Robust Detection and Classification of Apple Leaf Diseases at Early Stage by utilizing Reconnaissance Cognitive SDS Method with Enhanced IWO Algorithm

Donu V Jose[1], Dr. K.Shanti[2]

[1]Research Scholar, Department of Computer Science, Dr.NGP Arts & Science College
[2]Professor, Department of Information Technology, Dr.NGP Arts & Science College, Coimbatore, Tamilnadu, India

***Corresponding author:** Donu V Jose, **E-Mail:** donuscholar@gmail.com

ABSTRACT

Background: Apples are grown all over the world, and they are one of the most widely consumed fruits everywhere. A variety of diseases affect the apple leaf, caused by bacteria, viruses, fungi, etc. Identification and diagnosis of apple leaf diseases is one of the foremost ways to increase productivity and quality. More accurate early detection of leaf diseases is required to minimize plant degradation.

Objective: To improve the detection accuracy and efficiency, a robust detection method is proposed in this paper, which is called Reconnaissance Cognitive Stochastic Diffusion Search Method with Enhanced Invasive Weed Optimization (RSDS-EIWO). RSDS with EIWO extracts the features from the apple leaf dataset (collected from the Apple Experiment Station of Northwest A&F University, China) and selects the appropriate function to perform classification and detection of disease at an early stage with high accuracy and also this approach also detect the leaves spots which are likely to be affected in future and it helps farmers to diagnose at an early stage.

Novelty: A machine learning technique called the Random Forest Classifier is used to classify the disease in leaves by identifying the spots. The Conjugate Gradient Method (CGM) and Edge-based Colour Segmentation (ECS) are used to detect leaf colour segments and identify the disease at an early stage based on shape, texture, and colour features.

Findings: The analysis was done using the MATLAB software tool, and the performance results were evaluated and compared to the existing models such as Faster R-CNN, R-SSD, and INARSSD. The experimental results showed that the accuracy of 97% and speed of apple leaf disease detection are enhanced in a robust manner, and the results showed that the proposed method outperformed existing methods.

Keywords: Apple Leaf Disease Detection, Invasive Weed Optimization, Stochastic Diffusion Search, Image Processing, Machine Learning

DOI Number: 10.48047/nq.2022.20.19.NQ99154 **NeuroQuantology2022; 20(19): 1728-1742**

1. INTRODUCTION

The use of technology in this fifth generation is highly prevalent everywhere to solve problems for critical solutions in all sectors. This paper deals with how advanced machine learning technology along with a bio-inspired algorithm helps in spotting the apple leaf disease and identifying it at an early stage to maximize the production of apples and minimize plant degradation. As everyone is aware, apples are rich in nutrition and have medicinal value. They are one of the most productive fruits in the world. A variety of diseases occur frequently that stop the yield and production on a large scale, leading to economic loss. In that case, timely detection of disease in an effective manner is essential to ensure that the diseases are diagnosed at an early stage. Various techniques have been identified to detect plant leaf diseases, but the accuracy has not improved. Traditional deep learning methods are utilized by the researchers to improve the accuracy level in a real-time environment, but object detection accuracy is not achieved remarkably. At an early stage, only visual observance is done to identify the plant's leaf diseases and the same is diagnosed subject to risk and disease spotting time. To overcome the challenges, genetic algorithms with deep learning techniques have been studied to discover a novel method called Reconnaissance Cognitive Stochastic Diffusion Search Method with Enhanced Invasive Weed Optimization to spot the disease at its early occurrence, which helps farmers to diagnose the disease at the right time in order to increase production.

2. BACKGROUND STUDY

One of the common diseases that affect apple production is apple leaf disease. Early detection and treatment are necessary to prevent it from spreading throughout the entire plant. The object detection method [1] is used to improve SSD performance. This method uses root scanning to identify objects in real time. This methodology hasn't been successful in quickly finding infected objects because it takes so long to detect objects in real time. The authors propose a faster R-CNN model for real-time object detection [2], in which the DL method is used for OD with the help of a combinational algorithm called CBFM, and the accuracy is up to 91%. During the real-time implementation, the accuracy is slightly reduced as the number of iterations increases. An improved CNN model [3] was proposed to detect the apple leaf disease at an early stage, and it was tested with the help of the Matlab tool. The model performs well in terms of disease detection and identifying colour differences in leaves. But the speed and accuracy of object detection remain slow if the number of rust particles is high in leaves. The author proposed Performance of software defect prediction using an advanced ML approach [4] to identify the defect that occurs in software during implementation using available datasets. IFPA with the MCSVM-SVI model was proposed [5] to identify the apple leaf disease at an early stage, and the speed and accuracy were improved up to 95% during the implementation process in real time. However, it lacks the ability to analyse neighboring leaves and those likely to be affected for future prediction. RABCRPM [6] was introduced for optimization with the help of a bio-inspired bee colony approach, and the pixel optimization accuracy was achieved up to 94% where the image pixels could be optimized better. The authors presented deep learning approaches for disease detection and diagnosis [7], which work well for detecting a variety of leaf diseases with a few drawbacks such as real-time prediction slowdown, time consumption, deep detection failure, and so on. The V3MobileNet [8] model was proposed, and the same is being implemented for easy mobile scanning of images and identification of rusts with the help of the CNN Net approach. The model works well with high sensitivity and specificity and good speed in object detection. The drawback of the model is that it will slow down in a real-time environment. PTV disease prediction in stored leaves and fruits was proposed [9] using a new KLL model with an object detection speed of 97%. The approach works well with stored fruits, and the deep scanning method is getting down to its final iterations. Deep Learning models [10] were used to identify apple tree leaf diseases, and the approach achieved up to 87% accuracy in terms of detection speed alone, whereas disease spotting is done for all image testing iterations. To detect the disease in tomato leaves, an AERCNN model [11] was proposed, with detection accuracy of up to 90% and detection speed of 86%. The speed of object detection is increased with the help of the residual CNN approach, where it is embedded in real time. The RVSRP model [12] is used as one of the optimizing models using bio-inspired nature, as viruses are one of the particles used for object-sensing failure detection during the implementation process, and it achieves up to 96% accuracy. The classification of fruit diseases application [13] is designed by the authors, where the disease classification and spotting of differences in colours are identified in real-time scanning, which helps the agriculture sector detect the disease in a speedy manner. The model has drawbacks in that it consumes more time during the deep scanning. 3-D-layered, AI-based, feature optimization and CCDF models [14–17] were introduced for the purposes of deep scanning, texture identification, leaf segmentation, colour spotting, and classification. The accuracy is not up to par, and the error rate is high during the process of real-time implementation. Genetic methods, DIP, and IPT techniques [18–20] were found to identify the disease at an early stage in apple tree leaves, and the same has been achieved. The lack of accuracy, speed, and time consumption was the major drawback. To address all of these shortcomings, the new model RSDS-EIWO method is proposed for rapid disease detection as well as identifying likely affected leaves for early diagnosis.

2. PROPOSED METHODOLOGY

To minimize plant degradation, it is essential to effectively detect apple tree leaf diseases at an early stage when they are simple to diagnose. The Reconnaissance Cognitive Stochastic Diffusion Search Method with Enhanced Invasive Weed Optimization Technology (RSDS-EIWO) is a new method that aims to classify leaf diseases early on while also identifying nearby leaves that are likely to be affected, which aids farmers in spotting the disease at an extremely early stage. Based on the deep sense and detection of objects in leaves, the disease is classified. For testing and implementation of this new RSDS approach, 5 prevalent diseases of apple tree leaves are chosen, including Alternaria Leaf Spot, Brown Spot, Mosaic Spot, Grey Spot, and Rust Spot. For the purposes of extraction, classification, noise removal, colour segment identification, etc., ML and DL with bio-inspired approaches are used. Assume that the two datasets $S1\ and\ S2$ used for training and testing represent infected and non-infected leaf sets. Following the automatic detection of leaf sets, the extraction and classification of image types, the removal of duplicate images, and the provision of the output sets $OT1\ and\ OT2$ along with the deep sensing marked pattern values TPR and TNR follow. The following equation yields the values,

$$OT1 = F_1 \sum_{i-\max(n)}^{il(in-leaves)} \left(S1\ MinTrace\ value = \mathrm{n} - \frac{\text{TPR (True Positive Rate)}}{OT2\ (Derived\ Sets)} \right), max\ (TPR) \qquad (1)$$

where, TPR is True Positive rate, il determines the infected leaf images sensed with RSDS-EIWO throughout the process. The crucial optimizing parameters employed to raise the level of accuracy with regard to colour spotting and disease identification in apple tree leaves include noise removal, pixel masking, and image resizing based on pixel detection.

2.1 Data Collection and Utilization

The datasets for pre-processing apple leaf images were totally retrieved from the core database for apple leaf disease (collected from the Apple Experiment Station of Northwest A&F University, China). The datasets include 26,377 images of diseased leaves in the five categories listed above. The primary goal of the RSDS-EIWO model is to determine disease patterns, where leaf diseases vary from season to season due to environmental conditions such as humidity, rainy season, unfavourable weather, illuminance, and so on. For the purpose of testing and implementation, all of the images were collected under various climatic conditions. The images are chosen and labeled with the five disease groups [5]. The apple leaves below were affected by the five distinct disease classes.

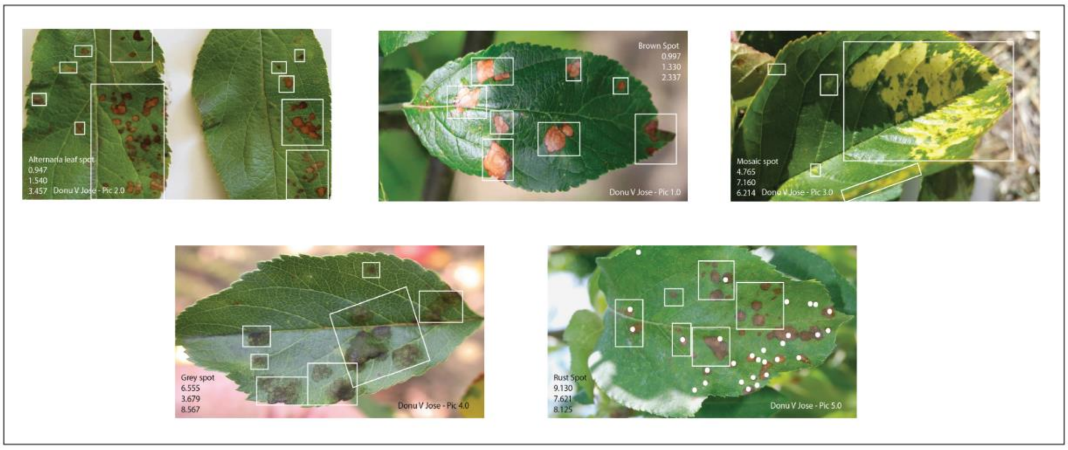

Figure 1: Alternaria Leaf Spot, Brown Spot, Mosaic Spot, Grey Spot, and Rust Spot

2.2 RSDS-EIWO - Stochastic Diffusion Search with Enhanced Weed Optimization

The RSDS-EIWO algorithm is a population-based weed optimization algorithm inspired by the colonization of invasive weeds in the colony to solve critical problems with the simplest solutions. Normally, a weed is nothing but an unwanted plant specified in a geographical area where it grows depending on the situation. Weed has a high fitness value and survival rate due to its robust growth nature. The lowest-fitness weed will not produce enough seeds for multiple weed productions, whereas the highest-fitness weed will produce maximum feed and reproduce a large number of weeds in a colony. The parent plant is surrounded by invasive weeds with high and low fitness values. The stochastic diffusion search method is adopted to search the invasive weeds in the colony with highest fitness value and the values are marked for calculation. The weeds which have lowest fitness value will destroy automatically or produce seeds very late. In the real time implementation, assume that $W1\ and\ W2$ is infected and non infected areas in the apple tree leaves. Invasive Weeds (Affected Areas in Leaves) are identified with highest fitness values and classified and the type of disease is identified. Also the W2 is also identified. The invasive weeds in the colony with best fitness value will produce maximum seeds and reproduce new weeds. Here the best fitness weeds to be identified to find out the areas where the leaves likely to be affected in future.

$$IWeed = Population(IW^{best+h},\eta) \ -\left(q^{i+1}.Weed^{IW+h} + q^{i-2}\ x\ Wpop^{i+1}\right) \quad (2)$$

where $IWeed$ is invasive weed denotes the IW growth in the weed colony with H and L fitness values. In this RSDS-EIWO approach the infected leaves are identified with the help of weed fitness value concept and also the likely affected leaves also will be marked with the help of stochastic diffusion search and root scanning. the fitness value will be measured with the help of following equation,

$$IWeedpop^{i+1} = Gaussian(H^{best+h},\eta) \ -\left(q^{i+1}.H^{best+h} + q^{i+2}.U\ pop^{i+1}\right) \quad (3)$$

Here in the above equation, where j represents the value of random indication ranging from$[0,1,2,\dots,IWeed]$ and $Iweed$ represents the size of population in the leaves or search area. H^{best+h} represents the solution that has the best value in generating h. q^{i+1} and q^{i+2} trusted as the values that are generated in an arbitrary manner that lies between 0 and 1. As soon as the fitness value is identified the weeds are marked which one has lowest and highest fitness value.

RSDS-EIWO Algorithm

1. **Input:** The Matlab Settings with Images
2. **Begin**: Initialize the datasets with the position and evaluate the fitness
3. **If** fitness value is better than best fitness value $IWeed^{best}$
4. **Then** set new value $IWeed^{best+h}$
5. Compute the values
6. Set accumulative metrics $D^{\emptyset} = (\pi^{x} - 2) * (M - \pi^{x} - 3), D^{D} = 4 * (M - 4)$
7. ***for*** each process of Weed set $\left(q^{i+1}.H^{best+h} + q^{i+2}.Upop^{i+1}\right)\left(G^{pop\ i+1}\right)$
8. **If** the population increases set $\log(h) \times h)$
9. **Else** $Gaussian(Weed^{best+h},\eta)$ is calculated
10. Calculate the position in the search space
11. Detect the host infected leaves using D^{i+1}
12. Use D^{h} for neighbor leaf prediction
13. Update the population in search space using $\log(h) \times h)$
14. Compute the values
15. Randomly select two indices from population, then generate a new candidate solution

16. Update the best position $D^{\pi} = (\pi^{x} + 1)D^{i+1}$
17. Coverage updation of virus in search space using $IWeedpop^{j+\pi best}$
18. End ***for***
19. Return *F*
20. **Output:** Optimal Solution with High and Low fitness value of Weeds

2.3 Conjugate Gradient Method for Optimization

The NL-CGM is a nonlinear optimization method that is used in conjunction with the RSDA-EIWO to detect leaf disease at an early stage. The leaf dimension is measured by CGM, and the measurement is marked. The colour difference is identified using the root scanning method, which marks the infected and non-infected curves and records the values. For many iterations the CGM method is proposed along with RSDS-EIWO.

$$Q(\alpha^{j}) = \int_{\alpha}^{\alpha^{i}} \{(\delta''\alpha > \delta(LeafCurve)) \cup (\delta \epsilon T(Curve))\}, \alpha \epsilon T \complement Dimension \quad (4)$$

The CGM spots the colours in the leaves and classifies the type if disease affected with the help of the above equation. The six steps of CGM are,

1. Measure the leaf dimension
2. Spot the leaf colour
3. Differentiate the colour and mark the values
4. Optimize the values
5. Record the infected areas with dimensional values
6. Measure the optimal value

The optimal value denotes the type of disease where identified by the CGM method by its texture, colour, shape and dimension.

2.4 RFC, ECS for Classification, Extraction and Colour Segmentation

The RFC is used for better disease classification and prediction. For the purpose of predicting five prevalent leaf diseases, numerous datasets are retrieved and categorized in this work. Some decision trees may predict the correct output, while others may not, because the RFC combines numerous trees to forecast the class of the dataset to identify the type of disease. But when all the decision trees are combined, they forecast the right result. Consequently, two presumptions for a better RFC are 1) actual values in the feature dataset so that the classifier produces an actual result, and 2) predictions in DTs must have low correlations. The ECS is edge-based colour segmentation that is employed to differentiate colours in the leaves by using the edge pixel measurements in the objects (weeds and leaves). Here, the image colour segmentation is done by linking the adjacent edges and combining the entire objects. The parallel and orthogonal edges are measured in invasive weeds to calculate their growth and fitness value.

$$WeedFitness = Edges\ (Iweed - Ni)\ - \left(IWeed + j^{i-2}\ x\ Fitness\ Value\right) \qquad (5)$$

where, the ECS calculates the edge values in the pixels and differentiates the colours. It also detects the original leaf colours and disease leaf colours and compared in the repository and shows the infected leaves and likely to be infected leaves with the help of colour segmentation.

2.5 Identification of Disease at early stage by RSDS-EIWO and spotting of LTBIL

RSDS-EIWO with CGM, ECS methods extract the features and select the appropriate functions to identify the fitness value of the invasive weeds and mark the fitness weeds and non-fitness weeds in the weed colony. Once the optimal value is identified, the result is obtained with the help of multiple iterations. In the real-time implementation, the fitness invasive weeds are leaf diseases that infect the other leaves. The CGM and ECS methods are deployed along with the SDS search method to search for colour spots at an early stage and also mark the colour difference in the initial stage. The results are used to judge performance. All five diseases are categorized as Class 1 and Class 2 sets for further extraction. The following are the early detection steps,

1. Select the features from the dataset
2. Search the weeds by SDS
3. Apply the appropriate function
4. Calculate the fitness value
5. Spot the colours
6. Differentiate the colours in all edges
7. Classify the diseases with the help of colours
8. Detect the disease in leaves
9. Spot the likely to be affected leaves by CGM and ECS

3. ABOUT IMPLEMENTATION PROCESS IN MATLAB R2020A TOOL

Using Matlab R2020a performance analysis tool, the novel method using the nature-inspired model RSDS-EIWO is evaluated against the baseline versions currently in use, as shown in the literature study. When using machine learning and bio-inspired algorithms to analyse image and deep image datasets, Matlab is one of the most commonly used tools. MATLAB is very user-friendly and used in many different industries, including supporting engineering and IT applications, hospitals, and research domains. Math functions that are incorporated and built into Matlab are numerous and can be used to handle a variety of scientific challenges. Due to the accuracy of the answers, Matlab is frequently used to solve iteration-based problems.

4. PERFORMANCE ANALYSIS METRICS OF RSDS-EIWO

The following performance analysis metrics were utilised to compare the performance and accuracy of the proposed novel algorithm RSDS-EIWO to the current methods R-SSD, Faster R-CNN, and INAR-SSD in terms of early detection of apple leaf disease and colour segmentation of leaves with a disease. For implementation, the following metrics were chosen:

- **Accuracy Level Metrics** - Calculates the accuracy level in terms of detecting the disease spots and colour segments at the highest level in order to detect and diagnose the plant leaf disease at early stage.
- **RSDS-EIWO Detection Speed** - Calculates the detection speed and time for better performance for the given data sets.
- **Sensitivity and Specificity Analysis** - Comparison of finite samples between TP and FN and TN and FP with the help of statistical method.
- **Precision and Recall Analysis** - Utilize the offered datasets or samples to do a continuous determination analysis ratio to recall the measurements of valid finite examples.
- **F-Score Analysis** - Used to determine the level of accuracy and remove noise from datasets before classifying them as positive or negative.
- **True Positive Rate and True Negative Analysis** - Accuracy classification in the provided datasets or the tested samples

5. RESULTS AND DISCUSSIONS

The results portray the implementation and performance values of the newly proposed method for apple leaf disease detection at early stage and how the algorithm identifies the forthcoming disease with the colour segmentation of leaves with the help of deep scanning techniques. The RSDS-EIWO implementation results were compared to the existing versions R-SSD, Faster R-CNN, and INAR-SSD. When compared to the values of baseline versions, the new proposed method RSDS-EIWO produces exemplary results in terms of root scanning images, colour segmentation, leaf partitioning in scanning, early disease prediction, object detection, identification of upcoming affecting leaves, and so on. The following graphs indicate the X axis plotted with performance metrics and the Y axis plotted with final output values.

5.1 Accuracy in Detection Analysis

Figure 2 showcases the performance analysis of the accuracy level of detecting apple plant leaf disease at an early stage of the proposed RSDS-EIWO against R-SSD, Faster R-CNN, and INAR-SSD. As RSDS-EIWO used both the Random Forest Classifier and CGM, where it optimizes the image with the help of a quadratic equation and the feature extraction and classification are done at the maximum level, it resulted in high accuracy in identifying the infected leaves at a premature stage and also spotted the forthcoming disease spreading areas to diagnose early. The accuracy level was met up to 96.98%, and it exceeded the existing versions.

5.2 Detection Speed Time Analysis

Figure 3 compares the existing R-SSD, Faster R-CNN, and INAR-SSD methods to the proposed new bio-inspired algorithm, the RSDS-EIWO method in terms of detection speed and time analysis. It is determined that the novel method works well in terms of detection time and speed, as it employs ECS (Edge Based Color Segmentation) methods for spotting colour segments in diseased and non-diseased leaves in a short period of time using deep colour scanning. The precise object detection, colour detection, texture detection, and root scanning aid in the early detection of disease. The speed is maximized to 95% and the time is minimized to 47 seconds, which is less than one minute.

Table 1: Accuracy in Detection - Performance Comparison

Metrics / Schemes	Faster R-CNN	R-SSD	INAR-SSD	RSDS-EIWO
Accuracy IT-1	79.01	81.02	85.07	96.98
Accuracy IT-N	76.01	82.05	87.04	95.08

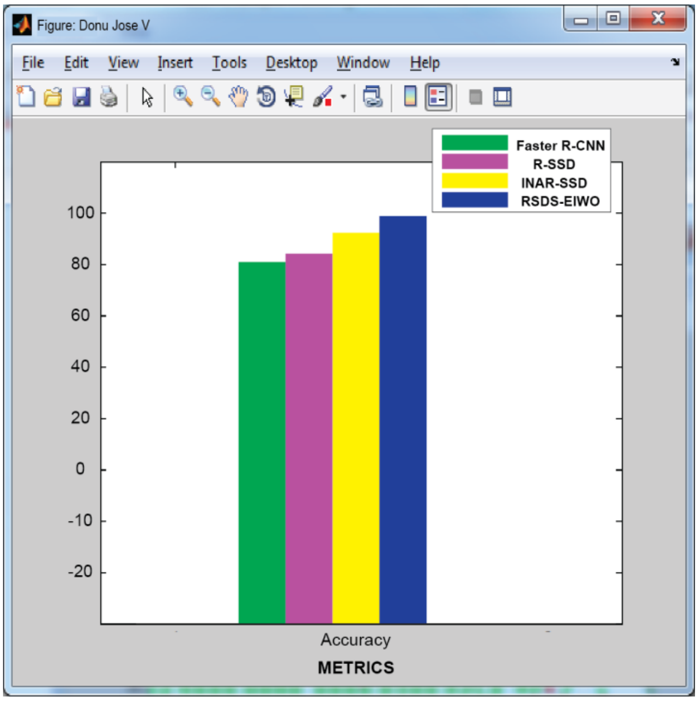

Figure 2: Accuracy Analysis

Table 2: Detection Speed and Time Analysis - Performance Comparison

Metrics / Schemes	Faster R-CNN	R-SSD	INAR-SSD	RSDS-EIWO
Speed	62.03	71.02	79.14	95.03
Time (in seconds)	98	79	76	47

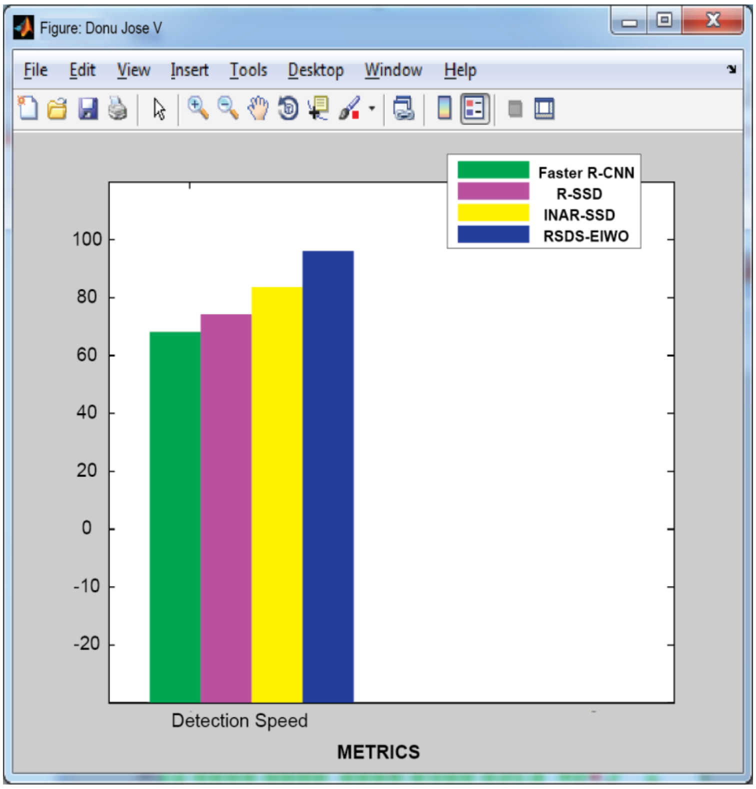

Figure 3: Speed Detection Analysis

5.3 Sensitivity and Specificity Analysis

The baseline algorithms R-SSD, Faster R-CNN, and INAR-SSD were compared to the performance of the novel bio-inspired machine learning approach, RSDS-EIWO, in terms of sensitivity and specificity, as shown in Figure 4. It is highlighted that RSDS-EIWO performs admirably and produces exceptional results. SDS, ECS, and CGM are used to detect disease, and a random forest classifier is used to choose the best functions for classification. The suggested ML technique performs well in terms of differentiating between diseased and healthy leaves as well as the upcoming leaves that are likely to be affected due to extensive categorization and data extraction.

Table 3: Sensitivity and Specificity Analysis - Performance Comparison

Metrics / Schemes	Faster R-CNN	R-SSD	INAR-SSD	RSDS-EIWO
Sensitivity	80.07	82.08	83.64	97.02
Specificity	79.13	80.17	83.76	94.21

5.4 Precision and Recall Analysis

Figure 5 displays a detailed assessment of the proposed new RSDS-EIWO against R-SSD, Faster

R-CNN, and INAR-SSD. The new approach outperforms the conventional approaches and yields the desired results in terms of data processing and classification utilizing combinational algorithms. Accuracy is attained together with speed and time due to its root scanning and edge-based colour spotting approach. When compared to baseline models, the performance is improved up to 97% and 94% P and R.

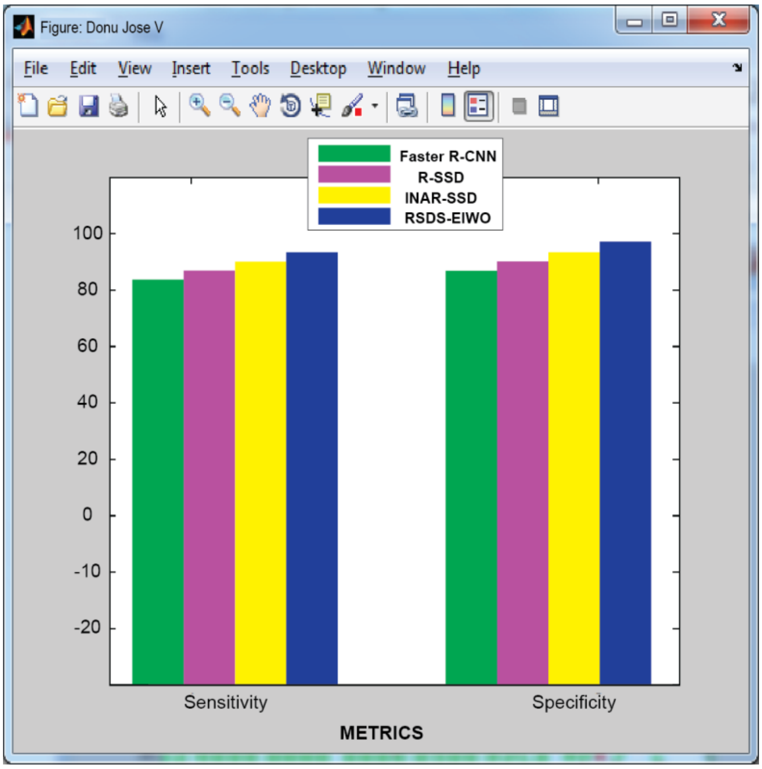

Figure 4: Sensitivity and Specificity Analysis

Table 4: Precision and Recall - Performance Comparison

Metrics / Schemes	Faster R-CNN	R-SSD	INAR-SSD	RSDS-EIWO
Precision	84.08	87.03	90.01	97.09
Recall	80.02	83.08	89.07	94.27

5.5 F-Score Analysis

The suggested RSDS-EIWO against R-SSD, Faster R-CNN, and INAR-SSD is thoroughly analysed in Figure 6 for F-Score analysis results. After extraction, the new method outperforms conventional technologies on the datasets of selected images. The Weed Optimization Technique used by the RSDS-EIWO, which spreads the weed strategy with excellent extraction and classification by RFC, performs well in image prediction and optimization. Even with several iterations, performance and accuracy are up to 94% better than with the existing approaches.

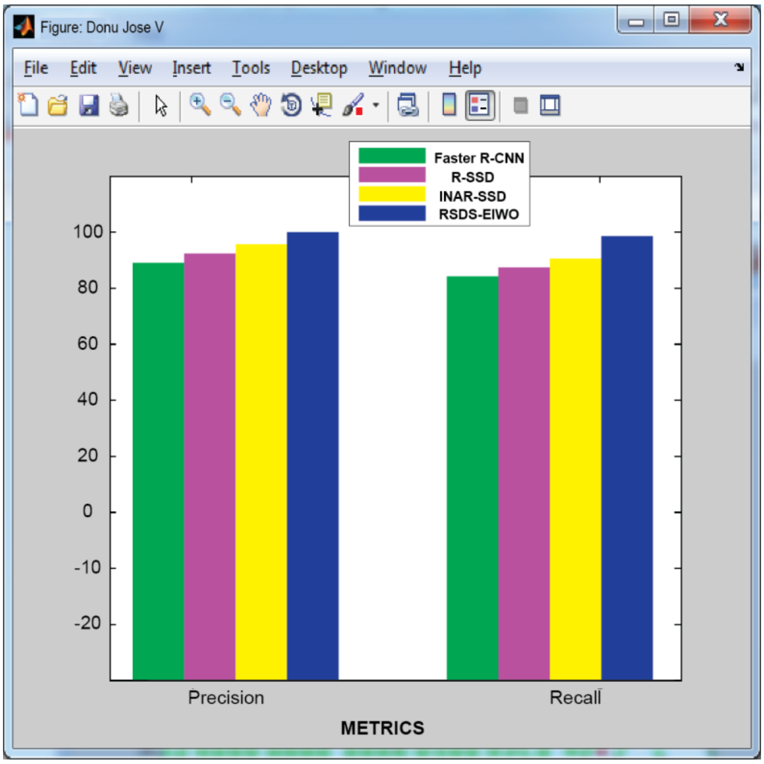

Figure 5: Precision and Recall Analysis

Table 5: Performance Comparison of F-Score Analysis

Metrics / Schemes	Faster R-CNN	R-SSD	INAR-SSD	RSDS-EIWO
F-Score (It 1)	79.08	81.02	88.08	94.03
F-Score (It N)	77.11	80.01	87.04	92.17

5.6 True Positive and True Negative Rate Performance Analysis

Figure 7 compares the novel method RSDS-EIWO to current R-SSD, Faster R-CNN, and INAR-SSD in terms of True Positive and True Negative performance. On the chosen datasets, the performance of the RSDS bio-inspired model is superior to that of the current methods. The diffusion search optimization approach with ECS's colour segmentation detection provides high prediction levels at the fastest possible rates. The TP and TN demonstrate that RSDS-accuracy EIWO's level is improvised.

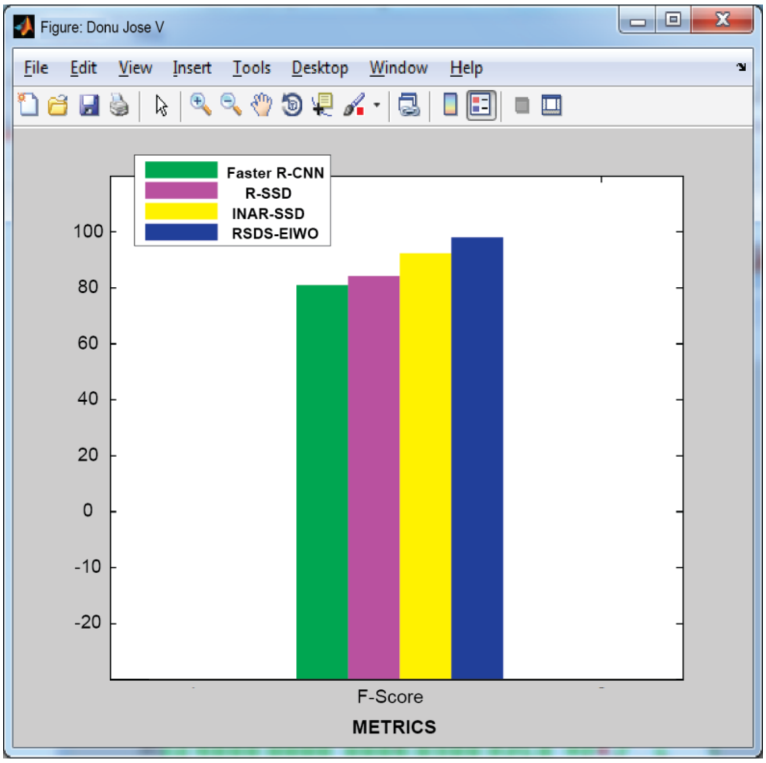

Figure 6: F-Score Analysis

Table 6: Performance Values of TP and TN Analysis

Metrics / Schemes	R-SSD	Faster R-CNN	INAR-SSD	RSDS-EIWO
True Positive	150	169	180	195
True Negative	130	140	120	115

6. CONCLUSION

This research analysis suggests RSDS-EIWO, a new machine and deep learning bio-inspired technique for early detection of apple leaf disease and identification of the subsequent leaf that is likely to be afflicted. The baseline methods only attain up to 87% of the accuracy level with a speed of 79.14 with a speed of 76 seconds, but the high detection speed of 95% in 47 seconds results in an accuracy level of up to 97%. The apple leaf dataset used for testing and implementation by RSDS-EIWO was obtained from the Apple Experiment Station of Northwest A&F University, China. The collection of feature values is chosen using the Reconnaissance Cognitive Stochastic Diffusion Search Method with Enhanced Invasive Weed Optimization. Using a deep root scanning approach based on form, texture, and colour attributes, CGM and ECS were utilised to detect colour segments in the leaves to distinguish between infected and non-infected regions. With a lot of iterations, the extracted training and test data are compared to the datasets that are accessible to assess the detection level. The outcomes demonstrate

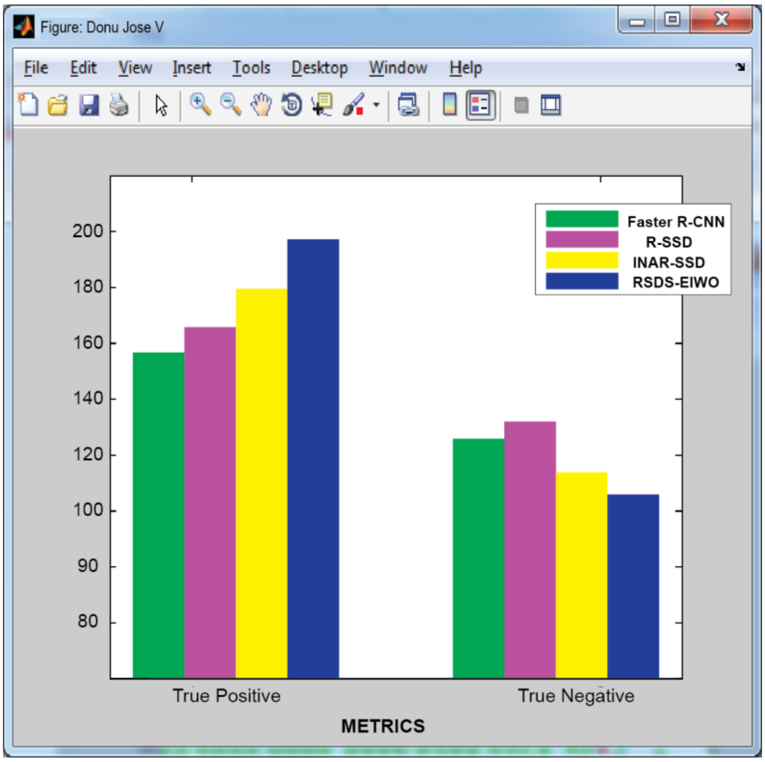

Figure 7: True Positive and True Negative Analysis

that RSDS-EIWO outperforms other detection methods. The reality that RSDS-EIWO is exclusively based on the prediction of apple leaf disease, even if prediction and accuracy levels may vary in other plant leaves like guava, vegetable leaves, and so forth, is one of its drawbacks. The algorithm may be enhanced in the future to detect leaf disease more reliably and accurately in all kinds of plants in real-time, which would benefit both computer science stream and agriculture.

References

[1]. Jeong J, Park H, and Kwak N. Enhancement of SSD by concatenating feature maps for object detection. 2018, *Arxiv Online,* 01(05), 01-20.

[2]. Ren, S., He, K., Girshick, R., & Sun, J. Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2018, 39(6), 1137–1149.

[3]. Jiang P, Chen Y, Liu B, He D and Liang C. Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks, *IEEE Access,* 2019, 7, 59069-59080.

[4]. Eldho K J. (2022) Impact of Unbalanced Classification on the Performance of Software Defect Prediction Models. *Indian Journal of Science and Technology*. 15(6), 237-242.

[5]. Donu V Jose, Santhi K. (2022) Early Detection and Classification of Apple Leaf Diseases by utilizing IFPA Genetic Algorithm with MC-SVM, SVI and Deep Learning Methods. *Indian Journal of Science and Technology*. 15(29), 1440-1450.

[6]. Nithyanandh S and Jaiganesh V. Reconnaissance Artificial Bee Colony Routing Protocol to Detect Dynamic Link Failure In Wireless Sensor Network, *International Journal of Scientific & Technology Research,* 2019, 8(10), 3244-3251.

[7]. K. P. Ferentinos. (2018) Deep Learning Models for Plant Disease Detection and Diagnosis, *Computers and Electronics in Agriculture*. 145, 311-318.

[8]. Howard, A., Sandler, M., Chen, B., Wang, W., Chen, L., Tan, M., et al. (2019). Searching for MobileNetV3. *IEEE Conference,* 1314–1324

[9]. Dutot, M., Nelson, L., and Tyson, R. (2013). Predicting the Spread of Postharvest Disease in Stored Fruit, With Application to Apples. *Postharvest Biology and Technology.* 85(1), 45–56.

[10]. Chao, X., Sun, G., Zhao, H., Li, M., and He, D. (2020). Identification of apple tree leaf diseases based on deep learning models. *Symmetry,* 12(2), 1065-1079.

[11]. Karthik, R., Hariharan, M., Anand, S., Mathikshara, P., Johnson, A., and Menaka, R. (2020). Attention Embedded Residual CNN for Disease Detection in Tomato Leaves. *Applied Soft Computing,* 86, 105933.

[12]. Nithyanandh S and Jaiganesh V. Dynamic Link Failure Detection using Robust Virus Swarm Routing Protocol in Wireless Sensor Network, *International Journal of Recent Technology and Engineering,* 2019, 8(2), 1574-1578.

[13]. I. M. Nasir, A. Bibi, J. H. Shah, M. A. Khan, M. Sharif, K. Iqbal, (2021). Deep learning-based classification of fruit diseases: An application for precision agriculture. *CMC-Computers Materials & Continuation*, 66(2), 1949-1962.

[14]. K.Nagasubramanian, S. Jones, A.K. Singh, S. Sarkar, A. Singh and B. Ganapathysubramanian (2019). Plant disease identification using explainable 3D deep learning on hyper spectral images, *Plant Methods*, 15(98).

[15]. J.S.H. Albayati and B.B. Ustundag (2020). Evolutionary Feature Optimization for Plant Leaf Disease Detection by Deep Neural Networks, *International Journal of Computational Intelligence Systems*, 13, 12-23.

[16]. Sinwar. D, DhakaV.S, Sharma M.K and Rani G (2020). AI-based yield prediction and smart irrigation. *Internet of Things and Analytics for Agriculture*, 2(67), 155-180.

[17]. Khan MA, Akram T, Sharif M, Awais M, Javed K, Ali H (2018). CCDF: Automatic system for segmentation and recognition of fruit crops diseases based on correlation coefficient and deep CNN features. *Computers and Electronics in Agriculture*, 155(2), 20-36.

[18]. Zhang C, Zhang S, Yang J, Shi Y, Chen J (2017). Apple leaf disease identification using genetic algorithm and correlation based feature selection method. *International Journal of Agricultural and Biological Engineering*. 10(2), 16-29.

[19]. Gargade A, and Khandekar S.A. A Review: Custard Apple Leaf Parameter Analysis and Leaf Disease Detection using Digital Image Processing. 2019*, International Conference on Computing Methodologies and Communication (ICCMC),* 267–271.

[20]. Zahid Iqbal, Muhammad Attique Khan, Muhammad Sharif, Jamal Hussain Shah, Muhammad Habibur Rehman and Kashif Javed. An automated detection and classification of citrus plant diseases using image processing techniques: A review, *Computers and Electronics in Agriculture*, 2018, 153, 12-32.