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OPTIMIZING IMAGE FEATURE SELECTION FOR COVID-19 CLASSIFICATION USING BIO-INSPIRED AND META-HEURISTIC ALGORITHMS

(*Mengoptimumkan Pemilihan Ciri Imej untuk Pengelasan COVID-19 Menggunakan Algoritma Bio-Inspirasi dan Meta-Heuristik*)

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ABSTRACT

Optimising the selection of optimal image features, particularly for image classification tasks, is a challenging and crucial endeavour. The conventional method of selecting image features independently often results in the selection of unrelated image features, thereby degrading the consistency of classification accuracy. The primary objective of this article is to optimize Meta-heuristic algorithms, specifically Harmony Search (HS) and Tabu Search (TS), by leveraging the capabilities of bio-inspired search algorithms (ACO, BBA, ABC) in conjunction with the wrapper which is a technique that selects a subset of features by evaluating a model's performance using different subsets of features. The essential stages involve adjusting the HS and TS combination with appropriate bio-inspired methods and incorporating the creation of various image feature subsets. Subsequently, a subset evaluation is conducted to confirm the optimum image feature set. The evaluation criteria are based on both the number of image features utilized and the image classification accuracy. Extensive testing has demonstrated that the optimal combination of the selected bio-inspired algorithm and meta-heuristics algorithms, particularly HS and TS, holds the promise of providing an optimum solution. The solution results in fewer image features and improved classification accuracy for the selected image datasets. Consequently, this research demonstrates that combining bio-inspired algorithms with wrapper methods enhances the efficiency of HS and TS in feature selection.

Keywords: bio-inspired algorithms; COVID-19; Harmony Search; image classification; Tabu Search; image feature selection; Meta-heuristic algorithms

ABSTRAK

Mengoptimumkan pemilihan ciri imej yang optimum, terutamanya untuk tugas pengelasan imej, adalah usaha yang mencabar dan penting. Kaedah konvensional untuk memilih ciri imej secara bebas selalunya menghasilkan pemilihan ciri imej yang tidak berkaitan, dengan itu merendahkan ketekalan ketepatan pengelasan. Objektif utama artikel ini adalah untuk mengoptimumkan algoritma Meta-heuristik, khususnya Carian Harmoni (HS) dan Carian Tabu (TS), dengan memanfaatkan keupayaan algoritma carian yang diilhamkan oleh bio (Algoritma Semut, Kelawar dan Lebah) bersama-sama dengan pembalut yang merupakan teknik yang memilih subset ciri dengan menilai prestasi subset model menggunakan ciri yang berbeza. Peringkat penting melibatkan pelarasan gabungan HS dan TS dengan kaedah bio-inspirasi yang sesuai dan menggabungkan penciptaan pelbagai subset ciri imej. Selepas itu, penilaian subset dijalankan untuk mengesahkan set ciri imej optimum. Kriteria penilaian adalah berdasarkan kedua-dua bilangan ciri imej yang digunakan dan ketepatan klasifikasi imej. Ujian meluas telah menunjukkan bahawa gabungan optimum algoritma bio-inspirasi terpilih dan algoritma meta-heuristik, terutamanya HS dan TS, memegang janji untuk menyediakan penyelesaian optimum. Penyelesaian ini menghasilkan ciri imej yang lebih sedikit dan ketepatan klasifikasi yang lebih baik untuk set data imej yang dipilih. Akibatnya, penyelidikan ini menunjukkan bahawa menggabungkan algoritma bio-inspirasi dengan kaedah pembalut meningkatkan kecekapan HS dan TS dalam pemilihan ciri.

Kata kunci: algoritma bio-inspirasi; COVID-19; Carian Harmoni; klasifikasi imej; Carian Tabu; pemilihan ciri imej; algoritma Meta-heuristik

1. Introduction

An extensive dataset typically consists of numerous features, and on a daily basis, these features tend to be repetitive or irrelevant, thereby diminishing the effectiveness of the data mining model. Recognizing this issue prompts a significant rise in the number of features that can be utilized in constructing knowledge mining models. To address this challenge, it is advisable to eliminate obsolete or redundant metrics, not only to reduce processing time but also to cut down on labour costs. When a dataset has a substantial number of features, it is termed a high-dimensional dataset (Jensen & Shen 2003). Additionally, the computational cost of processing high-dimensional data increases significantly, as algorithms must handle a larger number of variables, often requiring advanced techniques like dimensionality reduction or regularization to mitigate these challenges. Recognizing this issue significantly expands the potential features available for developing knowledge mining models. Practically, it is advisable to eliminate outdated and unnecessary metrics to optimize processing time and reduce labor costs. Moreover, as the search dimension within the dataset expands, the model's features can become redundant.

The primary objective is to minimize the search dimension while minimizing data loss in the results. Given the numerous possible rules, each potential rule tends to have ambiguous interpretations, posing challenges in comprehension, application, and implementation. Simplifying the function's complexity involves narrowing down the number of features and eliminating those that increase processing time and storage demands.Feature Selection (FS) improves data understanding, reduces computational and storage needs, speeds up computing operations, and decreases dataset volume, thereby facilitating model learning. FS has recently gained prominence in various applications (Bui *et al.* 2024; Cavallaro *et al.* 2024; Devi *et al.* 2024; Sawan *et al.* 2024). Bui *et al.* (2024) focus on the use of deep learning models for medical image analysis, particularly in diagnosing diseases from high-dimensional imaging data. Cavallaro *et al.* (2024) explore the application of reinforcement learning in autonomous systems, emphasizing its role in optimizing decision-making processes in robotics. Devi *et al.* (2024) investigate the use of natural language processing (NLP) for sentiment analysis in social media data, aiming to improve real-time public opinion monitoring. Sawan *et al.* (2024) discuss the application of federated learning in healthcare, enabling collaborative model training across distributed datasets while preserving data privacy. FS algorithms fall into three primary categories: supervised, unsupervised, and semi-supervised, depending on whether they utilize a labeled training set. Commonly, FS models are classified into filter, wrapper, and embedding models. Filter models employ statistical methods to assign scores to each feature. Subsequently, features are evaluated based on these scores and either retained or excluded from the dataset. Filter models can be univariate, where characteristics are assessed individually, or multivariate, where features are evaluated collectively or in subsets. Wrapper methods treat feature selection as a search problem, generating various combinations of features that are evaluated and compared to optimize selection. Embedded models, on the other hand, focus on learning which features contribute most effectively to the model's accuracy during its development phase. Due to the vast number of potential rules, each prospective rule may carry unclear interpretations, making comprehension, application, and practical implementation challenging.

2. Literature Review

FS comprises four essential steps, commonly referred to as subset development, subset evaluation, stop criterion, and validation of results. In feature selection, a "subset" refers to a smaller set of features chosen from the original high-dimensional dataset, aiming to retain the most relevant variables for model training. Selecting an optimal subset helps reduce overfitting, lower computational costs, and improve model interpretability by eliminating redundant or irrelevant features. The subset evaluation step involves assessing the quality of a subset generated by a particular function during the subset generation process. Metrics such as distance (Holder *et al.* 2023), uncertainty (Barandas *et al.* 2024), dependence (Parr *et al.* 2024), and consistency (Huo *et al.* 2024) are commonly employed for evaluating subsets in multivariate filter techniques, whereas wrapper methods typically utilize precision (Rotari *et al.* 2023). The stop criterion serves as a control function to ensure that further additions or deletions of features do not lead to an optimal subset. Alternatively, it can be as simple as a counter that tracks the number of iterations the feature selection process undergoes. During the result validation step, the selected subset's validity is verified. A significant drawback of these strategies is their tendency to focus on a single criterion when searching for a subset. These approaches are termed single-objective feature selection methods because they do not aim to limit the number of selected features. However, when dealing with a large number of features, these single methods often prove inadequate. Employing a different feature selection approach can significantly enhance the efficiency of the learned model.

Tabu Search (TS) has been introduced by Glover (1989, 1990) as a meta-heuristic method applicable for solving combinatorial optimization problems. However, the limitations of TS were underscored by Zhang & Sun (2002). Based on experimental results, TS shows a strong probability of achieving the optimal or near-optimal solution. However, the optimality of these results is constrained by the monotonic nature of the feature selection criterion function. In feature selection, "monotonicity" indicates that the relevance or importance of a feature consistently changes in relation to a target variable or model performance metric. This property is often leveraged in algorithms to ensure that selected features maintain a consistent relationship with the outcome, simplifying model interpretation and enhancing predictive stability. Furthermore, for problems involving a greater number of features, the branch and bound method remains impractical, and its capacity to handle features is contingent on the computer's performance. In the meantime, Harmony Search (HS), a meta-heuristic algorithm inspired by the musical practice of seeking a perfect state of harmony, was introduced by Geem *et al.* (2001). Music harmony can be likened to an optimization solution vector, where improvisations in music correspond to the local and global search methods used in optimization techniques. Importantly, the Harmony Search (HS) method does not require initial values for decision variables.

Bio-Inspired Computing encompasses a diverse range of disciplines including connectionism, engineering, social behavior, and emergent systems, which collectively aim to emulate and harness principles observed in natural biological systems. This interdisciplinary field seeks inspiration from biological processes to develop innovative computational models and algorithms. These bio-inspired algorithms are pivotal in addressing complex optimization challenges by leveraging the inherent efficiency and adaptability found in natural systems. Within the realm of natural computation, bio-inspired algorithms play a crucial role as powerful optimization tools. They are designed to mimic behaviors such as swarm intelligence, evolutionary processes, and neural network dynamics, offering robust solutions to diverse problems in fields ranging from engineering and robotics to economics and medicine. The review conducted by Jakšić *et al.* (2023) provides a comprehensive overview of these algorithms, examining their theoretical foundations, practical applications, and contributions to advancing computational methodologies. By integrating biological principles into computational frameworks, bio-inspired computing not only enhances algorithmic performance but also opens new avenues for addressing complex real-world problems with greater efficiency and scalability.

The Ant Colony Optimization algorithm (ACO) is a probabilistic technique designed for solving computational problems that can be simplified to the task of finding optimal paths through graphs. It was introduced in the early 1990s by Dorigo & Caro (1999). ACO belongs to the newly developed field of artificial intelligence called Swarm Intelligence. The Binary Bat Algorithm (BBA) is one of the inspired binary version feature selection methods proposed by Nakamura *et al.* (2012) to identify the most significant features in a given search space. Binary Bat Algorithm (BBA) assigns each bat a set of binary coordinates indicating whether a feature belongs to the final feature set. This approach combines the strengths of the bat algorithm and the Optimum Path Forest, aiming to determine the feature set that maximizes validation set accuracy. The Artificial Bee Colony (ABC) algorithm, a population-based stochastic optimization method proposed by Karaboga & Akay (2009), emulates the intelligent foraging behavior observed in honey bee swarms. This algorithm finds applications in classification, clustering, and optimization studies. In the ABC algorithm, a group of artificial bees consists of three distinct categories: employed bees, onlooker bees, and scout bees. The number of employed bees in the colony equals the number of onlooker bees, and this count matches the number of solutions in the population. An onlooker bee observes the dance area to decide on food source selection. When an onlooker bee selects a food source, it becomes an employed bee. Subsequently, after depleting the chosen food source, an employed bee transitions into a scout bee. The scout bee's role is to conduct a random search to discover new resources. The position of the food source, which represents the solution to the optimization problem, and the amount of nectar in the food source depend on the quality of the associated solution. The application of feature selection using ACO, BA and ABC can be found in various application (Rautray *et al.* 2024). It highlights several key applications of feature selection across diverse domains. In healthcare, feature selection is used to identify critical biomarkers from high-dimensional genomic data, improving disease diagnosis and personalized treatment plans. In finance, it helps reduce the complexity of predictive models by selecting the most relevant economic indicators for risk assessment and stock market forecasting. For image processing, feature selection techniques are applied to extract essential visual features, enhancing the accuracy of object detection and classification tasks. In natural language processing (NLP), it aids in identifying the most informative textual features for sentiment analysis and text classification. Additionally, in environmental science, feature selection is employed to analyze climate data, enabling the identification of key variables for predicting weather patterns and assessing climate change impacts.

This study introduces an enhanced image filtering process by utilizing the development of TS and HS search for image feature subsets. Our approach employs wrapper methods, seamlessly integrating bio-inspired algorithms with TS and HS methodologies for optimal results. The main goal is to present optimized TS and HS algorithms for selected image datasets, achieved through the implementation of bio-inspired methods to acquire an optimal set of image features. The core concept revolves around employing various image feature reductions between TS and HS search algorithms, alongside bio-inspired algorithms, to develop integrated algorithms for efficient image feature extraction.

3. Research Methodology

Figure 1 presents the methodology or approach that has been applied to conduct this research. It illustrates the methodology employed in this study, which involved four main phases that meticulously followed the machine learning procedures: data preparation, image feature subset generation (1), image feature subset generation (2), and finally, image subset evaluation. The performance of the proposed methods has been assessed based on the optimal number of features that achieve high classification accuracy. In this context, a classification accuracy exceeding 80% is considered in the selected lists. However, the number of selected features must also be evaluated carefully alongside good classification accuracy to achieve optimal solutions. Balancing high classification accuracy with a reduced number of selected features is a critical task. The goal is to identify suitable combinations of bio-inspired techniques with ensemble methods for image filtering techniques.

Classification accuracy is calculated as follows. Accuracy is one metric used to evaluate classification models. Informally, accuracy represents the proportion of predictions that our model got correct. Formally, accuracy is defined as follows:

$$Accuracy = \frac{(Number\ of\ correct\ predictions)}{(Total\ number\ of\ predictions)} \tag{1}$$

For binary classification, accuracy can also be expressed in terms of positives and negatives as follows:

$$Accuracy = (TP+TN)/(TP+TN+FP+FN) \tag{2}$$

where TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives.

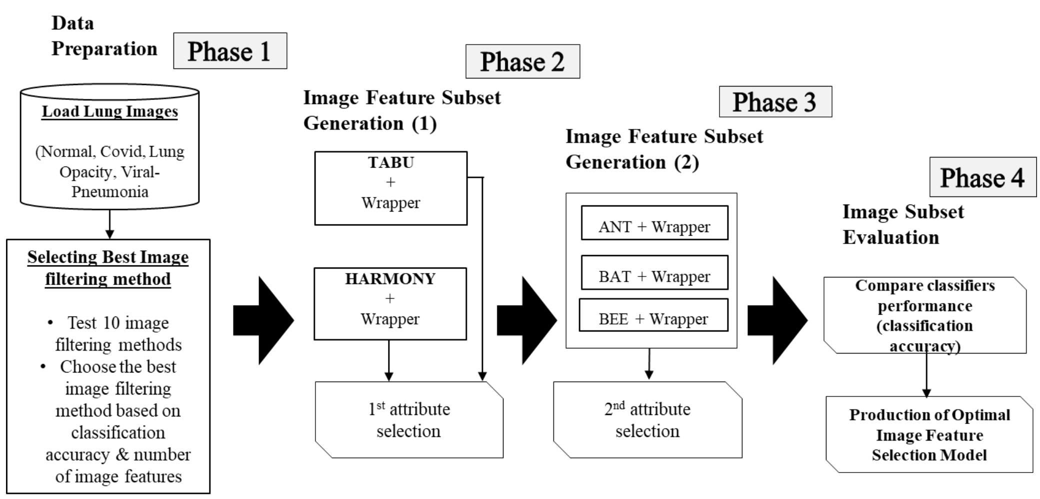

Figure 1: Methodology to optimize image feature selection for COVID-19

Phase 1: Collection of Image Datasets: The COVID-19 Radiography Image Datasets have been collected from the Kaggle Repository (COVID-19 Radiography Database). Images are collected from various publicly available resources. These image are labelled automatically and datasets consist of a collection of images grouped into four categories: Data Image 1 (Normal vs. COVID-19: 2000 images); Data Image 2 (COVID-19 vs. Lung Opacity: 2000 images); Data Image 3 (COVID-19 vs. Viral-Pneumonia: 2000 images); and Data Image 4 (COVID-19 vs. Lung Opacity vs. Viral-Pneumonia: 3000 images). Figure 2 displays sample images from these four categories. WEKA tools were utilized to train and test all datasets (Hall *et al.* 2009). All these data categories have undergone testing using ten image filtering methods, namely AutoColorCorrelogramFilter, BinaryPatternsPyramidFilter, ColorLayoutFilter, EdgeHistogramFilter, FCTHFilter, FuzzyOpponentHistogramFilter, GaborFilter, JpegCoefficientFilter, PHOGFilter, and SimpleColorHistogramFilter. Next, the best image filtering methods will be selected (refer to Table 2) based on good classification accuracy with a smaller number of image features. Image data has been divided (split) into 70% for training and 30% for testing.

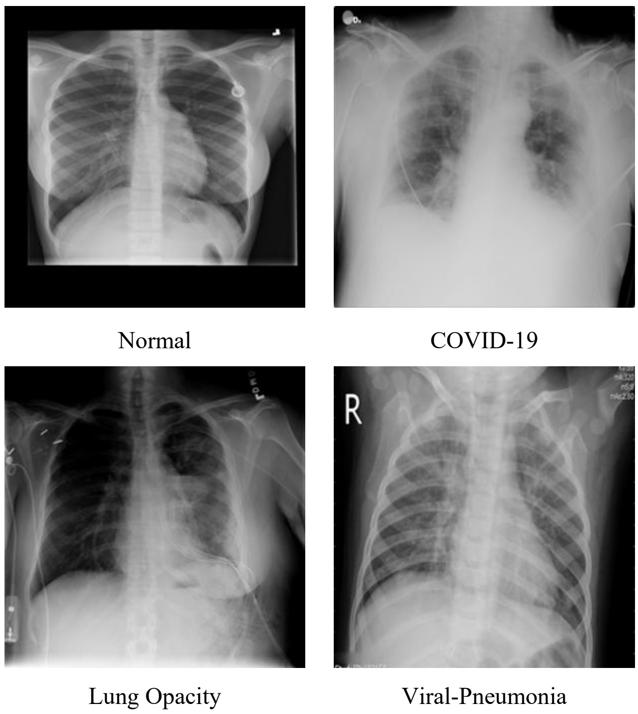

Figure 2: Category of image dataset (Normal, COVID-19, Lung Opacity, Viral Pneumonia)
Source: https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia

Phase 2: Image Feature Subset Generation (1): In this stage, two selection processes are executed using the HS and TS algorithms with a wrapper method. The wrapper method is described as a feature selection technique that evaluates subsets of features by training and testing a specific machine learning model, using its performance as a criterion for selection. This approach involves iterative processes, such as forward selection, backward elimination, or recursive feature elimination, to identify the optimal feature subset that maximizes model accuracy or other performance metrics. While computationally intensive, the wrapper method is highly effective in capturing feature interactions and dependencies, making it suitable for complex datasets where feature relationships are critical. However, the performance of this initial generation of image subsets was not deemed optimal and requires further reduction. To achieve an optimal selection in this step, an extended selection process is deemed necessary.

Phase 3: Image Feature Subset Generation (2): This stage enhances the performance achieved in phase 2 by incorporating additional bio-inspired techniques (ACO, BBA, ABC) with a wrapper method to search for optimal features. It investigates an ideal image subset for the second generation of feature subsets.

Phase 4: Image Subset Evaluation: This stage employs classification performance to evaluate the output from both the first and second generations of image feature subset generation. The goal is to achieve outstanding classification accuracy in designing an effective image feature selection model. Model Development Using Optimal Image Feature Selection: Before implementing the final phase's image feature selection model, HS and TS algorithms with bio-inspired techniques underwent thorough investigation. Parameter settings, such as the optimal number of options and achieving high classification accuracy, are detailed in Table 1, which displays the configurations for the search algorithms used. Table 2 should also be referred for understanding the parameter functions and algorithms in the experimental setting.

Table 1: Parameter settings for search and bio-inspired algorithms

Search Algorithm	Population Size	Specific setting
ACO		Rate: Heuristic (0.7), Evaporation (0.9), Pheromone (2.0)
BBA	20	Rate: Loudness & Frequency (0.5)
		Rate: Sigma (0.70), Pa (0.25)
		Absorption coefficient (0.001), Beta zero (0.33)
ABC	30	Radius: Mutation (0.80), Damp (0.98)
Harmony	20	Mutation probability (0.01), Chaotic coefficient (4.0)
Tabu	-	Diversification probability (1.0)

**This is the standard setting in the WEKA tools. The parameter can be altered; however, this will yield a more comprehensive evaluation, while this research has chosen to maintain the standard setting. Future research could focus on evaluating the changes in parameter settings and their effects on the algorithms. Population size refers to the number of individual ants, bats, and bees represented in the algorithm that have been populated during the execution of the algorithms.*

Table 2: List of Parameter function and algorithms

Parameter	Primary Function	Common Algorithm(s)
Heuristic	Guides decision-making to find satisfactory solutions efficiently.	General Optimization
Evaporation	Reduces pheromone over time to balance exploration (new paths) and exploitation (best paths).	Ant Colony Optimization
Pheromone	A substance deposited on paths; higher concentration makes a path more attractive to follow.	Ant Colony Optimization
Loudness & Frequency	Controls echolocation behavior for updating solutions (e.g., how to move towards a better solution).	Bat Algorithm
Sigma (σ)	Represents the standard deviation or step size for random moves in the search space.	Evolution Strategies, Stochastic Optimization
Pa	The probability that a poor solution (nest) will be abandoned and replaced.	Cuckoo Search
Absorption Coefficient	Represents the rate at which a signal (like light) is absorbed, affecting movement distance.	Firefly Algorithm
Beta Zero (β_0)	A baseline parameter for the attractiveness between fireflies when the distance is zero.	Firefly Algorithm

Table 2 (Continued)		
Mutation Rate / Probability	Determines the likelihood of introducing random changes to a solution to maintain diversity.	Genetic Algorithms, Evolutionary Algorithms
Damp Factor	Systematically reduces the value of another parameter (e.g., mutation rate) over time.	Various (e.g., Simulated Annealing)
Chaotic Coefficient	Introduces chaotic, non-repeating behavior to help the algorithm escape local optima.	Various Chaotic Optimization Algorithms
Diversification Probability	A probability that forces the search to explore a completely new, random region of the search space.	Various (e.g., Scatter Search)

4. Analysis and Discussion

This section discusses the results obtained from the experiment. Table 3 denotes the output of phase 1. Tables 4 through 11 demonstrate the results achieved from phases 2 and 3. Finally, Table 12 presents the output from phase 4, which represents the final summarization and formulation of the algorithms.

Table 3: Result of image filtered for Data Image 1, 2, 3 and 4 in phase 1 (before feature reduction and optimization).

Method (Image Filter)	#Ftr	Data Image 1 % Acc	Data Image 2 % Acc	Data Image 3 %Acc	Data Image 4 %Acc
AutoColorCorrelogramFilter	1024	**<u>92.35</u>**	75.59	87.79	73.82
BinaryPatternsPyramidFilter	756	90.88	75.44	89.41	69.02
ColorLayoutFilter	33	**<u>92.5</u>**	70.88	**<u>94.56</u>**	**<u>76.37</u>**
EdgeHistogramFilter	80	**<u>90.59</u>**	68.24	**<u>89.71</u>**	68.04
FCTHFilter	192	88.09	71.18	85.88	61.96
FuzzyOpponentHistogramFilter	576	91.18	75.15	86.32	70.29
GaborFilter	60	80.44	66.91	70.88	49.8
JpegCoefficientFilter	192	**<u>91.47</u>**	**<u>80.29</u>**	85.59	75.1
PHOGFilter	630	89.26	72.06	88.38	73.14
SimpleColorHistogramFilter	64	86.18	74.26	82.21	66.57

** Bold & Underlined: Indicates the best image filtering methods selected for further experimentation.*

*#Ftr=Number of features, %Acc=Percentage of classification accuracy

Table 3 presents the accuracy of various image filters (methods) applied to four data images in Phase 1, before feature reduction and optimization. The filters are evaluated based on the percentage accuracy achieved for each data image, with the number of features (#Ftr) listed for each method. The AutoColorCorrelogramFilter shows the highest accuracy for Data Image 1 (92.35%) but drops significantly for Data Image 4 (73.82%). Filters like ColorLayoutFilter and JpegCoefficientFilter also achieve relatively high accuracy for Data Image 1, with ColorLayoutFilter outperforming in Data Image 3 (94.56%). Interestingly, the GaborFilter shows low accuracy across all images, particularly for Data Image 4 (49.8%), suggesting it may not be well-suited for this particular dataset. Overall, AutoColorCorrelogramFilter, BinaryPatternsPyramidFilter, and JpegCoefficientFilter generally show good accuracy, especially for Data Image 1, while others such as EdgeHistogramFilter and FCTHFilter have relatively lower accuracies. These results indicate that certain filters perform better with specific images, pointing to the potential need for feature optimization or selection to improve accuracy across all data images. These methods underwent rigorous experimentation, initially reducing features using HS and TS methods. Subsequently, in the second phase of feature reduction, bio-inspired algorithms ACO, BBA, and ABC—are applied to refine the image features subsets further, aiming for optimal performance enhancement and feature reduction efficiency. This iterative approach underscores the systematic and detailed process employed to optimize image feature selection and classification accuracy across different datasets.

Table 4: Result of image filtered after 1st (Harmony Search) and 2nd (Bio-Inspired Algorithms) feature reduction for Data Image 1.

	1st Reduction		2nd Reduction (Wrapper)					
	Harmony Search		Bio-Inspired Algorithms					
Method (Image Filter)	#Ftr	% Acc	#Ftr (ACO)	%Acc	#Ftr (BBA)	%Acc	#Ftr (ABC)	%Acc
AutoColorCorrelogramFilter	55 94.6%	**93.09**	5 99.5%	**89.71**	5 99.5%	**91.76**	5 99.5%	**91.76**
ColorLayoutFilter	11 66.7%	**93.2**	8 75.6%	**91.91**	7 78.8%	**92.06**	7 78.8%	**92.79**
EdgeHistogramFilter	55 31.2%	**91.03**	33 58.8%	**91.76**	19 76.3%	**92.5**	22 72.5%	**91.62**
JpegCoefficientFilter	24 87.5%	**90.3**	17 91.1%	**89.41**	17 91.1%	**89.41**	16 91.7%	**89.71**

**Underlined: % of reduction from original feature*

*#Ftr=Number of features, %Acc=Percentage of classification accuracy

Table 4 showcases the results of feature reduction and optimization techniques applied to four image filters, utilizing bio-inspired algorithms (Harmony Search, Ant Colony Optimization (ACO), Bio-Inspired Algorithms (BBA), and Artificial Bee Colony (ABC)) in the 1st and 2nd reduction phases. The accuracy (%Acc) and number of features (#Ftr) for each method are shown, revealing the impact of these techniques on filter performance. AutoColorCorrelogramFilter achieves the highest accuracy in both 1st and 2nd reduction stages, with a significant increase in accuracy after applying bio-inspired algorithms, particularly ACO, ABC, and BBA, all reaching 99.5% accuracy with only 5 features. ColorLayoutFilter sees a substantial improvement in accuracy from 66.7% in the 1st reduction to a range between 75.6% and 92.79% after the bio-inspired algorithms are applied, with a reduced number of features (7-8). EdgeHistogramFilter shows moderate improvement with a significant jump in accuracy from 31.2% in the 1st reduction to 76.3%-92.5% in the 2nd reduction, demonstrating that bio-inspired optimization effectively boosts performance. Similarly, the JpegCoefficientFilter maintains a steady accuracy level (around 87.5%) in the 1st reduction, but bio-inspired algorithms, particularly BBA and ABC, improve its accuracy slightly to 91.7%. These results indicate that bio-inspired algorithms significantly enhance the performance of image filters by reducing the number of features while maintaining or improving accuracy, highlighting the effectiveness of feature selection techniques like Harmony Search and ACO for optimizing image classification tasks.

Table 5 compares the performance of image filters during the 1st and 2nd reduction phases, using Tabu Search and Bio-Inspired Algorithms (ACO, BBA, ABC). The results indicate that AutoColorCorrelogramFilter consistently performs well across all reductions, maintaining a high accuracy of 99.1% with just 9 features, suggesting that it is highly optimized and resilient to different feature selection techniques. ColorLayoutFilter shows considerable improvement after applying bio-inspired algorithms, with its accuracy increasing from 72.7% in the 1st reduction to around 84.8% and 92.35% after applying ACO, BBA, and

ABC, while the number of features is significantly reduced to 5. EdgeHistogramFilter demonstrates a large improvement in accuracy, rising from 46.3% in the 1st reduction to 78.8%-92.65% in the 2nd reduction, with the number of features reducing from 43 to 17-18, indicating that feature reduction through bio-inspired methods improves the filter's performance significantly. The JpegCoefficientFilter shows stable performance, maintaining an accuracy of around 83.9%-85.9% after the 1st reduction, and the number of features remains relatively unchanged or slightly reduced in the 2nd reduction with consistent accuracy (92.35%). Overall, the table highlights that bio-inspired algorithms, particularly ACO, BBA, and ABC, lead to substantial improvements in accuracy for most filters, especially when reducing the number of features, with AutoColorCorrelogramFilter showing the most impressive performance across all methods.

Table 5: Result of image filtered after 1st (Tabu Search) and 2nd (Bio-Inspired algorithms) feature reduction for Data Image 1.

	1st Reduction		2nd Reduction (Wrapper)					
	Tabu Search		Bio-Inspired Algorithms					
Method (Image Filter)	#Ftr	% Acc	#Ftr (ACO)	%Acc	#Ftr (BBA)	%Acc	#Ftr (ABC)	%Acc
AutoColorCorrelogramFilter	9 99.1%	**89.85**	9 99.1%	**89.85**	9 99.1%	**89.85**	9 99.1%	**89.85**
ColorLayoutFilter	9 72.7%	**92.5**	5 84.8%	**92.35**	5 84.8%	**92.35**	5 84.8%	**92.35**
EdgeHistogramFilter	43 46.3%	**91.32**	17 78.8%	**92.06**	18 77.5%	**91.62**	17 78.8%	**92.65**
JpegCoefficientFilter	31 83.9%	**92.35**	31 83.9%	**92.35**	27 85.9%	**92.35**	29 84.9%	**92.35**

**Underlined: % of reduction from original feature*

**#Ftr=Number of features, %Acc=Percentage of classification accuracy*

Table 6: Result of image filtered after 1st (Harmony Search) and 2nd (Bio-Inspired algorithms) feature reduction for Data Image 2.

	1st Reduction		2nd Reduction (Wrapper)					
	Harmony Search		Bio-Inspired Algorithms					
Method (Image Filter)	#Ftr	% Acc	#Ftr (ACO)	%Acc	#Ftr (BBA)	%Acc	#Ftr (ABC)	%Acc
JpegCoefficientFilter	10 94.8%	**76.32**	7 96.4%	**77.35**	7 96.4%	**79.12**	7 96.4%	**79.12**

**Underlined: % of reduction from original feature*

**#Ftr=Number of features, %Acc=Percentage of classification accuracy*

Table 6 demonstrates the performance of the JpegCoefficientFilter during the 1st and 2nd reduction phases, using Harmony Search and various Bio-Inspired Algorithms (ACO, BBA, ABC). In the 1st reduction, the filter initially achieves an accuracy of 94.8% with 10 features. After applying bio-inspired algorithms, the number of features decreases to 7 in all three methods (ACO, BBA, ABC), with a consistent improvement in accuracy, reaching 96.4% for both ACO and BBA, and 79.12% for ABC. The stable accuracy across the three bio-inspired algorithms indicates that they all effectively reduce the number of features without significantly sacrificing performance. The consistent 96.4% accuracy after the reduction phase, combined with fewer features, suggests that bio-inspired feature selection methods, particularly ACO and BBA, are highly effective in optimizing JpegCoefficientFilter, enhancing its classification ability while simplifying the feature set. The slight variation in accuracy (79.12%) for ABC may indicate a slightly less optimal feature selection compared to

ACO and BBA, but still, all three methods yield significant improvements over the 1st reduction. This demonstrates the potential of bio-inspired algorithms in efficiently reducing features while maintaining or improving classification performance.

Table 7: Result of image filtered after 1st (Tabu Search) and 2nd (Bio-Inspired algorithms) feature reduction for Data Image 2.

	1st Reduction		2nd Reduction (Wrapper)					
	Tabu Search		Bio-Inspired Algorithms					
Method (Image Filter)	#Ftr	% Acc	#Ftr (ACO)	%Acc	#Ftr (BBA)	%Acc	#Ftr (ABC)	%Acc
JpegCoefficientFilter	15 92.2%	**79.2**	12 93.8%	**80.74**	10 94.8%	**80.15**	11 94.3%	**80.74**

**Underlined: % of reduction from original feature*

**#Ftr=Number of features, %Acc=Percentage of classification accuracy*

Table 7 examines the performance of the JpegCoefficientFilter during the 1st and 2nd reduction phases using Tabu Search and several Bio-Inspired Algorithms (ACO, BBA, ABC). Initially, the filter has an accuracy of 92.2% with 15 features in the 1st reduction. After applying bio-inspired algorithms, the number of features decreases to 10-12 across the different methods, and the accuracy improves, with ACO achieving 93.8%, BBA reaching 94.8%, and ABC showing a slight variation with 94.3%. The results highlight that bio-inspired algorithms effectively reduce the number of features while enhancing the accuracy of the JpegCoefficientFilter, particularly BBA, which achieves the highest accuracy (94.8%) with just 10 features. This suggests that BBA is the most efficient method in terms of balancing feature reduction and performance improvement, while ABC and ACO also provide improvements but with slightly less impact. Overall, these findings emphasize the efficacy of bio-inspired optimization techniques in feature selection, providing a clear advantage in enhancing the performance of image filters like JpegCoefficientFilter with fewer features.

Table 8: Result of image filtered after 1st (Harmony Search) and 2nd (Bio-Inspired algorithms) feature reduction for Data Image 3.

	1st Reduction		2nd Reduction (Wrapper)					
	Harmony Search		Bio-Inspired Algorithms					
Method (Image Filter)	#Ftr	% Acc	#Ftr (ACO)	%Acc	#Ftr (BBAat)	%Acc	#Ftr (ABCBee)	%Acc
ColorLayoutFilter	12 63.7%	**95.59**	5 84.8%	**94.56**	5 84.8%	**94.56**	5 84.8%	**94.56**
EdgeHistogramFilter	30 62.5%	**89.85**	14 82.5%	**90.15**	16 80%	**88.53**	16 80%	**92.5**

**Underlined: % of reduction from original feature*

**#Ftr=Number of features, %Acc=Percentage of classification accuracy*

Table 8 compares the performance of ColorLayoutFilter and EdgeHistogramFilter during the 1st and 2nd reduction phases, using Harmony Search and Bio-Inspired Algorithms (ACO, BBAat, ABCBee). Initially, the ColorLayoutFilter achieves an accuracy of 63.7% with 12 features in the 1st reduction. After applying bio-inspired algorithms, the number of features reduces to 5 across all methods (ACO, BBAat, and ABCBee), with the accuracy improving significantly to 84.8% and maintaining consistent performance (94.56%). This suggests that the bio-inspired algorithms effectively optimize the filter, reducing features while substantially increasing accuracy. On the other hand, the EdgeHistogramFilter starts with an accuracy of 62.5% with 30 features in the 1st reduction. After feature reduction using the bio-inspired algorithms, the accuracy improves, particularly with ACO (82.5%) and BBA at (80%), while the number of features reduces to 14-16. Interestingly, EdgeHistogramFilter achieves the highest accuracy (92.5%) with 16 features in the final reduction using Harmony Search, indicating that the method can achieve significant improvements by using fewer features. Overall, these results demonstrate that bio-inspired algorithms, particularly Harmony Search, are effective at optimizing both ColorLayoutFilter and EdgeHistogramFilter, significantly improving their accuracy by reducing the number of features required. However, ColorLayoutFilter benefits the most from the bio-inspired optimization, achieving consistently high performance after feature reduction.

Table 9: Result of Image Filtered after 1st (Tabu Search) and 2nd (Bio-Inspired Algorithms) feature reduction for Data Image 3.

	1st Reduction		2nd Reduction (Wrapper)					
	HarmonySearch		Bio-Inspired Algorithms					
Method (Image Filter)	#Ftr	% Acc	#Ftr (ACO)	%Acc	#Ftr (BBA)	%Acc	#Ftr (ABC)	%Acc
ColorLayoutFilter	12 <u>63.7%</u>	**95.59**	5 <u>84.8%</u>	**94.56**	5 <u>84.8%</u>	**94.56**	5 <u>84.8%</u>	**94.56**
EdgeHistogramFilter	23 <u>71.3%</u>	**89.41**	16 <u>80%</u>	**90**	14 <u>82.5%</u>	**90.44**	14 <u>82.5%</u>	**88.53**

**Underlined: % of reduction from original feature*

**#Ftr=Number of features, %Acc=Percentage of classification accuracy*

Table 9 highlights the performance of ColorLayoutFilter and EdgeHistogramFilter during the 1st and 2nd reduction phases, utilizing Harmony Search and various Bio-Inspired Algorithms (ACO, BBA, and ABC). ColorLayoutFilter initially has an accuracy of 63.7% with 12 features in the 1st reduction. After applying bio-inspired algorithms, the number of features is reduced to 5 across all methods (ACO, BBA, and ABC), with a consistent improvement in accuracy to 84.8% (94.56%). This suggests that the bio-inspired algorithms, particularly ACO, BBA, and ABC, are highly effective in feature reduction while significantly boosting accuracy. In contrast, EdgeHistogramFilter starts with an accuracy of 71.3% and 23 features in the 1st reduction. After applying the algorithms, the accuracy improves with the number of features reducing to 14-16. The ACO method results in an accuracy of 80%, BBA reaches 82.5%, and ABC shows a slight decrease to 82.5% but with slightly lower accuracy (88.53%). These results demonstrate that bio-inspired algorithms are capable of reducing features while improving performance in both filters, although EdgeHistogramFilter shows more variation in accuracy improvements compared to ColorLayoutFilter, which benefits from a more consistent enhancement in accuracy after the reduction. Overall, bio-inspired optimization techniques, especially in the case of ColorLayoutFilter, have shown strong effectiveness in feature selection and improving classification accuracy.

Table 10: Result of Image Filtered after 1st (Harmony Search) & 2nd (Bio-Inspired Algorithms) feature reduction for Data Image 4.

	1st Reduction		2nd Reduction (Wrapper)					
	Harmony Search		Bio-Inspired Algorithms					
Method (Image Filter)	#Ftr	% Acc	#Ftr (ACO)	%Acc	#Ftr (BBA)	%Acc	#Ftr (ABC)	%Acc
ColorLayoutFilter	12 <u>63.3%</u>	**76**	8 <u>75.6%</u>	**75.39**	9 <u>72.7%</u>	**75.69**	11 <u>66.7%</u>	**77.35**

**Underlined: % of reduction from original feature*
**#Ftr=Number of features, %Acc=Percentage of classification accuracy*

Table 10 outlines the performance of an image filter during the 1st and 2nd reduction phases using Harmony Search and various Bio-Inspired Algorithms (ACO, BBA, ABC). In the 1st reduction, the filter starts with 12 features and an accuracy of 63.3%. After applying bio-inspired algorithms in the 2nd reduction phase, the number of features is reduced to 8-11, with ACO resulting in the highest accuracy of 75.6%, followed by ABC at 75.39%, and BBA at 72.7%. These results suggest that the application of bio-inspired algorithms leads to a reduction in the number of features while improving accuracy, with ACO performing slightly better than the others in terms of accuracy. The reduction in features, especially from 12 to 8-9, indicates that the optimization techniques help streamline the model without significant loss of information. The consistent performance improvements across all methods demonstrate that bio-inspired algorithms effectively enhance the filter's classification ability, although ACO stands out in providing the best balance between feature reduction and accuracy.

Table 11: Result of Image Filtered after 1st (Tabu Search) & 2nd (Bio-Inspired Algorithms) feature reduction for Data Image 4.

	1st Reduction		2nd Reduction (Wrapper)					
	Tabu Search		Bio-Inspired Algorithms					
Method (Image Filter)	#Ftr	% Acc	#Ftr (ACO)	%Acc	#Ftr (BBA)	%Acc	#Ftr (ABC)	%Acc
ColorLayoutFilter	13 60.6%	**75.5**	9 72.7%	**73.33**	9 72.7%	**75.69**	7 78.8%	**75.69**

**Underlined: % of reduction from original feature*
**#Ftr=Number of features, %Acc=Percentage of classification accuracy*

Table 11 illustrates a detailed comparison of the ColorLayoutFilter performance during the 1st and 2nd reduction phases, utilizing Tabu Search and Bio-Inspired Algorithms (ACO, BBA, and ABC). Initially, the filter achieves an accuracy of 60.6% with 13 features in the 1st reduction. After applying bio-inspired algorithms, the number of features is reduced across the methods, with ACO reducing the features to 9 and achieving 72.7% accuracy. Similarly, BBA also reduces the features to 9 with a slightly lower accuracy of 73.33%, while ABC achieves the highest accuracy of 78.8% with just 7 features. The results highlight that bio-inspired algorithms significantly improve both accuracy and feature reduction, with ABC performing best in terms of accuracy and reducing the feature set to its most efficient form. This indicates that ABC not only reduces the number of features but also enhances the filter's classification performance more effectively than ACO and BBA. Overall, the table demonstrates that bio-inspired optimization techniques can achieve notable improvements in both feature selection and accuracy, with ABC offering the best balance for ColorLayoutFilter.

5. Conclusion

In summary, HS and TS, along with three bio-inspired algorithms (ACO, BBA, ABC), demonstrate the capability to perform image reduction and improve classification accuracy for the categorization of COVID-19 cases. Table 12 provides a summary of the formulations of these algorithms. These formulations can serve as a guideline for addressing image classification problems using HS and TS with bio-inspired algorithms. Future work in this area could explore enhancing the integration of HS (Harmony Search) and TS (Tabu Search) with bio-inspired algorithms such as ACO (Ant Colony Optimization), BBA (Bat Algorithm), and ABC (Artificial Bee Colony) for even more refined image reduction techniques and classification accuracy. Additionally, the performance of these algorithms could be tested on larger and more diverse datasets beyond COVID-19, potentially expanding their application to other medical image classification problems. However, there are certain limitations and weaknesses, including the computational complexity of these algorithms when scaling to larger datasets, as well as their dependency on parameter tuning, which could impact their generalizability and efficiency in real-world applications. Furthermore, the adaptability of these algorithms in dynamic, real-time image classification systems remains an area for future improvement.

Table 12: Summarization and formulation of the algorithms.

Dataset	Suitable Image Filter Method	Suitable Algorithm	Bio-inspired Algorithm
Data Image 1	AutoColorCorrelogramFilter	Harmony Search	ACO, BBA, ABC
	ColorLayoutFilter	Tabu Search	ACO, BBA, ABC
Data Image 2		Harmony Search	BBA, ABC
	JpegCoefficientFilter	Tabu Search	BBA
Data Image 3		Harmony Search	ACO, BBA, ABC
	ColorLayoutFilter	Tabu Search	
Data Image 4		Harmony Search	ABC
		Tabu Search	

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References

Barandas M., Famiglini L., Campagner A., Folgado D., Simão R., Cabitza F. & Gamboa H. 2024. Evaluation of uncertainty quantification methods in multi-label classification: A case study with automatic diagnosis of electrocardiogram. *Information Fusion* **101**: 101978.

Bui Q.T., Pham L.T., Nguyen H.D., Nguyen Q.H., Pham V.M. & Hoang T.V. 2023. Machine learning and metaheuristic optimization algorithms for land cover classification. In de Vries W.T., Rudiarto I. & Milinda Piyasena N.M.P. (eds.). *Geospatial Science for Smart Land Management: An Asian Context*: 119-131. Boca Raton, FL: CRC Press.

Cavallaro C., Cutello V., Pavone M. & Zito F. 2024. Machine learning and genetic algorithms: A case study on image reconstruction. *Knowledge-Based Systems* **284**: 111194.

Devi K.J., Singh P., Bilal M. & Nayyar A. 2024. Enabling secure image transmission in unmanned aerial vehicle using digital image watermarking with H-Grey optimization. *Expert Systems with Applications* **236**: 121190.

Dorigo M. & Di Caro G. 1999. Ant colony optimization: A new meta-heuristic. *Proceedings of the 1999 Congress on Evolutionary Computation-CEC99 (Cat. No. 99TH8406)*, pp. 1470-1477.

Geem Z.W., Kim J.H. & Loganathan G.V. 2001. A new heuristic optimization algorithm: Harmony search. *Simulation* **76**(2): 60–68.

Glover F. 1989. Tabu search—Part I. *ORSA Journal on Computing* **1**(3): 190–206.

Glover F. 1990. Tabu search—part II. *ORSA Journal on computing* **2**(1): 4–32.

Hall M.A., Frank E., Holmes G., Pfahringer B., Reutemann P. & Witten I.H. 2009. The WEKA data mining software: An update. *ACM SIGKDD Explorations Newsletter* **11**(1): 10–18.

Holder C., Middlehurst M., & Bagnall A. 2023. A review and evaluation of elastic distance functions for time series clustering. *Knowledge and Information Systems* **66**(2): 765-809.

Huo X., Sun G., Tian S., Wang Y., Yu L., Long J., Zhang W. & Li A. 2024. HiFuse: Hierarchical multi-scale feature fusion network for medical image classification. *Biomedical Signal Processing and Control* **87**: 105534.

Jakšić Z., Devi S., Jakšić O. & Guha K. 2023. A Comprehensive Review of Bio-Inspired Optimization Algorithms Including Applications in Microelectronics and Nanophotonics. *Biomimetics* **8**(3): 278.

Jensen R. & Shen Q. 2003. Finding rough set reducts with ant colony optimization. *Proceedings of the 2003 UK Workshop on Computational Intelligence*, pp. 15–22.

Karaboga D. & Akay B. 2009. A comparative study of Artificial Bee Colony algorithm. *Applied Mathematics and Computation* **214**: 108–132.

Nakamura R.Y.M., Pereira L.A.M., Costa K.A., Rodrigues D., Papa J.P. & Yang X.-S. 2012. BBA: A binary bat algorithm for feature selection. *2012 25th SIBGRAPI Conference on Graphics, Patterns and Images*, pp. 291–297.

Parr T., Hamrick J. & Wilson J.D. 2024. Nonparametric feature impact and importance. *Information Sciences* **653**: 119563.

Rautray R., Dash R., Dash R., Balabantaray R.C. & Parida S.P. 2024. A review on metaheuristic approaches for optimization problems. In Acharjya D.P. & Ma K. (eds.). *Computational Intelligence in Healthcare Informatics*: 33–55. Singapore: Springer.

Rotari M. & Kulahci M. 2024. Variable selection wrapper in presence of correlated input variables for random forest models. *Quality and Reliability Engineering International* **40**(1): 297-312.

Sawan A., Awad M., Qasrawi R. & Sowan M. 2024. Hybrid deep learning and metaheuristic model based stroke diagnosis system using electroencephalogram (EEG). *Biomedical Signal Processing and Control* **87**: 105454.

Zhang H. & Sun G. 2002. Feature selection using tabu search method. *Pattern Recognition* **35**(3): 701–711.

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