory of individuals.
   Input: LB: Lower boundaries of the search space.
   Input: UB: Upper boundaries of the search space.
   Input: $N$: The population size.
   Input: $D$: The dimensionality of the search space.
   Input: JR: The jumping rate.
   Input: Initialize the parameters of the GWCA.
   Output: $X^*$: The best solution.
 1 for $i \leftarrow 1$ to $N$ do
 2     for $j \leftarrow 1$ to $D$ do
 3         $X_{i,j}^{(0)}$ is initialized using Equation 3.1;
 4         $M_{i,j} \leftarrow X_{i,j}$;
 5     end
 6 end
 7 while Termination Condition is not Satisfied do
 8     if $rand(0,1) \leq JR$ then
 9         Update the population $P$ using Algorithm 11;
10         Update individuals' memory using Algorithm 5;
11     end
12     else
13         for $i \leftarrow 1$ to $N$ do
14             Generate a random integer number $I \in \{1, 2, 3\}$;
15             if $I = 1$ then
16                 for $j \leftarrow 1$ to $D$ do
17                     $X_{i,j}^{(t)}$ is updated using Equation 3.2;
18                 end
19             else if $I = 2$ then
20                 for $j \leftarrow 1$ to $D$ do
21                     $X_{i,j}^{(t)}$ is updated using Equation 3.3;
22                 end
23             else
24                 for $j \leftarrow 1$ to $D$ do
25                     $X_{i,j}^{(t)}$ is updated using Equation 3.4;
26                 end
27             for $j \leftarrow 1$ to $D$ do
28                 $X_{i,j}^{(t)}$ is updated using Algorithm 4;
29             end
30             $M_i$ is updated using Algorithm 5;
31         end
32         Replace undesired individuals using Algorithm 2;
33         Update individuals' memory using Algorithm 5;
34     end
35     Update the population $P$ using Algorithm 9;
36     Update individuals' memory using Algorithm 5;
37 end
38 $X^* \leftarrow \underset{i \in \{1,\dots,N\}}{\operatorname{argmin}} \left\{ f\left(X_i^{(t)}\right) \right\}$;
```

Algorithm 11: The opposition-based learning.

```
Input: $P = \{X_1, \dots, X_N\}$: The population of individuals.
Input: DT: The diversity threshold.
Output: $P = \{X_1, \dots, X_N\}$: The updated population of individuals.
1 Compute the population's diversity normDiv using Equation 3.7;
2 if $normDiv > DT$ then
3     Update the individuals within $P$ using Algorithm 6;
4 end
5 else
6     Update the individuals within $P$ using Algorithm 7;
7 end
```

having fewer than 20 features classified as small, those with 21 to 100 features as medium, and datasets with more than 100 features categorized as large. To evaluate the impact of selected feature subsets, each dataset underwent division into training, testing, and validation sets using the cross-validation method. Subsequently, the KNN classifier was applied to calculate the objective function as defined by Equation 2.1 (the number of neighbours to use is 5).

Table 3.3: The description of datasets used in the comparative study.

ID	Name	Number of features	Number of instances	Number of classes
		Small datasets		
d_1	Tic-Tac-Toe Endgame	9	958	2
d_2	Breast Cancer Wisconsin (Original)	10	699	2
d_3	Statlog (Heart)	13	270	2
d_4	Wine	13	178	3
d_5	Congressional Voting Records	16	435	2
d_6	Zoo	16	101	7
d_7	Lymphography	18	148	4
d_8	Hepatitis	19	155	2
d_9	German Credit Dataset Analysis	20	1000	2
		Medium datasets		
d_{10}	Waveform	21	5000	3
d_{11}	Breast Cancer Wisconsin (Diagnostic)	30	569	2
d_{12}	Ionosphere	34	351	2
d_{13}	Dermatology	34	366	6
d_{14}	Soybean (Small)	35	47	4
d_{15}	Lung Cancer	56	32	3
d_{16}	Connectionist Bench (Sonar, Mines vs. Rocks)	60	208	2
d_{17}	Hill-Valley	100	1212	2
		Large datasets		
d_{18}	Musk Version 1	166	476	2
d_{19}	Semeion Handwritten Digit	265	1593	2
d_{20}	Malware Executable Detection	531	373	2
d_{21}	Parkinson's Disease Classification	754	756	2
d_{22}	CNAE-9	856	1080	3

In Table 3.4, a comprehensive overview of the parameter settings for the various variables employed in our proposed algorithm dedicated to addressing the FS problem is presented.

3.4.2 Benchmark Algorithms

In evaluating the efficacy of the suggested algorithm, a comprehensive performance analysis was conducted through a comparative study with ten prominent state-of-the-art methodologies. Seven of the algorithms are novel methods introduced between 2020 and

Table 3.4: The parameters used in the proposed algorithm.

Parameter	**Value**
N	30
D	The number of features present in the considered dataset.
LB	**0**
UB	**1**
$T_{\max}$	100
T	8.3
m	3
g	9.8
P	9
Q	6
$C_{\min}$	e^2
$C_{\max}$	e^3
ρ	0.25
JR	0.05
DT	10^{-6}
α	Random in the range $[0, 1]$
γ	0.05
δ	1
μ	0
σ	0.5

2023, while the remaining three are classical approaches, including particle swarm optimization, genetic algorithms, and differential evolution. The selected algorithms were scrutinized in depth, and their respective parameter configurations have been succinctly outlined in Table 3.5 for clarity and reference. It is worth pointing out that these parameters have been extracted from the original published papers.

1. Binary Arithmetic Optimization Algorithm (BAOA)[92].
2. Binary Sand Cat Swarm Optimization algorithm (BSCSO)[93].
3. Improved Bald Eagle Search algorithm (IBES)[94].
4. Chaotic Binary Reptile Search Algorithm (CBRSA)[95].
5. Chaotic Vortex Search Algorithm (CVSA)[60] .
6. Chaotic Gaining Sharing Knowledge-based optimization algorithm (CBi-GSK)[96].
7. Chaotic Atom Search Optimization (CASO)[97].
8. Particle Swarm Optimization (PSO)[98].
9. Differential Evolution (DE)[99].
10. Genetic Algorithm (GA)[100].

Table 3.5: The parameters' values of the algorithms used for the comparative study.

Parameter	**Value**
BAOA	
Min_{MOA}	0.2
Min_{MOA}	1
μ	0.49
α	5
BSCSO	
r_G	$[2, 0]$
R	$[-2r_G, 2r_G]$
IBES	
a	10
R	1.5
CBRSA	
α	0.1
β	0.005
CVSA	
μ_0	0.5
CBi-GSK	
ρ	0.1
K	10
$N_p(\leq 20)$	50
$N_p(\geq 20)$	100
CASO	
α	50
β	0.2
PSO	
c_1	2
c_2	2
w	$[0.2, 0.9]$
DE	
F	0.7
Cr	0.8
GA	
P_c	0.7
P_m	0.1

3.4.3 Numerical Results and Discussion

To assess and compare the performance of the various algorithms employed in the comparative study, we utilized a set of evaluation metrics. These metrics were chosen to provide a comprehensive analysis of algorithmic effectiveness and efficiency, enabling a thorough examination of their performance across different criteria.

1. Average of Classification Accuracy (ACA): It furnishes the average of accuracy values calculated through Equation 3.16 over the specified number of runs.
2. Average of Fitness Values (AFV): It presents the mean of fitness values derived from Equation 2.1 across the designated number of runs.
3. Minimum of Fitness Values (MiFV): It gives the minimum of fitness values calculated from Equation 2.1 across the designated number of runs.
4. Maximum of Fitness Values (MaFV): It provides the maximums of fitness values computed from Equation 2.1 across the designated number of runs.
5. Average of Selected Features (ASF): It offers the average number of selected features over the specified runs.
6. Average of Completion Time (ACT): It provides the mean of completion times over the designated number of runs. The time is given in seconds.

To evaluate the impact of reducing the number of features on the performance of the preceding metrics, we additionally calculated various average values when considering the inclusion of all available features. The obtained numerical results are summarized in Table 3.6. Furthermore, Table 3.7 provides a comprehensive summary of the values for various metrics achieved through the proposed algorithm.

Tables 3.10, 3.11, 3.12, 3.13, 3.14, and 3.15 showcase diverse metric values derived from the algorithms under consideration for the comparative study. Each table serves as input for the Friedman and the Wilcoxon signed ranks tests, facilitating the examination of subtle differences among the algorithms concerning the specified evaluation criteria. It is worth noting that the best values for each metric are presented in bold font. The initial observation reveals that the accuracy values achieved by the proposed algorithm surpass those attained when utilizing all features, indicating a substantial positive impact on performance due to the reduction in the number of features. For each table, we have considered small, medium, and large datasets separately to perform the Friedman and Kruskal-Wallis tests and compute the mean ranks. First, the Friedman test is a non-parametric statistical test used to detect differences in treatments across multiple related groups. It is often employed when the data violate the assumptions of normal distribution

Table 3.6: The values of various metrics when considering all features.

ID	ACA	AFV	MiFV	MaFV	ASF	ACT
d_1	0.8211	0.1872	0.1872	0.1872	9.0000	0.1369
d_2	0.5362	0.4691	0.4691	0.4691	10.0000	0.0095
d_3	0.6296	0.3767	0.3767	0.3767	13.0000	0.0208
d_4	0.6471	0.3594	0.3594	0.3594	13.0000	0.0068
d_5	0.9302	0.0791	0.0791	0.0791	16.0000	0.0065
d_6	0.9000	0.1090	0.1090	0.1090	16.0000	0.0109
d_7	0.5000	0.5050	0.5050	0.5050	18.0000	0.0065
d_8	0.6000	0.4060	0.4060	0.4060	19.0000	0.0065
d_9	0.6300	0.3763	0.3763	0.3763	20.0000	0.0073
d_{10}	0.8260	0.1823	0.1823	0.1823	21.0000	0.0176
d_{11}	0.9821	0.0277	0.0277	0.0277	30.0000	0.0067
d_{12}	0.9143	0.0949	0.0949	0.0949	34.0000	0.0068
d_{13}	0.8889	0.1200	0.1200	0.1200	34.0000	0.0067
d_{14}	1.0000	0.0100	0.0100	0.0100	35.0000	0.0065
d_{15}	0.6667	0.3400	0.3400	0.3400	56.0000	0.0063
d_{16}	0.8500	0.1585	0.1585	0.1585	60.0000	0.0069
d_{17}	0.5702	0.4355	0.4355	0.4355	100.0000	0.0108
d_{18}	0.8511	0.1574	0.1574	0.1574	166.0000	0.0076
d_{19}	0.9811	0.0287	0.0287	0.0287	265.0000	0.0253
d_{20}	0.9459	0.0635	0.0635	0.0635	531.0000	0.0104
d_{21}	0.7600	0.2476	0.2476	0.2476	754.0000	0.0216
d_{22}	0.9352	0.0742	0.0742	0.0742	856.0000	0.0367

Table 3.7: The values of various metrics obtained by the proposed algorithm.

ID	ACA	AFV	MiFV	MaFV	ASF	ACT
d_1	0.8842	0.1202	0.1202	0.1202	5.0000	28.7156
d_2	0.9913	0.0122	0.0060	0.0163	3.6000	25.1408
d_3	0.9185	0.0842	0.0764	0.1131	4.6000	23.3756
d_4	1.0000	0.0015	0.0015	0.0015	2.0000	22.6313
d_5	1.0000	0.0019	0.0019	0.0019	3.0000	24.1523
d_6	0.9600	0.0421	0.0025	0.1015	4.0000	22.7894
d_7	1.0000	0.0017	0.0017	0.0017	3.0000	22.5171
d_8	1.0000	0.0005	0.0005	0.0005	1.0000	22.6201
d_9	0.8560	0.1457	0.1327	0.1515	6.2000	27.0323
d_{10}	0.8584	0.1456	0.1404	0.1537	11.4000	56.0294
d_{11}	1.0000	0.0007	0.0007	0.0007	2.0000	23.4479
d_{12}	1.0000	0.0006	0.0006	0.0009	2.2000	22.3402
d_{13}	1.0000	0.0012	0.0012	0.0012	4.0000	22.0240
d_{14}	1.0000	0.0003	0.0003	0.0003	1.0000	21.5273
d_{15}	1.0000	0.0004	0.0004	0.0004	2.0000	20.7130
d_{16}	1.0000	0.0007	0.0007	0.0008	4.2000	21.7060
d_{17}	0.7256	0.2724	0.2545	0.2951	7.4000	29.1522
d_{18}	1.0000	0.0004	0.0004	0.0004	6.6000	24.5433
d_{19}	1.0000	0.0004	0.0002	0.0006	9.8000	58.7090
d_{20}	1.0000	0.0000	0.0000	0.0000	1.2000	29.0329
d_{21}	0.8640	0.1347	0.1189	0.1717	7.0000	53.4145
d_{22}	0.9648	0.0362	0.0192	0.0468	115.0000	89.7991

or when the data are measured on an ordinal scale. Second, the Kruskal-Wallis test is a non-parametric statistical test used to determine whether there are any statistically significant differences between the medians of three or more independent (unrelated) groups. It is an extension of the Wilcoxon rank-sum test (Mann-Whitney U test) for two groups to multiple groups. We consider the null hypothesis (H_0), representing the statement of no effect or no difference, and the alternative hypothesis (H_1), representing the statement that contradicts the null hypothesis (i.e., suggesting the presence of an effect or difference). The significance level, denoted as α, is the probability of rejecting the null hypothesis when it is actually true. In our study, α is set to 0.05. Tables 3.8 and 3.9 summarize the p-values associated with the Friedman and Kruskal-Wallis tests, respectively, indicating the likelihood of obtaining the observed differences among the groups due to random chance. In other words, if the p-value is less than the chosen significance level (i.e., 0.05), the null hypothesis is rejected. From Table 3.8, it is observed that all the p-values are less than 0.05, which suggests to reject the null hypothesis. From Table 3.9, it is observed that all the p-values are less than 0.05, which suggests to reject the null hypothesis, except for large datasets suggesting to retain the null hypothesis. On the other side, mean ranks refer to the average ranks assigned to each treatment or group across different levels of the independent variable: Mean Rank 1 and Mean Rank 2 are computed using the Friedman and Kruskal-Wallis tests, respectively. They provide a summary measure of the average performance or rank order of each treatment under varying conditions. Higher mean ranks, signifying smaller values, indicate superior performance or a higher position in the rank order. As observed in Tables 3.10, 3.11, 3.12, and 3.13, BGWCA consistently secures the first place, reflecting the best values in terms of accuracy and fitness, as computed using Equations 3.16 and 2.1. However, according to Table 3.15, BGWCA attains medium ranks in the majority of cases (i.e., either the fourth or the sixth place out of the 11 algorithms). This behavior arises from the conflicting relationship between optimality and computing time.

Table 3.8: Summary of the Friedman test results.

	ACA	**AFV**	**MiFV**	**MaFV**	**ASF**	**ACT**
Small datasets	7.4397e-10	6.2937e-10	7.8794e-09	7.8722e-10	3.4652e-11	8.4144e-15
Medium datasets	1.4949e-09	6.0471e-10	4.7091e-07	1.9101e-09	5.4992e-11	1.3981e-12
Large datasets	0.0029	0.0019	0.0083	7.3662e-04	2.1260e-06	7.2312e-07

Table 3.9: Summary of the Kruskal-Wallis test results.

	ACA	**AFV**	**MiFV**	**MaFV**	**ASF**	**ACT**
Small datasets	3.2282e-09	1.6740e-09	0.0012	4.3553e-10	9.7190e-11	7.2472e-16
Medium datasets	1.2725e-04	3.2282e-05	0.0056	1.7810e-06	1.6376e-08	2.4180e-11
Large datasets	0.1650	0.0974	0.6199	0.0478	6.9207e-04	1.9551e-05

Figures 3.1 and 3.2 represent box-and-whisker plots for small, medium and large datasets for all the optimizers. The box-and-whisker plots shown in Figure 3.1 reveal dis-

Table 3.10: The ACA values for all algorithms.

ID	BGWCA	BAOA	BSCSO	IBES	CBRSA	CVSA	DE	CASO	BPSO	CBi-GSK	GA	ALL
						Small datasets						
d_1	**0.8842**	0.7095	0.3979	0.7474	0.8084	0.6842	0.6779	0.7958	0.7495	0.8632	0.7368	0.8211
d_2	0.9913	0.9594	0.5507	0.5362	0.7942	0.8203	0.7623	0.9884	0.8319	**1.0000**	0.7623	0.5362
d_3	0.9185	0.8444	0.5778	0.7630	0.5630	0.7111	0.6667	0.8889	0.8074	**0.9630**	0.6593	0.6296
d_4	**1.0000**	0.8471	0.3412	0.6235	0.7765	0.8941	0.7882	0.9294	0.9059	**1.0000**	0.8000	0.6471
d_5	**1.0000**	0.9628	0.5395	0.7070	0.9442	0.8744	0.9395	0.9907	0.9953	0.9767	0.9302	0.9302
d_6	0.9600	0.8600	0.3600	0.5200	0.8000	0.8600	0.8600	0.9800	**1.0000**	**1.0000**	0.9800	0.9000
d_7	**1.0000**	0.7143	0.6286	0.5714	0.7857	0.6143	0.8286	0.9286	0.6286	0.9714	0.7143	0.5000
d_8	**1.0000**	0.9200	0.5600	0.4000	0.6667	0.7733	0.8000	0.7600	0.7467	0.9733	0.7333	0.6000
d_9	**0.8560**	0.7200	0.3920	0.6940	0.6600	0.6520	0.6360	0.8220	0.6540	0.8420	0.7620	0.6300
Mean Ranks 1	**1.7222**	5.3889	10.3889	9.0000	7.3333	7.4444	7.3889	3.5000	5.1111	1.8889	6.8333	
	1	5	11	10	7	9	8	3	4	2	6	
Mean Ranks 2	**16.2222**	43.1667	92.6111	80.0000	57.9444	56.7778	55.1111	30.5000	46.7778	17.1667	53.7222	
	1	4	11	10	9	8	7	3	5	2	6	
						Medium datasets						
d_{10}	**0.8584**	0.7488	0.2316	0.6168	0.8064	0.7320	0.7832	0.8152	0.8240	0.8416	0.7680	0.8260
d_{11}	**1.0000**	0.9321	0.7929	0.6679	0.9250	0.8643	0.9107	0.9536	0.9143	0.9893	0.8500	0.9821
d_{12}	**1.0000**	0.9371	0.6914	0.8914	0.8743	0.8914	0.8229	0.9429	0.8971	0.9829	0.8571	0.9143
d_{13}	**1.0000**	0.8944	0.4444	0.7889	0.8444	0.8278	0.9444	0.9833	0.9500	**1.0000**	0.8889	0.8889
d_{14}	**1.0000**	**1.0000**	0.2500	0.9000	**1.0000**	0.9000	0.9000	**1.0000**	0.9500	**1.0000**	0.8500	**1.0000**
d_{15}	**1.0000**	0.8000	0.4000	0.6000	0.9333	0.7333	0.4667	0.8000	0.8667	**1.0000**	0.4000	0.6667
d_{16}	**1.0000**	0.8900	0.7500	0.6500	0.7600	0.7800	0.8900	0.8900	0.8900	0.9800	0.7700	0.8500
d_{17}	**0.7256**	0.5421	0.4479	0.5074	0.5355	0.5554	0.4314	0.5190	0.6215	0.6347	0.5702	0.5702
Mean Ranks 1	**1.3750**	5.1250	10.5625	9.1875	6.0000	7.4375	7.5625	4.2500	4.4375	2.0000	8.0625	
	1	5	11	10	6	7	8	3	4	2	9	
Mean Ranks 2	**18.6250**	39.5625	76.5625	60.6875	41.8125	52.4375	48.3125	35.0625	36.6875	22.8125	56.9375	
	1	5	11	10	6	8	7	3	4	2	9	
						Large datasets						
d_{18}	**1.0000**	0.8596	0.8383	0.8936	0.8255	0.8340	0.8340	0.9319	0.8553	0.9660	0.8723	0.8511
d_{19}	**1.0000**	0.9774	0.7572	0.9371	0.9849	0.9610	0.9623	0.9836	0.9899	0.9987	0.9736	0.9811
d_{20}	**1.0000**	0.9892	0.5784	0.8324	**1.0000**	0.9946	**1.0000**	0.9459	0.9730	**1.0000**	0.9838	0.9459
d_{21}	**0.8640**	0.7653	0.7760	0.6747	0.6773	0.6800	0.8533	0.7120	0.7733	0.8347	0.6933	0.7600
d_{22}	**0.9648**	0.6167	0.2407	0.5093	0.8019	0.6222	0.6889	0.8556	0.6667	0.8093	0.7093	0.9352
Mean Ranks 1	**1.3000**	6.6000	9.0000	9.0000	6.3000	8.1000	5.6000	5.2000	6.0000	2.5000	6.4000	
	1	8	11	11	6	9	4	3	5	2	7	
Mean Ranks 2	**10.9000**	28.8000	44.0000	36.8000	27.3000	31.9000	26.4000	25.6000	28.8000	19.3000	28.2000	
	1	7	11	10	5	9	4	3	8	2	6	

Table 3.11: The AFV values for all algorithms.

ID	BGWCA	BAOA	BSCSO	IBES	CBRSA	CVSA	DE	CASO	BPSO	CBi-GSK	GA	ALL
						Small datasets						
d_1	**0.1202**	0.2907	40.2008	0.2561	0.1977	0.3177	0.3238	0.2071	0.2538	0.1410	0.2670	0.1872
d_2	0.0122	0.0430	40.0494	40.0667	0.2101	0.1829	0.2417	0.0165	0.1712	**0.0020**	0.2383	0.4691
d_3	0.0842	0.1555	20.2206	0.2404	0.4417	0.2906	0.3345	0.1143	0.1948	**0.0390**	0.3418	0.3767
d_4	**0.0015**	0.1536	60.0589	20.1789	0.2281	0.1094	0.2141	0.0728	0.0975	0.0023	0.2025	0.3594
d_5	**0.0019**	0.0392	20.2585	20.0978	0.0610	0.1283	0.0661	0.0125	0.0087	0.0236	0.0733	0.0791
d_6	0.0421	0.1412	40.2381	40.0841	0.2035	0.1422	0.1450	0.0236	0.0037	**0.0019**	0.0233	0.1090
d_7	**0.0017**	0.2843	0.3684	20.2320	0.2196	0.3863	0.1747	0.0742	0.3723	0.0297	0.2871	0.5050
d_8	**0.0005**	0.0810	20.2380	40.2019	0.3377	0.2283	0.2027	0.2418	0.2550	0.0286	0.2676	0.4060
d_9	**0.1457**	0.2798	40.2062	0.3075	0.3423	0.3485	0.3654	0.1810	0.3464	0.1594	0.2403	0.3763
Mean Ranks 1	**1.6667**	5.2222	10.4444	9.0000	7.2222	7.4444	7.5556	3.5556	5.2222	1.8889	6.7778	
	1	5	11	10	7	8	9	3	5	2	6	
Mean Ranks 2	**15.3889**	43.0000	92.4444	82.2222	57.6667	56.3333	55.0000	30.4444	46.7778	17.6111	53.1111	
	1	4	11	10	9	8	7	3	5	2	6	
						Medium datasets						
d_{10}	**0.1456**	0.2522	60.1670	20.1870	0.1995	0.2701	0.2203	0.1893	0.1803	0.1616	0.2349	0.1823
d_{11}	**0.0007**	0.0689	0.2055	20.1359	0.0824	0.1381	0.0939	0.0494	0.0901	0.0114	0.1537	0.0277
d_{12}	**0.0006**	0.0641	20.1078	0.1114	0.1320	0.1115	0.1808	0.0612	0.1064	0.0181	0.1460	0.0949
d_{13}	**0.0012**	0.1074	0.5506	0.2156	0.1607	0.1747	0.0599	0.0214	0.0542	0.0025	0.1152	0.1200
d_{14}	**0.0003**	0.0019	0.7428	0.1055	0.0065	0.1030	0.1041	0.0026	0.0545	0.0006	0.1525	0.0100
d_{15}	**0.0004**	0.2003	20.3961	0.4014	0.0724	0.2677	0.5333	0.2021	0.1373	0.0004	0.5985	0.3400
d_{16}	**0.0007**	0.1111	0.2479	20.1537	0.2431	0.2216	0.1140	0.1132	0.1141	0.0216	0.2320	0.1585
d_{17}	**0.2724**	0.4560	20.3487	0.4911	0.4653	0.4440	0.5681	0.4810	0.3794	0.3635	0.4304	0.4355
Mean Ranks 1	**1.0000**	4.8750	10.7500	9.2500	6.2500	7.3750	7.5000	4.3750	4.6250	2.0000	8.0000	
	1	5	11	10	6	7	8	3	4	2	9	
Mean Ranks 2	**17.3750**	38.7500	77.6250	64.8750	42.1250	52.0000	47.2500	35.2500	36.5000	22.0000	55.7500	
	1	5	11	10	6	8	7	3	4	2	9	
						Large datasets						
d_{18}	**0.0004**	0.1415	0.1604	0.1116	0.1797	0.1685	0.1694	0.0722	0.1481	0.0359	0.1315	0.1574
d_{19}	**0.0004**	0.0251	20.0425	0.0671	0.0222	0.0432	0.0423	0.0209	0.0148	0.0032	0.0309	0.0287
d_{20}	**0.0000**	0.0131	0.4175	0.1707	0.0074	0.0098	0.0049	0.0579	0.0316	0.0006	0.0209	0.0635
d_{21}	**0.1347**	0.2348	0.2218	0.3259	0.3273	0.3214	0.1502	0.2898	0.2292	0.1650	0.3083	0.2476
d_{22}	**0.0362**	0.3822	0.7519	0.4898	0.2040	0.3784	0.3129	0.1480	0.3350	0.1913	0.2928	0.0742
Mean Ranks 1	**1.0000**	6.6000	9.0000	8.8000	7.0000	8.0000	5.8000	5.0000	6.0000	2.4000	6.4000	
	1	7	11	10	8	9	4	3	5	2	6	
Mean Ranks 2	**10.0000**	28.4000	46.2000	36.2000	28.4000	31.4000	26.8000	25.2000	28.8000	19.0000	27.6000	
	1	6	11	10	7	9	4	3	8	2	5	

Table 3.12: The MiFV values for all algorithms.

ID	BGWCA	BAOA	BSCSO	IBES	CBRSA	CVSA	DE	CASO	BPSO	CBi-GSK	GA	ALL
					Small datasets							
d_1	0.1202	0.2036	0.3346	0.2173	**0.1142**	0.2661	0.2754	0.1920	0.1663	0.1410	0.2080	0.1872
d_2	0.0060	0.0327	0.0584	0.0193	0.0347	0.0347	0.0357	0.0050	0.0183	**0.0020**	0.0460	0.4691
d_3	0.0764	0.1123	0.2574	0.1505	0.3369	0.1528	0.2597	0.0428	0.1115	**0.0390**	0.2979	0.3767
d_4	**0.0015**	**0.0015**	0.1188	0.0621	0.0621	**0.0015**	0.1211	0.0598	0.0031	0.0023	0.0621	0.3594
d_5	**0.0019**	0.0268	0.2539	0.0952	0.0268	0.0529	0.0299	**0.0019**	0.0031	0.0236	0.0044	0.0791
d_6	0.0025	0.1015	0.1993	0.1084	0.1040	0.0037	0.1052	0.0037	0.0025	**0.0019**	0.0031	0.1090
d_7	**0.0017**	0.1431	0.3541	0.2205	0.0779	0.2884	0.0757	0.0033	0.2149	**0.0017**	0.0757	0.5050
d_8	**0.0005**	0.0665	0.2645	0.2661	0.2687	0.2001	0.1357	0.0692	0.1352	0.0021	0.2012	0.4060
d_9	**0.1327**	0.2505	0.3173	0.2525	0.3253	0.2911	0.3223	0.1649	0.2698	0.1421	0.1827	0.3763
Mean Ranks 1	**1.9444**	5.2778	10.1111	8.0000	7.7778	7.2222	8.5000	3.5556	4.7222	2.2778	6.6111	
	1	5	11	9	8	7	10	3	4	2	6	
Mean Ranks 2	**24.3333**	47.6111	78.5556	62.1111	59.6667	55.5556	61.0556	36.0556	46.5556	25.9444	52.5556	
	1	5	11	10	8	7	9	3	4	2	6	
					Medium datasets							
d_{10}	**0.1404**	0.2008	0.3178	0.1834	0.1575	0.1972	0.1952	0.1442	0.1562	0.1483	0.1670	0.1823
d_{11}	**0.0007**	0.0540	0.1421	0.0617	0.0604	0.1111	0.0744	0.0384	0.0574	0.0010	0.0397	0.0277
d_{12}	**0.0006**	0.0015	0.0569	0.0884	0.0902	0.0625	0.1473	0.0330	0.0321	0.0012	0.1173	0.0949
d_{13}	**0.0012**	0.0576	0.3590	0.0872	0.0609	0.0328	0.0047	0.0044	0.0041	0.0021	0.0065	0.1200
d_{14}	**0.0003**	0.0014	0.4953	0.0031	0.0031	0.0023	0.0043	0.0014	0.0037	0.0006	0.0034	0.0100
d_{15}	**0.0004**	0.0018	0.3302	0.3305	0.0045	0.0036	0.3346	0.0045	0.0052	**0.0004**	0.3334	0.3400
d_{16}	**0.0007**	0.0515	0.1488	0.1020	0.1528	0.1510	0.0050	0.0535	0.0052	0.0013	0.1525	0.1585
d_{17}	**0.2545**	0.4117	0.4011	0.4603	0.4412	0.4208	0.5453	0.4469	0.3159	0.3451	0.4060	0.4355
Mean Ranks 1	**1.0625**	5.4375	8.7500	8.1875	7.6250	7.2500	8.5000	4.7500	4.8750	2.1875	7.3750	
	1	5	11	9	8	6	10	3	4	2	7	
Mean Ranks 2	**19.6250**	39.3125	68.7500	55.4375	49.6250	48.1250	52.5000	39.5000	39.6250	23.5000	53.5000	
	1	3	11	10	7	6	8	4	5	2	9	
					Large datasets							
d_{18}	**0.0004**	0.1076	0.1059	0.0701	0.1571	0.1315	0.1313	0.0473	0.0888	0.0231	0.1106	0.1574
d_{19}	**0.0002**	0.0210	0.0376	0.0407	0.0174	0.0300	0.0300	0.0167	0.0048	0.0015	0.0106	0.0287
d_{20}	**0.0000**	0.0020	0.0269	0.0003	0.0048	0.0037	0.0046	0.0577	0.0312	0.0003	0.0048	0.0635
d_{21}	**0.1189**	0.1479	0.1848	0.3049	0.3219	0.3202	0.1501	0.2555	0.2289	0.1334	0.3082	0.2476
d_{22}	**0.0192**	0.2960	0.5139	0.1815	0.1473	0.2340	0.2708	0.0692	0.2340	0.1581	0.2524	0.0742
Mean Ranks 1	**1.0000**	6.2000	8.2000	6.1000	7.7000	7.8000	7.4000	5.6000	6.2000	2.5000	7.3000	
	1	6	11	4	9	10	8	3	6	2	7	
Mean Ranks 2	**11.4000**	28.6000	34.0000	29.7000	31.5000	32.2000	30.4000	28.0000	30.2000	20.9000	31.1000	
	1	4	11	5	9	10	7	3	6	2	8	

Table 3.13: The MaFV values for all algorithms.

ID	BGWCA	BAOA	BSCSO	IBES	CBRSA	CVSA	DE	CASO	BPSO	CBi-GSK	GA	ALL
					Small datasets							
d_1	**0.1202**	0.3253	100.0000	0.2891	0.2869	0.3483	0.3483	0.2244	0.3055	0.1410	0.3193	0.1872
d_2	0.0163	0.0470	100.0000	100.0000	0.3247	0.3914	0.3810	0.0327	0.3800	**0.0020**	0.3627	0.4691
d_3	0.1131	0.1841	100.0000	0.3315	0.5226	0.4821	0.4821	0.1856	0.2995	**0.0390**	0.4079	0.3767
d_4	**0.0015**	0.3517	100.0000	100.0000	0.3594	0.2376	0.2958	0.1195	0.3571	0.0023	0.2414	0.3594
d_5	**0.0019**	0.0479	100.0000	100.0000	0.1425	0.2327	0.0965	0.0517	0.0286	0.0236	0.1649	0.0791
d_6	0.1015	0.1993	100.0000	100.0000	0.3014	0.4975	0.2036	0.1009	0.0056	**0.0019**	0.1009	0.1090
d_7	**0.0017**	0.4956	0.4254	100.0000	0.2929	0.4989	0.2183	0.1459	0.4994	0.0718	0.4994	0.5050
d_8	**0.0005**	0.1341	100.0000	100.0000	0.4060	0.2698	0.3368	0.3353	0.4657	0.0681	0.3347	0.4060
d_9	**0.1515**	0.3079	100.0000	0.4361	0.3525	0.3980	0.3896	0.2035	0.4198	0.1718	0.3203	0.3763
Mean Ranks 1	**1.6667**	5.1111	10.1667	9.3889	6.8889	7.6667	7.0000	3.7222	6.5000	**1.6667**	6.2222	
	1	3	10	9	6	8	7	2	5	1	4	
Mean Ranks 2	**13.2778**	41.2222	90.5556	81.3333	56.2222	63.0000	52.8889	29.8333	53.6111	14.9444	53.1111	
	1	4	11	10	8	9	5	3	7	2	6	
					Medium datasets							
d_{10}	**0.1537**	0.2781	100.0000	100.0000	0.3009	0.3315	0.2523	0.2795	0.2002	0.1706	0.3573	0.1823
d_{11}	**0.0007**	0.0904	0.3362	100.0000	0.1284	0.1801	0.1284	0.0734	0.1131	0.0183	0.2165	0.0277
d_{12}	**0.0009**	0.1429	100.0000	0.1231	0.1771	0.1724	0.2307	0.0904	0.1747	0.0295	0.1744	0.0949
d_{13}	**0.0012**	0.1682	0.7428	0.6056	0.4160	0.3063	0.1688	0.0585	0.1697	0.0026	0.2794	0.1200
d_{14}	**0.0003**	0.0026	0.9903	0.2575	0.0100	0.4996	0.4993	0.0040	0.2526	0.0006	0.7468	0.0100
d_{15}	**0.0004**	0.6625	100.0000	0.6664	0.3366	0.6637	0.6659	0.3343	0.3361	0.0005	0.9955	0.3400
d_{16}	**0.0008**	0.1508	0.4952	100.0000	0.3507	0.3005	0.2532	0.2018	0.3512	0.0512	0.3020	0.1585
d_{17}	**0.2951**	0.4775	100.0000	0.5162	0.5040	0.4628	0.5952	0.5121	0.4132	0.3867	0.4717	0.4355
Mean Ranks 1	**1.0000**	4.5000	10.6875	8.9375	7.0625	7.0000	7.0625	4.2500	5.5000	2.0000	8.0000	
	1	4	11	10	8	6	8	3	5	2	9	
Mean Ranks 2	**12.7500**	35.7500	77.3750	67.5000	45.1875	52.8750	48.3125	33.6250	41.5000	18.6250	56.0000	
	1	4	11	10	6	8	7	3	5	2	9	
					Large datasets							
d_{18}	**0.0004**	0.1704	0.2741	0.1706	0.2155	0.2152	0.2165	0.0891	0.2157	0.0654	0.1521	0.1574
d_{19}	**0.0006**	0.0338	100.0000	0.1309	0.0283	0.0560	0.0488	0.0298	0.0236	0.0082	0.0483	0.0287
d_{20}	**0.0000**	0.0292	0.6422	0.8295	0.0096	0.0308	0.0051	0.0581	0.0317	0.0008	0.0316	0.0635
d_{21}	0.1717	0.2664	0.2509	0.3454	0.3349	0.3230	**0.1503**	0.3216	0.2296	0.1860	0.3085	0.2476
d_{22}	**0.0468**	0.4701	0.8893	0.8710	0.2984	0.4265	0.4174	0.2617	0.4084	0.2141	0.3718	0.0742
Mean Ranks 1	**1.2000**	6.2000	9.6000	9.6000	6.0000	7.8000	5.8000	5.6000	6.0000	2.2000	6.0000	
	1	8	11	11	6	9	4	3	6	2	6	
Mean Ranks 2	**10.0000**	27.8000	47.0000	40.0000	26.4000	30.8000	25.8000	26.4000	27.4000	18.0000	28.4000	
	1	7	11	10	4	9	3	5	6	2	8	

Table 3.14: The ASF values for all algorithms.

ID	BGWCA	BAOA	BSCSO	IBES	CBRSA	CVSA	DE	CASO	BPSO	CBi-GSK	GA
Small datasets											
d_1	5.0000	2.8000	**0.6000**	5.4000	7.2000	4.6000	4.4000	4.4000	5.2000	5.0000	5.8000
d_2	3.6000	2.8000	**0.6000**	3.6000	6.4000	5.0000	6.4000	5.0000	4.8000	2.0000	3.0000
d_3	4.6000	2.0000	**0.8000**	7.4000	11.8000	6.0000	5.8000	5.6000	5.4000	3.0000	5.8000
d_4	2.0000	2.8000	**0.8000**	5.4000	8.8000	6.0000	5.8000	3.8000	5.6000	3.0000	5.8000
d_5	3.0000	3.8000	**1.0000**	9.2000	9.2000	6.4000	10.0000	5.2000	6.6000	**1.0000**	6.8000
d_6	4.0000	4.2000	**0.8000**	7.8000	8.8000	5.8000	10.2000	6.0000	6.0000	3.0000	5.6000
d_7	3.0000	2.6000	**1.2000**	10.2000	13.4000	8.0000	9.0000	6.2000	8.2000	2.6000	7.6000
d_8	1.0000	3.4000	**0.8000**	7.4000	14.6000	7.4000	9.0000	8.0000	8.0000	4.2000	6.8000
d_9	6.2000	5.2000	**0.6000**	9.2000	11.4000	8.0000	10.0000	9.6000	7.8000	6.0000	9.4000
Mean Ranks 1	3.7778	2.8333	**1.0556**	8.0556	10.6667	7.1111	9.0000	6.4444	7.0000	3.1667	6.8889
	4	2	1	9	11	8	10	5	7	3	6
Mean Ranks 2	29.5556	23.8333	**5.3333**	68.2778	86.8889	61.0556	73.3333	54.7222	60.5556	26.4444	60.0000
	4	2	1	9	11	8	10	5	7	3	6
Medium datasets											
d_{10}	11.4000	7.4000	**0.6000**	11.8000	16.4000	10.0000	12.0000	13.4000	12.8000	10.0000	11.0000
d_{11}	2.0000	5.2000	**1.4000**	15.2000	24.6000	11.2000	16.4000	10.4000	15.8000	2.4000	15.6000
d_{12}	2.2000	6.2000	**1.2000**	13.4000	25.6000	13.6000	18.4000	15.6000	15.4000	4.0000	15.4000
d_{13}	4.0000	9.8000	**2.2000**	22.4000	22.8000	14.4000	16.8000	16.6000	16.0000	8.4000	17.6000
d_{14}	**1.0000**	6.8000	**1.0000**	22.6000	22.6000	14.0000	17.8000	9.2000	17.4000	2.0000	14.0000
d_{15}	2.0000	12.8000	**0.8000**	30.0000	35.8000	21.0000	29.6000	22.8000	29.6000	2.2000	25.4000
d_{16}	4.2000	13.2000	**2.2000**	31.0000	33.2000	22.6000	30.6000	25.8000	31.2000	10.8000	25.6000
d_{17}	7.4000	27.4000	**1.4000**	34.2000	54.8000	38.6000	51.8000	48.2000	46.8000	18.8000	49.8000
Mean Ranks 1	2.4375	3.7500	**1.0625**	7.9375	10.9375	5.3750	8.9375	7.1250	8.1250	3.0625	7.2500
	2	4	1	8	11	5	10	6	9	3	7
Mean Ranks 2	15.5000	32.0000	**6.1875**	59.9375	71.4375	49.3750	62.2500	52.4375	59.6875	24.3125	56.3750
	2	4	1	9	11	5	10	6	8	3	7
Large datasets											
d_{18}	6.6000	41.4000	**5.6000**	103.8000	116.2000	70.0000	84.6000	79.8000	81.0000	36.4000	84.8000
d_{19}	9.8000	71.8000	**4.2000**	129.2000	192.8000	123.0000	130.2000	125.2000	129.0000	51.4000	124.8000
d_{20}	**1.2000**	129.0000	3.4000	253.0000	394.2000	234.8000	262.0000	234.0000	257.8000	29.4000	254.8000
d_{21}	7.0000	185.4000	**6.2000**	285.2000	591.8000	347.0000	379.0000	351.4000	360.6000	100.6000	354.8000
d_{22}	115.0000	234.2000	**17.0000**	341.8000	666.4000	379.6000	423.2000	427.2000	425.4000	211.4000	426.6000
Mean Ranks 1	1.8000	4.0000	**1.2000**	7.2000	11.0000	5.6000	9.0000	7.0000	8.2000	3.0000	8.0000
	2	4	1	7	11	5	10	6	9	3	8
Mean Ranks 2	8.8000	24.1000	**4.6000**	34.0000	42.6000	33.0000	37.0000	34.6000	36.1000	17.4000	35.8000
	2	4	1	6	11	5	10	7	9	3	8

Table 3.15: The ACT values for all algorithms.

ID	BGWCA	BAOA	BSCSO	IBES	CBRSA	CVSA	DE	CASO	BPSO	CBi-GSK	GA
Small datasets											
d_1	28.7156	38.0384	41.6302	118.2242	27.0558	**10.2790**	106.9746	52.4825	71.5778	14.6554	63.8113
d_2	25.1408	36.9417	24.9287	102.5099	17.3524	**8.2044**	86.9156	47.1840	51.9768	12.8589	44.1263
d_3	23.3756	36.3869	30.5004	91.5272	16.7273	**7.7271**	79.5666	44.7517	47.3552	12.2842	42.2124
d_4	22.6313	36.6425	21.3329	88.7779	14.9685	**7.3813**	77.1497	42.2566	46.1027	11.6944	40.5524
d_5	24.1523	38.1455	34.1675	95.6723	17.3903	**8.0237**	82.5427	46.8641	48.9759	11.6226	42.7269
d_6	22.7894	36.2016	28.9366	91.3360	15.1493	**7.3505**	75.9122	42.1123	48.0479	11.3167	33.8477
d_7	22.5171	37.2596	36.5782	94.9737	15.2269	**7.3926**	76.6874	42.2797	48.1238	11.8195	39.8507
d_8	22.6201	36.1458	31.6999	92.7664	15.1530	**7.3565**	75.3608	40.4018	46.7110	12.1871	40.7094
d_9	27.0323	43.2949	31.8707	106.6652	17.5505	**8.8556**	87.3392	47.5865	53.8650	13.9367	46.2095
Mean Ranks 1	4.2222	6.0000	4.8889	11.0000	3.0000	**1.0000**	10.0000	7.7778	9.0000	2.0000	7.1111
	4	6	5	11	3	1	10	8	9	2	7
Mean Ranks 2	32.4444	50.7778	41.4444	94.1111	24.1111	**5.0000**	86.8889	66.1111	74.4444	14.0000	60.6667
	4	6	5	11	3	1	10	8	9	2	7
Medium datasets											
d_{10}	56.0294	89.2570	46.8782	246.5173	41.3572	**19.9459**	216.2988	112.0510	127.1671	32.2413	104.1206
d_{11}	23.4479	41.5256	41.5889	101.5365	15.3877	**7.5935**	76.6837	41.9898	46.5929	12.6921	40.3735
d_{12}	22.3402	40.0553	32.6971	100.6279	17.0740	**7.3215**	75.0268	39.6506	47.1553	12.5177	39.3907
d_{13}	22.0240	40.6899	39.7109	99.4054	17.1199	**7.3724**	75.8701	39.7341	45.8135	12.1673	41.0414
d_{14}	21.5273	36.8123	35.1491	94.0244	15.7149	**6.8368**	70.7577	37.8871	42.4545	10.9314	37.0902
d_{15}	20.7130	37.7596	28.4173	96.2899	17.4421	**6.7944**	70.5405	36.9916	41.7841	10.6181	36.7558
d_{16}	21.7060	39.3899	38.4887	100.4231	17.4111	**7.1343**	74.1653	38.8706	43.8900	10.6436	41.8556
d_{17}	29.1522	47.5488	41.0740	142.6224	24.6003	**9.2286**	98.7750	51.6531	60.1765	12.7464	55.2281
Mean Ranks 1	4.1250	6.7500	5.1250	11.0000	3.0000	**1.0000**	10.0000	7.1250	9.0000	2.0000	6.8750
	4	6	5	11	3	1	10	8	9	2	7
Mean Ranks 2	30.5000	50.3750	43.2500	81.1250	23.1250	**6.1250**	74.2500	51.5000	63.6250	13.5000	52.1250
	4	6	5	11	3	1	10	7	9	2	8
Large datasets											
d_{18}	24.5433	41.4347	43.5527	115.6920	20.1663	**7.8200**	82.6446	43.0339	49.6717	11.8932	46.9283
d_{19}	58.7090	56.5792	48.1766	308.0451	51.1045	**17.1175**	199.0906	103.8325	121.9219	18.7708	110.8297
d_{20}	29.0329	41.9633	42.4373	140.5478	24.9949	**8.7386**	92.7163	48.0460	55.1904	11.8685	51.7729
d_{21}	53.4145	52.0373	49.1810	254.5666	53.1255	**16.3041**	176.7385	90.0803	104.7303	16.8776	96.5373
d_{22}	89.7991	74.9907	59.4617	438.3906	79.0751	**26.0981**	287.7076	150.7883	170.5160	30.6294	155.4842
Mean Ranks 1	5.2000	4.6000	4.4000	11.0000	4.0000	**1.0000**	10.0000	6.8000	9.0000	2.0000	8.0000
	6	5	4	11	3	1	10	7	9	2	8
Mean Ranks 2	24.2000	24.6000	22.8000	50.2000	21.6000	**5.4000**	45.8000	33.0000	38.0000	7.0000	35.4000
	5	6	4	11	3	1	10	7	9	2	8

tinct patterns in the distribution of the ACA values. For the left figure, the majority of data is clustered around zero, with a small interquartile range and whiskers extending to a maximum value of 0.1440. Two non-zero values, 0.0087 and 0.0400, could be considered potential outliers. The middle figure shows a concentration of values around zero, with a small interquartile range and whiskers extending to a maximum value of 0.2744. The right figure consists mainly of zero values, with a larger interquartile range and whiskers extending from the minimum to the maximum values of 0 and 0.1360, respectively. The presence of a non-zero value, 0.0352, could be considered an outlier in the context of this figure. The box-and-whisker plots shown in Figure 3.2 divulge insights into the distribution of the AFV values. For the left figure, the majority of the data is concentrated around zero, with a small interquartile range and whiskers extending to a maximum value of 0.1457. The middle figure exhibits a concentration of values near zero, with a small interquartile range and whiskers extending to a maximum value of 0.2724. In the right figure, the data is primarily composed of zero values, with a larger interquartile range and whiskers extending from the minimum to the maximum values of 0 and 0.1347, respectively. The presence of a non-zero value, 0.0362, in the right figure could be considered an outlier. In conclusion, these box-and-whisker plots provide a visual summary of the central tendency, spread, and potential outliers in each figure, aiding in the comparison of their respective distributions.

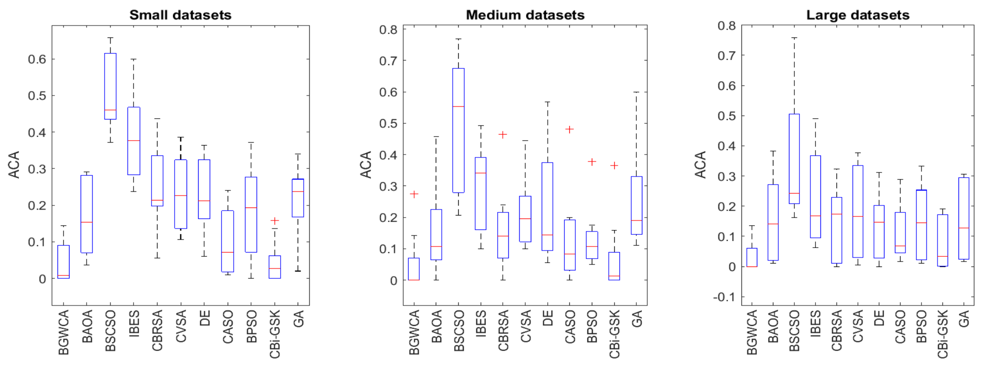


Figure 3.1: The box-and-whisker plot for all the optimizers over all the datasets for ACA values.

According to Table 3.8, it is obvious that the Friedman test indicates significant differences. Therefore, we opted to apply the Dunn's post-hoc test in order to identify specific pairs of treatments that are significantly different from each other after finding a significant result in the Friedman test. Tables 3.16, 3.17, 3.18, 3.19, 3.20, and 3.22 summarize the p-values computed by the Dunn's post-hoc test. The p-values obtained from the Dunn's test provide information about the significance of the differences between specific pairs of groups. P-values below the significance threshold of 0.05 are emphasized in bold font. To interpret a particular value at the intersection of a row (representing an algorithm, e.g., BGWCA) and a column (representing another algorithm, e.g., IBES), if

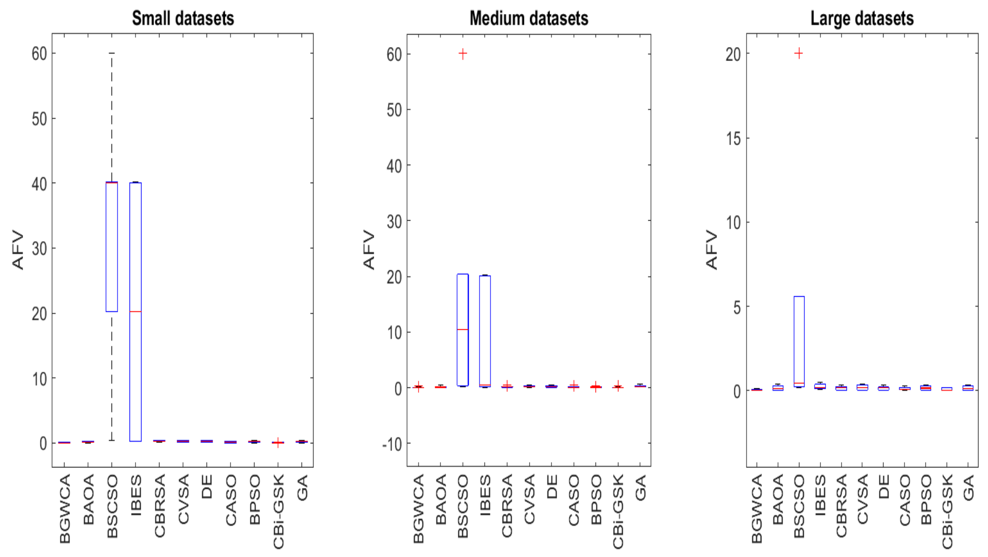


Figure 3.2: The box-and-whisker plot for all the optimizers over all the datasets for AFV values

the associated p-value is less than 0.05, it signifies a significant difference between these algorithms, suggesting that the algorithm denoted by the row label outperforms the one denoted by the column label. Conversely, if the p-value is greater than or equal to 0.05, we infer nearly similar performance between the two algorithms.

Tables 3.23, 3.24, 3.25, 3.26, 3.27, and 3.28 summarize the p-values obtained by the Wilcoxon signed ranks test. As evident from the results, the algorithm put forward demonstrates superior performance in addressing the FS problem compared to all other contenders across datasets of varying sizes, considering a predetermined threshold of $\alpha = 0.05$.

Tables 3.23, 3.24, 3.25, 3.26, 3.27, and 3.28 summarize the p-values obtained by the Wilcoxon signed ranks test. As evident from the results, the algorithm put forward demonstrates superior performance in addressing the FS problem compared to all other contenders across datasets of varying sizes, considering a predetermined threshold of $\alpha = 0.05$.

In Figures 3.3, 3.4, and 3.5, the convergence curves of fitness values over 100 iterations, calculated using Equation 2.1, are depicted for each dataset across the range of considered optimizers. These visualizations offer a comprehensive view of the optimization process, showcasing how the fitness values evolve over iterations. The comparison across multiple optimizers provides insights into their respective convergence behaviors and performance on diverse datasets. Figures 3.3, 3.4, and 3.5 clearly illustrate the high convergence rates achieved across various datasets, demonstrating the efficacy of the proposed algorithm. Importantly, the algorithm maintains optimal solutions throughout the convergence process, underscoring its reliability. Notably, the algorithm successfully avoids premature convergence in the majority of cases, a critical aspect in ensuring

Table 3.16: The p-values obtained by the post hoc Dunn's test for Table 3.10.

		BGWCA	BAOA	BSCSO	IBES	CBRSA	CVSA	DE	CASO	BPSO	CBi-GSK	GA
	BGWCA		0.6462	**0.0000**	**0.0002**	**0.0175**	**0.0133**	**0.0153**	1.0000	0.8104	1.0000	0.0560
	BAOA			0.0714	0.6814	1.0000	1.0000	1.0000	1.0000	1.0000	0.7489	1.0000
	BSCSO				1.0000	0.9407	0.9648	0.9539	**0.0005**	**0.0385**	**0.0000**	0.7158
	IBES					1.0000	1.0000	1.0000	**0.0229**	0.5033	**0.0003**	0.9999
	CBRSA						1.0000	1.0000	0.5387	0.9999	**0.0261**	1.0000
Samll	**CVSA**							1.0000	0.4686	0.9996	**0.0200**	1.0000
	DE								0.5033	0.9998	**0.0229**	1.0000
	CASO									1.0000	1.0000	0.8381
	BPSO										0.8866	1.0000
	CBi-GSK											0.0804
	GA											
	BGWCA		0.7092	**0.0000**	**0.0001**	0.2324	**0.0119**	**0.0088**	0.9895	0.9701	1.0000	**0.0025**
	BAOA			**0.0490**	0.5194	1.0000	0.9999	0.9997	1.0000	1.0000	0.9596	0.9848
	BSCSO				1.0000	0.2575	0.9596	0.9784	**0.0065**	**0.0103**	**0.0000**	0.9994
	IBES					0.9467	1.0000	1.0000	0.1336	0.1877	**0.0006**	1.0000
	CBRSA						1.0000	1.0000	1.0000	1.0000	0.5576	1.0000
Medium	**CVSA**							1.0000	0.9467	0.9784	**0.0490**	1.0000
	DE								0.9128	0.9596	**0.0374**	1.0000
	CASO									1.0000	1.0000	0.6722
	BPSO										0.9997	0.7789
	CBi-GSK											**0.0119**
	GA											
	BGWCA		0.4589	**0.0123**	**0.0123**	0.6015	0.0599	0.8902	0.9698	0.7419	1.0000	0.5532
	BAOA			1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9386	1.0000
	BSCSO				1.0000	1.0000	1.0000	0.9975	0.9800	0.9999	0.0965	1.0000
	IBES					1.0000	1.0000	0.9975	0.9800	0.9999	0.0965	1.0000
	CBRSA						1.0000	1.0000	1.0000	1.0000	0.9800	1.0000
Large	**CVSA**							1.0000	0.9999	1.0000	0.3314	1.0000
	DE								1.0000	1.0000	0.9997	1.0000
	CASO									1.0000	1.0000	1.0000
	BPSO										0.9955	1.0000
	CBi-GSK											0.9698
	GA											

Table 3.17: The p-values obtained by the post hoc Dunn's test for Table 3.11.

		BGWCA	BAOA	BSCSO	IBES	CBRSA	CVSA	DE	CASO	BPSO	CBi-GSK	GA
	BGWCA		0.6462	**0.0000**	**0.0002**	**0.0175**	**0.0133**	**0.0153**	1.0000	0.8104	1.0000	0.0560
	BAOA			0.0714	0.6814	1.0000	1.0000	1.0000	1.0000	1.0000	0.7489	1.0000
	BSCSO				1.0000	0.9407	0.9648	0.9539	**0.0005**	**0.0385**	**0.0000**	0.7158
	IBES					1.0000	1.0000	1.0000	**0.0229**	0.5033	**0.0003**	0.9999
	CBRSA						1.0000	1.0000	0.5387	0.9999	**0.0261**	1.0000
Samll	**CVSA**							1.0000	0.4686	0.9996	**0.0200**	1.0000
	DE								0.5033	0.9998	**0.0229**	1.0000
	CASO									1.0000	1.0000	0.8381
	BPSO										0.8866	1.0000
	CBi-GSK											0.0804
	GA											
	BGWCA		0.7092	**0.0000**	**0.0001**	0.2324	**0.0119**	**0.0088**	0.9895	0.9701	1.0000	**0.0025**
	BAOA			**0.0490**	0.5194	1.0000	0.9999	0.9997	1.0000	1.0000	0.9596	0.9848
	BSCSO				1.0000	0.2575	0.9596	0.9784	**0.0065**	**0.0103**	**0.0000**	0.9994
	IBES					0.9467	1.0000	1.0000	0.1336	0.1877	**0.0006**	1.0000
	CBRSA						1.0000	1.0000	1.0000	1.0000	0.5576	1.0000
Medium	**CVSA**							1.0000	0.9467	0.9784	**0.0490**	1.0000
	DE								0.9128	0.9596	**0.0374**	1.0000
	CASO									1.0000	1.0000	0.6722
	BPSO										0.9997	0.7789
	CBi-GSK											**0.0119**
	GA											
	BGWCA		0.4589	**0.0123**	**0.0123**	0.6015	0.0599	0.8902	0.9698	0.7419	1.0000	0.5532
	BAOA			1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9386	1.0000
	BSCSO				1.0000	1.0000	1.0000	0.9975	0.9800	0.9999	0.0965	1.0000
	IBES					1.0000	1.0000	0.9975	0.9800	0.9999	0.0965	1.0000
	CBRSA						1.0000	1.0000	1.0000	1.0000	0.9800	1.0000
Large	**CVSA**							1.0000	0.9999	1.0000	0.3314	1.0000
	DE								1.0000	1.0000	0.9997	1.0000
	CASO									1.0000	1.0000	1.0000
	BPSO										0.9955	1.0000
	CBi-GSK											0.9698
	GA											

Table 3.18: The p-values obtained by the post hoc Dunn's test for Table 3.12.

		BGWCA	**BAOA**	**BSCSO**	**IBES**	**CBRSA**	**CVSA**	**DE**	**CASO**	**BPSO**	**CBi-GSK**	**GA**
	BGWCA		0.6462	**0.0000**	**0.0002**	**0.0175**	**0.0133**	**0.0153**	1.0000	0.8104	1.0000	0.0560
	BAOA			0.0714	0.6814	1.0000	1.0000	1.0000	1.0000	1.0000	0.7489	1.0000
	BSCSO				1.0000	0.9407	0.9648	0.9539	**0.0005**	**0.0385**	**0.0000**	0.7158
	IBES					1.0000	1.0000	1.0000	**0.0229**	0.5033	**0.0003**	0.9999
	CBRSA						1.0000	1.0000	0.5387	0.9999	**0.0261**	1.0000
Samll	**CVSA**							1.0000	0.4686	0.9996	**0.0200**	1.0000
	DE								0.5033	0.9998	**0.0229**	1.0000
	CASO									1.0000	1.0000	0.8381
	BPSO										0.8866	1.0000
	CBi-GSK											0.0804
	GA											
	BGWCA		0.7092	**0.0000**	**0.0001**	0.2324	**0.0119**	**0.0088**	0.9895	0.9701	1.0000	**0.0025**
	BAOA			**0.0490**	0.5194	1.0000	0.9999	0.9997	1.0000	1.0000	0.9596	0.9848
	BSCSO				1.0000	0.2575	0.9596	0.9784	**0.0065**	**0.0103**	**0.0000**	0.9994
	IBES					0.9467	1.0000	1.0000	0.1336	0.1877	**0.0006**	1.0000
	CBRSA						1.0000	1.0000	1.0000	1.0000	0.5576	1.0000
Medium	**CVSA**							1.0000	0.9467	0.9784	**0.0490**	1.0000
	DE								0.9128	0.9596	**0.0374**	1.0000
	CASO									1.0000	1.0000	0.6722
	BPSO										0.9997	0.7789
	CBi-GSK											**0.0119**
	GA											
	BGWCA		0.4589	**0.0123**	**0.0123**	0.6015	0.0599	0.8902	0.9698	0.7419	1.0000	0.5532
	BAOA			1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9386	1.0000
	BSCSO				1.0000	1.0000	1.0000	0.9975	0.9800	0.9999	0.0965	1.0000
	IBES					1.0000	1.0000	0.9975	0.9800	0.9999	0.0965	1.0000
	CBRSA						1.0000	1.0000	1.0000	1.0000	0.9800	1.0000
Large	**CVSA**							1.0000	0.9999	1.0000	0.3314	1.0000
	DE								1.0000	1.0000	0.9997	1.0000
	CASO									1.0000	1.0000	1.0000
	BPSO										0.9955	1.0000
	CBi-GSK											0.9698
	GA											

Table 3.19: The p-values obtained by the post hoc Dunn's test for Table 3.13.

		BGWCA	**BAOA**	**BSCSO**	**IBES**	**CBRSA**	**CVSA**	**DE**	**CASO**	**BPSO**	**CBi-GSK**	**GA**
	BGWCA		0.6462	**0.0000**	**0.0002**	**0.0175**	**0.0133**	**0.0153**	1.0000	0.8104	1.0000	0.0560
	BAOA			0.0714	0.6814	1.0000	1.0000	1.0000	1.0000	1.0000	0.7489	1.0000
	BSCSO				1.0000	0.9407	0.9648	0.9539	**0.0005**	**0.0385**	**0.0000**	0.7158
	IBES					1.0000	1.0000	1.0000	**0.0229**	0.5033	**0.0003**	0.9999
	CBRSA						1.0000	1.0000	0.5387	0.9999	**0.0261**	1.0000
Samll	**CVSA**							1.0000	0.4686	0.9996	**0.0200**	1.0000
	DE								0.5033	0.9998	**0.0229**	1.0000
	CASO									1.0000	1.0000	0.8381
	BPSO										0.8866	1.0000
	CBi-GSK											0.0804
	GA											
	BGWCA		0.7092	**0.0000**	**0.0001**	0.2324	**0.0119**	**0.0088**	0.9895	0.9701	1.0000	**0.0025**
	BAOA			**0.0490**	0.5194	1.0000	0.9999	0.9997	1.0000	1.0000	0.9596	0.9848
	BSCSO				1.0000	0.2575	0.9596	0.9784	**0.0065**	**0.0103**	**0.0000**	0.9994
	IBES					0.9467	1.0000	1.0000	0.1336	0.1877	**0.0006**	1.0000
	CBRSA						1.0000	1.0000	1.0000	1.0000	0.5576	1.0000
Medium	**CVSA**							1.0000	0.9467	0.9784	**0.0490**	1.0000
	DE								0.9128	0.9596	**0.0374**	1.0000
	CASO									1.0000	1.0000	0.6722
	BPSO										0.9997	0.7789
	CBi-GSK											**0.0119**
	GA											
	BGWCA		0.4589	**0.0123**	**0.0123**	0.6015	0.0599	0.8902	0.9698	0.7419	1.0000	0.5532
	BAOA			1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9386	1.0000
	BSCSO				1.0000	1.0000	1.0000	0.9975	0.9800	0.9999	0.0965	1.0000
	IBES					1.0000	1.0000	0.9975	0.9800	0.9999	0.0965	1.0000
	CBRSA						1.0000	1.0000	1.0000	1.0000	0.9800	1.0000
Large	**CVSA**							1.0000	0.9999	1.0000	0.3314	1.0000
	DE								1.0000	1.0000	0.9997	1.0000
	CASO									1.0000	1.0000	1.0000
	BPSO										0.9955	1.0000
	CBi-GSK											0.9698
	GA											

Table 3.20: The p-values obtained by the post hoc Dunn's test for Table 3.14.

		BGWCA	BAOA	BSCSO	IBES	CBRSA	CVSA	DE	CASO	BPSO	CBi-GSK	GA
	BGWCA		0.6462	**0.0000**	**0.0002**	**0.0175**	**0.0133**	**0.0153**	1.0000	0.8104	1.0000	0.0560
	BAOA			0.0714	0.6814	1.0000	1.0000	1.0000	1.0000	1.0000	0.7489	1.0000
	BSCSO				1.0000	0.9407	0.9648	0.9539	**0.0005**	**0.0385**	**0.0000**	0.7158
	IBES					1.0000	1.0000	1.0000	**0.0229**	0.5033	**0.0003**	0.9999
	CBRSA						1.0000	1.0000	0.5387	0.9999	**0.0261**	1.0000
Samll	**CVSA**							1.0000	0.4686	0.9996	**0.0200**	1.0000
	DE								0.5033	0.9998	**0.0229**	1.0000
	CASO									1.0000	1.0000	0.8381
	BPSO										0.8866	1.0000
	CBi-GSK											0.0804
	GA											
	BGWCA		0.7092	**0.0000**	**0.0001**	0.2324	**0.0119**	**0.0088**	0.9895	0.9701	1.0000	**0.0025**
	BAOA			**0.0490**	0.5194	1.0000	0.9999	0.9997	1.0000	1.0000	0.9596	0.9848
	BSCSO				1.0000	0.2575	0.9596	0.9784	**0.0065**	**0.0103**	**0.0000**	0.9994
	IBES					0.9467	1.0000	1.0000	0.1336	0.1877	**0.0006**	1.0000
	CBRSA						1.0000	1.0000	1.0000	1.0000	0.5576	1.0000
Medium	**CVSA**							1.0000	0.9467	0.9784	**0.0490**	1.0000
	DE								0.9128	0.9596	**0.0374**	1.0000
	CASO									1.0000	1.0000	0.6722
	BPSO										0.9997	0.7789
	CBi-GSK											**0.0119**
	GA											
	BGWCA		0.4589	**0.0123**	**0.0123**	0.6015	0.0599	0.8902	0.9698	0.7419	1.0000	0.5532
	BAOA			1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9386	1.0000
	BSCSO				1.0000	1.0000	1.0000	0.9975	0.9800	0.9999	0.0965	1.0000
	IBES					1.0000	1.0000	0.9975	0.9800	0.9999	0.0965	1.0000
	CBRSA						1.0000	1.0000	1.0000	1.0000	0.9800	1.0000
Large	**CVSA**							1.0000	0.9999	1.0000	0.3314	1.0000
	DE								1.0000	1.0000	0.9997	1.0000
	CASO									1.0000	1.0000	1.0000
	BPSO										0.9955	1.0000
	CBi-GSK											0.9698
	GA											

Table 3.21: The p-values obtained by the post hoc Dunn's test for Table 3.15.

		BGWCA	BAOA	BSCSO	IBES	CBRSA	CVSA	DE	CASO	BPSO	CBi-GSK	GA
	BGWCA		0.6462	**0.0000**	**0.0002**	**0.0175**	**0.0133**	**0.0153**	1.0000	0.8104	1.0000	0.0560
	BAOA			0.0714	0.6814	1.0000	1.0000	1.0000	1.0000	1.0000	0.7489	1.0000
	BSCSO				1.0000	0.9407	0.9648	0.9539	**0.0005**	**0.0385**	**0.0000**	0.7158
	IBES					1.0000	1.0000	1.0000	**0.0229**	0.5033	**0.0003**	0.9999
	CBRSA						1.0000	1.0000	0.5387	0.9999	**0.0261**	1.0000
Samll	**CVSA**							1.0000	0.4686	0.9996	**0.0200**	1.0000
	DE								0.5033	0.9998	**0.0229**	1.0000
	CASO									1.0000	1.0000	0.8381
	BPSO										0.8866	1.0000
	CBi-GSK											0.0804
	GA											
	BGWCA		0.7092	**0.0000**	**0.0001**	0.2324	**0.0119**	**0.0088**	0.9895	0.9701	1.0000	**0.0025**
	BAOA			**0.0490**	0.5194	1.0000	0.9999	0.9997	1.0000	1.0000	0.9596	0.9848
	BSCSO				1.0000	0.2575	0.9596	0.9784	**0.0065**	**0.0103**	**0.0000**	0.9994
	IBES					0.9467	1.0000	1.0000	0.1336	0.1877	**0.0006**	1.0000
	CBRSA						1.0000	1.0000	1.0000	1.0000	0.5576	1.0000
Medium	**CVSA**							1.0000	0.9467	0.9784	**0.0490**	1.0000
	DE								0.9128	0.9596	**0.0374**	1.0000
	CASO									1.0000	1.0000	0.6722
	BPSO										0.9997	0.7789
	CBi-GSK											**0.0119**
	GA											
	BGWCA		0.4589	**0.0123**	**0.0123**	0.6015	0.0599	0.8902	0.9698	0.7419	1.0000	0.5532
	BAOA			1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9386	1.0000
	BSCSO				1.0000	1.0000	1.0000	0.9975	0.9800	0.9999	0.0965	1.0000
	IBES					1.0000	1.0000	0.9975	0.9800	0.9999	0.0965	1.0000
	CBRSA						1.0000	1.0000	1.0000	1.0000	0.9800	1.0000
Large	**CVSA**							1.0000	0.9999	1.0000	0.3314	1.0000
	DE								1.0000	1.0000	0.9997	1.0000
	CASO									1.0000	1.0000	1.0000
	BPSO										0.9955	1.0000
	CBi-GSK											0.9698
	GA											

Table 3.22: The p-values obtained by the post hoc Dunn's test for Table 3.15.

		BGWCA	**BAOA**	**BSCSO**	**IBES**	**CBRSA**	**CVSA**	**DE**	**CASO**	**BPSO**	**CBi-GSK**	**GA**
	BGWCA		0.6462	**0.0000**	**0.0002**	**0.0175**	**0.0133**	**0.0153**	1.0000	0.8104	1.0000	0.0560
	BAOA			0.0714	0.6814	1.0000	1.0000	1.0000	1.0000	1.0000	0.7489	1.0000
	BSCSO				1.0000	0.9407	0.9648	0.9539	**0.0005**	**0.0385**	**0.0000**	0.7158
	IBES					1.0000	1.0000	1.0000	**0.0229**	0.5033	**0.0003**	0.9999
	CBRSA						1.0000	1.0000	0.5387	0.9999	**0.0261**	1.0000
Samll	**CVSA**							1.0000	0.4686	0.9996	**0.0200**	1.0000
	DE								0.5033	0.9998	**0.0229**	1.0000
	CASO									1.0000	1.0000	0.8381
	BPSO										0.8866	1.0000
	CBi-GSK											0.0804
	GA											
	BGWCA		0.7092	**0.0000**	**0.0001**	0.2324	**0.0119**	**0.0088**	0.9895	0.9701	1.0000	**0.0025**
	BAOA			**0.0490**	0.5194	1.0000	0.9999	0.9997	1.0000	1.0000	0.9596	0.9848
	BSCSO				1.0000	0.2575	0.9596	0.9784	**0.0065**	**0.0103**	**0.0000**	0.9994
	IBES					0.9467	1.0000	1.0000	0.1336	0.1877	**0.0006**	1.0000
	CBRSA						1.0000	1.0000	1.0000	1.0000	0.5576	1.0000
Medium	**CVSA**							1.0000	0.9467	0.9784	**0.0490**	1.0000
	DE								0.9128	0.9596	**0.0374**	1.0000
	CASO									1.0000	1.0000	0.6722
	BPSO										0.9997	0.7789
	CBi-GSK											**0.0119**
	GA											
	BGWCA		0.4589	**0.0123**	**0.0123**	0.6015	0.0599	0.8902	0.9698	0.7419	1.0000	0.5532
	BAOA			1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9386	1.0000
	BSCSO				1.0000	1.0000	1.0000	0.9975	0.9800	0.9999	0.0965	1.0000
	IBES					1.0000	1.0000	0.9975	0.9800	0.9999	0.0965	1.0000
	CBRSA						1.0000	1.0000	1.0000	1.0000	0.9800	1.0000
Large	**CVSA**							1.0000	0.9999	1.0000	0.3314	1.0000
	DE								1.0000	1.0000	0.9997	1.0000
	CASO									1.0000	1.0000	1.0000
	BPSO										0.9955	1.0000
	CBi-GSK											0.9698
	GA											

Table 3.23: The p-values obtained by the Wilcoxon signed ranks test for Table 3.10.

		BAOA	**BSCSO**	**IBES**	**CBRSA**	**CVSA**	**DE**	**CASO**	**BPSO**	**CBi-GSK**	**GA**
	Small	**0.0077**	**0.0077**	**0.0077**	**0.0077**	**0.0077**	**0.0077**	**0.0209**	**0.0152**	0.7794	**0.0109**
BGWCA	**Medium**	**0.0180**	**0.0117**	**0.0117**	**0.0180**	**0.0117**	**0.0117**	**0.0180**	**0.0116**	**0.0431**	**0.0116**
	Medium	**0.0431**	**0.0431**	**0.0431**	0.0679	**0.0431**	0.0679	**0.0431**	**0.0431**	0.0679	**0.0431**

Table 3.24: The p-values obtained by the Wilcoxon signed ranks test for Table 3.11.

		BAOA	**BSCSO**	**IBES**	**CBRSA**	**CVSA**	**DE**	**CASO**	**BPSO**	**CBi-GSK**	**GA**
	Small	**0.0077**	**0.0077**	**0.0077**	**0.0077**	**0.0077**	**0.0077**	**0.0209**	**0.0152**	0.6784	**0.0109**
BGWCA	**Medium**	**0.0117**	**0.0117**	**0.0117**	**0.0117**	**0.0117**	**0.0117**	**0.0117**	**0.0117**	**0.0117**	**0.0117**
	Medium	**0.0431**	**0.0431**	**0.0431**	**0.0431**	**0.0431**	**0.0431**	**0.0431**	**0.0431**	**0.0431**	**0.0431**

Table 3.25: The p-values obtained by the Wilcoxon signed ranks test for Table 3.12.

		BAOA	**BSCSO**	**IBES**	**CBRSA**	**CVSA**	**DE**	**CASO**	**BPSO**	**CBi-GSK**	**GA**
	Small	**0.0117**	**0.0077**	**0.0077**	**0.0109**	**0.0117**	**0.0077**	0.0929	**0.0117**	0.4838	**0.0077**
BGWCA	**Medium**	**0.0117**	**0.0117**	**0.0117**	**0.0117**	**0.0117**	**0.0117**	**0.0117**	**0.0117**	**0.0180**	**0.0117**
	Medium	**0.0431**	**0.0431**	**0.0431**	**0.0431**	**0.0431**	**0.0431**	**0.0431**	**0.0431**	**0.0431**	**0.0431**

Table 3.26: The p-values obtained by the Wilcoxon signed ranks test for Table 3.13.

		BAOA	**BSCSO**	**IBES**	**CBRSA**	**CVSA**	**DE**	**CASO**	**BPSO**	**CBi-GSK**	**GA**
	Small	**0.0077**	**0.0077**	**0.0077**	**0.0077**	**0.0077**	**0.0077**	**0.0109**	**0.0152**	0.6784	**0.0109**
BGWCA	**Medium**	**0.0117**	**0.0117**	**0.0117**	**0.0117**	**0.0117**	**0.0117**	**0.0117**	**0.0117**	**0.0117**	**0.0117**
	Medium	**0.0431**	**0.0431**	**0.0431**	**0.0431**	**0.0431**	0.1380	**0.0431**	**0.0431**	**0.0431**	**0.0431**

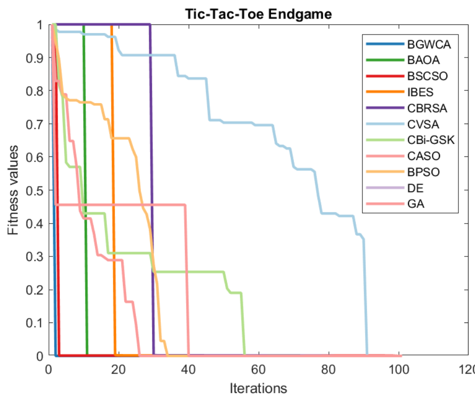
Table 3.27: The p-values obtained by the Wilcoxon signed ranks test for Table 3.14.

		BAOA	**BSCSO**	**IBES**	**CBRSA**	**CVSA**	**DE**	**CASO**	**BPSO**	**CBi-GSK**	**GA**
	Small	0.5132	**0.0077**	**0.0117**	**0.0077**	**0.0107**	**0.0108**	**0.0109**	**0.0076**	0.3615	**0.0108**
BGWCA	**Medium**	**0.0296**	**0.0180**	**0.0116**	**0.0117**	**0.0173**	**0.0117**	**0.0117**	**0.0117**	**0.0499**	**0.0172**
	Medium	**0.0431**	0.2249	**0.0431**	**0.0431**	**0.0431**	**0.0431**	**0.0431**	**0.0431**	**0.0431**	**0.0431**

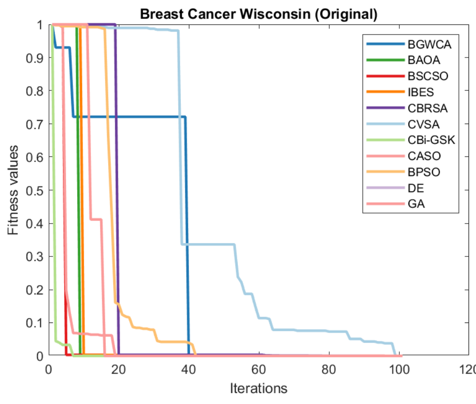
Table 3.28: The p-values obtained by the Wilcoxon signed ranks test for Table 3.15.

		BAOA	**BSCSO**	**IBES**	**CBRSA**	**CVSA**	**DE**	**CASO**	**BPSO**	**CBi-GSK**	**GA**
	Small	**0.0077**	**0.0209**	**0.0077**	**0.0077**	**0.0077**	**0.0077**	**0.0077**	**0.0077**	**0.0077**	**0.0077**
BGWCA	**Medium**	**0.0117**	**0.0251**	**0.0117**	**0.0117**	**0.0117**	**0.0117**	**0.0117**	**0.0117**	**0.0117**	**0.0117**
	Medium	0.8927	0.8927	**0.0431**	**0.0431**	**0.0431**	**0.0431**	**0.0431**	**0.0431**	**0.0431**	**0.0431**

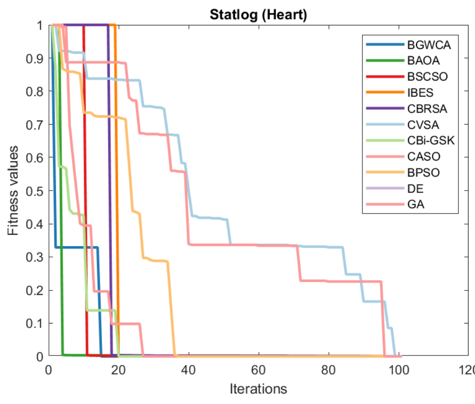
robust optimization. The incorporation of opposition-based learning and Gaussian mutation emerges as a key contributing factor to the enhanced performance of the GWCA. This conclusion highlights the significance of these innovative techniques in improving the algorithm's convergence behavior and overall effectiveness in solving the FS problem across diverse datasets.



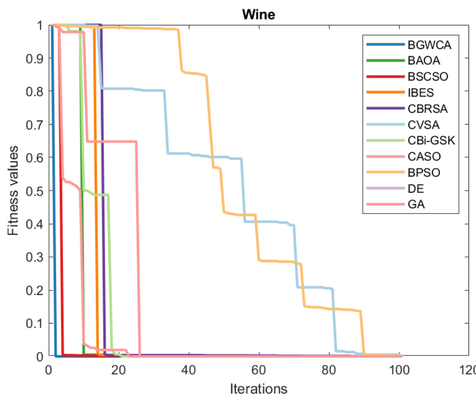
(a) Convergence analysis of fitness values for dataset d_1.



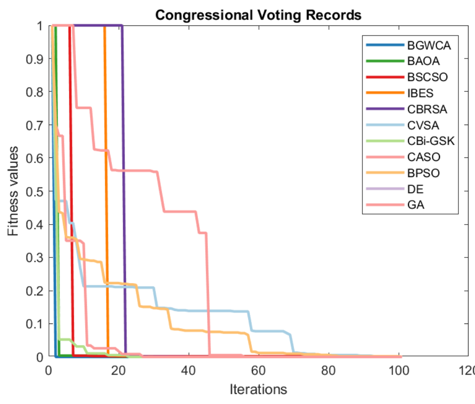
(b) Convergence analysis of fitness values for dataset d_2.



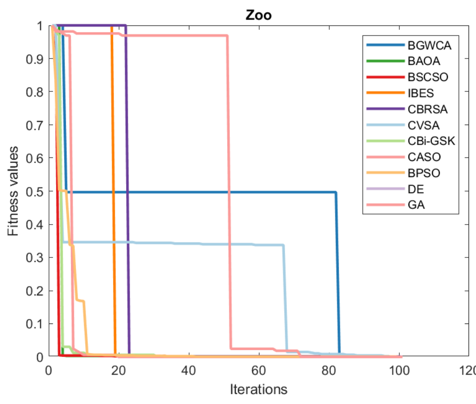
(c) Convergence analysis of fitness values for dataset d_3.



(d) Convergence analysis of fitness values for dataset d_4.

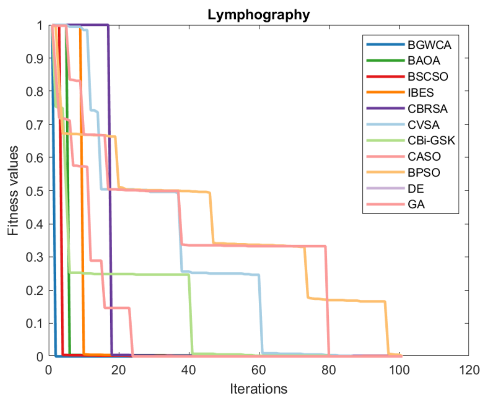


(e) Convergence analysis of fitness values for dataset d_5.

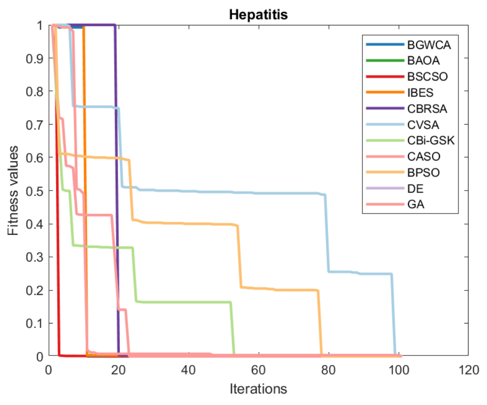


(f) Convergence analysis of fitness values for dataset d_6.

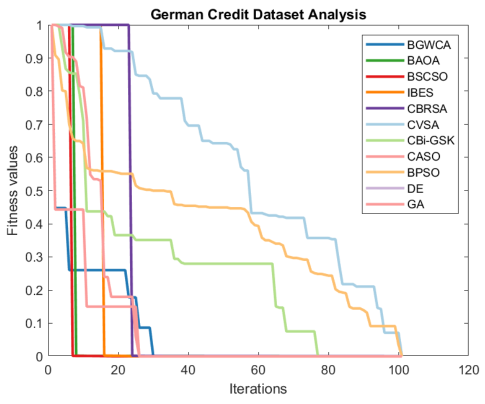
Figure 3.3: Convergence analysis of fitness values across optimizers for small dataset (d_1 to d_6).



(g) Convergence analysis of fitness values for dataset d_7.

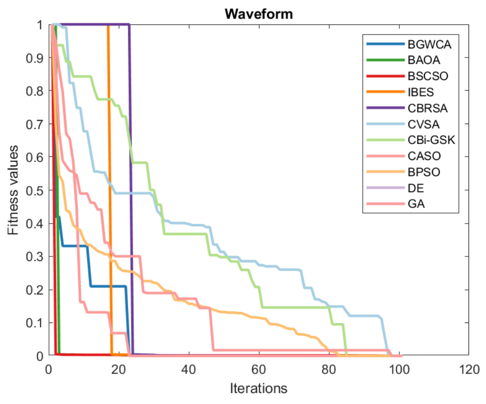


(h) Convergence analysis of fitness values for dataset d_8.

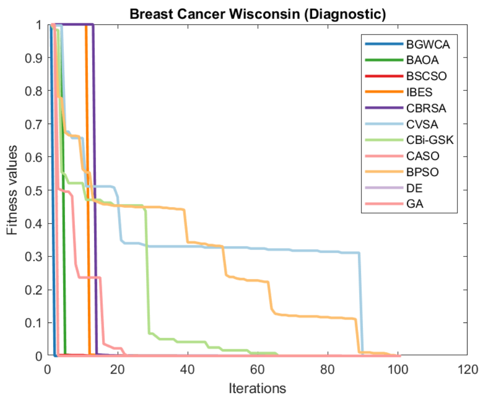


(i) Convergence analysis of fitness values for dataset d_9.

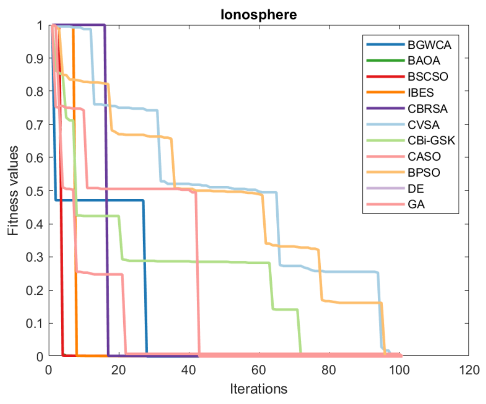
Figure 3.3: Convergence analysis of fitness values across optimizers for small dataset (d_7 to d_9).



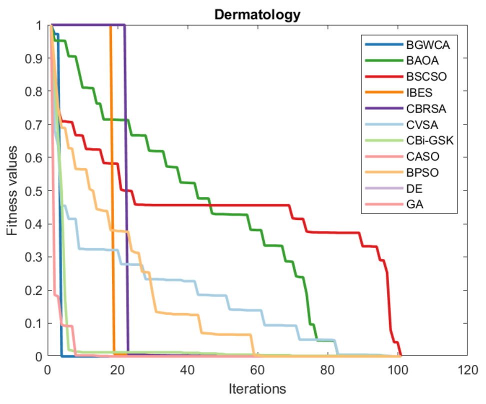
(a) Convergence analysis of fitness values for dataset d_{10}.



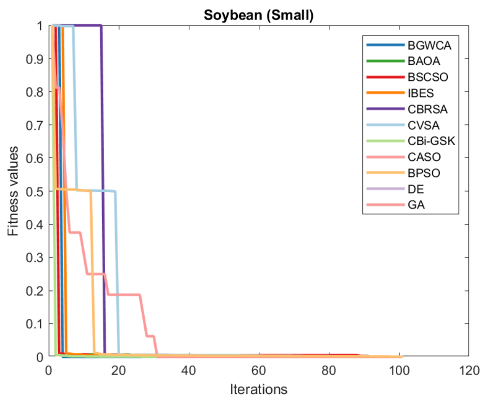
(b) Convergence analysis of fitness values for dataset d_{11}.



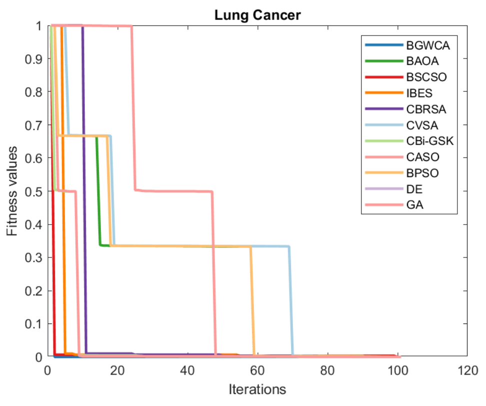
(c) Convergence analysis of fitness values for dataset d_{12}.



(d) Convergence analysis of fitness values for dataset d_{13}.

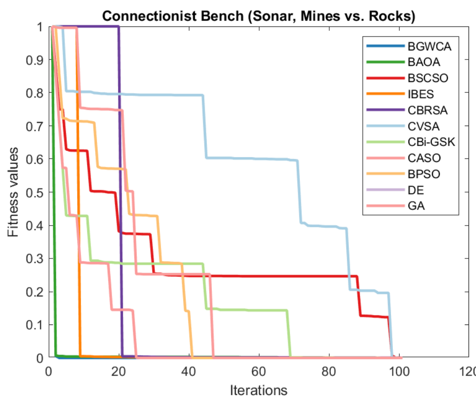


(e) Convergence analysis of fitness values for dataset d_{14}.

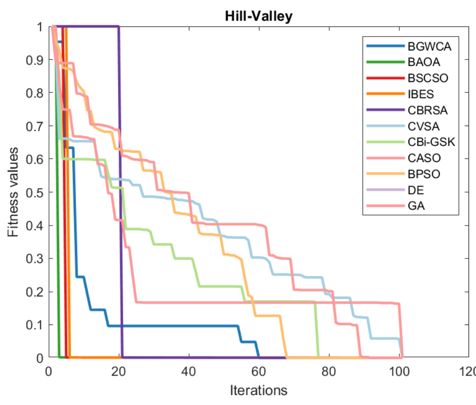


(f) Convergence analysis of fitness values for dataset d_{15}.

Figure 3.4: Convergence analysis of fitness values across optimizers for medium datasets (d_{10} to d_{15}).



(g) Convergence analysis of fitness values for dataset d_{16}.



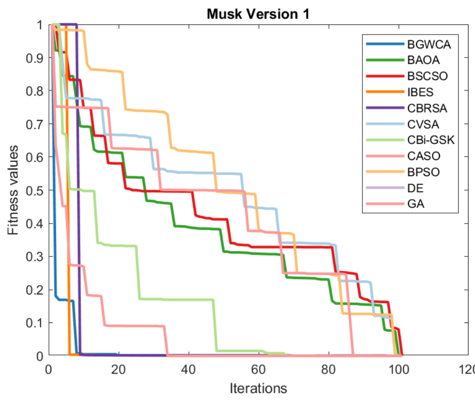
(h) Convergence analysis of fitness values for dataset d_{17}.

Figure 3.4: Convergence analysis of fitness values across optimizers for medium datasets (d_{16} to d_{17}).

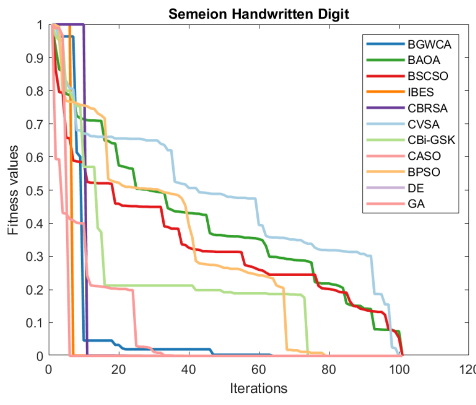
3.5 Conclusion

In conclusion, we presented a comprehensive exploration of the feature selection problem, emphasizing the critical role of selecting relevant features for enhancing machine learning model performance. The inherent complexity of this problem, stemming from a vast search space, was tackled through the utilization of the Great Wall Construction Algorithm, a recently proposed metaheuristic approach. To further augment the algorithm's effectiveness, opposition-based learning and Gaussian mutation techniques were integrated, addressing challenges related to exploration, exploitation, and local optima avoidance.The empirical evaluation of the proposed algorithm involved a thorough comparative analysis against ten state-of-the-art methodologies, encompassing both contemporary and classical algorithms. The assessment spanned 22 datasets of varying sizes, providing a diverse testing ground ranging from 9 to 856 features. Six distinct evaluation metrics, covering aspects such as accuracy, classification error rate, number of selected features, and completion time, were employed to ensure a comprehensive understanding of the algorithm's performance.

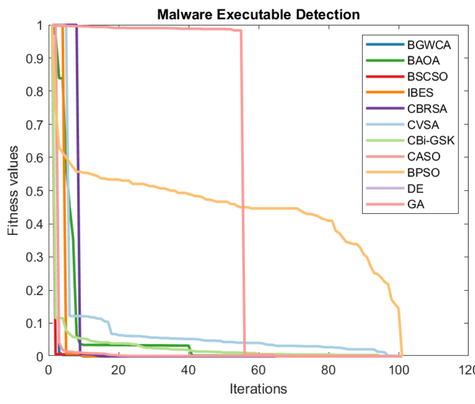
The rigorous validation of results was conducted through non-parametric statistical tests, including the Friedman test, post hoc Dunn's test, and the Wilcoxon signed ranks test. The obtained mean ranks and p-values conclusively demonstrated the superior efficacy of the proposed algorithm in addressing the feature selection problem. The algorithm showcased its prowess by outperforming competing methodologies across multiple metrics, establishing itself as a robust and promising solution for enhancing the efficiency and accuracy of feature selection in machine learning models. The findings of this research contribute valuable insights to the field, offering a compelling approach to addressing one of the fundamental challenges in machine learning model optimization.



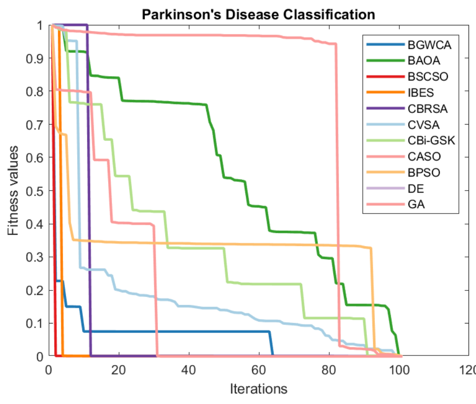
(a) Convergence analysis of fitness values for dataset d_{18}.



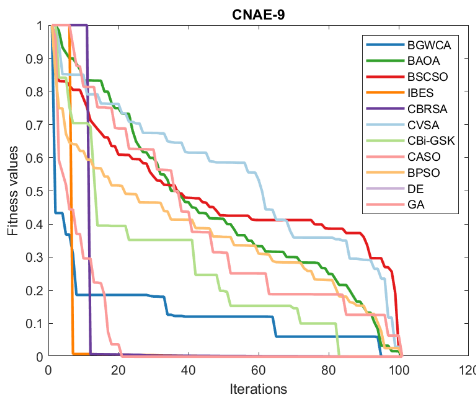
(b) Convergence analysis of fitness values for dataset d_{19}.



(c) Convergence analysis of fitness values for dataset d_{20}.



(d) Convergence analysis of fitness values for dataset d_{21}.



(e) Convergence analysis of fitness values for dataset d_{22}.

Figure 3.5: Convergence analysis of fitness values across optimizers for large datasets d_{18} to d_{22}.

3.6 Table of used symbols

Table 3.29 serves to summarize and elucidate the list of symbols utilized in the paper, aiming to enhance the clarity and ease of comprehension for readers.

Table 3.29: The list of symbols used in the paper.

Symbol	**Explanation**
ML	Machine Learning
FS	Feature Selection
MA	Metaheuristic Algorithm
GWCA	Great Wall Construction Algorithm
OBL	Opposition-Based Learning
GM	Gaussian Mutation
KNN	K-Nearest Neighbors
TP	True Positives
TN	True Negatives
FP	False Positives
FN	False Negatives
CER	Classification Error Rate

General Conclusion and Perspectives

Our thesis has delved into the field of metaheuristics and its fundamental concepts in Chapter 1.We focused on a comprehensive study of metaheuristics classification .We uncover the root of our problem, which is feature selection and its approaches in chapter 2. Chapter 3 fully clarifies the algorithm used to solve our problem of selecting feature and provides an outline of the inspiration, mathematical formulation, and code implementation of the new proposed great wall construction algorithm. Furthermore, the novel proposed great wall construction algorithm was extensively evaluated by conducting experiments on 22 of diverse set from varing sizes (9 to 856 features). The performance of the great wall construction algorithm was rigorously analyzed using several non-parametric statistical tests, including the Friedman test, the post hoc Dunn's test,and the Wilcoxon signed ranks test , providing statistical evidence of its efficacy and competitiveness in solving feature selection problems .

Future research in the field of meta-heuristic algorithm can focus on several directions, firstly they can solve many problems by optimizing them or combining them with other algorithms, making them able to improve their performance. Furthermore, experimenting with the widespread feature selection problem will provide insights into scalability and durability great wall construction metahuristic algorithme,expanding the areas of application of this algorithm to cover diverse real-world problems can prove effective and efficient. In general, these future research trends will contribute to the development of great wall construction metahuristic algorithme which allows to solve the problems of feature selection.

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