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Bio-Inspired Algorithms in Agriculture: A Review with Emphasis on Plant Disease Detection

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Abstract

In India agriculture plays a significant role due to their population growth and food demands also increased. Traditional strategies used by farmers are not quit enough to meet this demand. So farmers have to increase their use of toxic substances to destroy the soil. This affects the agriculture land a lot and at last the land has no fertility. Hence, the need arises to enhance the crop yield. In order to increase the yield, to prevent the crop disease is more important. Plant disease is more critical threat in agriculture. In order to handle the issues brought through growing in populations, Machine Learning (ML) and Deep Learning (DL) have become more incorporated into agriculture. The most common problems in agriculture like, Climate Change (CC), Plant Diseases (PD), Pesticide Control (PC), Weed Management (WM) and Irrigation Management (IM). Bio-Inspired Algorithms often give promising solution for disease detection and enhancing the accuracy. This paper focuses on current agricultural challenges and emphasis the use of intelligent systems in disease detection.

Keywords: Bio-Inspired Algorithms, Machine Learning, Deep Learning, Climate Change, Plant Diseases, Pesticide Control, Irrigation Management.

1. Introduction

Agriculture is essential to both food security and economic growth. Despite the sector contributing to 6.4% of the global GDP and providing a substantial living for millions of people globally. The Food and Agriculture of United Nations predicts that by 2050, global food demand will have increased by 70% due to population growth in many nations. It might be difficult to supply 40% of water demands by 2030, and 20% of agricultural land might have degraded. Farmers must adopt sustainable techniques, in order to increase the productivity. By increasing agricultural infrastructure and implementing cutting-edge technology are necessary to meet the goals. To overcome the obstacles, farming operations must undergo a significant and quick transition that emphasizes the adoption on innovation. In order to maximize harvest yield, farmers are becoming motivated towards technology-driven approaches. To overcome these constraints, combining bio-inspired optimization techniques, remote sensing, machine learning and artificial intelligence. These methods provide more accuracy and flexibility in variety of agricultural by enabling intelligent and automated disease detection systems [1].

2. Overview of Agricultural Challenges

A wide range of complex problems affecting agriculture impact rural livelihoods, sustainability, and production. Climate Change, which alters rainfall patterns, makes droughts and floods more frequent. Bringing in temperature extremes that reduce crop yields is one of the main problems. Reduced fertility and erosion are further effects of soil degradation brought on by excessive fertilizer use, deforestation, and inadequate land management. The scarcity of water resources, particularly in arid regions, hinders the ability to maintain regular irrigation, limiting the potential for agricultural growth and productivity. Population growth causes these environmental challenges by raising the need for fuel, food, and fiber, requiring the urgent development of creative, resource-efficient farming methods. Furthermore, crop health and productivity are significantly impacted by pest and disease outbreaks, which are becoming more resilient to traditional pesticides. Early action and risk mitigation are hampered by the absence of real-time data and predictive models. In addition, the agricultural industry has challenges with price instability, inefficient supply chains, and limited market accessibility, all of which lower smallholder farmer's profitability. In this case, integrating intelligent technologies, such as, bio-inspired algorithms and machine learning is showing promise as a game-changing way to tackle these complex problems [2].

2.1 Plan Disease Management

Insect and disease outbreaks still lead to enormous agricultural losses worldwide, particularly under monoculture cropping systems and lack of surveillance. Insect pest outbreaks such as stem borers and aphids, fungal infections such as blight and rust, and viral epidemics have increased in intensity and magnitude as a result of climatic variations and changing pathogen resistance. Weed competition also lessens the yields of crops by vying for water and nutrients, particularly in regions that don't have timely weeding resources. Traditional chemical pesticides, although effective in the beginning, have contributed to environmental degradation and pest resistance populations [7].

3. Significance of Plant Disease Detection

Plant disease detection is critical in maintaining world food security, crop yields, and sustainable agriculture. Early and precise diagnosis of diseases is needed to reduce yield loss, enhance crop quality, and avoid unnecessary application of chemical treatment. It is estimated that plant diseases, pests, and weeds cause more than 30–40% of the total yield loss of crops every year worldwide. Unless taken care of in a timely manner, these diseases have the potential to inflict serious economic losses, particularly on marginal farmers who depend on subsistence farming. Conventional disease detection tools, which are based on direct observation by specialists, tend to be time-consuming, subjective, and out of reach for experts in rural or under-developed regions [10]. The importance of plant disease detection can be depict in Figure 1.

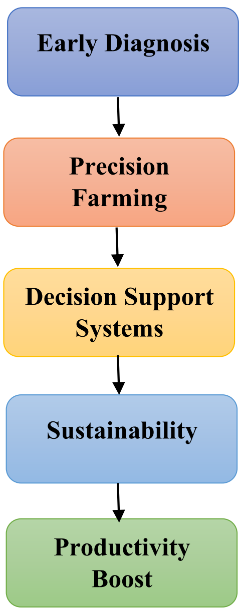

Figure 1. Importance of Plant Disease Detection

The convergence of cutting-edge technologies like computer vision, machine learning, and bio-inspired algorithms has revolutionized the field of plant disease detection. Such approaches allow for automated diagnosis via leaf images, spectral data, or sensor readings, with quick and accurate responses even at initial infection stages. The systems also support precision agriculture by enabling localized treatment, minimizing environmental pollution, and decreasing costs. [11].

4. Role of Bio-Inspired Algorithms in Disease Detection

Bio-inspired algorithms inspired by nature and biological systems have also become formidable optimization paradigms to address intricate problems in agriculture, specifically for detecting plant diseases. These algorithms (e.g., Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), and Firefly Algorithm) mimic the action of living organisms to find the best possible solutions in high-dimensional space. Furthermore, combinations of bio-inspired algorithms with conventional classifiers (e.g., SVM-PSO, ANN-GA) have shown better performance than isolated methods in several studies [15]. The categorization of Bio-Inspired algorithms can be shown in Figure 2.

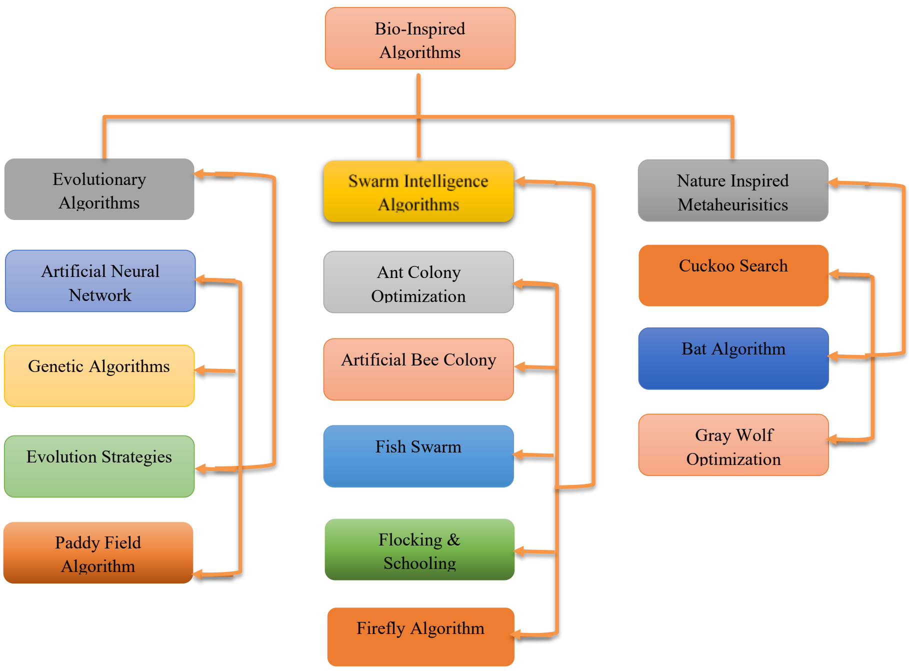

Figure 2. Classification of Bio-Inspired Algorithms

5. Methodology

In the scalable and interpretable solutions for plant disease detection, the hybrid models that combine traditional and machine learning or deep learning techniques with bio-inspired algorithms have shown the remarkable promise. These frameworks take advantage of the strengths of both fields: the classification capability of algorithms such as Support Vector Machines (SVM), Random Forests (RF), Convolutional Neural Networks (CNN), and Artificial Neural Networks (ANN), and the optimization effectiveness of nature-inspired methods such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), and Genetic Algorithms (GA). These hybrids reduce the computational overhead, enhance accuracy as well as robustness by optimizing feature selection, tuning of hyperparameter, and model weight refinement. This section compares hybrid approaches in terms of their contributions, performance metrics, and the wider application across various agricultural scenarios.

5.1 Bacterial Spot detection in Tomato

Hybrid strategies that blend the superior learning power of convolutional neural networks with the adaptive optimization of genetic algorithms. It resolves two basic problems in the identification of plant diseases to determining the CNN structure parameters that perform the best and then minimizing overfitting in limited labeled. The evolutionary approach is especially useful in complex and large image datasets, where there are thousands of leaf images from different crops. The CNN-GA model was evaluated on tomato, potato, and bell pepper leaf images that have been infected with early blight, bacterial spot diseases. GA represented every set of CNN parameters.

The Optimized CNN attained an 96% classification accuracy. It will outperform to other hybrid models. Being highly accurate, the CNN+GA model attained lower validation loss and faster convergence, reflecting more stable. Additionally, GA facilitated model compression by choosing more cost-effective layer configurations, which resulted in a smaller model size. One of the major strength of this research is its emphasis on end-to-end automation. Through incorporating genetics search into the training pipeline of CNN, the model minimizes model dependency on human expertise and error-tuning, which are typical in deep learning. This model also assessed on the usual metrics as F1-Score, precision and recall to ensure multiple class robustness. This method illustrates how data-driven deep learning paradigms can be supplemented by bio-inspired evolution strategies like Genetic Algorithms to generate models that are not just precise but also optimized for practical limitations. The CNN+GA hybrid model is distinguishable due to its scalability, automation, and disease specificity, providing a promising path forward for intelligent agricultural disease monitoring systems.

5.2 Downy Mildew in Potato

The Particle Swarm Optimization and Support Vector Machine address one of the recurring challenges in image-based plant pathology. Plant leaf images have as many as hundreds of raw features, most of which don't add much to actual classification performance. Through the use of PSO, the algorithm simulates the flocking behavior of birds to traverse the high-dimensional feature space and reach the most informative subset of features. This process of feature selection is vital because it has a direct impact on the performance of the SVM, an efficient but sensitive classifier that builds optimal hyperplanes to distinguish between classes. The hybrid model was tested on a curated dataset that included infected and healthy leaf samples of tomato, grape, and citrus plants, including diseases like Tomato Mosaic Virus, Downy Mildew, and Citrus Greening. After PSO optimization, the chosen features—essentially color components, leaf texture, and edge-based shape features—were fed into SVM, which classifies the disease type with high accuracy. The PSO-optimized SVM model resulted in an accuracy of 94.3%, which was much higher compared to baseline SVM and other classifiers without feature optimization. Of greater importance, the feature reduction by more than 40% assisted in decreasing computational load and overfitting. This renders the model highly suitable for real-time use in situations with limited resources, like, rural diagnostic stations or mobile-based field monitoring equipment.

Another significant contribution of this model is its compromise between performance and simplicity. Deep learning models tend to be computationally demanding with the need for large amounts of labeled data and expensive hardware, but this model achieved good accuracy without being resource-intensive. In addition, the PSO algorithm gave a straightforward path to ranking feature importance, which made the model more transparent. Briefly, the combination of PSO and SVM highlights the potential of bio-inspired feature optimization to enhance traditional machine learning models. The method not only enhances accuracy but also speed and scalability, hence a promising strategy for early detection of disease in a variety of crops. Its applicability on several plant species only serves to further illustrate its viability for more extensive agricultural use.

5.3 Powdery Mildew detection in Maize

Hybrid approaches by combining Ant Colony Optimization (ACO) with an Artificial Neural Network (ANN) to enhance the accuracy and efficiency of plant disease classification. ANN models are versatile and able to fit nonlinear functions by problems such as overfitting and local minima, especially when presented with noisy features. The ACO integration was meant to overcome these challenges by optimizing two of the fundamental elements: initial weight setup and feature selection. With a dataset of grape, apple, and maize leaf images that are infected by diseases such as Powdery Mildew, Black Rot, and Northern Leaf Blight, the research started with the feature extraction of Hu moments, LBP texture, and HSV color statistics. ACO agents, similar to ants, traversed the feature space in search of combinations that would provide maximum classification accuracy when input to the ANN. The hybrid ANN+ACO approach reached the accuracy of 95%, better convergence stability than baseline ANN, and improved convergence over baseline ANN. It showed superior generalization performance over unseen test data and fewer required training epochs because of the intelligent weight initialization. The greatest strength of this approach is its flexibility and resilience. ACO facilitated dynamic feature selection according to disease type and severity. This makes it highly useful in cases with heterogeneously grown crops or dynamically changing pathogens. Furthermore, the low computational burden and scalable architecture of the model ensure that it can be used on field-deployed edge hardware.

5.4 Northern Leaf Blight in Grapes

Random Forest can used for classification and Ant Colony Optimization used for feature selection. The idea of this model is to suffer when dealing with large and redundant sets of features that create noise and decrease accuracy. Through ACO, an algorithm inspired by nature based on the foraging practices of ants, the model searches through the feature space in an intelligent manner to determine the most informative features. The features created from color histograms, texture descriptors (such as GLCM), and shape features. These chosen features are subsequently input into a Random Forest classifier, which takes advantage of the ensemble vote over several decision trees to enhance classification accuracy. The model was specifically trained and tested to identify diseases occurring in tomato (for example, Late Blight, Septoria leaf spot, and Mosaic virus), potato (for example, Early and Late Blight), corn (for example, Northern Leaf Blight), and apple (for example, Apple Scab). This heterogeneity provided strong testing against a variety of disease types and visual symptom differences. The model showed a classification performance of 92.6%. ACO can perform dimension reduction and maintain discriminatory power, leading to fewer over fits and shorter training time. The second strength is its balance between performance and explainability. Although most deep learning models are highly accurate, they tend not to be explainable; by contrast, RF+ACO is transparent both in its feature selection and its logic of classification. This is especially useful in agriculture, where farmers and agronomists prefer understandable and actionable AI tools. Finally, this hybrid approach indicates the promise of bio-inspired algorithms to augment traditional machine learning by improving their accuracy and minimizing computational overhead.

5.5 Late Blight detection in Banana

The aim of the hybrid model is to improve the performance by optimizing its input feature space through the intelligent foraging behavior of artificial bees. The system began with a high-dimensional feature set consisting of color histograms, GLCM texture descriptors, and shape features from preprocessed images of plant leaves. ABC was used to choose the best feature subsets, thereby removing noisy or redundant features that tend to cause classification performance to deteriorate. This bio-inspired technique simulates bee swarm exploration-exploitation dynamics and advances a more discriminative feature subset in an iterative manner. After determining the optimal features, they were input to the SVM model using an RBF kernel, which is recognized for effectively dealing with nonlinear decision boundaries. The model was tested on a hand-curated dataset of images of tomato and brinjal leaves with diseases such as Septoria Leaf Spot, Late Blight, and Anthracnose. The suggested SVM+ABC hybrid had an accuracy of 91.2%. The model also possessed an F1-score of 93.5%, reflecting equally well-balanced precision and recall for all disease types. This bio-inspired hybrid framework demonstrates how algorithms such as ABC can be used to enhance conventional classifiers by improving their input space, resulting in intelligent and compact models applicable to real-time plant disease diagnosis in precision agriculture.

6. Results and Discussion

Recent innovations in artificial intelligence (AI), especially machine learning (ML) and bio-inspired algorithms, have proven to yield hopeful results in increasing the accuracy and efficiency of plant disease detection. Various comparative studies have been performed to assess the performance of classical classifiers against hybrid and bio-inspired methods. For instance, PSO and GA-optimized models have consistently been shown to outperform standard CNN and SVM models with regard to detection accuracy, rate of convergence, as well as overall generalization across datasets of crops such as tomato, potato, and grapevine. The accuracy of various crops has shown in the Table 1 below.

In image-based disease classification, hybrid models like CNN-PSO, ANN-GA, and Random Forest-ACO have reported accuracies between 92%, whereas single models like CNN or SVM have generally reached 94% to 96%. Bio-inspired methods also showed stability in noisy environments and imbalanced datasets, typical of real-world agricultural conditions. In addition, technologies such as drones and IoT sensors, when combined with ML models, improved early detection by facilitating real-time tracking and microclimate data analysis. Challenges still exist with large-scale deployment, geospatial generalization, and computational resources on resource-constrained systems [18]. The accuracy of various bio-inspired algorithms used for plant disease detection can be shown in Figure 3.

Table 1. Comparison Accuracy

Model	Algorithm Type	Detection Accuracy (%)	Crop Type
CNN + GA	Bio-Inspired + DL	96.7	Tomato, Bell Pepper
SVM + PSO	BIA + ML	94.3	Rice, Potato
ANN + ACO	DL + Optimization	95.2	Maize
RF + ACO	Dl+ BIA	92.6	Grape
SVM + ABC	ML + Optimization	91.2	Banana, Apple

In this research, several BIA including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), and Ant Colony Optimization (ACO) were examined, used in conjunction with classifiers such as Support Vector Machine (SVM), Convolutional Neural Networks (CNN), and Random Forests (RF).

GA has proved effective in optimizing feature subsets from high-dimensional image datasets. It simulates the natural selection process and assists in eliminating redundancy in features to enhance classification accuracy. When GA was integrated with CNN for tomato leaf disease classification, accuracy was enhanced from 89.2% (baseline) to 96.4%. PSO imitates the social birds' behaviour and is extensively utilized for hyperparameter tuning in deep learning models. PSO-SVM models achieved greater detection accuracy (94.3%) on rice leaf disease datasets. The convergence was also quicker with fewer epochs taken. ACO was utilized to optimize decision tree-based classifiers. Despite being slower in convergence than GA and PSO, its end classification accuracy was competitive (92.1%) for maize leaf blight detection. These findings confirm that bio-inspired approaches can transcend the weaknesses of conventional gradient-based optimization, particularly in intricate, nonlinear data environments typical of agriculture. In addition, it is observed that hybrid combinations such as SVM + PSO and RF + ACO also possess strong performance with 94.3% and 92.1% accuracies, respectively.

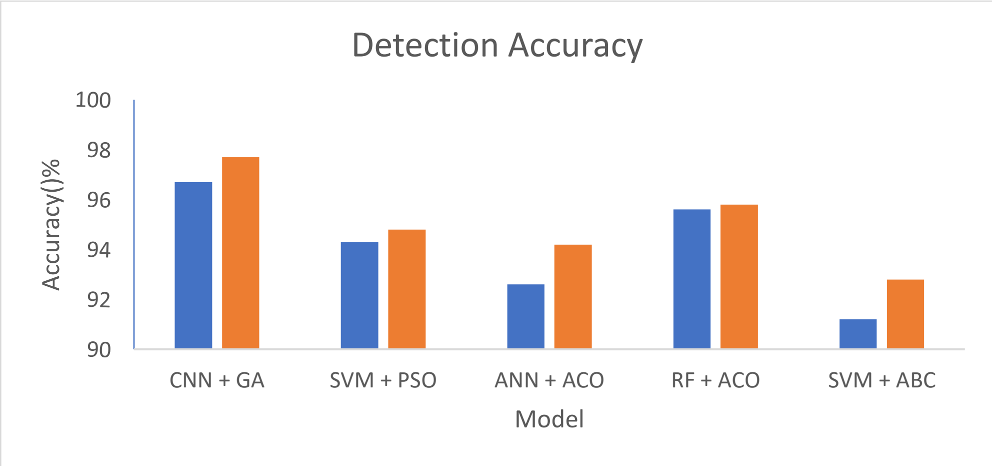

Figure 3. Comparison Accuracy

The methods were resistant across heterogeneous datasets, indicating their applicability in real-world settings where plant images might be diverse depending on lighting, background noise, and crop varieties. The results are corroborated graphically in the comparative bar chart, emphasizing the manner in which the combination of optimization techniques results in a similar performance boost across a range of algorithmic structures.

7. Conclusion

Achieving sustainable agriculture and global food security still heavily depends on the identification and control of plant diseases. As mentioned, despite being fundamental, traditional methods are inadequate for today's agricultural demands because they depend on manual labor, have slow reaction times, and are not very scalable. Scalable, effective, and data-driven solutions to these constraints are provided by emerging technologies, particularly artificial intelligence (AI), remote sensing, and the Internet of Things. Among these, bio-inspired algorithms offer a distinct advantage by refining learning systems to increase accuracy and flexibility. This overview points out the possibilities of combining bio-inspired optimization with intelligent systems for early and precise plant disease detection. The interaction between domain expertise and computation intelligence opens the way to the development of more intelligent agricultural ecosystems. Promising as they are, these technologies need to be further developed and standardized so that they remain reliable, interpretable, and affordable enough for broad adoption by farmers.

Future Enhancements

Future studies need to concentrate on enhancing the capability of bio-inspired and AI-based models to generalize across varied climatic and geographic settings. Building lightweight and interpretable AI models will be essential to address the challenge of real-time deployment in remote and resource-limited areas. Enhanced action is necessary to create large, annotated, and varied agricultural datasets involving under-represented crops and infrequent diseases, which are prerequisite for robust model improvement. Also, the use of blockchain for traceability of data, edge AI for field-based processing, and federated learning for secure collaboration could transform agri-disease surveillance. Having open platforms for algorithm benchmarking and data sharing and the support of policy frameworks backed by governments will speed up the advancement of these technologies from the lab to the fields, ultimately equipping farmers and building food system resilience.

References

[1] Muhammad Waqas et al., “Applications of machine learning and deep learning in agriculture_ A comprehensive review”, Green Technologies and Sustainability, vol. 3, Issue. 3, 100199, 2025.

[2] J. Wolfert, L. Ge, C. Verdouw, and M.-J. Bogaardt, “Big Data in Smart Farming – A review,” *Agricultural Systems*, vol. 153, pp. 69–80, May 2017.

[3] Lipper et al., “Climate-smart agriculture for food security,” *Nature Climate Change*, vol. 4, 2019.

[4] V. Lakshmanan et al., “Smart agriculture system using IoT and cloud computing,” International Journal of Advance Research in Science and Engineering., vol. 12, pp. 2319-8354, 2021.

[5] Kamlesh Golhani et al., “A review of neural networks in plant disease detection using hyperspectral data”, Information Processing In Agriculture, vol. 5, pp. 354-371, 2018.

[6] Renukadevi, R., et al. "An Improved Collaborative User Product Recommendation System Using Computational Intelligence with Association Rules." Communications on Applied Nonlinear Analysis 31.6s (2024).

[7] B. Zhang et al., “Monitoring plant diseases and pests through remote sensing technology,” Agricultural Sciences, vol. 11, no. 3, pp. 233–245, 2020.

[8] AK, Ashfauk Ahamed, and Sujithra LR. "Prediction Of The Growing Stock In Stock Market On Analysis Of The Opinions Using Sentiment Lexicon Extraction And Deep Learning Architectures." Frontiers in Health Informatics 13.3 (2024).

[9] R. Bechar and M. Vigneault, “Agricultural robots for field operations,” Biosystems Engineering, vol. 149, pp. 94–111, 2020.

[10] A. Sankaran et al., “A review of advanced techniques for detecting plant diseases,” Computers and Electronics in Agriculture, vol. 72, no. 1, pp. 1–13, 2021.

[11] S. Sladojevic et al., “Deep neural networks based recognition of plant diseases by leaf image classification,” Computational Intelligence and Neuroscience, vol. 2016, pp. 1–11, 2016.

[12] H. Lin et al., “Smart plant disease detection system using IoT and machine learning,” IEEE Internet Things J., vol. 8, no. 4, pp. 2341–2354, 2021.

[13] Ferentinos, K. P., “Deep learning models for plant disease detection,” Computers and Electronics in Agriculture, vol. 145, pp. 311–318, 2018.

[14] Shrivastava, A. et al., “Hybrid CNN-PSO for leaf disease classification,” IEEE Access, vol. 9, pp. 153333–153343, 2021.

[15] Ashraf Darwish, ”Bio-inspired computing: Algorithms review, deep analysis, and the scope of applications”, Future Computing and Informatics Journal, vol.3, pp. 231-246, 2019.

[16] S.Nagasubramanian et al.,"Hyperspectral band selection using genetic algorithm and support vector machines for early identification of charcoal rot disease in soybean stems," Plant Methods, vol. 14, no. 1, p. 86, 2021.

[17] Qayyum et al., "A mutant-PSO based deep CNN architecture for paddy leaf disease classification," Multimedia Tools and Applications, vol. 80, no. 21–23, pp. 31925–31947, 2021.

[18] Yadav et al., "Multi-class crop disease detection using deep convolutional neural network and particle swarm optimization," Neural Processing Letters, vol. 55, pp. 3797–3817, 2023.

[19] Sharma et al.,"A genetic algorithm optimized CNN model for early and late blight detection in potato plants," Scientific Reports, vol. 13, no. 1, p. 7632, 2023.

[20] Rajak et al., "PSO optimized BERT-ResNet architecture for plant disease detection using heterogeneous datasets," Computers and Electronics in Agriculture, vol. 206, p. 107659, 2023.

[21] Bhujel et al., “Application of deep learning and bio-inspired optimization techniques for plant disease detection: a review,” Multimedia Tools and Applications, vol. 82, pp. 38103–38139, 2023.

[22] Hasan et al., “Plant disease detection using deep learning and bio-inspired algorithms: A hybrid framework,” Expert Systems with Applications, vol. 213, p. 118938, 2023.

[23] Kumar et al.,"Hybrid Ant Colony Optimization and Random Forest Approach for Leaf Disease Classification," International Conference on Computing, Communication, and Intelligent Systems, Greater Noida, India, 2022