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A comparative analysis of optimized CNN models using bio-inspired algorithms

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Abstract

Nitrogen is a macronutrient that is responsible for crop development. Accurate nitrogen prediction improves crop productivity. This study aims to enhance nitrogen prediction in wheat crops using convolutional neural networks (CNN) with bio-inspired algorithms. CNN, which is widely used for image classification, relies on carefully chosen parameters such as the number of layers, learning rate and kernel sizes to perform effectively. These parameters were optimized using five bio-inspired algorithms. Optimization algorithms aid in selecting the parameters of CNNs to make them more accurate and efficient. The algorithms are genetic algorithms grey wolf optimizer, particle swarm optimization, ant bee colony, and evolutionary algorithms. These findings indicate that employing bio-inspired optimization visibly increases the performance of CNN. The genetic algorithm achieved the best accuracy, making the model more accurate. Overall, these methods helped CNN model predict the nitrogen levels better. This methodology provides essential insights into precision farming, enabling the creation of more efficient nutrient management plans.

Subject Classification: *65k10.*

Keywords: *Bio-inspired algorithm, Nitrogen, Optimizer, Grey wolf optimization, Genetic algorithm, PSO.*

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1. Introduction

In agriculture, managing nitrogen is essential for healthy crops and high yields. While nitrogen is a key nutrient, its precise application is crucial. Traditional methods like manual checks and soil tests are often time-consuming and inaccurate [1]. As a result, the rise of precision agriculture has created a demand for advanced technological solutions that provide accurate, real-time monitoring of nutrient levels. Sustainable crop production and nutrient management support SDG 2 (Zero Hunger) by enhancing food security and environmental health [2]. Convolutional Neural Networks (CNN) have emerged as an effective tool to address this need. The primary components include convolutional layers, pooling layers, and fully connected layers [3]. By integrating bio-inspired optimization algorithms, the study aims to enhance the predictive accuracy of CNN models, providing farmers with more precise tools for nutrient management. The authors [4] propose a genetic algorithm-based hyperparameter optimization approach for pre-trained CNN models to classify insect pests. Using MobileNetV2, DenseNet121, and InceptionResNetV2, they tested the approach on three datasets: Wu's IP102 (102 classes), Xie2's D0 (40 classes), and Deng's (10 classes). The optimized models achieved state-of-the-art accuracies of 99.89% on D0 and 97.58% on Deng's dataset, while obtaining 71.84% on IP102, closely matching existing performance. The author [5] proposed the Plant-CNN-ViT ensemble model, combining Vision Transformer, ResNet-50, DenseNet-201, and Xception to efficiently capture leaf properties and patterns. Tested on four plant leaf datasets (Flavia, Folio, Swedish, MalayaKew), it achieved impressive accuracy rates of 100%, 100%, 100%, and 99.83%, respectively. This paper [6] proposes a quantum CNN that optimizes the number of convolutional layers during training using quantum bits. Tested on the CIFAR-10 dataset, accuracy dropped from 90% to 80% without optimization as layers increased but remained above 90% when parameters were halved. This approach reduces processing needs and prevents performance issues from excessive layers. The subsequent objectives are as follows:

1. To implement convolutional neural network for nitrogen prediction in wheat leaves.
2. To test and compare different bio-inspired optimization algorithms, including Particle Swarm Optimization (PSO), Genetic Algorithms

(GA), Grey Wolf Optimization (GWO), Ant Bee Colony (ABC), and Evolutionary Algorithms, for refining CNN parameters.

3. To identify the best fit optimization technique for nitrogen prediction with respect to accuracy.

After the introduction, Section 2 presents the methodology. Section 3 discusses the bio-inspired algorithm. Section 4 summarizes findings and implications, while Section 5 concludes the paper.

2. Methodology

The dataset was collected manually during the Rabi season in Jaipur district, Rajasthan, India. The region has a semi-arid climate, with temperatures ranging from 45.5°C in summer to 4°C in winter. Annual rainfall in the area varies between 500- and 700-mm [7]. The raw image data was preprocessed using resizing, normalization, and augmentation to improve consistency and model performance. The dataset is publicly available on the Mendeley Data Repository [8]. The descriptive analysis of dataset is shown in the previous research [9]. CNNs effectively classify images by learning patterns through layered feature extraction, making them ideal for object detection and recognition [10]. In this research, a CNN model was developed to classify leaf images into six categories based on the Leaf Color Chart (LCC) [11]. Figure 1 illustrates the proposed methodology. Input images are resized to 128×128 pixels and normalized to keep pixel values range between 0 and 1. The CNN begins with an input layer, followed by a convolutional layer with 32 filters (3×3) to detect basic features like edges and textures. A MaxPooling layer is then applied. Next, the network deepens, with another convolutional layer having 64 filters, followed by another pooling operation to further reduce the feature map size. A third convolutional layer with 128 filters captures even more. complex patterns. Each convolutional layer is followed by MaxPooling, which simplifies the feature maps while retaining the most important information. The final layer is the Output layer, which has six neurons corresponding to the six categories of the Leaf Color Chart. Different optimization algorithms applied to improve the model's performance, like GWO [12], GA [13], PSO [14], ABC [15], and EA [16] were used. By adjusting hyperparameters like learning rate, batch size, and dropout rate, these techniques assisted in improving the model's accuracy. Finally, the trained model accurately classifying the leaf images into six categories

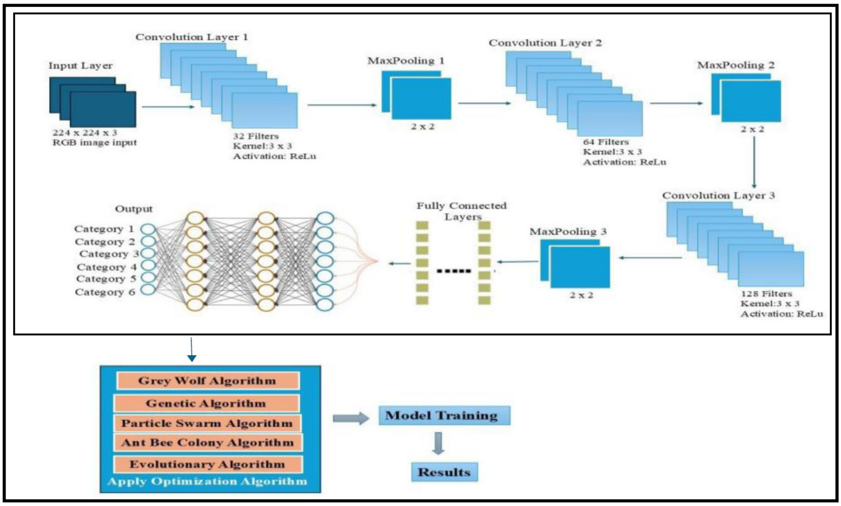


Figure 1

Proposed methodology of convolutional neural network with bio-inspired algorithm

based on the LCC, showing that CNN combined with optimization techniques is a powerful tool for leaf classification.

2.1 *Genetic Algorithm*

The Genetic Algorithm (GA) is based on natural selection principles, where the most suitable candidates are selected to generate the next set of solutions. In CNN optimization, GA helps identify the best set of hyperparameters by iterating through processes such as selection, crossover, and mutation. These evolutionary steps guide the algorithm toward more optimal solutions over time. GA starts with an initial population of random solutions (sets of hyperparameters) [17]. Each solution is evaluated based on how well CNN performs with that set of hyperparameters. Over several generations, the algorithm selects the best-performing solutions, applies crossover and mutation operations to create new solutions, and replaces the less fit solutions. This process repeats until the algorithm identifies an optimal or near-optimal set of hyperparameters. The goal is to search for the most effective combination of parameters that improve the model's performance.

2.2 *Grey Wolf Optimization Algorithm*

Grey Wolf Optimizer (GWO) uses a hierarchical approach inspired by the hunting strategies of grey wolves. In GWO, wolves represent candidate solutions, and their positions are adjusted based on the leading wolves alpha, beta, and delta. This method efficiently optimizes weights and biases by focusing on top-performing solutions [18]. Key parameters include population size, maximum iterations, and the roles of alpha, beta, and delta wolves. Typically, a population of 20 wolves, iterating for up to 50 steps, effectively guides the search for optimal solutions. Overall, these optimization algorithms significantly enhance the CNN model's ability to classify images accurately. By carefully tuning hyperparameters and leveraging the principles of nature, each algorithm contributes uniquely to improving the model's performance.

2.3 *Evolutionary Algorithm*

The Evolutionary Algorithm (EA) is based on principles of biological evolution, where potential solutions to a problem are refined over multiple generations through processes like mutation, recombination, and selection. In this context, EA is used for optimizing the weights and biases of a Convolutional Neural Network (CNN). By evolving a population of candidate solutions, the algorithm gradually improves the model's performance. EA is specifically applied to optimize CNN weights and biases, enhancing the network's ability to classify data more accurately.

2.4 *Particle Swarm Optimization*

Particle Swarm Optimization (PSO) is an algorithm inspired by the way birds flock together. In PSO, each particle represents a possible solution to a problem. These particles move through the solution space, working together to find the best solution available. The best-known positions of neighboring particles as well as the movements of each individual particle are used to steer its motion. Thus, the motion of each particle is shaped by social interaction as well as individual experience [19]. This shared behavior helps particles move toward the best solutions. In this study, PSO is used to adjust the weights and biases of CNN. By fine-tuning these parameters, PSO enhances the model's performance.

2.5 *Ant Bee Colony Algorithm*

The Ant Bee Colony (ABC) algorithm imitates the food foraging behavior of ants and bees, leveraging their natural ability to search for the

Table 1

Parameter Values for Compared Algorithms

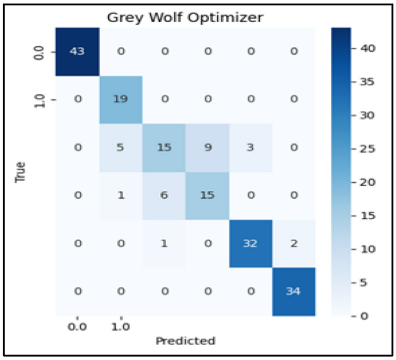
Algorithms	Population Size	Mutation Rate	Crossover Rate	Generations/ Iterations
Genetic Algorithm (GA)	20	0.01 - 0.05	0.8	20
Particle Swarm Optimization (PSO)	30	-	-	50
Ant Bee Colony (ABC)	25	-	-	30
Evolutionary Algorithm (EA)	20	0.02 - 0.05	0.8	20
Grey Wolf Optimizer (GWO)	20	-	-	50

best food sources. ABC is used for hyperparameter adjustment in the context of Convolutional Neural Networks (CNN) optimizations. The algorithm, which directs the movement of various agents (ants/bees) through the solution space, strikes a balance between exploitation the process of improving already existing solutions and exploration the hunt for new ones [20]. The ABC algorithm is applied to tune CNN hyperparameters, including weights, biases, and learning rates, to improve model performance.

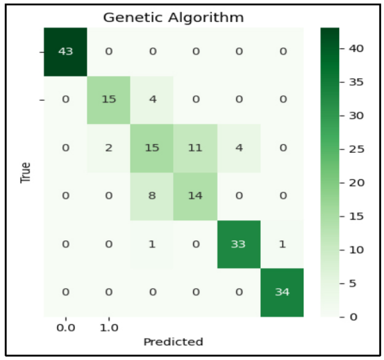
Table 1 shows the parameter values for the algorithms compared. The Genetic Algorithm (GA) has a population size of 20, with a mutation rate between 0.01 to 0.05, a crossover rate of 0.8 and it runs for 20 generations. The Particle Swarm Optimization (PSO) uses 30 particles and runs for 50 iterations, without mutation or crossover rates since it doesn't apply these concepts. The Ant Bee Colony (ABC) algorithm has a population size of 25 and runs for 30 iterations, also without mutation or crossover rates. The Evolutionary Algorithm (EA) shares similar settings with GA, using a population size of 20, a mutation rate between 0.02 to 0.05, a crossover rate of 0.8, and running for 20 generations. Finally, the Grey Wolf Optimizer (GWO) operates with a population size of 20 and runs for 50 iterations, without mutation or crossover rates. Each algorithm uses a different approach to search for optimal solutions.

3. Results and Discussion

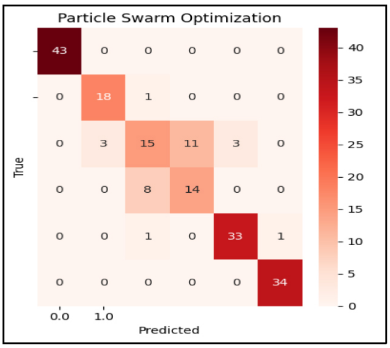
In this study, the performance of various optimization algorithms specifically, ABC, GA, PSO, GWO and EA are evaluated over 20 training



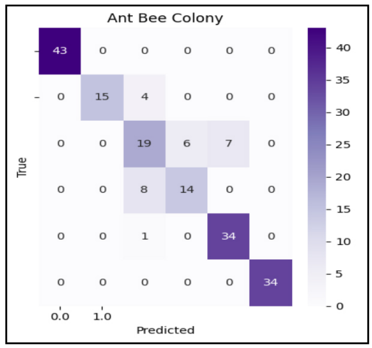
(a)



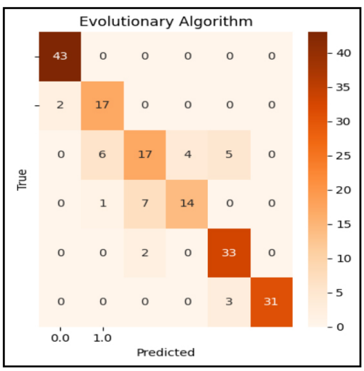
(b)



(c)



(d)



(e)

Figure 2

Confusion matrix of each algorithm

Table 2

Accuracy of Compared Algorithms (In Percentage)

Algorithms	Accuracy
Grey Wolf Optimization	98.71
Genetic Algorithm	99.33
Particle Swarm Optimization	98.76
Ant Bee Colony optimization	99.12
Evolutionary Algorithm	98.50

epochs. The Genetic Algorithm achieved the best accuracy in this metric as well, with a recall of 0.85. The confusion matrix results confirm that Genetic Algorithm (GA) achieved the highest accuracy (99.3%) and recall (0.85), making it the most reliable. Grey Wolf Optimizer (GWO) (98.7%) and Ant Bee Colony (ABC) (97.8%) also performed well, with ABC excelling in precision (0.87). Particle Swarm Optimization (PSO) and Evolutionary Algorithm (EA) both reached 97.3% accuracy. Overall, all algorithms showed significant improvements, with GA standing out in classification performance. Figure 2 shows the confusion matrix for five algorithms: (a) Grey Wolf, (b) Genetic, (c) Particle Swarm, (d) Ant Bee Colony, and (e) Evolutionary.

The result of the study shows the accuracy of five different optimization algorithms. GA has the highest accuracy at 99.33% in this study. The ABC was second with an accuracy of 99.12%. PSO achieved 98.76%, the GWO and EA accuracies 98.71% and 98.50%, respectively as shown in table 2.

4. Conclusion

This study focused on improving nitrogen prediction models in wheat crops. CNN is optimized by five bio-inspired algorithms: GA, GWO, PSO, ABC and EA. The hyper parameters of CNN are fine tuned. The results showed that the Genetic Algorithm performed best, with accuracy of 99.33%, Ant Bee Colony at 99.12%. This demonstrates the potential of these optimization techniques to significantly enhance the performance of CNN. However, some limitations were noted, such as the study's dependence on a specific type of dataset, which may not represent all agricultural aspects, and the possibility that different algorithms could achieve more accuracy depending on the dataset.

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