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Research Article

Plant Disease Detection Using CNN with The Optimization Called Beluga Whale Optimization Mechanism

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Abstract:

Plant disease detection is critical for ensuring agricultural productivity. Early and accurate identification of plant diseases can help in the timely application of remedies, reducing yield loss and improving crop quality. This paper presents a deep learning(DL) approach using Convolutional Neural Networks (CNN) for plant disease detection, combined with an advanced optimization technique named the Beluga Whale Optimization Mechanism (BWOM). The CNN is implemented to extract and features from plant images, providing a robust model capable of differentiating between healthy and diseased plants. The BWOM is utilized to optimize the CNN's hyper parameters and weights, enhancing model accuracy and efficiency by reducing overfitting and improving generalization. The BWOM mimics the social behaviour and echolocation techniques of beluga whales to navigate and optimize solution spaces effectively. By iterating through population-based exploration and exploitation phases, BWOM provides a balanced search mechanism to fine-tune CNN parameters. Further the results demonstrate the effectiveness of combining CNN with BWOM in achieving high accuracy rates for plant disease classification.

1. Introduction

Agriculture is often regarded as the foundation of a country, undergoing its own revolution in parallel with industrial advancements. Crops are essential to human survival and play a vital role in food security, a critical concern due to the significant impact of crop diseases [1]. Plant diseases pose serious threats to global food security and have widespread effects on daily life. Therefore, maintaining crop health is essential for economic stability and ensuring a safe food supply. The condition of a crop's growth and leaves often reflects its overall health, and understanding various plant diseases relies on analysing symptoms seen on leaves.

Diseases affecting common crops like potatoes, tomatoes, and peppers can result in substantial financial losses for farmers each year. For instance, blight, a prevalent disease, has two forms: early blight, caused by a fungus, and late blight, caused by specific bacteria [2-9]. By detecting these diseases early, farmers can mitigate costs and prevent waste. With the global population projected to surpass 9 billion in the next few decades, there will be a pressing need to boost food production to meet growing demands. Crop diseases are a significant obstacle, especially in agriculture-focused countries, and the impact on essential crops like potatoes, the world's most widely consumed vegetable, is particularly concerning. Peppers and tomatoes face similar challenges. In line with the idea that prevention is better than cure, agricultural scientists are exploring deep learning methods to combat these diseases in crops, especially potatoes. Advancements in computing have allowed machine learning techniques to process real-time image data, showing promise in detecting and preventing crop diseases effectively.

Existing solutions in plant disease detection encompass a different approach, starting with innovative technologies like early disease monitoring and precise diagnosis through advanced automatic plant surveillance systems. These solutions extend to fine-tuning pre-trained models, leveraging the robustness of CNN-based frameworks for disease detection in diverse and challenging agricultural environments. The use of large datasets during training has enhanced the model's generalization, which is pivotal for achieving high accuracy in detecting various plant diseases and safeguarding global food security.

This research introduces an optimized approach to CNN-based plant disease detection, incorporating the Beluga Whale Optimization Mechanism (BWOM) to improve hyperparameters and weights. This optimization technique, inspired by beluga whale behavior, strengthens the CNN model's accuracy and efficiency by navigating complex solution spaces effectively, reducing overfitting, and enhancing adaptability to new data. Unlike conventional methods relying solely on transfer learning and data augmentation, our BWOM-CNN model allows for fine-tuning that dynamically adapts to environmental challenges, offering enhanced performance in real-time plant monitoring.

This approach builds upon the historical application of DL models in plant disease detection, particularly CNNs, by addressing issues of dataset variability and limitations. While prior research has explored techniques like transfer learning, and data augmentation to improve disease detection accuracy, BWOM-CNN provides an added layer of optimization, refining model accuracy and minimizing computational inefficiencies. Moreover, studies on detector families are also referenced to illustrate the diverse methods employed in plant disease detection, with BWOM-CNN positioning itself as a powerful tool within this evolving landscape.

Contribution of the Research:

1. The research proposes the new methodology of integrating the BWO technique over the deep CNN which can be used for better identification of disease.
2. The recommended scheme is assessed with the different residing artificial intelligence algorithms with the huge datasets.

2. Related Works

Abbas et al. [10], suggested a DL-based technique for detecting tomato diseases that creates artificial pictures of tomato plant leaves using the Conditional Generative Adversarial Network (C-GAN). then use transfer learning models to detect the disease. The development of generative networks has made previously costly, time-consuming, and Real-time data collecting or painstaking data acquisition is now feasible.

Anh et al. [11], in their study, proposed the most widely used models for multi-leaf disease detection in order to determine which model is most suited for practical use.

Astani et al [12], a multi-class ensemble classifier for diagnosing tomato disease. Taiwan Tomato Leaves and Plant Village were the two datasets utilized to examine the performance of the best ensemble classifier. Based on background clutter, many leaves from the same plant, brightness fluctuations, and shadow conditions, the top ensemble classifier was able to distinguish between various illnesses.

Pradeep et al. [13] presented the EfficientNet model for multi-label and multi-class classification using a convolutional neural network. The detection of diseases was improved by the CNN's hidden layer network. Yet, when tested with benchmark datasets, the model fared poorly.

Enkvetchakul and Surinta [14] CNN network with a transfer learning strategy was suggested. Plant disease detection utilized two pre-trained network models: NASMobileNet and MobileNetV2. Among these, the NASMobileNet technique exhibited the highest precision in prediction. To counter overfitting in deep learning, the data augmentation method was applied. Our experimental setup incorporated cut-out, rotation, zoom, shift, brightness adjustments, and mix-up to effectively implement the data augmentation approach. The examination resulted in a maximum test accuracy of 84.51%.

Trivedi, et al. [15] There have been several uses of identification and classification techniques for some illnesses. To thoroughly detail and organize tomato infection types, CNN is utilized.

Agarwal et al. [16] This study condensed on CNN model with 8 hidden layers is suggested. The suggested low weight model performs better than the conventional machine learning algorithms using the publicly accessible dataset PlantVillage.

Fuentes et al. [17] consider three main families of detectors: Faster Region-based Convolutional Neural Network (Faster R-CNN), Single Shot Multibox Detector (SSD), and Region-based Fully Convolutional Network (R-FCN).

3. Background Views

This section details about the working mechanism of the convolutional neural networks, Beluga whale optimization.

3.1 Convolutional neural networks

CNN share similarities with traditional Artificial Neural Networks (ANNs) in that they consist of neurons that optimize themselves through learning. Every neuron processes inputs through an operation—typically involving a scalar product and a non-linear function—fundamental to the structure of many neural networks. From the raw image input to the final class score output, the network operates as a single perceptual scoring function represented by weights. The final layer incorporates loss functions associated with each class, and the usual methods and techniques applied in traditional ANNs remain relevant for CNNs as well.

Neural Networks (NNs) consist of three primary layer types: convolutional layers, pooling layers, and fully connected layers. When these layers are combined, a CNN architecture is formed:input, convolution with ReLU, pooling, and two fully connected layers with ReLU activation.This basic CNN can be described in four main stages: In CNN the input layer holds the image’s pixel values, similar to other types of Artificial Neural Networks (ANNs). The convolutional layer computes the output of neurons that are connected to specific local areas of the input by taking the dot product between their weights and the corresponding input region. Following this, the Rectified Linear Unit (ReLU) layer applies an "elementwise" activation function to the output, similar to how the sigmoid function operates. Next, the pooling layer performs downsampling over the spatial dimensions of the input, thereby reducing the number of parameters within the feature map. Finally, the fully connected layers operate like those in conventional ANNs, creating class predictions from the activations to facilitate classification. ReLU activation is also commonly applied between these layers to improve the network's performance.

3.2 Beluga whale optimization

In this segment, we introduce the proposed **Beluga Whale Optimization Mechanism (BWOM)** for effective selection of predictive features (figüre 3). BWOM is a nature-inspired meta-heuristic scheme that mimics the echolocation, cooperative hunting, and social behaviors of beluga whales. The significant aim of this algorithm is to detect the most relevant attributes to enhance prediction accuracy while remaining computationally efficient. Like other meta-heuristic algorithms, BWOM aims to strike a balance between exploration (broadly searching for global solutions) and exploitation (fine-tuning local solutions) to achieve an optimal outcome. Traditional optimization approaches often struggle to maintain this balance, which can lead to premature convergence or excessive computational demands.

BWOM addresses this challenge by organizing search agents into roles based on beluga whale behavior, wherein leading agents use echolocation signals to direct group movement, while follower agents adaptively adjust their paths based on the signals from the leaders. This echolocation-driven navigation and cooperation enable adaptive exploration of the search space, increasing the likelihood of reaching global optima while ensuring stability during the exploitation phase. By emulating these natural dynamics, BWOM demonstrates a strong ability to efficiently converge toward optimal solutions, minimizing computational overhead and avoiding common pitfalls like getting trapped in local optima. As a result, BWOM achieves high robustness and computational efficiency in feature selection and other optimization tasks.

Process mechanism

1) Initialization Phase: Eq. (1) is employed to initialize the different agents within the initial population of the BWO algorithm.

$$X_{i,j}^{0}=\alpha(UB-LB)+LB, i\in\{1,\ldots,N\}, j\in\{1,\ldots,D\} \quad (1)$$

2) Exploration Phase: In this method, the positions of search agents are guided by a paired swimming pattern, in which two beluga whales move together in a coordinated or reflective manner. This cooperative approach enables search agents to cover the search space more comprehensively and efficiently, often leading to the identification of improved or novel solutions. The agents' positions are iteratively updated based on this dual-movement strategy, enhancing the overall exploration process

$Xi,jt+1=Xi,\rho t+(Xr,1t-Xi,\rho t)(1+r1)\sin(2\pi r2),j=2k$
2)

$Xi,jt+1=Xi,\rho t+(Xr,1t-Xi,\rho t)(1+r1)\cos(2\pi r2),j=2k+1$

3) Exploitation Phase: The agents exchange details regarding their present locations and evaluate both the optimal solution and nearby alternatives to adjust their own positions. This process allows the agents to move effectively toward promising areas within the search space. Such an approach supports improved convergence of agents toward the global solution. The positions of the agents are updated through

$$Xit+1=r3Xbestt-r4Xit+2r4(1-tTmax) \qquad (3)$$

$LF(Xrt-Xit)LF=0.05(\upsilon\times\sigma|\nu|1\beta)$

$\sigma=(\Gamma(1+\beta)\times\sin(\pi\times\beta 2)\Gamma(1+\beta 2)\times\beta\times 2\beta-12)1\beta$

4) Balance between Exploration and Exploitation: In the search process, the balance between exploration and exploitation is governed by a swapping factor, referred to as Bf, calculated as per Eq. (4). When B_f meets or exceeds a designated threshold (such as 0.5), the process engages in exploration using Eq. (2). Otherwise, if bf falls below this threshold, exploitation is performed following Eq. (3).

$$Bf=B0(1-t2Tmax) \qquad (4)$$

5) Whale Fall: The whale fall phase embodies the process wherein deceased beluga whales become a food source for surrounding marine life. In the BWO algorithm, this phase functions as a stochastic mechanism designed to enhance variety, reducing the risk of the search process settling into local optima prematurely (figure 4). This step is mathematically represented as.

$$Xit+1=r5Xit-r6Xrt+r7 \qquad (5)$$

$XstepXstep=(UB-LB)\exp(-C2tTmax)$

$C2=2\times Wf\times N(6)$

$$Wf=0.1-0.05tTmax \qquad (6)$$

4. System Design:

Figure 1 shows the proposed architecture. This proposed system aims to predict plant disease using the optimized deep learning. Figure 2 is the proposed whale Optimization exploration, exploitation, and local optima avoidance. **4.2 Data pre processing**

Preprocessing a plant dataset for disease detection typically involves several key steps to ensure data quality and improve model performance. First, images are resized to a uniform shape, commonly used dimensions 224x22, to standardize inputs for the model. Next, data augmentation techniques such as rotation, flipping, scaling, and color adjustments are applied to empower dataset diversity and help the model generalize better. Following augmentation, images are normalized,

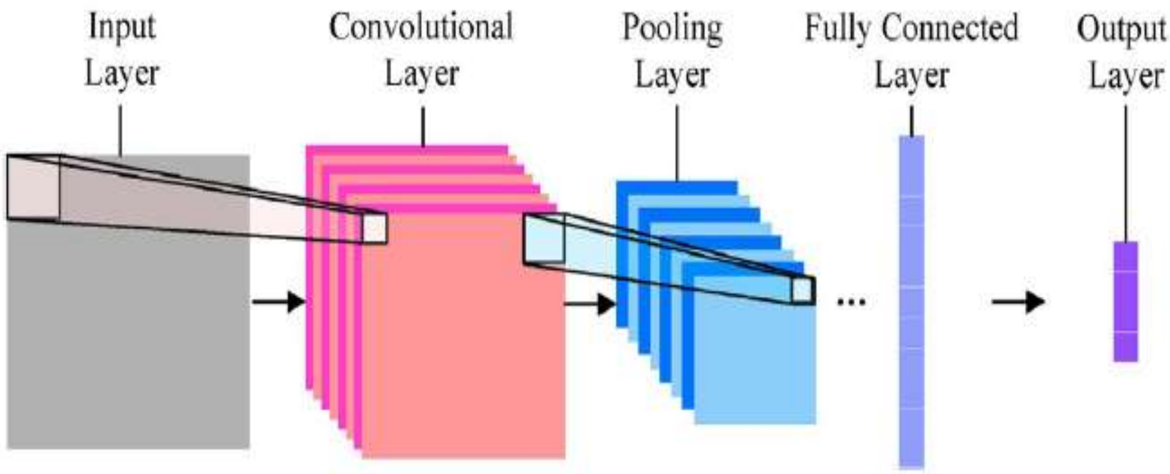

Figure 1: *Convolutional Neural Network Architecture*

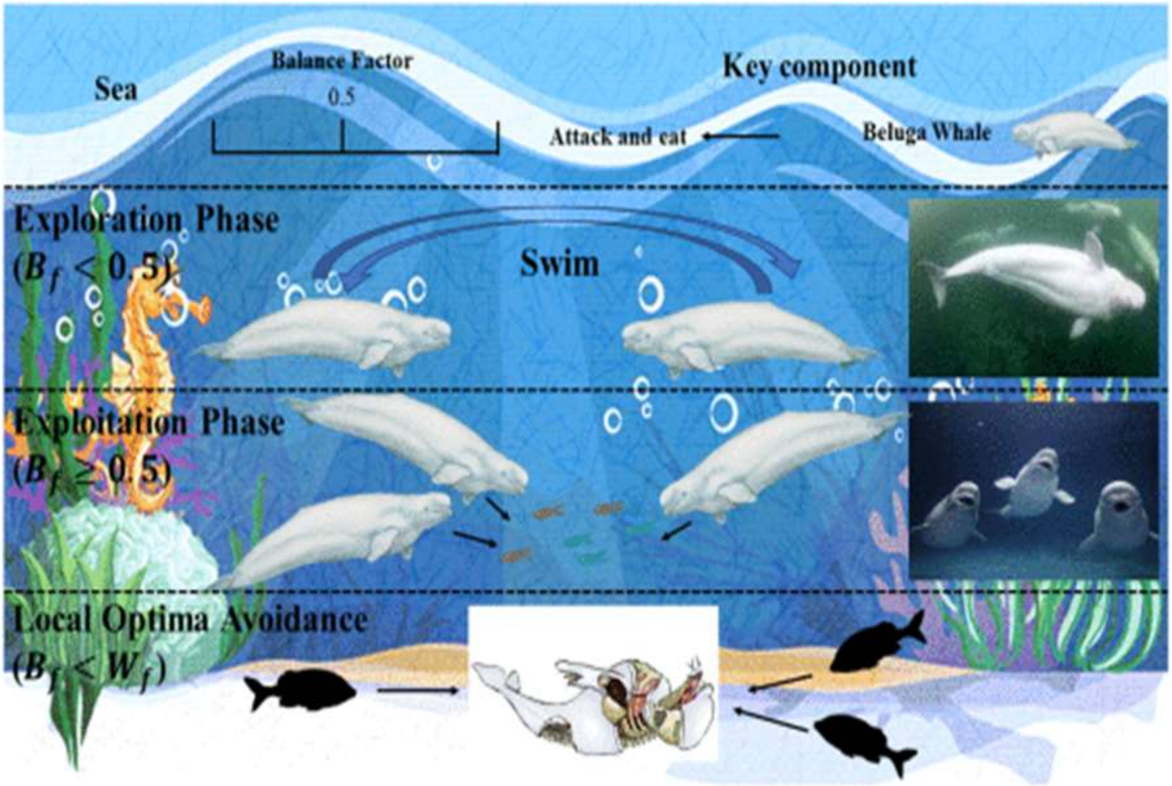

Figure 2: *Proposed whale Optimization exploration, exploitation, and local optima Avoidance*

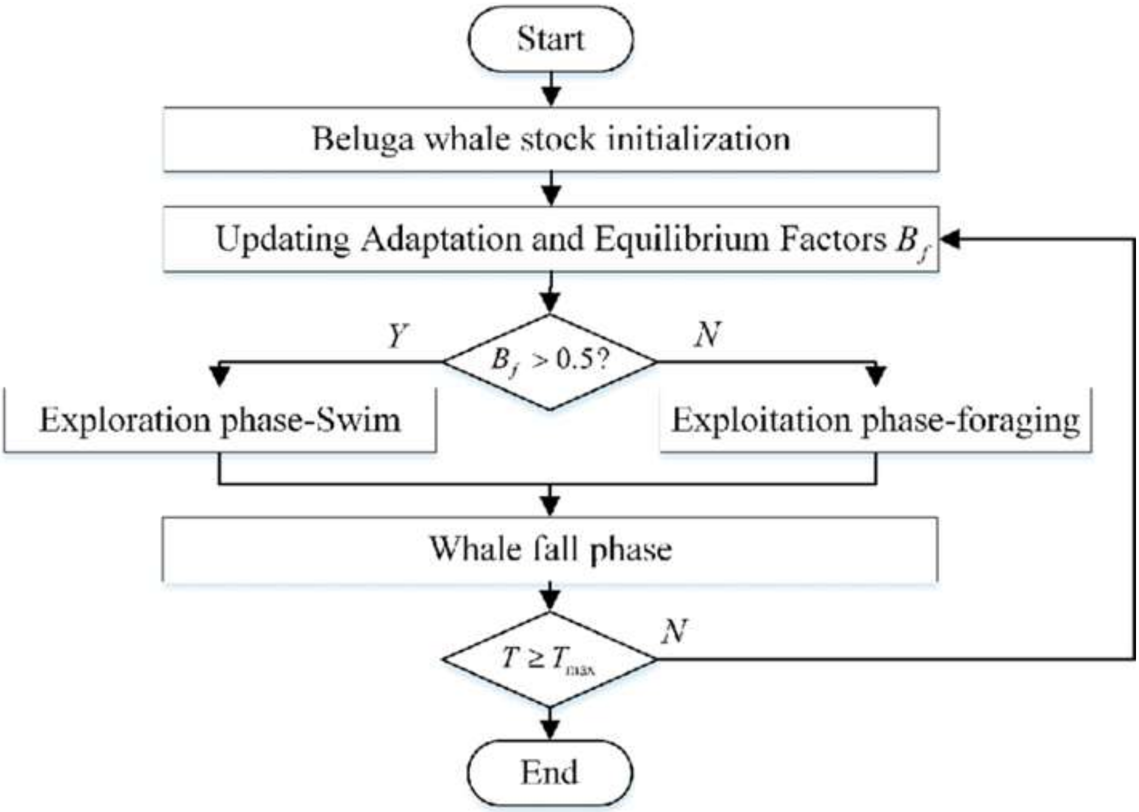

Figure 3: *Mechanism of Beluga Whale Optimization*

```
Input: Algorithmic parameters (population size, maximum iteration)
Output: The best solution
Initialize the population and evaluate fitness values, obtain the best solution (P*)
While T≤T_max Do
    Obtain probability of whale fall W_f by Eq. (10) and balance factor B_f by Eq. (3)
    For each beluga whale (X_i) Do
        If B_f(i) > 0.5
            // In the exploration phase
            Generate p_j (j = 1,2,…,d) randomly from dimension
            Choose a beluga whale X_r randomly
            Update new position of i-th beluga whale using Eq. (4)
        Else If B_f(i) ≤ 0.5
            // In the exploitation phase
            Update the random jump strength C_1 and calculate the Levy flight function
            Update new position of i-th beluga whale using Eq. (5)
        End If
        Check the boundaries of new positions and evaluate the fitness values
    End For
    For each beluga whale (X_i) Do
        // the whale fall phase
        If B_f(i) ≤ W_f
            Update the step factor C_2
            Calculate the step size X_step
            Update new position of i-th beluga whale using Eq. (8)
            Check the boundaries of new position and calculate fitness value
        End If
    End For
    Find the current best solution P*
    T = T+1
End While
Output the best solution
```

Figure 4: *Pseudocode of BWO*

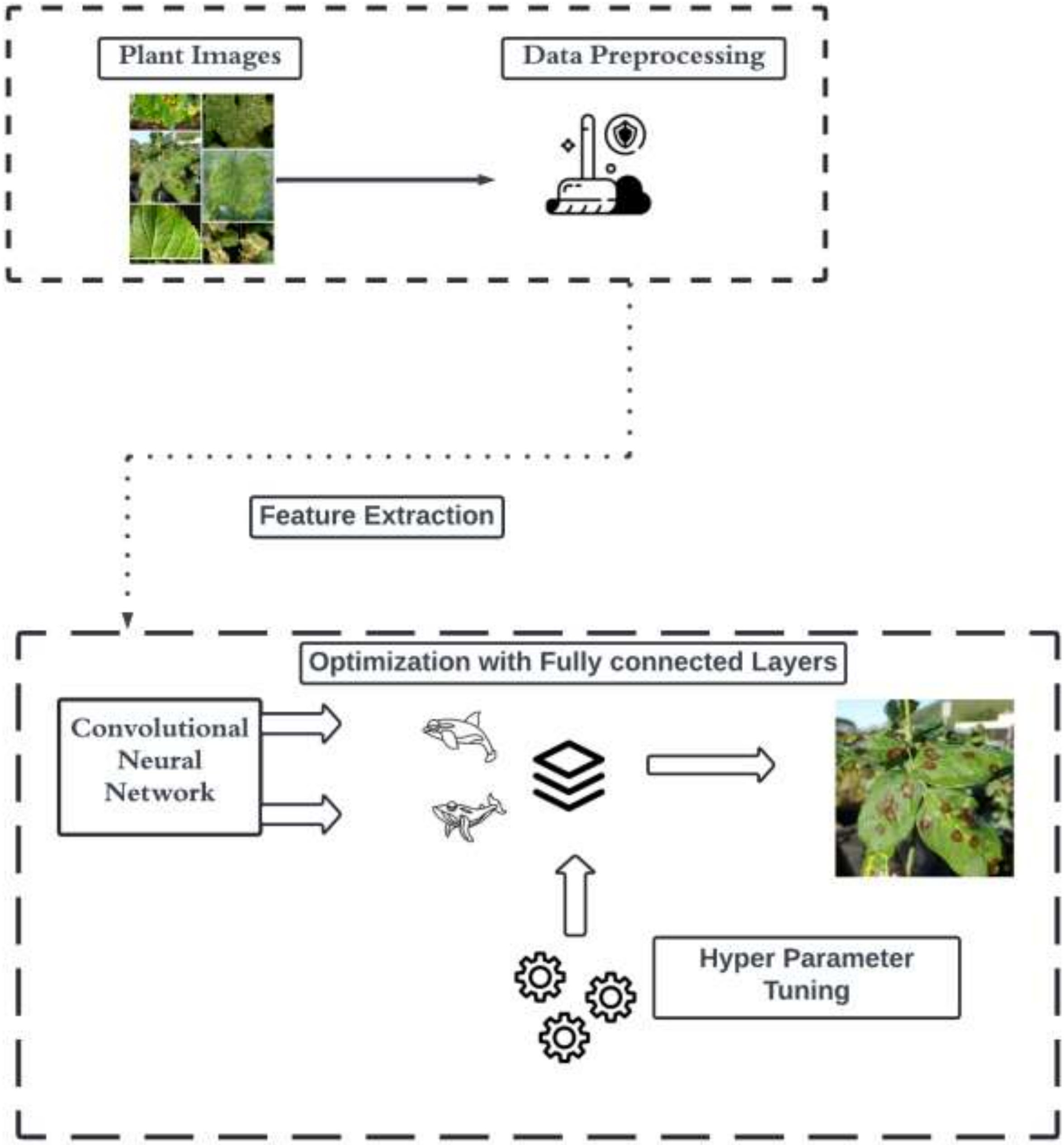

Figure 5: *Proposed Architecture for plan disease detection*

often by scaling pixel values between 0 and 1 or by subtracting the mean and dividing by the standard deviation of the dataset, which helps stabilize training. In some cases, background noise is reduced using image filtering techniques, and annotations or labels are verified to ensure correct categorization of healthy or diseased samples. The dataset is ultimately divided into training, validation, and test sets, which allows for a thorough evaluation of model accuracy and helps reduce overfitting.

4.3 Proposed convolutional neural network

The detailed process for the optimized CNN layer is shown in Figure 5. At first, a random set of bias weights and layers is provided to the convolutional networks, with no preset number of epochs to allow it to integrate into the deep learning network. The fitness function, based on prediction and verification accuracy, is established as a fixed criterion. During every iteration, input bias and layer configurations are measured utilising mathematical equations including an epoch count compatible with the learning network. These configurations are then fed into the convolutional training network, where the fitness function is evaluated. If the fitness function meets the threshold value, the process concludes; otherwise, it continues iteratively.

4.4 Hyper parameter tuning

Hyper-parameter selection for algorithm varies widely among researchers, resulting in different optimization objectives. Some approaches take a focused view, adjusting the hyper-parameters within each layer while keeping the network's architecture constant. Others adopt a broader view, modifying parameters such as the number of layers, learning rate, and dropout rate. In this paper, we concentrate on the first approach. After finalizing the CNN architecture, we apply beluga whale Optimization and tune its hyper-parameters.

Hyperparameter tuning in optimization with fully connected layers focuses on finding the ideal configurations to improve model performance while balancing computational efficiency. Key hyperparameters in fully connected layers include the number of neurons, the learning rate, the batch size, and the activation functions. Adjusting the number of neurons impacts the model's capacity to learn complex patterns—too few may lead to underfitting, while too many can result in overfitting and increased computational cost. And also based on the hyperparameter tuning the exploitation and exploration of the optimization works well. The learning rate is crucial for controlling the speed and stability of the optimization process, where a high learning rate can lead to divergence, and a low rate may cause slow convergence. Batch size influences the gradient estimates and overall training time, with larger batches providing more stable gradients but requiring more memory.

5. Dataset

5.1 Dataset description:

This dataset was generated by performing offline augmentation on an existing dataset, which is accessible on the associated GitHub repository. It comprises approximately 87,000 RGB images showcasing both healthy and diseased crop leaves, classified into 38 distinct categories. The dataset is divided into training and validation sets in an 80/20 split, maintaining the original directory structure. Additionally, a separate directory containing 33 test images was later created for prediction purposes. Table 1 is the varied attributes while experimentation.

5.2 Findings and analysis:

DL models are assessed and analyzed in terms of their effectiveness, utilizing the following performance indicators derived from the confusion matrix presented in table 2. In this context, **TP** refers to True Positives, where the model correctly identifies a leaf as diseased, and it indeed is diseased. **TN** stands for True Negatives, indicating the model accurately classifies a leaf as healthy when it is, in fact, healthy. **FN** denotes False Negatives, which occur when the model wrongly identifies a diseased leaf as healthy. Lastly, **FP** signifies False Positives, where the model incorrectly categorizes a healthy leaf as diseased.

Table 1 : *Varied attributes while experimentation*

Parameters	Values
Learning Rate	.001
Drop out	0.01
Optimizer	BWO
Batch Size	32
Validation split	0.2

Table 2: *Confusion matrix.*

Empty Cell	**Actual positive**	**Actual negative**
Predicted positive	TP	FP
Predicted negative	FN	TN

Accuracy: The share of test cases yielding accurate predictions can be represented as follows

Accuracy=TP+TNTP+FP+FN+TN (7)

Precision: The fraction of correctly identified disease-affected leaves to the total number of leaves predicted positively by the model is termed precision and can be described as follows:

Precision=TPTP+FP (8)

Recall: Recall is articulated as the percentage of correctly classified leaves showing disease symptoms in relation to the total instances classified as positive in the test case:

Recall=TPTP+FN (9)

F1-Score:

F1−score=2*Precision*recallPrecision+recall (10)

To evaluate the effectiveness of the suggested model, we have used the different epochs with learning rate of 0.001. It was determined that the optimal outcomes during the tuning process were achieved with 20 epochs, a learning rate of 0.001, and an output batch size configured to 32 (table 3). Table 4 is the performance metric analysis between the proposed framework with the other existing framework.

***Table 3**: Training Accuracy Performance using the no of batches =32*

Sl.no	No of batches	No of Epochs	Training Accuracy (%)
01	32	10	96.45%
02	32	15	97.7%
03	32	20	98.6%
07	32	25	98.30%

***Table 4:** Performance metric Analysis Between the Proposed Framework with the Other existing Framework*

Algorithms	**Performance metrics**				
	Accuracy	**Precision**	**Recall**	**Specificity**	**F1-score**
Vgg16	0.92	0.92	0.924	0.94	0.932
Vgg19	0.96	0.966	0.960	0.93	0.940
Proposed Model	0.986	0.986	0.975	0.975	0.986

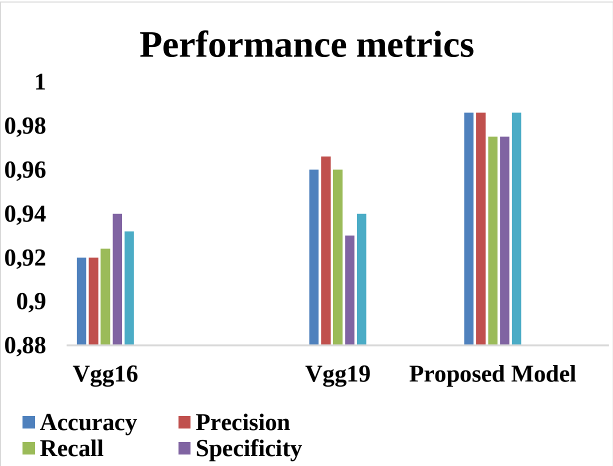

***Figure 6.** Performance metrics*

6. Conclusions

In this work, we introduced a novel scheme for plant disease detection using a CNN optimized with the Beluga Whale Optimization Mechanism (BWOM). Our approach addresses key challenges in plant disease identification by effectively selecting relevant features and enhancing model accuracy across various crop diseases. The recommended scheme illustrated significant improvements in both computational efficiency and classification accuracy of 98%, offering a reliable solution for early and precise plant disease detection. This advancement not only aids in reducing crop loss but also contributes to food security and agricultural sustainability. Deep learning is important and it is used in different application [18-34].

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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References

[1] P.W. Bidwell (1921). The agricultural revolution in new England, *Am. Hist. Rev.*, 26(4);683-702.

[2] Z.B. Husin, A.Y.B.M. Shakaff, A.H.B.A. Aziz, R.B.S.M (2012). Farook, Feasibility study on plant chili disease detection using image processing techniques, 2012 *Third International Conference on Intelligent Systems Modelling and Simulation, IEEE* 291-296

[3] Kalpana, P., Anandan, R. (2023). A capsule attention network for plant disease classification. *Traitement du Signal*, 40(5);2051-2062. https://doi.org/10.18280/ts.400523.

[4] Kalpana, P., Anandan, R., Hussien, A.G. *et al.* (2024). Plant disease recognition using residual convolutional enlightened Swin transformer networks. *Sci Rep* 14;8660. https://doi.org/10.1038/s41598-024-56393-8.

[5] P. Kalpana, S. Sridevi (2022). A survey on recognition and classification of paddy leaf diseases using image processing and machine learning techniques. *AIP Conf. Proc*. 2463(1);020009. https://doi.org/10.1063/5.0080336.

[6] Mohsin Kabir, M.; Quwsar Ohi, A.; Mridha, M.F. (2023). A Multi-plant disease diagnosis method using convolutional neural network. arXiv 2020,

arXiv:2011.05151. *Plant Disease Detection Using Deep Learning* 15(6);49

[7] Aldhyani, T.H.; Alkahtani, H.; Eunice, R.J.; Hemanth, D.J. (2022). Leaf Pathology Detection in Potato and Pepper Bell Plant using Convolutional Neural Networks. In Proceedings of the 2022 *7th International Conference on Communication and Electronics Systems (ICCES),* Coimbatore, India, pp. 1289–1294.

[8] Prodeep, A.R.; Hoque, A.M.; Kabir, M.M.; Rahman, M.S.; Mridha, M.F. (2022). Plant Disease Identification from Leaf Images using Deep CNN's EfficientNet. *In Proceedings of the 2022 International Conference on Decision Aid Sciences and Applications (DASA),* Chiangrai, Thailand, pp. 523–527.

[9] Kalpana, P.,Y. Chanti, R. G, R. D and P. K. Pareek, (2023). SE-Resnet152 Model: Early Corn Leaf Disease Identification and Classification using Feature Based Transfer Learning Technique, *2023 International Conference on Evolutionary Algorithms and Soft Computing Techniques (EASCT),* Bengaluru, India, pp. 1-6, https://doi.org/10.1109/EASCT59475.2023.10392328..

[10] Abbas, A.; Jain, S.; Gour, M.; Vankudothu, S. (2021) Tomato plant disease detection using transfer learning with C-GAN synthetic images. *Comput. Electron. Agric*. 187;106279.

[11] Anh, P.T.; Duc, H.T.M. (2021). A Benchmark of Deep Learning Models for Multi-leaf Diseases for Edge Devices. *In Proceedings of the 2021 International Conference on Advanced Technologies for Communications (ATC),* Ho Chi Minh City, Vietnam, 14–16 October 2021; pp. 318–323.

[12] Astani, M.; Hasheminejad, M.; Vaghefi, M. (2022). A diverse ensemble classifier for tomato disease recognition. *Comput. Electron. Agric.* 198;107054.

[13]Prodeep, A.R.; Hoque, A.M.; Kabir, M.M.; Rahman, M.S.; Mridha, M.F. (2022). Plant Disease Identification from Leaf Images using Deep CNN's EfficientNet. *In Proceedings of the 2022 International Conference on Decision Aid Sciences and Applications (DASA),* Chiangrai, Thailand, 23–25 March 2022; pp. 523–527.

[14] Enkvetchakul, P.; Surinta, O. (2022). Effective Data Augmentation and Training Techniques for Improving Deep Learning in Plant Leaf Disease Recognition. *Appl. Sci. Eng. Prog.* 15;3810.

[15] Trivedi, N.K.; Gautam, V.; Anand, A.; Aljahdali, H.M.; Villar, S.G.; Anand, D.; Goyal, N.; Kadry, S. (2021). Early Detection and Classification of Tomato Leaf Disease Using High-Performance Deep Neural Network. *Sensors* 21;7987.

[16]Agarwal, M.; Gupta, S.K.; Biswas, K.K. (2020). Development of Efficient CNN model for Tomato crop disease identification. Sustain. *Comput. Inform. Syst.* 28;100407. https://doi.org/10.1016/j.suscom.2020.100407

[17] Fuentes, A.; Yoon, S.; Kim, S.C.; Park, D.S. (2017). A Robust Deep-Learning-Based Detector for Real-Time Tomato Plant Diseases and Pests Recognition. *Sensors* 17(9);2022. https://doi.org/10.3390/s17092022

[18]Machireddy, C., & Chella, S. (2024). Reconfigurable Acceleration of Neural Networks: A Comprehensive Study of FPGA-based Systems. *International Journal of Computational and Experimental Science and Engineering,* 10(4);1007-1014. https://doi.org/10.22399/ijcesen.559

[19]Nagalapuram, J., & S. Samundeeswari. (2024). Genetic-Based Neural Network for Enhanced Soil Texture Analysis: Integrating Soil Sensor Data for Optimized Agricultural Management. *International Journal of Computational and Experimental Science and Engineering,* 10(4);962-970. https://doi.org/10.22399/ijcesen.572

[20]Priti Parag Gaikwad, & Mithra Venkatesan. (2024). KWHO-CNN: A Hybrid Metaheuristic Algorithm Based Optimzed Attention-Driven CNN for Automatic Clinical Depression Recognition. *International Journal of Computational and Experimental Science and Engineering,* 10(3);491-506. https://doi.org/10.22399/ijcesen.359

[21]Ay, S. (2024). Vehicle Detection And Vehicle Tracking Applications On Traffic Video Surveillance Systems: A systematic literature review. *International Journal of Computational and Experimental Science and Engineering,* 10(4);1059-1068. https://doi.org/10.22399/ijcesen.629

[22]S.D.Govardhan, Pushpavalli, R., Tatiraju.V.Rajani Kanth, & Ponmurugan Panneer Selvam. (2024). Advanced Computational Intelligence Techniques for Real-Time Decision-Making in Autonomous Systems. *International Journal of Computational and Experimental Science and Engineering,* 10(4);928-937. https://doi.org/10.22399/ijcesen.591

[23]Serap Çatli dinç, akmansu, m., bora, h., üçgül, a., çetin, b. e., erpolat, p., … şentürk, e. (2024). Evaluation of a Clinical Acceptability of Deep Learning-Based Autocontouring: An Example of The Use of Artificial Intelligence in Prostate Radiotherapy. *International Journal of Computational and Experimental Science and Engineering,* 10(4);1181-1186. https://doi.org/10.22399/ijcesen.386

[24]Rakesh Jha, & Singh, M. K. (2024). Analysing the Impact of Social Influence on Electric Vehicle Adoption: A Deep Learning-Based Simulation Study in Jharkhand, India. *International Journal of Computational and Experimental Science and Engineering,* 10(4);639-646. https://doi.org/10.22399/ijcesen.371

[25]P, P., P, D., R, V., A, Y., & Natarajan, V. P. (2024). Chronic Lower Respiratory Diseases detection based on Deep Recursive Convolutional Neural Network. *International Journal of Computational and Experimental Science and Engineering*, 10(4);744-752. https://doi.org/10.22399/ijcesen.513

[26]Suneetha Madduluri, & T. Kishorekumar. (2024). Multimodal Biometric Authentication System for Military Weapon Access: Face and ECG Authentication. *International Journal of*

Computational and Experimental Science and Engineering, 10(4);952-961. https://doi.org/10.22399/ijcesen.565

[27]PATHAPATI, S., N. J. NALINI, & Mahesh GADIRAJU. (2024). Comparative Evaluation of EEG signals for Mild Cognitive Impairment using Scalograms and Spectrograms with Deep Learning Models. *International Journal of Computational and Experimental Science and Engineering*, 10(4);859-866. https://doi.org/10.22399/ijcesen.534

[28]J Jeysudha, K. Deiwakumari, C.A. Arun, R. Pushpavalli, Ponmurugan Panneer Selvam, & S.D. Govardhan. (2024). Hybrid Computational Intelligence Models for Robust Pattern Recognition and Data Analysis . *International Journal of Computational and Experimental Science and Engineering*, 10(4);1032-1040. https://doi.org/10.22399/ijcesen.624

[29]U. S. Pavitha, S. Nikhila, & Mohan, M. (2024). Hybrid Deep Learning Based Model for Removing Grid-Line Artifacts from Radiographical Images. *International Journal of Computational and Experimental Science and Engineering*, 10(4);763-774. https://doi.org/10.22399/ijcesen.514

[30]P. Jagdish Kumar, & S. Neduncheliyan. (2024). A novel optimized deep learning based intrusion detection framework for an IoT networks. *International Journal of Computational and Experimental Science and Engineering*, 10(4);1169-1870. https://doi.org/10.22399/ijcesen.597

[31]Rama Lakshmi BOYAPATI, & Radhika YALAVARTHI. (2024). RESNET-53 for Extraction of Alzheimer's Features Using Enhanced Learning Models. *International Journal of Computational and Experimental Science and Engineering*, 10(4);879-889. https://doi.org/10.22399/ijcesen.519

[32]M, V., V, J., K, A., Kalakoti, G., & Nithila, E. (2024). Explainable AI for Transparent MRI Segmentation: Deep Learning and Visual Attribution in Clinical Decision Support. *International Journal of Computational and Experimental Science and Engineering*, 10(4);575-584. https://doi.org/10.22399/ijcesen.479

[33]Venkatraman Umbalacheri Ramasamy. (2024). Overview of Anomaly Detection Techniques across Different Domains: A Systematic Review. *International Journal of Computational and Experimental Science and Engineering*, 10(4);898-910. https://doi.org/10.22399/ijcesen.522

[34]Agnihotri, A., & Kohli, N. (2024). A novel lightweight deep learning model based on SqueezeNet architecture for viral lung disease classification in X-ray and CT images. *International Journal of Computational and Experimental Science and Engineering*, 10(4);592-613. https://doi.org/10.22399/ijcesen.425