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Ensemble Image Feature Selection Method based on Bio-Inspired Algorithms for COVID-19 Classification Problem

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ABSTRACT

Feature selection poses a considerable challenge, particularly in achieving an optimal solution. This difficulty arises from the challenge of selecting the most suitable feature selection methods, which often work independently, resulting in the selection of incorrect features and subsequently impacting classification accuracy. The primary objective of this research is to harness the potential of ensemble methods, specifically boosting, in conjunction with bio-inspired techniques to enhance the performance of image feature selection model in terms of the optimum image feature set. A crucial stage in this research involves optimizing three bio-inspired search algorithms that utilize ensemble methods. The subsequent step is to validate the optimal selected image feature set by conducting an image classification task. Evaluation metrics are determined based on the number of selected image features exhibiting good image classification accuracy. Experimental results revealed that both algorithms, when utilizing selected bio-inspired search algorithms with ensemble methods, successfully achieved superior solutions. Specifically, they demonstrated an optimum set of image features, comprising fewer image features with greater image classification accuracy, across the selected COVID-19 datasets. This discovery implies that the combination of bio-inspired algorithms with ensemble methods, particularly boosting, has the potential to enhance the performance of bio-inspired algorithms for image feature selection and classification tasks.

Keywords: Bio-inspired, COVID-19, Ensemble, Feature, Harmony Search, Image Classification

INTRODUCTION

The loss of information becomes a critical concern in the complexity of feature reduction. The challenges associated with feature reduction can be delineated into two main aspects: 1) the optimality degree of features, which encompasses the dependency degree and subset size, and 2) the time required to achieve the optimality of features. Numerous researchers have extensively explored the strengths and weaknesses of existing feature selection approaches (Ge et al., 2022; Htun et al., 2023; Lyu et al., 2023; Skaka - Čekić & Baraković Husić, 2023). Nevertheless, identifying the "suitable" approach for a given problem remains a formidable task. With the goal of striking a better trade-off between stability and performance accuracy, researchers are actively experimenting with more advanced feature selection techniques. One compelling idea involves leveraging ensemble approaches as a framework to enhance the robustness of the selection process, particularly in high-dimensional and smaller sample size settings where extracting stable feature subsets is inherently more challenging.

Ensemble selection methods have been discussed in recent literature (Huang et al., 2024; Liu et al., 2024; Zhao et al., 2024) and can be categorized into two primary groups: "functionally heterogeneous" and "functionally homogeneous" approaches. The first group entails employing different selection algorithms on the same dataset, while the second group utilizes the same selection algorithm on various perturbed versions of the original data—akin to bagging and boosting techniques (Bühlmann, 2012) within the context of multi-classifier systems. In both practices, diverse outcomes are obtained and subsequently amalgamated to generate a unified feature subset. This condition contributes to better approximation and, optimistically, achieving the optimal solution for the stated problem.

Bio-Inspired Computing spans multiple disciplines, including connectionism, engineering, social behavior, and emergent systems, with the collective goal of replicating and harnessing principles observed in natural biological systems. This interdisciplinary field draws inspiration from biological processes to innovate computational models and algorithms. Bio-inspired algorithms are pivotal in tackling intricate optimization challenges by capitalizing on the inherent efficiency and adaptability found in natural systems. In the realm of natural computation, these algorithms serve as potent optimization tools, mirroring behaviors such as swarm intelligence, evolutionary processes, and neural network dynamics. They provide robust solutions across diverse domains, from engineering and robotics to economics and medicine. The comprehensive review by (Jakšić, Devi, Jakšić, & Guha, 2023) offers a detailed examination of these algorithms, exploring their theoretical underpinnings, practical applications, and contributions to advancing computational methodologies. By embedding biological principles into computational frameworks, bio-inspired computing not only enhances algorithmic performance but also unlocks novel approaches to solving complex real-world problems with enhanced efficiency and scalability. This integration promises to drive innovation and effectiveness in computational sciences, leveraging nature's design principles to tackle modern challenges more effectively.

The Ant Colony Optimization algorithm (ACO) stands as a probabilistic technique crafted for addressing computational problems that can be simplified to the task of uncovering optimal paths within graphs. Originating in the early 1990s, it was introduced by (Dorigo & Caro, 1999), aligning itself with the burgeoning field of artificial intelligence known as Swarm Intelligence. ACO combined with ensemble methods has found application and exploration across various fields. The Binary Bat Algorithm (BBA) emerges as a binary version feature selection method inspired by (Nakamura et al., 2012), aiming to pinpoint the most consequential features within a designated search space. In this method, each bat corresponds to a set of binary coordinates, signifying whether a particular feature is part of the final feature set. By merging the capabilities of the bat algorithm and the Optimum Path Forest (Papa, Falcão, & Suzuki, 2009), the goal is to ascertain the feature set maximizing the accuracy of validating sets.

The Artificial Bee Colony (ABC) algorithm, a stochastic optimization method proposed by (Karaboga & Akay, 2009), replicates the intelligent foraging behaviour observed in honeybee swarms. This versatile algorithm finds applications in classification, clustering, and optimization studies. Within the ABC algorithm, an artificial bee colony consists of three distinct categories: employed bees, onlooker bees, and scout bees. The number of employed bees aligns with the count of onlooker bees, and both correspond to the number of solutions within the population. An onlooker bee awaits in the dance area to make decisions regarding food source selection. Upon selecting a food source, it transforms into an employed bee. Once the employed bee exhausts the chosen food source, it transitions into a scout bee, responsible for a random search to discover new resources. The position of the food supply, symbolizing the solution to the optimization problem, and the quantity of nectar in the food source hinge on the quality of the associated solution. In metaheuristics algorithm, ensemble feature selection, has been implemented across diverse applications, as underscored by (Asif et al., 2023; Darekar et al., 2023; Pattanaik et al., 2023; Shokouhifar et al., 2023; Ye et al., 2023; Zhang et al., 2023).

METHODS

Figure 1 delineates the methodological framework employed in this research, adhering rigorously to established machine learning protocols. This comprehensive approach encompasses four distinct phases: systematic data collection, meticulous selection of optimal image filtering methods, integration of sophisticated reduction techniques inspired by ant colony optimization, bat algorithm, and bee algorithm, and refinement of ensemble-based image feature selection strategies. The evaluation criteria prioritize the identification of feature subsets achieving classification accuracy exceeding 80% in specified contexts.

Achieving a balance between high accuracy and minimal feature complexity is pivotal for optimizing results. The study explores synergies between bio-inspired methodologies—such as ant colony optimization for exploring feature space, bat algorithm for adaptive parameter tuning, and bee algorithm for local search—and ensemble methods in the domain of image filtering. The assessment of classification accuracy employs the standard formula:

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions}$$

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

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where TP (True Positives), TN (True Negatives), FP (False Positives), and FN (False Negatives) serve as metrics to gauge the model's predictive efficacy, emphasizing precision and recall in binary classification scenarios.

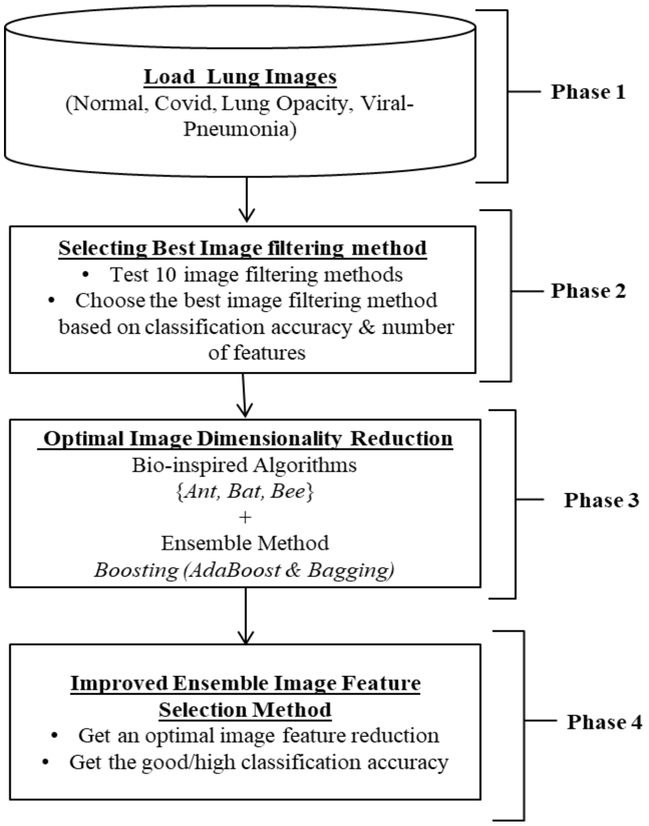
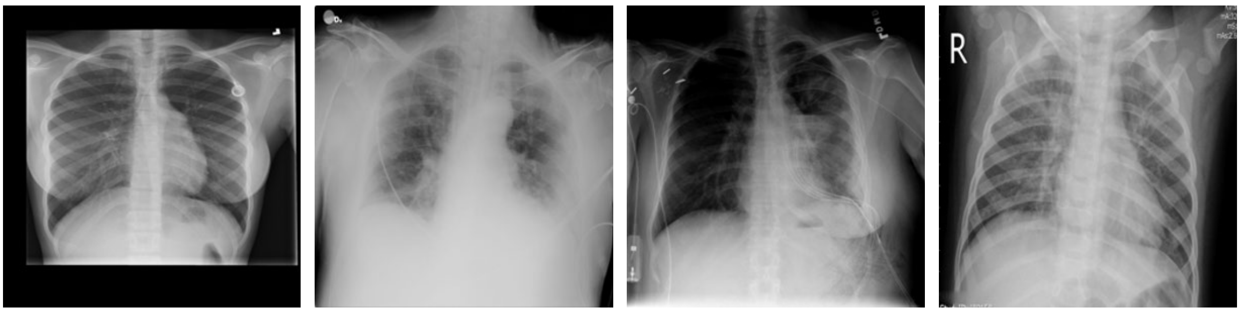


Figure 1: Methodology

Phase 1 – Selection of image dataset: Image datasets were sourced from the Kaggle Repository (COVID-19 Radiography Database). These datasets comprise 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 presents sample images from these four categories. The training and testing of all image datasets were conducted using WEKA tools (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.



Normal COVID-19 Lung Opacity Viral-Pneumonia

Figure 2: Category of image datasets (Normal, COVID-19, Lung Opacity, Viral-Pneumonia)

Phase 2 – Selecting best image filtering method: All these data categories underwent testing using 10 image filtering methods, including AutoColorCorrelogramFilter, BinaryPatternsPyramidFilter, ColorLayoutFilter, EdgeHistogramFilter, FCTHFilter, FuzzyOpponentHistogramFilter, GaborFilter, JpegCoefficientFilter, PHOGFilter, and SimpleColorHistogramFilter. Subsequently, the optimal image filtering methods will be selected (refer to Table 2) based on superior classification accuracy while utilizing a smaller number of image features.

Phase 3 – Optimal Image Dimensionality Reduction: During this phase, a reduction process has been implemented, utilizing three bio-inspired search methods along with an ensemble method, namely boosting (AdaBoost Algorithm) and bagging, for an optimal search. This process ensures a balance between the exploitation and exploration mechanisms within the solution space. Three widely used learning algorithms, namely Decision Tree (DT), K-nearest Neighbor (KNN), and Naïve Bayes (NB), have been employed in conjunction with the filtered methods.

Phase 4 – Improved Ensemble Image Feature Selection Method: In this phase, the selection of an improved ensemble image feature method with high classification accuracy is considered a crucial criterion for the decision-making process.

Table 1 displays the parameter settings for Bio-Inspired Algorithms.

Table 1: Parameter setting for Bio-Inspired Algorithms

Bio Inspired Algorithm	Population Size	Specific setting
Ant	20	Rate: Heuristic (0.7), Evaporation (0.9), Pheromone (2.0)
Bat		Rate: Loudness & Frequency (0.5)
		Rate: Sigma (0.70), Pa (0.25)
		Absorption coefficient (0.001), Beta zero (0.33)
Bee	30	Radius: Mutation (0.80), Damp (0.98)

**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.*

RESULTS AND DISCUSSION

This section discusses the results obtained from the experiment. Table 2 denotes the output of phase 1. Tables 3 through 10 demonstrate the results achieved from phases 2 and 3. Finally, Table 11 presents the output from phase 4, which represents the final summarization and formulation of the algorithms.

Table 2: Result of Image Filtered for Data Image 1, 2, 3 and 4 before feature reduction and optimization.

		Data Image 1	Data Image 2	Data Image 3	Data Image 4
Method (Image Filter)	**#Ftr**	**% Acc**	**% Acc**	**%Acc**	**%Acc**
AutoColorCorrelogramFilter	1024	**92.35**	75.59	87.79	73.82
BinaryPatternsPyramidFilter	756	90.88	75.44	89.41	69.02
ColorLayoutFilter	33	**92.5**	70.88	**94.56**	**76.37**
EdgeHistogramFilter	80	**90.59**	68.24	**89.71**	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	**91.47**	**80.29**	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: The best image filtering methods selected to be further experiment.*
**#Ftr=Number of features, %Acc=percentage of classification accuracy*

Table 2 illustrates the number of features obtained using 10 different image filters. For Data Image 1, four image filter methods (AutoColorCorrelogramFilter, ColorLayoutFilter, EdgeHistogramFilter, JpegCoefficientFilter) have been identified as the optimal methods based on the highest percentage of classification accuracy. In the case of Data Image 2, only one image filter (JpegCoefficientFilter) has been identified as the most effective method, achieving over 80% classification accuracy compared to other methods. Furthermore, two image filter methods, namely ColorLayoutFilter and EdgeHistogramFilter, have been chosen for Data Image 3. Similar to Data Image 2, only one image filter method is selected for Image Data 4, achieving a classification accuracy of 76.37% under these conditions. All these selection methods have undergone further experimentation involving feature reduction using three bio-inspired algorithms (ant, bat, bee) along with ensemble methods, specifically boosting and bagging. The utilization of boosting and bagging aims to enhance the classification accuracy of the bio-inspired algorithms, representing an optimal ensemble image feature selection method.

Table 3: Result of Image Filtered after reduction using Bio-Inspired Algorithms + Ensemble (Boosting) for Data Image 1

	Feature Reduction (Filtered) + Ensemble (Boosting)								
Method (Image Filter)	**#Ftr (Ant)**	**%Acc**	**Ada boost**	**#Ftr (Bat)**	**%Acc**	**Ada boost**	**#Ftr (Bee)**	**%Acc**	**Ada boost**
AutoColorCorrelogramFilter	159 84.5%	**92.35**	**92.5**	165 83.9%	**90.74**	**91.32**	91 91.1%	**90.29**	**92.65**
ColorLayoutFilter	11 66.7%	**92.79**	**94.12**	10 69.7%	**90.88**	**91.76**	4 87.9%	**91.76**	**90.6**
EdgeHistogramFilter	41 48.8%	**91.76**	**93.38**	56 30%	**91.47**	**94.26**	42 47.5%	**90.59**	**93.38**
JpegCoefficientFilter	53 72.4%	**89.71**	**93.1**	31 83.9%	**90.15**	**91.76**	26 86.5%	**90.74**	**92.06**

**Underlined: % of reduction from original feature*
**#Ftr=Number of features, %Acc=percentage of classification accuracy, Adaboost=Boosting method*

Table 3 validates the outcomes of image feature reduction employing Bio-Inspired Algorithms + Ensemble (Boosting) for Data Image 1. The bee algorithm is notable for achieving a substantial reduction of almost 91.1% in the number of image features, further enhanced by the boosting method for AutoColorCorrelogramFilter, resulting in the selection of 91 image features. In the case of ColorLayoutFilter, a more effective image feature reduction is observed, with 11 features and a notably high classification accuracy of 94.1%, further improved by the boosting method.

Table 4: Result of Image Filtered after reduction using Bio-Inspired Algorithms + Ensemble (Bagging) for Data Image 1

	Feature Reduction (Filtered) + Ensemble (Bagging)								
Method (Image Filter)	**#Ftr (Ant)**	**%Acc**	**Bag**	**#Ftr (Bat)**	**%Acc**	**Bag**	**#Ftr (Bee)**	**%Acc**	**Bag**
AutoColorCorrelogramFilter	159 84.5%	**92.35**	**91.76**	165 83.9%	**90.74**	**91.18**	91 91.1%	**90.29**	**91.62**
ColorLayoutFilter	11 66.7%	**92.79**	**92.94**	10 69.7%	**90.88**	**91.76**	4 87.9%	**91.76**	**92.06**
EdgeHistogramFilter	41 48.8%	**91.76**	**93.53**	56 30%	**91.47**	**92.94**	42 47.5%	**90.59**	**93.24**
JpegCoefficientFilter	53 72.4%	**89.71**	**91.18**	31 83.9%	**90.15**	**92.21**	26 86.5%	**90.74**	**91.91**

**Underlined: % of reduction from original feature*
**#Ftr=Number of features, %Acc=percentage of classification accuracy, Bag=Bagging method*

Table 4 presents the outcomes of image feature reduction using Bio-Inspired Algorithms + Ensemble (Bagging) for Data Image 1. The results demonstrate that the bee algorithm, when combined with the bagging method, enhances classification accuracy while utilizing a minimal number of image features for both ColorLayoutFilter and JpegCoefficientFilter. Specifically, ColorLayoutFilter achieves a more balanced reduction in image features, with only 4 selected features and a high classification accuracy of 92.1%. This performance surpasses the second-best selection, JpegCoefficientFilter, which involves 26 image features and achieves a classification accuracy of 91.2%.

Table 5: Result of Image Filtered after reduction using Bio-Inspired Algorithms + Ensemble (Boosting) for Data Image 2

	Feature Reduction (Filtered) + Ensemble (Boosting)								
Method (Image Filter)	**#Ftr (Ant)**	**%Acc**	**Adaboost**	**#Ftr (Bat)**	**%Acc**	**Adaboost**	**#Ftr (Bee)**	**%Acc**	**Adaboost**
JpegCoefficientFilter	50 74%	**77.8**	**84.12**	30 84.4%	**76.32**	**82.65**	18 90.6%	**77.8**	**81.32**

**Underlined: % of reduction from original feature*
**#Ftr=Number of features, %Acc=percentage of classification accuracy, Adaboost=Boosting method*

Table 5 showcases the reduction results for Data Image 2 using Bio-Inspired Algorithms + Ensemble (Boosting). In this particular instance, only one image filter method is deemed suitable for this image dataset, namely JpegCoefficientFilter. A consistent pattern is observed, where the bee algorithm is instrumental in reducing image features to 18, accompanied by a noteworthy improvement in classification accuracy with the boosting method, reaching 81.3%.

Table 6: Result of Image Filtered after reduction using Bio-Inspired Algorithms + Ensemble (Bagging) for Data Image 2

	Feature Reduction (Filtered) + Ensemble (Bagging)								
Method (Image Filter)	**#Ftr (Ant)**	**%Acc**	**Bag**	**#Ftr (Bat)**	**%Acc**	**Bag**	**#Ftr (Bee)**	**%Acc**	**Bag**
JpegCoefficientFilter	50 74%	**77.8**	**84.71**	30 84.4%	**76.32**	**83.24**	18 90.6%	**77.8**	**84.12**

**Underlined: % of reduction from original feature*
**#Ftr=Number of features, %Acc=percentage of classification accuracy, Bag=Bagging method*

Table 6 presents the reduction results for Data Image 2 using Bio-Inspired Algorithms + Ensemble (Bagging). Much like the boosting scenario, only one image filter method is deemed suitable for this image dataset, specifically JpegCoefficientFilter. Once again, the bee algorithm demonstrates its ability to reduce the image features by 90.6%, resulting in 18 features, and achieving an enhanced classification accuracy of 84.12% after applying the bagging method.

Table 7: Result of Image Filtered after reduction using Bio-Inspired Algorithms + Ensemble (Boosting) for Data Image 3

	Feature Reduction (Filtered) + Ensemble (Boosting)								
Method (Image Filter)	**#Ftr (Ant)**	**%Acc**	**Ada boost**	**#Ftr (Bat)**	**%Acc**	**Ada boost**	**#Ftr (Bee)**	**%Acc**	**Ada boost**
ColorLayoutFilter	8 75.6%	**94.71**	**96.62**	9 72.7%	**94.71**	**95.15**	5 84.8%	**93.09**	**94.85**
EdgeHistogramFilter	26 67.5%	**87.8**	**93.53**	24 70%	**88.24**	**92.94**	19 76.3%	**87.35**	**93.53**

**Underlined: % of reduction from original feature*
**#Ftr=Number of features, %Acc=percentage of classification accuracy, Adaboost=Boosting method*

Table 7 exhibits the reduction results for Data Image 3 using Bio-Inspired Algorithms + Ensemble (Boosting). Two image filter methods are deemed appropriate for this image dataset: ColorLayoutFilter and EdgeHistogramFilter. In this scenario, the ant algorithm demonstrates a notable capability to reduce the image features by 75.6%, resulting in 8 features, coupled with the highest classification accuracy of 96.6% for ColorLayoutFilter after the application of the boosting method.

Table 8: Result of Image Filtered after reduction using Bio-Inspired Algorithms + Ensemble (Bagging) for Data Image 3

	Feature Reduction (Filtered) + Ensemble (Bagging)								
Method (Image Filter)	**#Ftr (Ant)**	**%Acc**	**Bag**	**#Ftr (Bat)**	**%Acc**	**Bag**	**#Ftr (Bee)**	**%Acc**	**Bag**
ColorLayoutFilter	8 75.6%	**94.71**	**95.59**	9 72.7%	**94.71**	**95.74**	5 84.8%	**93.09**	**94.71**
EdgeHistogramFilter	26 67.5%	**87.8**	**91.47**	24 70%	**88.24**	**90.15**	19 76.3%	**87.35**	**91.47**

**Underlined: % of reduction from original feature*
**#Ftr=Number of features, %Acc=percentage of classification accuracy, Bag=Bagging method*

Table 8 presents the reduction results for Data Image 3 using Bio-Inspired Algorithms + Ensemble (Bagging). Similarly to the boosting scenario, two image filter methods are deemed relevant for use in this image dataset: ColorLayoutFilter and EdgeHistogramFilter. In this context, the bee algorithm achieves significant results by reducing the image features by 75.6%, resulting in 8 features, and attaining a high classification accuracy of 95.59% after employing the bagging method.

Table 9: Result of Image Filtered after reduction using Bio-Inspired Algorithms + Ensemble (Boosting) for Data Image 4

	Feature Reduction (Filtered) + Ensemble (Boosting)								
Method (Image Filter)	**#Ftr (Ant)**	**%Acc**	**Ada boost**	**#Ftr (Bat)**	**%Acc**	**Ada boost**	**#Ftr (Bee)**	**%Acc**	**Ada boost**
ColorLayoutFilter	9 <u>72.7%</u>	**74.41**	**78.63**	13 <u>60.6%</u>	**73.24**	**78.43**	8 <u>75.6%</u>	**73.73**	**77.94**

**Underlined: % of reduction from original feature*
**#Ftr=Number of features, %Acc=percentage of classification accuracy, Adaboost=Boosting method*

Table 9 illustrates the reduction results for Data Image 4 using Bio-Inspired Algorithms + Ensemble (Boosting). ColorLayoutFilter emerges as the sole suitable method for this image dataset. The ant algorithm demonstrates the capability to reduce the image features to 9, exhibiting a significant improvement in classification accuracy with boosting (78.6%). This can be attributed to the complexity introduced by Data Image 4, which comprises three categories of images, posing a challenge for the algorithms in terms of classification and model optimization.

Table 10: Result of Image Filtered after reduction using Bio-Inspired Algorithms + Ensemble (Bagging) for Data Image 4

	Feature Reduction (Filtered) + Ensemble (Bagging)								
Method (Image Filter)	**#Ftr (Ant)**	**%Acc**	**Bag**	**#Ftr (Bat)**	**%Acc**	**Bag**	**#Ftr (Bee)**	**%Acc**	**Bag**
ColorLayoutFilter	9 <u>72.7%</u>	**74.41**	**81.18**	13 <u>60.6%</u>	**73.24**	**80.88**	8 <u>75.6%</u>	**73.73**	**80.59**

**Underlined: % of reduction from original feature*
**#Ftr=Number of features, %Acc=percentage of classification accuracy, Bag=Bagging method*

Table 10 presents the reduction results for Data Image 4 using Bio-Inspired Algorithms + Ensemble (Bagging). ColorLayoutFilter emerges as the most suitable method for this image dataset. In this experimental setting, the bagging method, in combination with the ant algorithm, achieves a notable reduction in image features (9 features), coupled with a substantial improvement in classification accuracy (81.2%). Additionally, the bat and bee algorithms showcase significant enhancements in classification accuracy when utilizing the bagging method.

CONCLUSION

In summary, three bio-inspired algorithms (ant, bat, bee) demonstrate the ability to conduct image reduction and enhance classification accuracy through ensemble techniques (boosting and bagging) for the classification of COVID-19 cases. Table 11 provides a summary of the formulations of these algorithms, serving as a valuable guideline for addressing image classification problems using ensemble techniques (boosting and bagging) with bio-inspired algorithms.

Table 11: Summarization and formulation of the algorithms.

Dataset	Suitable Image Filter Method	Bio-inspired Algorithm	Ensemble Method
Data Image 1	AutoColorCorrelogramFilter	Bee	Boosting
	ColorLayoutFilter	Ant	Boosting
	ColorLayoutFilter	Bee	Bagging
	JpegCoefficientFilter	Bee	Bagging
Data Image 2	JpegCoefficientFilter	Bee	Boosting
			Bagging
Data Image 3	ColorLayoutFilte	Ant	Boosting
			Bagging
Data Image 4	ColorLayoutFilter	Ant	Boosting
			Bagging

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