Data and Metadata. 2023; 2:196
doi: 10.56294/dm2023196

ORIGINAL

Hybrid Convolutional Neural Network with Whale Optimization Algorithm (HCNNWO) Based Plant Leaf Diseases Detection

Red neuronal convolucional híbrida con algoritmo de optimización de ballenas (HCNNWO) basada en la detección de enfermedades de las hojas de las plantas

E.Banu[1], A.Geetha[2]

[1]Ph.D Research Scholar, PG and Research Department of Computer Science, Chikkanna Government Arts College. Tirupur, Tamil Nadu, India.
[2]Assistant Professor, Department of Computer Science, Government Arts and Science College. Avinashi, Tamil Nadu, India.

Cite as: Banu E, Geetha A. Hybrid Convolutional Neural Network with Whale Optimization Algorithm (HCNNWO) Based Plant Leaf Diseases Detection. Data and Metadata. 2023;2:196. https://doi.org/10.56294/dm2023196

Submitted: 22-09-2023 **Revised:** 13-11-2023 **Accepted:** 29-12-2023 **Published:** 30-12-2023

Editor: Prof. Dr. Javier González Argote

ABSTRACT

Plant diseases appear to be posing a serious danger to the production and availability of food globally. The main factor affecting the quality and productivity of agricultural products is the health of the plants. In this paper, we describe a modified plant disease detection using deep convolutional neural networks in real time. By employing image processing techniques to enlarge the plant illness photos, the plant disease sets of data were initially produced. To recognise plant illnesses, a system called Convolutional Neural Network combined with Wolf Optimisation algorithm (CNN-WO) was used. Finally, the Whale Optimization algorithm (WO) is used to maximise and optimizes getting input. And it is given to CNN's learning rate for classification process. This paper presents an image segmentation and classification technique to automatically identify plant leaf diseases. The suggested strategy increased accuracy, sensitivity, precision, F1 measure, and specificity of plant disease detection. According to this study, HCNNWO real detectors have improved, which would require deep learning. It would be an effective method for determining plant illnesses and other diseases within plants. According to the evaluation report, the suggested method offers good reliability. To evaluate how well the suggested algorithm performs in comparison to cutting-edge techniques such as SVM, BPNN and CNN, experiments are conducted on datasets that are openly accessible.

Keywords: Plant Leaf iseases; Convolutional Neural Network; Image Segmentation; Whale Optimization Algorithm; Classification; Big Data.

RESUMEN

Las enfermedades de las plantas parecen suponer un grave peligro para la producción y disponibilidad de alimentos en todo el mundo. El principal factor que afecta a la calidad y productividad de los productos agrícolas es la salud de las plantas. En este artículo, describimos una detección modificada de enfermedades de las plantas utilizando redes neuronales convolucionales profundas en tiempo real. Empleando técnicas de procesamiento de imágenes para ampliar las fotos de las enfermedades de las plantas, se produjeron inicialmente los conjuntos de datos de enfermedades de las plantas. Para reconocer las enfermedades de las plantas, se utilizó un sistema denominado Red Neuronal Convolucional combinada con el algoritmo de Optimización de Wolf (CNN-WO). Por último, se utiliza el algoritmo de Optimización de la Ballena (WO) para maximizar y optimizar la obtención de datos de entrada. Y se da a la tasa de aprendizaje de CNN para el proceso de clasificación. Este trabajo presenta una técnica de segmentación y clasificación de imágenes para identificar automáticamente las enfermedades de las hojas de las plantas. La estrategia sugerida aumentó la exactitud, sensibilidad, precisión, medida F1 y especificidad de la detección de enfermedades de las plantas. Según este estudio, los detectores reales HCNNWO han mejorado, lo que requeriría un aprendizaje profundo. Sería un método eficaz para determinar las enfermedades de las plantas y otras enfermedades dentro de las plantas. Según el informe de evaluación, el método sugerido ofrece una buena fiabilidad. Para evaluar el rendimiento del algoritmo sugerido en comparación con técnicas de aprendizaje profundo como SVM, BPNN y CNN, se realizan experimentos con conjuntos de datos de libre acceso.

Palabras clave: Enfermedades de las Hojas de las Plantas; Red Neuronal Convolucional; Segmentación de Imágenes; Algoritmo de Optimización de Ballenas; Clasificación; Big Data.

INTRODUCTION

The Food and Agriculture Organisation of India claims that the global hunger rate has been slowly increasing since 2022. According to the most recent estimates, there are approximately 692 million hungry people on the planet, or 9,0 % of the total population; this number has increased by roughly 60 million in only five years and by 10 million in just one year. Meanwhile, agriculture employs more than 90 % of the global workforce. Farmers grow 80 % of the world's food, but plant diseases and pests destroy more than half of crop production. As a result, it is vital and necessary to effectively identify and detect plant diseases. However, visual examination of leaf colour patterns and crown structures is still a key component of conventional crop disease scouting in the field.

Plant disease diagnosis needs time, labour, and specialised knowledge. Using knowledge and visual observation of disease symptoms on plant leaves, it is accomplished. The classification of plant diseases is further complicated by the fact that disease features vary between crops due to plant diversity Berg et al.[(1)]. The below figure 1 explain the types of stress in plants that causes the plant to make poor yield.

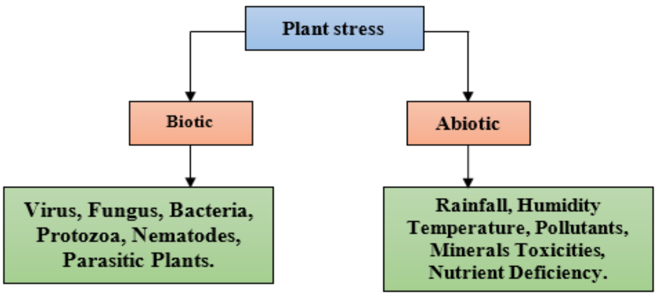


Figure 1. Stress in plants

Agronomists can benefit greatly from the availability of knowledgeable and sophisticated tools that can automatically and reliably identify plant diseases. They suggest using Particle Swarm Optimisation to execute feature selection using a feature vector that includes edge, colour, and texture-based features that were collected from image analysis. Providing such a system with an easy-to-use mobile application, on the other hand, is also a commendable accomplishment for farmers who lack an agronomic and phytopathological support infrastructure Geetha et al.[(2)]. The limitations of the traditional approach prompted scientists to provide technology remedies for plant disease prediction. Because there are so many research papers on using. It can be challenging for researchers to select an efficient model for machine learning and deep learning models to forecast plant diseases depending the dataset, parameters, hardware configuration, and experimental settings Karthik et al.[(3)]. The below a) b) and c) in figure 2 explain about the diseases that affected the plant leaf commonly.

Traditional computer vision methods, commonly used segmentation techniques include pixel-level segmentation, edge segmentation, region segmentation, and multi-scale segmentation. In crop disease detection application research before choosing the proper lesion characteristics and classifiers for detection, picture colour space and texture features are processed using different approaches. Image segmentation of grape diseased leaves in a three-dimensional colour space was achieved using a statistical threshold method, and downy mildew was judged based on colour differences De Luna et al.(4).The illness detection techniques that have been explored thus far, however, are all based on conventional image processing and classification algorithms. The majority of these traits are produced and extracted artificially. Depending on the problem, the extracted features will differ Xie et al.[(5)]. While certain machine learning techniques can successfully identify a blade disease, their flexibility and generalisation abilities are poor when the blade disease is not readily apparent or the data set is huge, making challenging accurately identify a blade disease in real-world applications.

https://doi.org/10.56294/dm2023196

a) Powdery mildew b) Cercospora c) Didymella

Figure 2. Common plant diseases

METHODS

This paper presents an image segmentation and classification technique to automatically identify plant leaf diseases. The suggested strategy increased accuracy, sensitivity, precision, F1 measure, and specificity of plant disease detection. According to this study, HCNNWO real detectors have improved, which would require deep learning. It would be an effective method for determining plant illnesses and other diseases within plants. According to the evaluation report, the suggested method offers good reliability.

Big Data

The bulk of big data definitions emphasise amount data that is stored. Although scale matters, big data also has two other crucial components: data variety and data velocity. Volume, Variety, and Velocity (the three Vs) are a comprehensive description of big data that dispels the misconception that big data is solely about data volume in the below figure 3. Furthermore, each of the three Vs has effects on analytics in and of themselves.

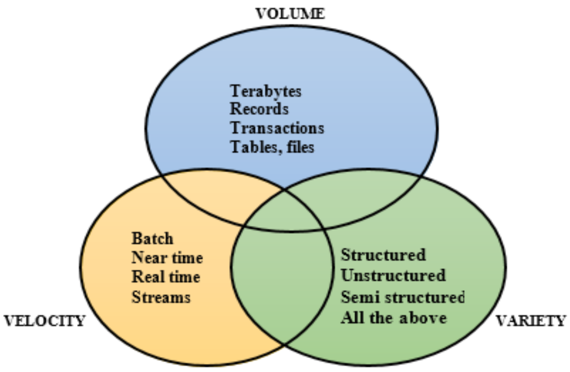


Figure 3. Big Data 3Vs

Image Pre-Processing

The brightness and chromaticity layers are identified using the colour transformation. The L*a*b* colour space is adapted from the RGB photographs of leaves. The conversion of colour spaces is used to improve visual analysis. Image pre-processing is used to improve the quality of an image before it is processed and analysed further. Image enhancement and colour space conversion are included Sharma et al.[6].

Image Segmentation

By lowering the squared distances between images, intensities and cluster centroids, the K-means clustering algorithm does segmentation. The process of simplifying an image's representation into meaningful form, such as highlighting an object of interest from the background, is known as image segmentation Singh[7]. The incremental Known also as the Lloyd's algorithm, the K-means clustering algorithm, separates data into k clusters with defined centroids and allots n observations to each one.

Feature extraction

With the help of feature extraction, there is less redundant information collected in the data set. In the end, data reduction expedites the machine learning process' learning and generalisation phases and makes it possible to construct the model with less manual labour. To identify typical body part forms and to obtain information on the appearance, location, and size of each plant leaf portion, a scale-invariant object part learning technique is proposed Kumari et al.[8].

Classification

For a specific input data sample, the class label is predicted in the machine learning of classification. On the basis of training data, new observations are categorised using a Supervised Learning methodology. In classification, a programme chooses which classes or groupings to assign new observations depending on the dataset or supplied observations Dai et al.[9].

This paper is designed into 5 parts the remainder 4 sessions are discussed in upcoming session clearly. session 2 discusses the current system and techniques in plant leaf diseases prediction using machine learning techniques, session 3 discusses the proposed system for plant leaf diseases prediction, session 4 discusses the results obtained in the proposed system, and session 5 concludes the research.

LITERATURE REVIEW

This session discussed the disadvantages and drawbacks of the current/existing system used in plant disease prediction.

The researchers Jogekar et al.[10] the accuracy and adaptability of picture recognition have substantially increased as a result of the recent computer vision and deep learning methods are developing quickly. The benefit of deep learning is that classification features can be directly extracted without the need for classifier creation. Deep learning has a high generality level and is appropriate for categorization in a range of contexts, especially for the extraction of complicated or unusual features said by Wang et al.[11]. It has been demonstrated how texture analysis can be used to detect plant diseases. The proposed method's primary goal is to identify the disease. The outcomes of the experiments demonstrate how quickly and easily the proposed approach may identify leaf diseases. Automatically identifying diseases from symptoms that show up on plant leaves is the study issue highlighted by Jiang et al.[12].

Alrudainy et al.[13] said about the few fungus-caused plant leaf diseases such as late blight caused by the fungus Phytophthora infesters. The outcomes of the experiments demonstrate how quickly and easily the proposed approach may identify leaf diseases. Automatically identifying diseases from symptoms that show up on plant leaves is the study issue highlighted. When fungal disease progresses, the spots darken and white fungal growth appears on the underside of the leaf. Alternariasolani is the fungus responsible for early blight. On older leaves, it appears as on the underside of the leaf, there are very little brown specks that look like a bull's eye and have concentric rings. When the disease matures, the leaf turns yellow due to the disease spreading outward discussed by Mathew et al.[14]. The upper surfaces of older leaves develop yellow to white patches due to soft mildew. In feature extraction, the basic geometric features extracted and so on. A traditional algorithm, To determine how spatially dependent a texture is, researchers commonly utilise the GLCM, or Grey level Co-occurrence Matrix explained by Saputra et al.[15] also told that similarly, HOG is another feature extraction algorithm.

After that, according to Kumar et al.[16]. In addition to presenting the disease category, confidence level, the model performs semantic segmentation and object detection throughout the processing of the image. It also performs object detection and object detection. We created an Android mobile app that allows farmers with limited resources photograph diseased plant leaves. On the user side, The CNN model is built into the Smartphone app. additionally, the programme displays the categorization time and confidence percentage needed to analyse the image. Bi et al.[17] the researcher make a Using deep learning techniques and enhanced CNNs, We talked about and discovered widespread apple leaf ailments like rust, grey spot, and brown spot. The diseased leaf dataset was generated, processed, and collected. To find tiny sick patches, a new deep CNN model was created by the way that classification, feature extraction, segmentation, and other techniques work to bring the result by Hassan et al.[18]. We looked into the automatic disease detection process and how the real-time project efficiently uses it. For disease research, training, testing, and detection, we used tomato plant leaves. Our work focuses on applying digital image processing quickly and accurately diagnose diseases so that neither the crop nor its yield is damaged. Early detection can prevent farmers from suffering huge losses. Additionally, the image processing techniques are quite helpful for feature extraction and segmentation, which is a crucial component of the project completely developed by Deepalakshmi et al.[19].

According to Hasnain et al.[20] said about Algorithms for representation learning optimises data representations to find the most useful one. Because feature extraction and categorization do not need to be separate in deep learning; the model extracts the features as it is being trained. It is applied in many different studies. To enhance the efficacy of plant disease identification, Deep Convolution Neural Network and GAN were utilised for image processing. Because the GAN sample image had limited but useful features, it was able to improve further achievements has investigated by Abbas et al.[21]. On the basis of photographs, plant diseases were classified using several Convolutional neural networks that had been fine-tuned. The framework have been examined and contrasted. Provided a unique method of using deep learning to swiftly identify and analyse plant diseases in photos of leaves. Photos of both contaminated and uncontaminated leaves are included in the dataset. With the use of this model, 97,13 % accuracy was attained by Gu et al.[22].

Deep Learning

Natural language processing, object detection, and picture classification are the main applications of the machine learning (ML) subfield of deep learning (DL).

The model's scaling, rotation, and translation are all invariant thanks to the pooling layer, which additionally takes feature samples from the higher layer feature map. The most common is maximum or average pooling was explained by Ashok et al.[23]. According to the filter's size, the input image is split into several rectangular areas during maximum pooling, and the maximum value for each region is produced. Average pooling produces the average for each region. Convolutional and pooling layers are frequently combined in applications said by Feng et al.[24].

The author Naik et al.[25] focuses primarily on the detection of leaf diseases and the treatment maize and peach so that farmers do not require a full detection if they only face insect attack on the leaf. For greater accuracy, modern technologies such as image processing and CNN (convolutional neural network) were used. Farmers can obtain real-time information about the current state of the harvest by using image processing. There haven't been many studies on the detection and treatment of corn and peach leaf diseases using image processing. So we tried to make the best of it.

System design

This talk covered our recently developed suggested system method and techniques for leaf disease detection using hybrid of Covolutional Neural Network with Whale Optimization algorithm (HCNNWO) greater accuracy, sensitivity, specificity, precision, and F1 score.

Illness detection is involved in steps including importing an image, pre-processing, segmentation, extraction, optimization and classification. Plant diseases are recognised using images of the leaves. Therefore, using image processing techniques to classify and identify diseases in agricultural applications is advantageous.

Pre-processing: an essential phase in the data mining process is data preparation. It outlines procedures for preparing data for analysis by cleaning, converting, and merging. Enhancing quality and usefulness the data for the particular data mining task is aim of data preparation.

Segmentation: a kind of machine learning that employs neural networks with three or more layers to simulate how the human brain learns from input. Picture segmentation is the process of dividing an image into sections or regions, each of which represents a different object or area of the image.

Feature extraction: the usage feedforward neural networks with a single hidden layer in a feature extraction method is presented. A network creation algorithm and a network pruning algorithm establish the topology of the networks.

Optimization: through optimisation, we repeatedly train the model to determine its maximum and lowest function. It is one of the most important phenomena in machine learning for enhancing results.

Whale Optimization Algorithm (WOA)

A revolutionary mathematical programme known as the whale optimisation algorithm works by replicating the cooperative predation tactics of humpback whales. The three methods of surrounding prey, bubble-net assaulting, and searching for prey make up the algorithm's updating mechanism as illustrated in below figure 4.

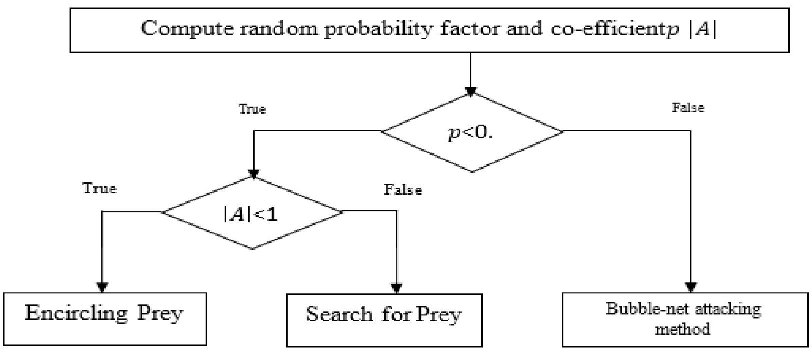


Figure 4. General Design of Whale Optimization

Encircling prey: if the whale population is N, then X i(i{1, 2,..., N}) indicates the position vector of i^{th} whale, particular whale, and suggests a workable answer to a specific optimisation issue. Because the optimum cannot be determined in advance The WO algorithm treats the top candidate solution at the time of population initialization as the prey or approximate optimum. Over the course of several cycles, other whales in the population adjust their postures to go closer to the prey after the prey (the ideal whale individual) has been located. The following is the definition of the relevant location update formula:

$\vec{D} = |\vec{C} \cdot \overrightarrow{X(t) - \vec{X}(t)}|$ ----------- Eqn (1)

$\vec{X}(t+1) = \vec{X}(t) - \vec{A} \cdot \vec{D}$----------- Eqn (2)

If t stands for the most recent iteration, $\vec{X}$ (t) indicates the current whale in question, $\vec{X}$ *(t) shows the best whale (the prey) so far, and X(t) is multiplied by one element to represent multiplication of one element by one element, updated in the event that a better place is found in a subsequent iteration $\vec{A}\cdot\vec{D}$ and denotes the length of the renew-step.

The following formulae can be used to determine and as the vectors of coefficients:

$\vec{A} = 2a\vec{r}^{1} - a$----------- Eqn (3)

$\vec{A} = 2a\vec{r}^{1} - a$---------- Eqn (4)

Where a=22t/$_{ax}$ is a convergence factor and t_{ax} represents the most iterations possible, and $\vec{r}_1$ and $\vec{r}_2$ are vectors of uniform randomness in the range [0,1].

Bubble – Net Attacking Technique

Here is the mathematical model: when WO algorithm is in the bubble-net attacking stage, it mimics the humpback whales' bubble-net feeding behaviour, and this is essentially a feasible zone spiral search procedure.

$\vec{D'} = |\vec{X}^{*}(t) - \vec{X}^{*}(t)|$----------- Eqn (5)

$\vec{X}(t+1) = D' \cdot e^{bl} \cdot \cos(2\pi l) + \vec{X}^{*}(t)$----------- Eqn (6)

Where $\vec{D}'$ is the separation between a moving whale and its prey, in [1, 1], l is a random number and a constant is indicated by 'b' that is typically equal to 1 and used to determine the spiral's form. When |A|<1 in the optimisation process, whales choose the optimum solution bubble-net approaching the victim with a 50 % likelihood while attacking or encircling it, This represents the WOA algorithm's exploitation stage. Consequently, the following is a description of the whale position updating mechanism:

$$\vec{X}(t+1) = \begin{cases} \vec{X}*(t) - \vec{A}\cdot\vec{D}, p < 0,5, p < 0,5 \\ \vec{X}*(t) + \vec{D'} \cdot e^{bl} \cdot \cos(2\pi l), p \geq 0,5 \end{cases}$$ ----------- Eqn (7)

Search for prey: to accomplish the exploration (global search) capabilities, the WOA algorithm uses the hunt for prey as a key location update mechanism. In order to improve the WOA algorithm's capacity to explore globally, the current individual whale updates its position by randomly selecting a person as its prey when |A|≥1. Its mathematical model is comparable to Eqn. (1) and (2) with the exception that a randomly selected person is used in place of the ideal human.

The equation reads as follows,

$\vec{D} = |\vec{C} \cdot \vec{X}_{rand}(t) - \vec{X}(t)|$----------- Eqn (8)

$\vec{X}(t+1) = \vec{X}_{rand}(t) - \vec{A} \cdot \vec{D}$------------ Eqn (9)

Where other expressions have the same meaning as *Sect*.2.1 and $\vec{X}_{Rand}$ stands for a randomly chosen whale from the existing population. It is crucial to remember that, during the optimisation process, the value of |A| influences scheduling a local search (exploitation) and a global search (exploration). The exploration stage is carried out if |A| ≥1; else, the exploitation stage is carried out.

Working Process of Whale Optimization Algorithm

To find prey, one might use the same strategy based on the A vector variation (exploration). Humpback whales actually conduct haphazard searches based on one another's positions. As a result, we employ A to make the search agent wander far away from the reference whale by using random values larger than or equal to −1. During the exploration phase, we update the position of a search agent in contrast to the exploitation phase based on a randomly. The overall working procedure of Whale Optimization Algorithm (WOA) is shown in the below figure 5.

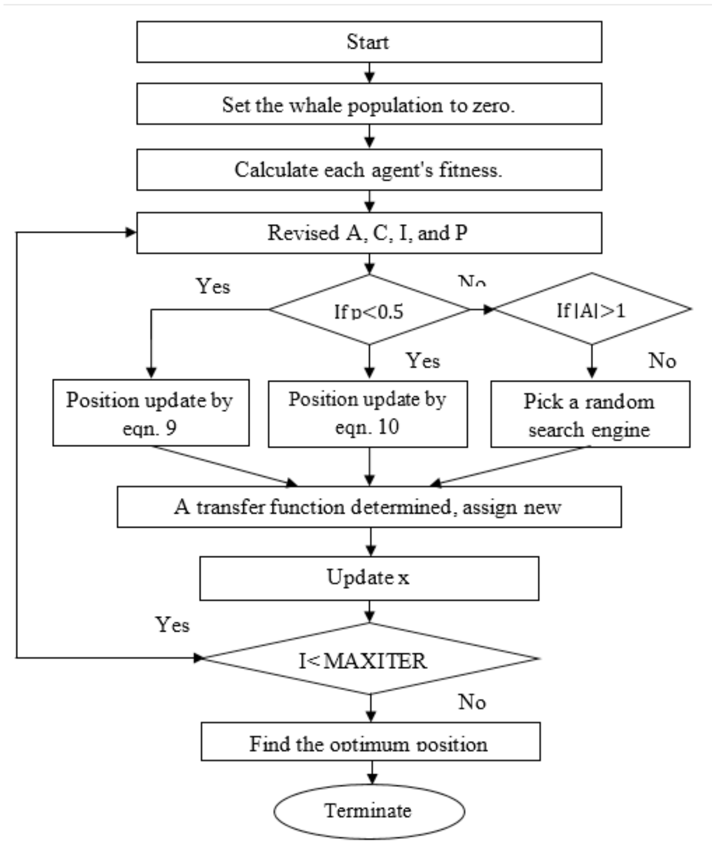


Figure 5. Process of Whale Optimization Algorithm

Because it possesses the exploration and exploitation capabilities created by a convergence factor a, the WOA algorithm is able to carry out the optimisation process with more efficiency. It is known to have several shortcomings, though, such as slow convergence, local solution placement, and poor precision, just like other meta-heuristic optimisation strategies.

Convolutional Neural Network (CNN)

Convolution neural networks are the most well-versed literature strategy for multilayer network training structures. They are generated through exciting design a visual system. The most often used technique for obtaining useful information from large datasets is probably a convolution neural network (CNN).

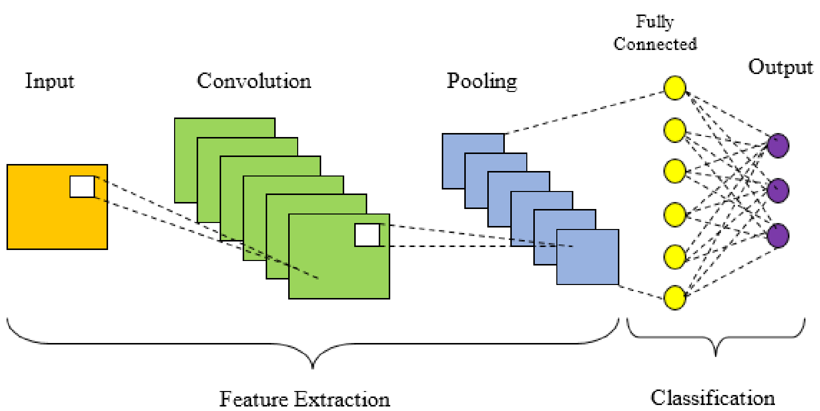


Figure 6. CNN Architecture Diagram

https://doi.org/10.56294/dm2023196

The architecture of CNN, which enables effective processing of image data, is depicted in below figure 6. Multiple layers of various kinds make up a deep CNN architecture. In most cases, starting with one or more convolution layers, as the structure grows, one or more grouping levels, activation layers, and one or more totally linked layers are attained. In the convolution layer, features are extracted via convolution, and the output is then transferred to activation function.

From input data, global features are extracted the convolution and pooling layers are then continually iterated through. The fully connected layer performs categorization this layer after receiving extracted features. The model is also being developed, with a later implementation planned. In the “Train” learning process, using our “CNN” model, we will use our “dataset” to extract patterns or other characteristics from an image. In order for him to detect plant illnesses on the leaves.

RESULTS

Validation of the developed diseased leaf detection method is done using data sets such as Plant Village and Plant Leaf Diseases. The Plant Village collection has a greater number of photographs of healthy plant leaves, and images of infected leaves, such as those caused by viruses, fungi, bacteria, protozoa, nematodes, and parasitic plants, are thought to be useful for predicting plant leaf diseases. The plant Leaf Diseases Data Set is used to classify diseased leaves, and the various diseases leaf images such as those of eucalyptus, potatoes, celery, and tomatoes are used for train image classification. Images of the four classes/diseases leaf rust, downy mildew, leaf blight, and early blight are collected to create a trained dataset. MATLAB 2013A on Intel(R) Core (TP) i3-2410M CPU @ 3.20GHz and 8GB RAM is used in the suggested image processing method to evaluate the performance of a classifier.

HCNNWO Algorithm Based Plant Leaf Diseases Detection

The input photos of plant leaves damaged by different illnesses are displayed in figure 7 below, along with the classification's efficacy. The newly built WO using CNN is compared to the current BPNN, SVM, and CNN in terms of sensitivity and accuracy metrics.

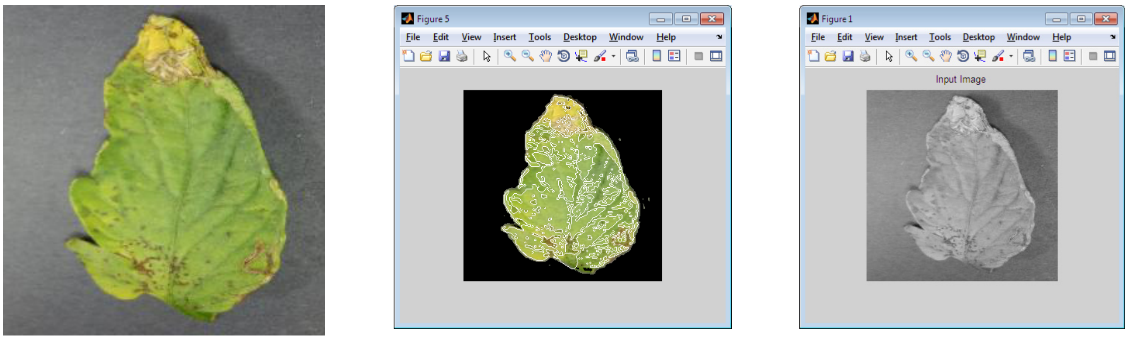


Figure 7. Input images

Pre-processing result: following the loading of the image, contrast enhancement, RGB to HSI conversion, feature extraction, and deep learning technique, the disease is identified. Most of them used Convolutional Neural Networks (CNNs) to build models that supported images with low resolution. The filtered images from the input images are displayed in figure 8 below. Picture processing is the activity of modifying a picture by employing various ways to enhance it or extract meaningful information. An image is used as the input in this type of signal processing. The output could be a different image, or it could have attributes or qualities related to the original image.

Segmentation result: when the pre-processing stage is finished, the system transfers a test image of a damaged plant leaf to the segmentation stage, where the filter of the system eliminates noise from the image to give a clear explanation of the image. A market is considered segmented when it is divided into distinct, profitable, manageable, and discrete segments with potential for growth. In other words, a company would not be able to target every market due to time, resource, and effort limitations. By applying the proposed algorithm, image segmentation is the process of splitting the images into distinct portions, or clusters. The segmented images are depicted in the following figure 9.

Feature extraction: using the HCNNWO method, image segmentation involves splitting the images into various portions or clusters. These features are fed into the classifier for further processing. The feature extraction for sick leaf cluster has been completed. These traits are used to identify and classify the leaf disease. The below figure 10 (a) depicts the test features. And figure 10 (b) shows the database. The results of feature extraction showed in following figures 10 (c).

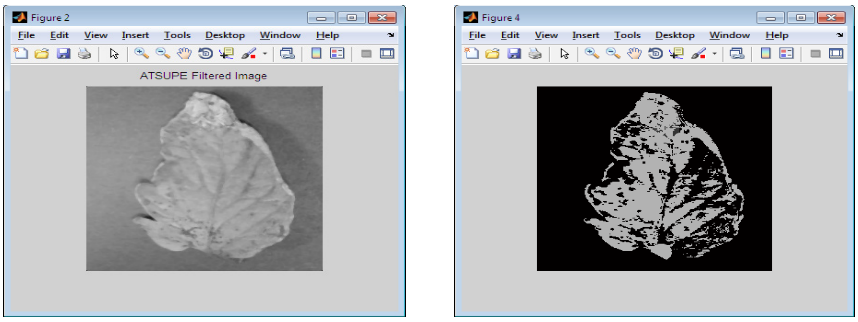


Figure 8. Filtered images

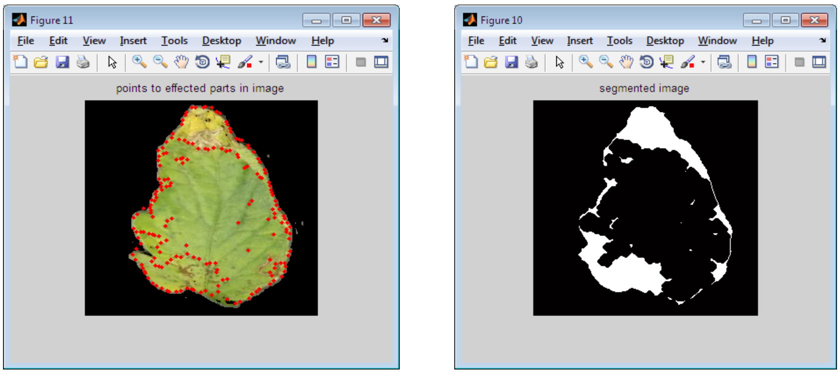


Figure 9. Segmented images

Optimization: the proposed algorithm is used to detect the leaf diseases based on optimization techniques. Here we are using the whale optimization thus the below figure 11 shows the optimization images.

Classification results: the CNN classifiers are taught the illnesses that affect each plant class. The classification findings are used to call up the classifier, which has been trained to categorise a variety of diseases in that plant. If they are missing, the leaves are regarded as "healthy".

The results of the classification of leaf diseases in comparison to the suggested and current systems are clearly explained in table 1 above. The accuracy values of the current SVM, BPNN, and CNN systems were 88,64, 90,61, and 92,27, respectively. In contrast, the suggested HCNNWO system produced a result of 97,02, which is 4,75 % higher than the current system. Furthermore, the identical current system obtained sensitivity values of 88,40, 91,56, and 93,36; however, the suggested technique yielded a result of 96,91, which is 3,55 % higher than the existing system. At precision values of 88,94, 90,49, and 87,83, respectively, the suggested approach produced a result of 97,43, 9,6 % greater than the current system. The suggested approach produced a result of 97,17, which is 6,66 % higher than the current system, with the F1-score values of 88,67, 91,02, and 90,51, respectively. The suggested method produced a result of 97,14, which is 5,58 % higher than the current system, with the specificity values of 88,87, 89,58, and 91,56, respectively.

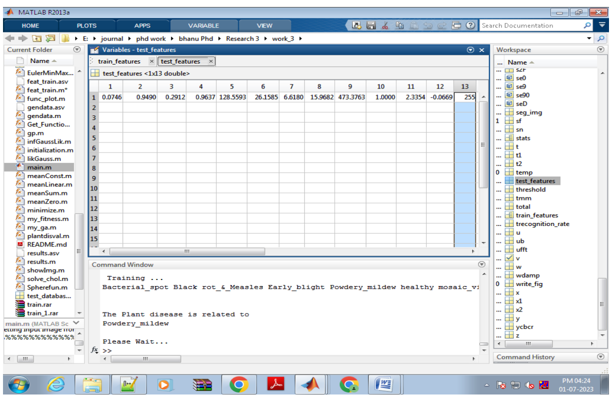


Figure 10. (a) Test features

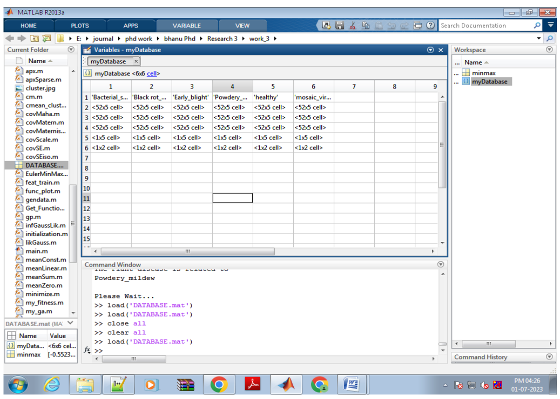


Figure 10. (b) Database

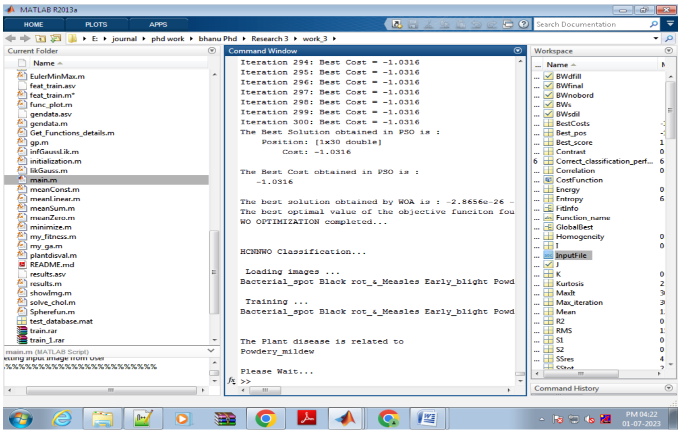


Figure 10. (c) Feature extraction results

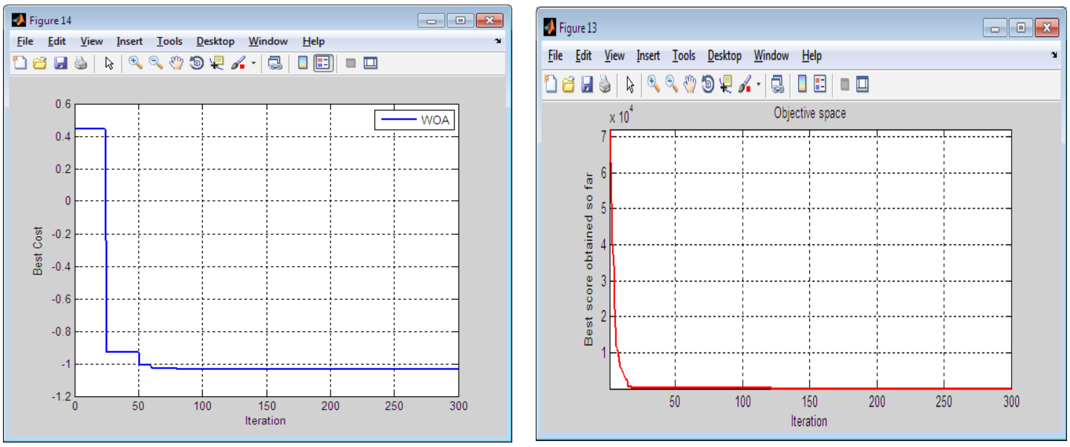
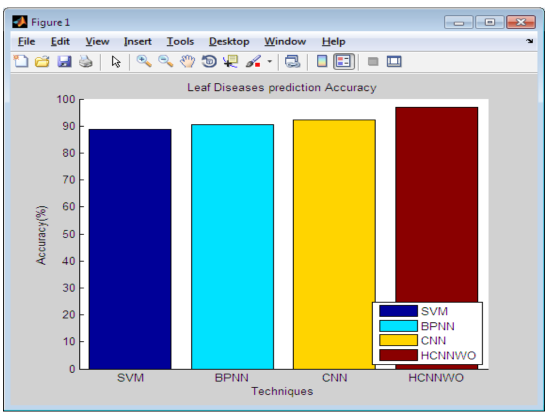
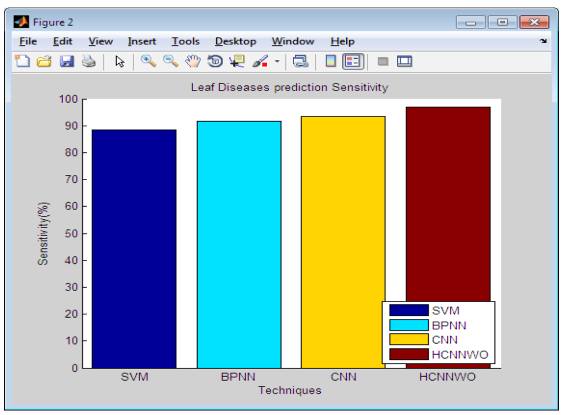


Figure 11. Optimization images

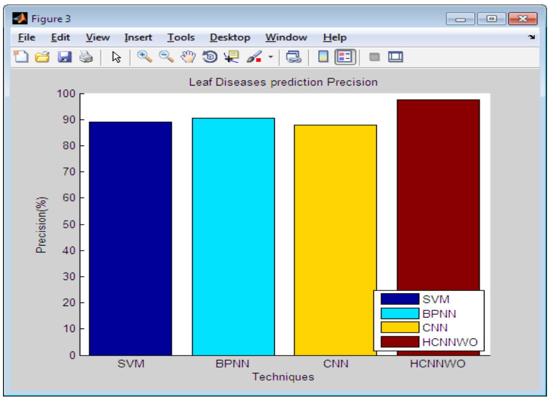
Table 1. Output results of existing and proposed systems				
Parameters	**SVM**	**BPNN**	**CNN**	**HCNNWO**
Accuracy	88,64	90,61	92,27	97,02
Sensitivity	88,40	91,56	93,36	96,91
precision	88,94	90,49	87,83	97,43
F1-score	88,67	91,02	90,51	97,17
Specificity	88,87	89,58	91,56	97,14



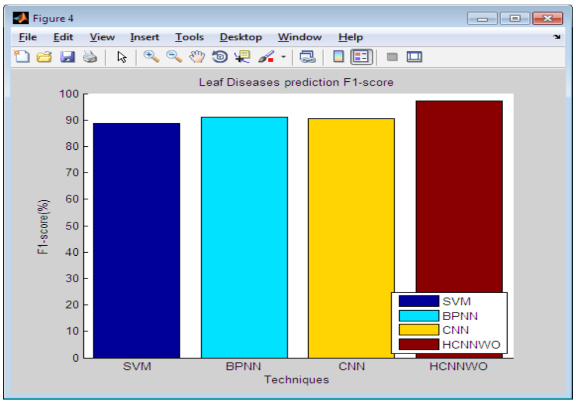
(a) Accuracy



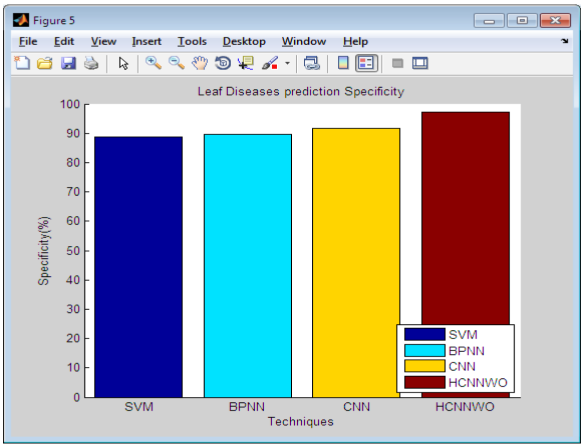
(b) Sensitivity



(c) Precision



(d) F1 Score



(e) Specificity

Figure 12. Output results graph

Comparing the proposed system to the current systems based on the following parameters. The final output results are shown in the above table 1. The output result graphs for specificity, F1 score, sensitivity, accuracy, and precision are plotted below in figures 12(a), 12(b), 12(c), 12(d), and 12(e), in that order. Our suggested system achieves 97,02 % accuracy, 96,91 % sensitivity, 97,43 % precision, 97,17 % F1 score, and 97,14 % specificity, as can be seen from the output graph.

CONCLUSION

The suggested study comes to the conclusion that the village farmers offer the most effective method for identifying plant leaf diseases utilising a significant quantity of visual data. The plant expert looks over these photos. Because leaf diseases are complicated and have unique characteristics, a manual assessment may yield erroneous results. Comparative testing results show that our proposed method can offer a new automated diagnostic tool with greater precision in identifying the afflicted leaf portion for plant leaf diseases. Numerous different kinds of fungus and bacteria have unique biochemistry and dangerous virus paths. The impacted cells may aid in the growth or maintenance of a plant leaf. We used pre-trained datasets in this study to save a time-consuming procedure. The suggested method for plant leaf detection was then compared to a hybrid CNN system using the Whale Optimisation algorithm (WO). Utilising Convolutional Neural Networks (CNN) is necessary for deep learning. CNN models have been used to identify plant diseases. The proposed system's promising accuracy, sensitivity, specificity, precision, and F1 measure findings on our collection of plant leaf data demonstrate the usefulness of the suggested approach for disease identification due to their powerful feature extraction and classification capabilities. These parameters are contrasted with those of the current models, including CNN, BPNN, and SVM. Overall, the findings from our newly merged HCNNWO system are superior. Classifying and segmenting brain tumours using more challenging information will be the focus of future research.

REFERENCES

1. Berg, G., & Cernava, T. (2022). The plant microbiota signature of the Anthropocene as a challenge for microbiome research. Microbiome, 10(1), 1-12.

2. Geetha, G., Samundeswari, S., Saranya, G., Meenakshi, K., &Nithya, M. (2020, December). Plant leaf disease classification and detection system using machine learning. In Journal of Physics: Conference Series (Vol. 1712, No. 1, p. 012012). IOP Publishing

3. Karthik, R., Hariharan, M., Anand, S., Mathikshara, P., Johnson, A., &Menaka, R. (2020). Attention embedded residual CNN for disease detection in tomato leaves. Applied Soft Computing, 86, 105933.

4. De Luna, R. G., Dadios, E. P., &Bandala, A. A. (2018, October). Automated image capturing system for deep learning-based tomato plant leaf disease detection and recognition. In TENCON 2018-2018 IEEE Region 10 Conference (pp. 1414-1419). IEEE.

5. Xie, X., Ma, Y., Liu, B., He, J., Li, S., & Wang, H. (2020). A deep-learning-based real-time detector for grape leaf diseases using improved convolutional neural networks. Frontiers in plant science, 11, 751.

6. Sharma, P., Hans, P., & Gupta, S. C. (2020, January). Classification of plant leaf diseases using machine learning and image preprocessing techniques. In 2020 10th international conference on cloud computing, data science & engineering (Confluence) (pp. 480-484). IEEE.

7. Singh, V. (2019). Sunflower leaf diseases detection using image segmentation based on particle swarm optimization. Artificial Intelligence in Agriculture, 3, 62-68.

8. Kumari, C. U., Prasad, S. J., &Mounika, G. (2019, March). Leaf disease detection: feature extraction with K-means clustering and classification with ANN. In 2019 3rd international conference on computing methodologies and communication (ICCMC) (pp. 1095-1098). IEEE.

9. Dai, T., Wen, D., Bates, C. T., Wu, L., Guo, X., Liu, S., ... & Yang, Y. (2022). Nutrient supply controls the linkage between species abundance and ecological interactions in marine bacterial communities. Nature Communications, 13(1), 175.

10. Jogekar, R. N., & Tiwari, N. (2021). A review of deep learning techniques for identification and diagnosis of plant leaf disease. Smart Trends in Computing and Communications: Proceedings of SmartCom 2020, 435-441.

11. Wang, J., Ma, P., Kim, D. H., Liu, B. F., & Demirci, U. (2021). Towards microfluidic-based exosome isolation and detection for tumor therapy. Nano Today, 37, 101066.

12. Jiang, P., Chen, Y., Liu, B., He, D., & Liang, C. (2019). Real-time detection of apple leaf diseases using deep learning approach based on improved convolutional neural networks. IEEE Access, 7, 59069-59080.

13. Alrudainy, A. M., & Mshari, A. (2022). EPIDEMIOLOGICAL STUDY OF EARLY BLIGHT ALTERNARIA SOLANI IN TOMATO. British Journal of Global Ecology and Sustainable Development, 7, 11-18.

14. Mathew, A., Antony, A., Mahadeshwar, Y., Khan, T., & Kulkarni, A. (2022). Plant disease detection using GLCM feature extractor and voting classification approach. Materials Today: Proceedings, 58, 407-415.

15. Saputra, R. A., Wasiyanti, S., Saefudin, D. F., Supriyatna, A., &Wibowo, A. (2020, November). Rice leaf disease image classifications using KNN based on GLCM feature extraction. In Journal of Physics: Conference Series (Vol. 1641, No. 1, p. 012080). IOP Publishing.

16. Kumar, S. S., &Raghavendra, B. K. (2019, March). Diseases detection of various plant leaf using image processing techniques: A review. In 2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS) (pp. 313-316). IEEE.

17. Bi, C., Wang, J., Duan, Y., Fu, B., Kang, J. R., & Shi, Y. (2022). MobileNet based apple leaf diseases identification. Mobile Networks and Applications, 1-9.

18. Hassan, S. M., Maji, A. K., Jasiński, M., Leonowicz, Z., &Jasińska, E. (2021). Identification of plant-leaf diseases using CNN and transfer-learning approach. Electronics, 10(12), 1388.

19. Deepalakshmi, P., Lavanya, K., &Srinivasu, P. N. (2021). Plant leaf disease detection using CNN algorithm. International Journal of Information System Modeling and Design (IJISMD), 12(1), 1-21.

20. Hasnain, M. S., Javed, M. N., Alam, M. S., Rishishwar, P., Rishishwar, S., Ali, S., & Beg, S. (2019). Purple Heart plant leaves extract-mediated silver nanoparticle synthesis: optimization by Box-Behnken design. Materials Science and Engineering: C, 99, 1105-1114.

21. Abbas, A., Jain, S., Gour, M., &Vankudothu, S. (2021). Tomato plant disease detection using transfer learning with C-GAN synthetic images. Computers and Electronics in Agriculture, 187, 106279.

22. Gu, J., Yu, P., Lu, X., & Ding, W. (2021, March). Leaf species recognition based on VGG16 networks and transfer learning. In 2021 IEEE 5th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC) (Vol. 5, pp. 2189-2193). IEEE.

23. Ashok, S., Kishore, G., Rajesh, V., Suchitra, S., Sophia, S. G., &Pavithra, B. (2020, June). Tomato leaf disease detection using deep learning techniques. In 2020 5th International Conference on Communication and Electronics Systems (ICCES) (pp. 979-983). IEEE.

24. Feng, S., Cao, Y., Xu, T., Yu, F., Zhao, D., & Zhang, G. (2021). Rice leaf blast classification method based on fused features and one-dimensional deep convolutional neural network. Remote Sensing, 13(16), 3207.

25. Naik, B. N., Malmathanraj, R., &Palanisamy, P. (2022). Detection and classification of chilli leaf disease using a squeeze-and-excitation-based CNN model. Ecological Informatics, 69, 101663.

FINANCING

The authors did not receive financing for the development of this research.

CONFLICT OF INTEREST

There is no conflict of interest.

AUTHORSHIP CONTRIBUTION

Conceptualization: E.Banu.
Data curation: E.Banu.
Formal Analysis: E.Banu.
Acquisition of funds: E.Banu.
Research Methodology: E.Banu.
Project Management: E.Banu.
Resources: E.Banu.
Software: E.Banu.
Supervision: A.Geetha.
Validation: E.Banu.
Display: E.Banu.
Drafting- original draft: E.Banu.
Writing- Proof reading and editing: E.Banu.

https://doi.org/10.56294/dm2023196