Crop Leaf Disease Prediction Using Graph Diffusion TCN with Fibroblast Optimization

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Abstract – Crop leaf disease prediction is plagued by insufficient generalization over different crop species, the lack of differentiation between similar disease symptoms, and variable environmental conditions affecting image quality. Poorly labelled datasets, model over-fitting, and real-time deployment issues all affect the accuracy and reliability of detecting illnesses in agriculture applications. With the PlantVillage dataset, the Random Graph Diffusion Dual Channel Temporal Convolutional Network with Synergistic Fibroblast Optimization (RGD-DCTCNet-SFO) is employed to resolve these challenges in crop leaf disease detection. The pre-processing by the Blind DE-blurring based Light Weight Wiener Filter (BDE-LWWF) is the first step in the process, which enhances image quality by reducing noise and blurring. Return-Aligned Decision Transformer (RADT) provides accurate boundary definition to enable segmentation by identifying regions using deviation analysis. After features have been obtained, the Random Graph Diffusion Dual Channel Temporal Convolutional Network (RGD-DCTCNet) is utilized for effective crop leaf disease classification. Synergistic Fibroblast Optimization (SFO), which boosts the accuracy of classification and minimizes errors, performs optimization on the search process of ill regions for further improved performance. The RGD-DCTCNet-SFO algorithm surpasses existing methods, recording 99.9% efficiency and 99.8% sensitivity, based on experimental outcomes of a Python-based study. The approach provides a robust and reliable solution for agricultural analysis by significantly improving the accuracy of crop leaf disease diagnosis.

Keywords – Crop Leaf Disease, Plant Village, Return-Aligned Decision Transformer, Synergistic Fibroblast Optimization, Wiener Filter.

I. INTRODUCTION

Maintaining the world's growing population depends heavily on agriculture. To fulfil the rising demand for food, agricultural productivity must be maximized while losses are minimized. Modern agriculture relies heavily on crop growth forecasts and analysis, and machine learning is becoming a potent tool for achieving these goals [1]. Precision agriculture, sometimes known as "smart farming," utilizes advanced technologies to enhance agricultural productivity and eliminate waste [2]. The goal of this strategy is to boost agricultural output while preserving resources like fertilizer, water, and energy. Since the agricultural and industrial revolutions coincided, agriculture is regarded as the cornerstone of any country. Human survival depends on crops, and food security and economic stability depend on crops remaining healthy [3].

Crop diseases are one of the main causes of food insecurity, which is still one of the most urgent issues facing the world today. In addition to endangering the world's food supply, plant diseases have a major detrimental influence on daily living and the state of the economy. The growth and state of a crop's leaves are among the most important markers of its general health [4]. Important information about a variety of plant diseases can be gleaned from visual signs on leaves. A significant amount of money is lost annually due to the high susceptibility of vegetable crops including potatoes, tomatoes, and peppers to a variety of illnesses. There are two types of blight, a prevalent and harmful illness: early blight, which is brought on by a fungus, and late blight, which is brought on by certain bacteria. Waste and financial loss can be avoided with early identification and efficient treatment of these illnesses [5]. Furthermore, this study explores how the integration of advanced deep learning techniques and optimized image processing workflows can enhance accuracy and efficiency, particularly in real-time medical applications and disease diagnosis [6]. Given that there will likely be more than 9 billion people on the planet in the next 25 years; food production must rise by 70% to keep up with demand. Crop diseases remain a serious concern, especially in agrarian and rural areas. Since potatoes are the most consumed vegetable in the world, infections affecting them are especially concerning, but diseases affecting tomatoes and peppers also pose a significant risk [7]. By combining cutting-edge algorithms, tools, and approaches, smart farming significantly depends on deep learning. Complex agricultural activities such as feature extraction, data transformation, pattern recognition, and image classification are addressed by machine learning [8]. The integration of artificial intelligence and machine learning techniques in rice disease detection enables early, accurate identification of infections, thereby reducing crop losses and enhancing decision-making to support sustainable agro-business practices [9].

Novelty and contribution

The Novelty and contribution of this paper are given below:

- Using the Plant Village dataset, the Random Graph Diffusion Dual Channel Temporal Convolutional Network with Synergistic Fibroblast Optimization (RGD-DCTCNet-SFO) is used to identify crop leaf diseases.
- The Blind DE-blurring based Light Weight Wiener Filter (BDE-LWWF) is used in pre-processing to improve image quality by lowering noise and blurring.
- By examining deviations, the Return-Aligned Decision Transformer (RADT) carries out segmentation, guaranteeing exact boundary delineation for accurate crop leaf disease identification.
- Following picture segmentation, the Random Graph Diffusion Dual Channel Temporal Convolutional Network (RGD-DCTCNet) efficiently recovers characteristics and categorizes agricultural leaf diseases.
- By minimizing prediction errors and streamlining the search for sick regions, Synergistic Fibroblast Optimization (SFO) improves classification accuracy.

II. LITERATURE REVIEW

In 2024, Naralasetti et al. [10] have presented, using sophisticated deep feature representations to improve plant leaf disease prediction: a transfer learning strategy. Using the Plant Village dataset and transfer learning, this work introduces a unique method for predicting plant diseases. The pre-processing, feature extraction, classification, and post processing phases are all part of the framework. Using deep feature extraction, VGG16 extracts complex disease-related patterns from leaf photos. A deep neural network is used to classify the retrieved features, with 96.56% accuracy. Prediction performance, F1 score, and Kappa score are all improved by this technique. Despite its great accuracy, it may over fit on small datasets and necessitates significant computational resources.

In 2024, Joseph et al. [11] have presented the creation of real-time plant disease datasets and deep learning-based plant disease detection. The goal of this research is to create specific rice, wheat, and maize datasets for the detection of plant illnesses, including bacterial and fungal diseases. Xception and MobileNet performed the best for maize (0.9580, 0.9464), MobileNetV2 for wheat (0.9632), and Xception for rice (0.9728) using the Plant Village dataset and eight fine-tuned deep learning models. Higher accuracy was achieved on all datasets by a new CNN model trained from scratch. The approach can have over fitting issues and is computationally intensive, even though it is very accurate.

In 2024, Pacal et al. [12] have presented employing a massive dataset and a sophisticated vision transformers model to detect maize leaf diseases to enhance agricultural production and sustainability. This study employs the Plant Village, PlantDoc, and CD&S datasets to provide a high-end Multi-axis Vision Transformer (MaxViT) model for detecting maize leaf diseases. The ConvNeXtV2-based Global Response Normalization (GRN)-based MLP and adding a Squeeze-and-Excitation (SE) block to the Stem enhance the model. It surpasses 28 CNN and 36 vision transformer models with a high inference speed and 99.24% accuracy. Although extremely accurate, the model requires a significant amount of processing power and may have scalability problems in a wide range of applications.

In 2024, Shabrina et al. [13] have presented a new dataset of potato leaf disease in uncontrolled conditions. This paper integrates image processing, computer vision, and deep learning techniques to enhance potato leaf disease detection. Although it is widely used, the Plant Village dataset lacks variation from the real world. Viruses, bacteria, fungus, pests, nematodes, phytophthora, and healthy leaves are the seven classes which are covered in the new dataset which contains 3076 images for solving this. This dataset, which was collected in uncontrolled conditions, enhances the accuracy of the disease diagnosis. For all its diversity, however, the dataset's random image viewpoints and complicated backgrounds might be challenging for model generalization.

Problem Statement

Proper identification and classification of various plant diseases from leaf images is the problem of crop leaf disease prediction to ensure food security and prevent yield loss. Traditional methods are time-consuming and error-prone.

Detection of disease at an early stage can enhance crop well-being and farming productivity using deep learning and machine learning algorithms to develop an automated, efficient, and precise system.

III. PROPOSED METHODOLOGY

The schematic block diagram of the suggested RGD-DCTCNet-SFO in **Fig 1** illustrates the procedure for identifying leaf diseases in agriculture based on the PlantVillage dataset.

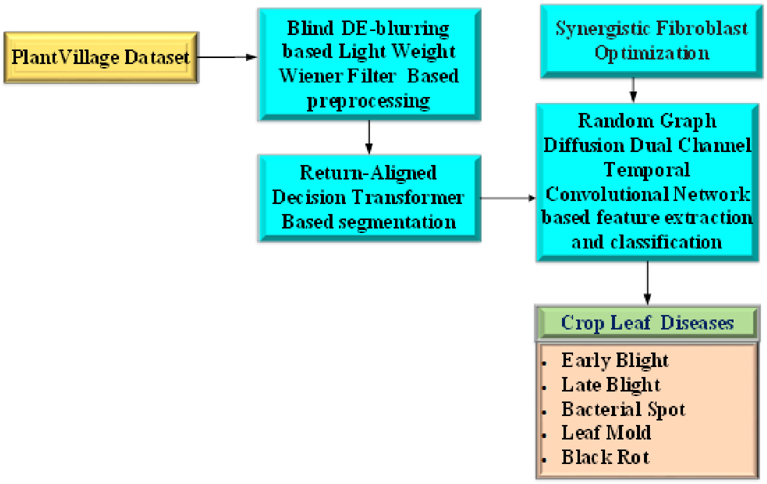

Fig 1. Block Diagram of Proposed RGD-Dctcnet-SFO.

Pre-processing with the Blind DE-blurring based Light Weight Wiener Filter (BDE-LWWF) is the initial step in the process, which enhances image quality through noise reduction and blurring. Segmentation is then performed by the Return-Aligned Decision Transformer (RADT), which identifies areas with high accuracy through deviation analysis. The Random Graph Diffusion Dual Channel Temporal Convolutional Network (RGD-DCTCNet) analyzes the segmented data to extract features and classify it. With enhanced search for sick regions, Synergistic Fibroblast Optimization (SFO) increases the classification accuracy. Black Rot, Bacterial Spot, Early Blight, Late Blight, and Leaf Mold diseases are identified by the system.

Data collection

54,305 images of 14 crop types and 38 disease categories, such as healthy leaves, comprise the PlantVillage dataset for predicting crop leaf disease. Photos of various crops, like potatoes, tomatoes, maize, and peppers, are collected in controlled environments. This dataset is often utilized to train and evaluate deep learning and machine learning models for accurate illness detection.

Preprocessing Using Blind DE-Blurring Based Light Weight Wiener Filter (BDE-LWWF)

In the case of predicting crop leaf disease, the PlantVillage dataset undergoes the application of Blind DE-blurring based Light Weight Wiener Filter (BDE-LWWF) [14], which is used to remove noise and blurring. It enhances diagnostic accuracy, remedies spatial distortions, and enhances image quality by incorporating region-warped kernels into a light Wiener filter in a CNN-based model.

Deep Learning-based Image DE-blurring

Deep learning-based picture de-blurring based on neural networks enhances the sharpness of images from the PlantVillage dataset and enables crop leaf disease identification. The Image Degradation Model is given by equation (1).

$$Q_a \approx P * Q_d + \upsilon \tag{1}$$

where, Q_a represent the blurry image. Q_d illustrate the de-blurred image. P represent the blur kernel. $*$ represent the convolution. υ represent the noise. Other models, such as CNNs, learn to minimize errors. Equation (2) can be represented by it.

$$\left\| Q_a - (P * Q_d + \upsilon \right\| \tag{2}$$

De-blurring images from the PlantVillage dataset using deep learning enhances the image quality and enhances the accuracy of crop leaf disease detection by reducing noise and restoring significant details.

Wiener Filter

In an attempt to identify crop leaf disease, the Wiener Filter minimizes the noise and distortion in images acquired from the PlantVillage dataset as well as enhancing the signal-to-noise ratio. Equation (3) is the formula for the Wiener Filter.

$$G(i,j) = \frac{H(i,j)}{H(i,j) + T(i,j)} \tag{3}$$

where, $H(i,j)$ represent the power spectrum of the signal. $T(i,j)$ reflect the power spectrum of the noise. Equation (4) shows how frequency domain multiplication is used to improve the images of the PlantVillage dataset for convolution-based crop leaf disease diagnosis.

$$E(i,j) = H(i,j) \bullet G(i,j) + T(i,j) \tag{4}$$

where, $E(i,j)$ represent the convolution of the signals. One of the common and effective methods of reducing noise in PlantVillage dataset images for diagnosing crop leaf diseases is the Wiener Filter. In the process of extracting features and enhancing accuracy in providing the image as input to the segmentation block, this pre-processing step enhances the image quality immensely.

Segmentation Using Return-Aligned Decision Transformer (RADT)

Through better border demarcation and feature extraction, the Return-Aligned Decision Transformer (RADT) [15] enhances crop leaf disease segmentation on the Plant Village dataset. By addressing the problems with attention allocation in conventional transformers, it guarantees accurate interpretation of context and greatly improves segmentation quality for accurate disease diagnosis and identification in smart agriculture applications. The return-to-go sequence χ_r and the state action sequence χ_{sa} are expressed in equations (5) and (6),

$$\chi_r = (\widehat{Z}_1, \widehat{Z}_2, ..., \widehat{Z}_t) \tag{5}$$

$$\chi_{sa} = (X_1, Y_1, X_2, Y_2, ..., X_t, Y_t) \tag{6}$$

where, $\widehat{Z}_t$ reflects the parts of the pattern at that instant t. X_t, Y_t represent the components of the activity and the current state t, respectively. The inquiry is the state-action sequence. χ_{sa}, and the key and value are the return-to-go sequence χ_r. This can be expressed in terms of equation (7).

$$V_n = \chi_{sa,n} D^V, \quad S_m = \chi_{r,m} D^S, \quad F_m = \chi_{r,m} D^F \tag{7}$$

where, V_n is the query matrix is derived from the projection matrix. D^V based on the state-action sequence $\chi_{sa,n}$. The key matrix S_m is obtained from the return-to-go sequence $\chi_{r,m}$ using the projection matrix D^S. Making use of the projection matrix D^F. F_m symbolizes the value matrix obtained from the return-to-go series $\chi_{r,m}$. The Return-Aligned Decision Transformer (RADT) enhances boundary demarcation and feature extraction in PlantVillage picture segmentation, ensuring precise crop leaf disease identification by efficiently integrating contextual and geographical information for precise classification and diagnosis. To guarantee precise disease diagnosis and classification, the segmented PlantVillage images are subsequently routed to the feature collection and classification block.

Feature Extraction and Classifications Are Done Using Random Graph Diffusion Dual Channel Temporal Convolutional Network (RGD-DCTCNet)

The Random Graph Diffusion Dual Channel Temporal Convolutional Network (RGD-DCTCNet) effectively extracts important features from segmented pictures for crop leaf disease prediction using the Plant Village dataset. While the random graph diffusion attention network guarantees quick, high-resolution feature extraction, the dual-channel temporal convolutional network improves classification accuracy, allowing for accurate disease identification across a variety of leaf samples.

Random Graph Diffusion Attention Network (RGDAN)

To predict agricultural leaf diseases, characteristics are extracted from the Plant Village dataset using the Random Graph Diffusion Attention Network (RGDAN) [16]. To lower mistakes and improve the precision of feature extraction and disease detection, it makes use of a transform attention layer, encoder, decoder, and spatiotemporal embedding generator.

Encoder-Decoder

Concatenation, linear layers, attention, and fusion are the processing and prediction methods used by the RGDAN encoder. This information is given by equation a (8).

$$F(z) = \gamma(Mz + t) \tag{8}$$

where, γ is symbolizes the activation role, M is symbolizes the variable parameter. t is suggests that the bias term is an extra variable that can be found and applied to change the result.

A Spatial-Temporal Generator for Embedding

The spatial-temporal embedding generator encodes day-of-week and time-of-day information by processing spatiotemporal data using embedding techniques (9).

$$G^{(h+B+1)} = z\left(Conca\left(G_{OUT}^{(H+b)}, K_P\right)\right) \tag{9}$$

where, $G_{OUT}^{(H+b)}$ is represents the initial encoder layer signal. K_P is represents the future's temporal and spatial embedding. z is shows the function, this is most likely an activation function or layer of a neural network. $Conca$ is represents merging the results of $F_{OUT}^{(G+D)}$ and M_R along a certain dimension.

These recovered Plant Village images are then used by the classification block to differentiate between the various leaf disease categories.

Channel Temporal Convolutional Network (DCTCNet)

Using the Plant Village dataset, the Dual-Channel Temporal Convolutional Network (DCTCNet) [17] is intended for the classification of crop leaf diseases. In order to extract spatial and temporal information, it analyzes data using two temporal routes (10).

$$TC_t = \sum_{n=0}^{m} h_n \cdot x_{t-n} + b \tag{10}$$

where, TC_t is illustrate the concealed condition. h_n is represent the kernel weights. x_{t-n} is represent the input sequences and b is represent the bias. The final categorization is performed using SoftMax activation. It can be seen in equation (11).

$$O(x/Z) = \frac{e^{MC+a}}{\sum_g e^{M_g C + a_g}} \tag{11}$$

where, $O(x/Z)$ is represent the class's odds. Historic and spatial data architectures are used by DCTCNet to effectively improve classification results.

Categorical Cross-Entropy (CCE) Loss

The Categorical Cross-Entropy (CCE) loss is frequently used to assess how well a model performs in diagnosing various crop leaf diseases. It is described by the equation (12), which follows:

$$CCE(Loss) = -\sum_{n=1}^{M} f_n \log(\widehat{f}_n) \tag{12}$$

where, f_n is symbolize the actual class label. $\widehat{f}_n$ is reflect the expected probability for the class n. Synergistic Fibroblast Optimization (SFO) is used to optimize the RGD-DCTCNet classification loss function.

Optimization Using Synergistic Fibroblast Optimization (Sfo)

One reliable and effective metaheuristic optimization method is Synergistic Fibroblast Optimization (SFO) [18]. SFO improves crop leaf disease classification accuracy by fine-tuning the RGD-DCTCNet loss function, which allows the model to identify subtle disease patterns for accurate diagnosis.

Step1: Initialization

By enhancing convergence, optimizing the loss function of RGD-DCTCNet, and fine-tuning search agents for improved parameter setup and solution selection, Synergistic Fibroblast Optimization (SFO) improves agricultural leaf disease detection.

Step 2: Random Generation

By boosting search diversity, avoiding premature convergence, and enhancing crop leaf disease detection, Random Generation improves Synergistic Fibroblast Optimization (SFO).

Step3: Fitness Function

According to equation (13), the RGD-DCTCNet fitness function guarantees convergence, minimizes misclassification errors, and strikes a balance between energy minimization and classification accuracy to provide optimal performance.

$$FF = Min[-\sum_{n=1}^{M} f_n \log(\widehat{f}_n)] \tag{13}$$

where, $-\sum_{n=1}^{M} f_n \log(\widehat{f}_n)$ is represent the RGD-DCTCNet loss function.

Step4: A Statistical Model Describing the Behaviour of Fibroblasts

Affected areas are used to establish the direction of propagation in crop leaf disease detection. Equation (14) illustrates how it is calculated by calculating a weighted mean of the direction of previous travel and the sickness patterns at the current location.

$$g(y,l) = \sum_{n=0}^{K} q_n(y,l) \frac{g^n(l-\tau)'}{\left\| g^n(l-\tau)' \right\|} \tag{14}$$

where, τ is a lag in time. K is the sum of each one. $q_n(y,l)$ is the function related to weight. It is described by the equation (15).

$$q_n(y,l) = b_1 b_2, \quad b_s = \max\{1 - \frac{\left| g^n(l)_s - y_s \right|}{L}, 0 \tag{15}$$

where, L is the dimension of a fibroblast that migrates; its typical range is around $100\mu m$.

Step 5: Termination

Until the target accuracy, fitness level, or maximum number of iterations is reached, the crop leaf disease recognition algorithm continues to run. By keeping an eye on accuracy and fitness and ceasing execution when progress stabilizes, the termination mechanism guarantees efficiency.

IV. RESULTS AND DISCUSSION

Following its implementation and evaluation on the Python platform, the proposed method is contrasted with existing analysis techniques. A thorough explanation of the simulation's parameters and an analysis of the outcomes are given in **Table 1**.

Table 1. Simulation Specifications

Specifications	Description
Programming Language	Python
Version	3.7.14
OS	Windows 10
Dataset	PlantVillage
Diseases	• Early Blight • Late Blight • Bacterial Spot • Leaf Mold • Black Rot
Training network	Random Graph Diffusion Dual Channel Temporal Convolutional Network (RGD-DCTCNet)
Algorithm	Synergistic Fibroblast Optimization (SFO)

Description of the Dataset

Plant Village dataset

The 54,305 annotated photos of both healthy and diseased crop leaves in the PlantVillage dataset are made publically available and are used to train and assess machine learning models for the identification and categorization of crop diseases.

Performance Analysis of Plant village Dataset

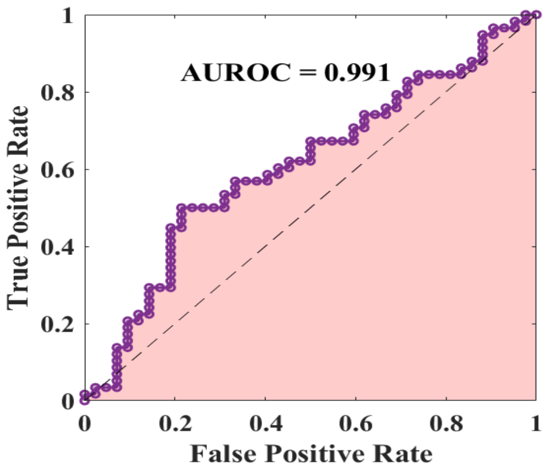

Fig 2.ROC Curve for Plant Village Dataset.

Model performance in identifying crop leaf diseases is shown in **Fig 2** ROC curve for the PlantVillage dataset. The classification accuracy is outstanding, as indicated by the Area Under the ROC Curve (AUROC) value of 0.991.

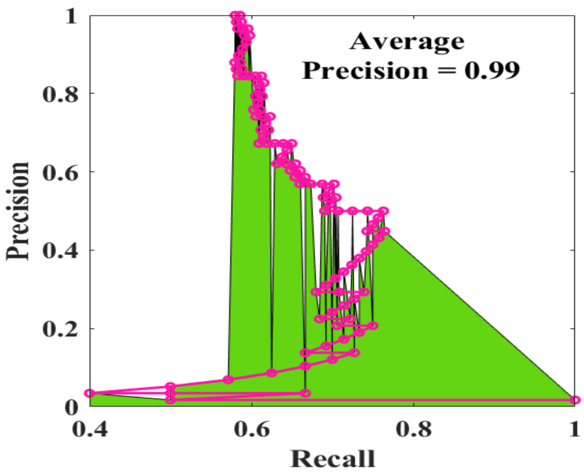

Fig 3. Performance Matrices of the Plant Village Dataset.

The precision-recall curve is displayed in **Fig 3.** Performance matrices of the Plant Village dataset and the model's high accuracy in identifying crop leaf diseases are indicated by an average precision of 0.99.

Table 2 Performance Analysis of RGD-DCTCNet-SFO shows improved detection performance by comparing the proposed RGD-DCTCNet-SFO model with current techniques (VGG16-DNN, Xception-MNet, MaxViT-SE, CV-DLM) for crop leaf disease detection. The proposed model achieves superior accuracy (99.9%), precision, recall, sensitivity, specificity, and F1-score for Early Blight and Late Blight.

Table 2. Performance Analysis of Rgd-Dctcnet-Sfo

Metrics	Diseases	(VGG16-DNN) [8]	(Xception-MNet) [9]	(MaxViT-SE) [10]	(CV-DLM) [11]	Proposed Technique (RGD-DCTCNet-SFO)
Accuracy%	Early Blight	87.4	84.9	89.3	83.4	99.8
	Late Blight	87.8	88.2	86.5	87.4	99.9
Precision%	Early Blight	82.5	89.1	88.3	89.9	98.8
	Late Blight	84.7	91.9	84.2	86.8	97.9
Recall%	Early Blight	83.1	89.7	84.4	88.4	99.9
	Late Blight	84.8	89.4	85.8	82.1	99.9
Sensitivity%	Early Blight	86.4	83.5	89.1	83.3	99.8
	Late Blight	86.6	89.2	85.9	89.8	99.7
Specificity%	Early Blight	86.2	82.4	83.9	87.9	98.8
	Late Blight	82.9	88.4	86.8	86.7	98.8
F1-score%	Early Blight	82.3	84.4	84.1	84.5	99.9
	Late Blight	89.1	86.9	87.2	84.6	97.8

V. CONCLUSION

Crop leaf disease detection problems, such as poor generalization, identical symptoms of the illness, and environmental variability, are successfully addressed by the suggested RGD-DCTCNet-SFO technique. Using the Plant Village dataset, the method guarantees precise region identification by segmentation using the Return-Aligned Decision Transformer (RADT) and improves picture quality through pre-processing with the Blind DE-blurring based Light Weight Wiener Filter (BDE-LWWF). Disease categorization is effectively carried out using the Random Graph Diffusion Dual Channel Temporal Convolutional Network (RGD-DCTCNet), and mistakes are decreased and accuracy is increased by Synergistic Fibroblast Optimization (SFO). With 99.9% efficiency and 99.8% sensitivity, the experimental findings show excellent performance, providing a reliable and accurate solution for crop leaf disease identification in agricultural industries.

CRediT Author Statement

The authors confirm contribution to the paper as follows:
Conceptualization: Sashi Kanth Betha, Pallavi L, Santosh Kumar Upadhyay, Satheesh Kumar S, Lakshmanarao A and KrishnaPrasad B; **Methodology:** Sashi Kanth Betha, Pallavi L and Santosh Kumar Upadhyay; **Writing- Original Draft Preparation:** Sashi Kanth Betha, Pallavi L, Santosh Kumar Upadhyay, Satheesh Kumar S, Lakshmanarao A and KrishnaPrasad B; **Visualization:** Satheesh Kumar S, Lakshmanarao A and KrishnaPrasad B; **Investigation:** Sashi Kanth Betha, Pallavi L and Santosh Kumar Upadhyay; **Supervision:** Satheesh Kumar S, Lakshmanarao A and KrishnaPrasad B; **Validation:** Sashi Kanth Betha, Pallavi L and Santosh Kumar Upadhyay; **Writing- Reviewing and Editing:** Sashi Kanth Betha, Pallavi L, Santosh Kumar Upadhyay, Satheesh Kumar S, Lakshmanarao A and KrishnaPrasad B; All authors reviewed the results and approved the final version of the manuscript.

Data Availability

No data was used to support this study.

Conflicts of Interests

The authors declare no conflict of interest.

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Competing Interests

There are no competing interests.

References

[1]. Md. M. Islam et al., "Deep Crop: Deep learning-based crop disease prediction with web application," Journal of Agriculture and Food Research, vol. 14, p. 100764, Dec. 2023, doi: 10.1016/j.jafr.2023.100764.
[2]. F. Arshad et al., "PLDPNet: End-to-end hybrid deep learning framework for potato leaf disease prediction," Alexandria Engineering Journal, vol. 78, pp. 406–418, Sep. 2023, doi: 10.1016/j.aej.2023.07.076.
[3]. G. Sravanthi and N. R. Moparthi, "An efficient IoT based crop disease prediction and crop recommendation for precision agriculture," Cluster Computing, vol. 27, no. 5, pp. 5755–5782, Feb. 2024, doi: 10.1007/s10586-023-04246-w.
[4]. K. Singh, A. Rao, P. Chattopadhyay, R. Maurya, and L. Singh, "Effective plant disease diagnosis using Vision Transformer trained with leafy-generative adversarial network-generated images," Expert Systems with Applications, vol. 254, p. 124387, Nov. 2024, doi: 10.1016/j.eswa.2024.124387.
[5]. Ashwini and V. Sellam, "An optimal model for identification and classification of corn leaf disease using hybrid 3D-CNN and LSTM," Biomedical Signal Processing and Control, vol. 92, p. 106089, Jun. 2024, doi: 10.1016/j.bspc.2024.106089.
[6]. N. K. Pegada, Vetrithangam, A. Fathima, and Arunadevi, "A survey on various image analysis techniques," Innovations in Computational and Computer Techniques: ICACCT-2021, vol. 2555, p. 040013, 2022, doi: 10.1063/5.0108909.
[7]. P. Bhuyan, P. K. Singh, S. K. Das, and A. Kalla, "SE_SPnet: Rice leaf disease prediction using stacked parallel convolutional neural network with squeeze-and-excitation," Expert Syst., vol. 40, no. 7, p. e13304, 2023. DOI: 10.1111/exsy.13304
[8]. D. J. Chaudhari and K. Malathi, "Detection and Prediction of Rice Leaf Disease Using a Hybrid CNN-SVM Model," Optical Memory and Neural Networks, vol. 32, no. 1, pp. 39–57, Mar. 2023, doi: 10.3103/s1060992x2301006x.
[9]. S. Aggarwal et al., "Rice Disease Detection Using Artificial Intelligence and Machine Learning Techniques to Improvise Agro-Business," Scientific Programming, vol. 2022, pp. 1–13, Jun. 2022, doi: 10.1155/2022/1757888.
[10]. Naralasetti and J. D. Bodapati, "Enhancing Plant Leaf Disease Prediction Through Advanced Deep Feature Representations: A Transfer Learning Approach," Journal of The Institution of Engineers (India): Series B, vol. 105, no. 3, pp. 469–482, Feb. 2024, doi: 10.1007/s40031-023-00966-0.
[11]. D. S. Joseph, P. M. Pawar, and K. Chakradeo, "Real-Time Plant Disease Dataset Development and Detection of Plant Disease Using Deep Learning," IEEE Access, vol. 12, pp. 16310–16333, 2024, doi: 10.1109/access.2024.3358333.
[12]. Pacal, "Enhancing crop productivity and sustainability through disease identification in maize leaves: Exploiting a large dataset with an advanced vision transformer model," Expert Systems with Applications, vol. 238, p. 122099, Mar. 2024, doi: 10.1016/j.eswa.2023.122099.
[13]. N. H. Shabrina et al., "A novel dataset of potato leaf disease in uncontrolled environment," Data in Brief, vol. 52, p. 109955, Feb. 2024, doi: 10.1016/j.dib.2023.109955.
[14]. C. Haywood and R. Younes, "Real-time Blind Deblurring Based on Lightweight Deep-Wiener-Network," 2023 International Joint Conference on Neural Networks (IJCNN), pp. 1–8, Jun. 2023, doi: 10.1109/ijcnn54540.2023.10191586.
[15]. T. Tanaka, K. Abe, K. Ariu, T. Morimura, and E. Simo-Serra, 2024. Return-Aligned Decision Transformer. arXiv preprint arXiv:.
[16]. Fan, W. Weng, H. Tian, H. Wu, F. Zhu, and J. Wu, "RGDAN: A random graph diffusion attention network for traffic prediction," Neural Networks, vol. 172, p. 106093, Apr. 2024, doi: 10.1016/j.neunet.2023.106093.
[17]. Ren, F. Zhang, Y. Sun, and Y. Liu, "A Novel Dual-Channel Temporal Convolutional Network for Photovoltaic Power Forecasting," Energies, vol. 17, no. 3, p. 698, Feb. 2024, doi: 10.3390/en17030698.
[18]. P. Subashini, T. T. Dhivyaprabha, and M. Krishnaveni, "Synergistic Fibroblast Optimization," Artificial Intelligence and Evolutionary Computations in Engineering Systems, pp. 285–294, 2017, doi: 10.1007/978-981-10-3174-8_25.