INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

RESEARCH ARTICLE

Early Detection and Classification of Apple Leaf Diseases by utilizing IFPA Genetic Algorithm with MC-SVM, SVI and Deep Learning Methods

Donu Jose V[1]*, **K Santhi**[2]

1 Research Scholar, Department of Computer Science, Dr.N.G.P Arts and Science College, Coimbatore, 641048, Tamilnadu, India
2 Professor, Department of Information Technology, Dr.N.G.P Arts and Science College, Coimbatore, 641048, Tamilnadu, India

OPEN ACCESS

Received: 12-06-2022
Accepted: 22-06-2022
Published: 28-07-2022

Citation: Jose V D, 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. https://doi.org/10.17485/IJST/v15i29.1235

* **Corresponding author**.

donuscholar@gmail.com

Funding: None

Competing Interests: None

Published By Indian Society for Education and Environment (iSee)

ISSN
Print: 0974-6846
Electronic: 0974-5645

Abstract

Objectives: To propose a new model for early detection and classification of apple leaf diseases by means of genetic algorithms and advanced deep learning methods in order to minimize plant degradation and maximize detection accuracy. **Methods:** A feature selection and extraction task is carried out by using an Improvised Flower Pollination Technique (IFPA) based genetic algorithm. Deep learning techniques such as Multi Class Support Vector Machine (MC-SVM) and Spectral Vegetation Indices (SVI) are used to classify and detect disease. The Region Growing Algorithm (RGA) and the Stochastic Gradient Descent Method (SGDM) are used to detect leaf colour segments and identify the disease at an early stage based on shape, texture, and colour features. IFPA-GA with MC-SVM and SVI extracts the features from the apple leaf dataset (collected from the Apple Experiment Station of Northwest A&F University, China) and then selects the appropriate function to perform classification and detection of disease at early occurrence and to improve the accuracy level. To demonstrate the efficiency of the proposed algorithm, MATLAB is used for implementation. The performance results are evaluated and compared to the existing models such as Faster R-CNN, R-SSD, and INAR-SSD. **Findings:** Early disease detection and classification of leaf diseases are achieved with 94.09% accuracy level, 93.07% Speed, 94.01% sensitivity, 93.38% specificity, 95.01% precision, 93.17% recall, 190 True Positive, 110 True Negative, and 92.07% F-Score to detect the disease and classify it in an optimized manner, which is high compared to the existing versions. **Novelty:** According to the findings of the comprehensive study, the proposed detection and classification method IFPA-GA with SVM-SVI outperforms Faster R-CNN, R-SSD, and INAR-SSD in terms of accuracy and speed of apple leaf disease detection at an early occurrence by classifying it in a robust manner.

Keywords: Apple Leaf Disease Detection; SVM; Genetic Algorithm; Deep Learning; Image Processing

1 Introduction

One of the key factors affecting productivity and quality is apple leaf diseases. Early detection and diagnosis are difficult to make with traditional methods. As image recognition is the latest research in the computer field, here the key task is taken to identify the diseased leaf in the real time scenario. In order to detect diseased apple leaves early in terms of real-time image capture, colour spotting, object identification, and classification for accurate diagnosis, the Nature Inspired Genetic Algorithm is utilized combined with advanced deep learning techniques called Multi Class Support Vector Machine and Spectral Vegetation Indices to overcome the traditional approaches. Although several methods have been developed to find plant leaf diseases, real-time accuracy has not increased. The researchers use conventional deep learning techniques to increase item identification accuracy in a real-time setting, but the results are not very impressive. Early diagnosis of plant leaf diseases is based only on visual observation and is risk and disease spotting time dependent. Advanced genetic algorithms and deep learning techniques have been researched to find a revolutionary approach to recognize the disease at its early onset, which assists farmers to diagnose the disease at the proper moment in order to maximize productivity. To distinguish between healthy and contaminated pixels, a 3D deep learning model on hyperspectral pictures using DCNN is used. However, the spotting of leaf disease is not done to a high degree and the outside and interior lesions are not performed with high precision, which results in pixel breakage[(1)]· Deep analysis is made in the era of machine learning to investigate the plant leaf disease detection and improvisation of accuracy level with the help of DL architectures and FMTT is utilized for the feature mining for dynamic prediction of the leaf disease and to eradicate the noise from images during the optimistic phases[(2)]· Image based detection using a classical approach is done by the researchers using CNN and SSD where the colour segmentation and classification are not demonstrated clearly in order to identify the leaf colors deeply to detect the disease[(3)]· DL models are employed for plant leaf disease detection and diagnosis where the tailor-made classification method is performed in real time. That leads to improvisation in accuracy compared to the traditional methods[(4)]·Image segmentation and the super pixel cluster method are employed to increase the convergence speed of plant leaf disease detection, but due to practical value and the bi-class pixel cut method, the absolute spotting is not matched[(5)]·The authors used image localization and classification techniques to reduce the amount of monitoring work in big farms of crops, and the result was achieved by disease symptom detection with an accuracy of 70% only[(6)]· An Android-based app is developed by using deep learning methods to detect plant leaf disease in real time by taking a photograph and checking if the leaf is sick or not, but the method fails to detect sickness at an early stage to stop the degradation of plants. CNN is also used for classification and segmentation[(7)]·The author applies deep neural multi-scale DCN to the disease analysis of 50,000 image sets with the help of automated feature extraction and classification with subsector machines. The suggested technique was tested and found to have more than 80% sensitivity and specificity and also Citrus plant disease detection was done automatically with the help of IM technique by employing an advanced classification method where the results show an accuracy level of up to 85% with few limitations and issues uncovered in order to detect at an initial stage[(8)]·Smart Framing with Deep Learning is used to identify plant diseases with discrete dynamics, and this method covers all anomalies in terms of extraction, segmentation, and deep scanning process. Also, the STFP technique is used to obtain disease information both in modular and in real-time areas[(9)]·3 Channel CNN is employed with the help of ML techniques to identify the vegetable leaf disease and diagnose it at an early occurrence, and the author explains how frequently the disease spreads in the leaves and how to control it. This results in the detection accuracy rate of up to 87% and the Fscore value reached up to 76% with certain limitations as it cannot be done in the real time agriculture labs[(10,11)]. LTSMB CNN is used to perform disease detection in apple leaves with a deployment model where the system automatically inherits the image segments and bifurcates them into different levels to identify the disease parts. But the limitation is that it cannot be used in different scenarios like climatic change, wet leaves etc. ML and DL comparison is done for effective detection techniques with few drawbacks and limitations[(12,13)]. PD2SEN, an automatic computer-assisted leaf disease diagnosis system, is identified and the system estimates the plant life based on the severity and infection and CA Leaf parameter analysis was done using digital image processing and the same was implemented in the real-time crop results with an accuracy level of 86% in terms of detection rate[(14)]. The Virus Particle Swarm algorithm is used for failure detection in CNN and the same is achieved in leaf detection with the random walk method with a failure rate of 14%. During the implementation in the extension farming, it helps with productivity and immediate diagnosis[(15,16)]. Several researchers proposed novel methods for early detection of plant disease symptoms using advanced deep and modern machine learning techniques to maximize accuracy and to minimizing disease detection error rates[(17,18)]. A mobile net-based detection technique is identified to capture the image and identify the infected part in a random classical way, and the CADRN method is jointly used by the authors where it helps to scan the images deeper and faster, helping to improve the accuracy level. Deep learning with particle swarm combinational methods has been employed to meet the objectives and resulted in detection by using colour combinations of apple leaves[(19)]· Enhancement of R-SSD is utilised for deep object detection in plant leaves by using different classifiers and results in a good accuracy level by replacing VGGNet1.0 and ResNet1.0 to increase the early occurrence detection with few limitations like optimizing image recognition, deep sensing, etc[(20)]· Faster R-CNN is used for real time object detection where sensing of images with deep scanning technique is optimally achieved to spot the colour difference, pattern analysis to improvise the accuracy. Few drawbacks and limitations are noticed during the pixel minute detection where it was not achieved(21). INAR-SSD is used to detect discriminant features in plant leaves automatically and detect disease at an early stage by combining algorithms such as rainbow concatenation and single- and multi-scale object detection methods(22). The author discusses imbalanced classification models in software defect prediction, where the object detection and accuracy levels are thoroughly tested without any flaws(23). Some of the methods comply to detect the apple leaf diseases in early stage is tested and it is mentioned below.

Leaf Object and Colour Segmentation: For the set of images of infected leaves, the algorithm senses a series of objects. The final observed difference in colour spotting gives the results whether the leaf is infected or not.

Image Analysis and Optimization: Optimize the images with fusion angles and boundaries and follow deep sensing and scanning methods for faster detection and identification of multi-scale disease spots.

Prediction of Leaf disease at early stage : After image noise removal, it should be able to forecast and perform at disease and non-disease accuracy levels.

To resolve the above said drawbacks and set out a dynamic object disease model, numerous techniques are employed and implemented. All the researchers focused only on disease prediction rather than obtaining the solution to the real time problem of detecting the apple leaves diseases at early stage by improvising accuracy levels of prediction. The aim of this work is to create a novel machine learning and deep learning model to i)detect the object with high accuracy (ii) early occurrence ofapple leaf diseaseand prediction for diagnosis (iii) maximize the prediction accuracy level by employing the IFPA-GA with SVM-SVI ML techniques iv) to identify the variations between the infected and non infected leaves.

2 Proposed Methodology

The efficient detection of apple leaf disease at an early stage minimizes plant degradation, leads to the maximization of productivity and impacts the agriculture economy. The proposed approach intends to extract and categorize the images of the diseased apple leaves and determine the disease type at an early stage for diagnosis. Disease detection is accomplished and the type of disease is categorized based on the object detection. This strategy chooses five prevalent apple leaf diseases, which is necessary for testing and implementation. The five classifications are Alternaria Leaf Spot, Brown Spot, Mosaic Spot, Grey Spot, and Rust Spot. For the objectives of extraction, categorization, annotation, colour segment identification, etc., deep learning techniques are used. Deep learning methods are employed for the purposes of extraction, classification, annotation, colour segment identification, etc. An IFPA genetic algorithm is used to identify the disease at an early stage for quick diagnosis and to reduce spread to the entire plant. Combinational methods and algorithms are also used to capture the deep sensing in the infected leaf images with high accuracy. Here, the training dataset and testing datasets are used for performance measures. Let'sassume that $F1$ *and* $F2$ are the two datasets denotes infected and non-infected leaf sets. Once the leaf sets are detected automatically the process begins with extracting and classifying the types of images andby eliminating the duplications and gives the output sets$O1$ *and* $O2$ along with the deep sensing marked pattern value TP and TN, the values are derived by the below equation,

$$O1 = F_1 + \sum_{i-max(n)}^{i(infected)} \left(S1\ Trace\ value = n - \frac{TPR\ (True\ Positive\ Rate)}{O2\ (Derived\ Sets)} \right), max\ (TPR) \tag{1}$$

where, TP is True Positive rate, i determines the infected leaf images sensed throughout the process. Resizing images based on pixel detection, noise removal, masking pixels, improve the sensing speed are the important optimizing parameters used to increase the level of accuracy with respect to disease detection in the apple leaves.

2.1 Data attainment and acquisition

The apple leaf image datasets for preprocessing are fully extracted from the Apple Leaf Disease Data Sets (collected by the Apple Experiment Station of Northwest A&F University, China). The dataset consists of 26,377 images with five classifications of disease leaves, which are mentioned above. The main focus of this algorithm is to identify the pattern of disease where the disease varies from season to season due to environmental factors such as humidity, rainy season, bad weather, illuminance, etc. All the images are collected under different climatic conditions to test and implement the algorithm. The images are selected and labeled with the respective classes of diseases. The five different classes of diseases that infected the apple leaves are given below. The images that are trained and tested are shown.

The data distribution fully matches the tested data and the training data, which is collected from the apple leaf datasets. SVM-SVI is utilised to test the data at all the levels before masking. Some of the steps involved in feature extraction and classification

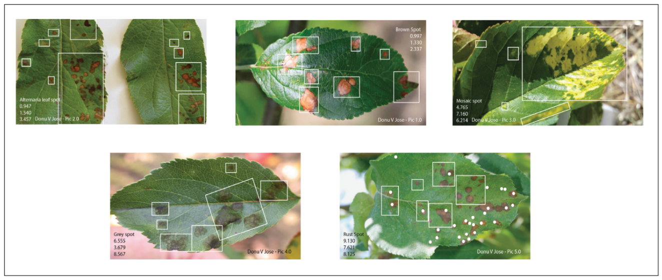

Fig 1. Five Types of Common Apple Leaf Diseases (Alternia Spot, Brown Spot, Mosaic Spot,Grey Spot and Rust Spot)

which includes,

- Data collection from apple leaf datasets to evaluate and test the accuracy level
- Data preprocessing for noise removal, filtering and segmentation
- Annotation and Augmentation is done to overcome over fitting issues at training stage
- Feature extraction is done with IFPA-GA pollination method
- Deep sensing and object detection for all trained data is done using MC-SVM
- Image disease patterns are identified and sent to system for early detection
- Detection of accuracy level and compared with tested data to measure the level

Image processing techniques were applied during the initial stage to bifurcate disease leaves and spot images. Segmentation and filtering were done at all scanning and object detection levels by using the below equation. The system automatically sets up the detection points where the colour difference is measured to detect the infected and diseased leaves. The colour measure is identified by using the below equation,

$$FColour\ (F1) = RGB\ (HSI) + \sum_{i=(n-1)}^{RGB} \left(HSI =\ a_n binom \frac{Colour\ Level}{Leaves\ Scanned} \right) \tag{2}$$

where, $FColour$represents thedifferent colors in diseased leaves and False rate of the prediction level. $a_n binom$ term represents the random colour components such as RGB, HIS, and CMYK for each execution.

2.2 IFPA-GA Genetic Algorithm for feature extraction

Nature's inspiration, the Flower Pollination Genetic Algorithm, is a population-based approach that begins with a collection of indiscriminate solutions. IFPA-GA with MC-SVM and SVI collects features from an apple leaf dataset (from the Apple Experiment Station of Northwest A&F University in China) and then selects the optimal function to perform disease classification and detection at an early stage and improve accuracy. Global Image Search Method (Biotic) is followed to identify the spot which is affected in plant leaf. Local Image Search Method (Abiotic) is followed to detect the disease spot which is affected in leaf. Pollinators such as Insects, Butterflies etc. are used and their moves will identify the disease spot in apple leaves. Here Insects are the pollinators used in IFPA-GA with SVM, SVI. Here, Pollen may travel a considerable distance since pollinators move and even fly at different rates and distances. This type of pollination is sometimes referred to as global pollination. Here the insects normally travel in the apple leaves at the non-infected areas where the non-travelled areas are calculated as disease spot area in the plant leaves.

The steps involved in IFPA-GA described as follows,

- Initialize the Population (Insects)
- Insects Pollination involves both biotic and Abiotic process
- During the pollination, the insects will not travel in the disease spot area up to 95%
- Spotting the area where the insects not travelled
- Find the Best Solution in the Initial Population
- Evaluate the new best solution by using Local and Global pollination method by switching the method randomly
- Update the new solution
- Find the new spots and solutions
- Repeat the steps with n number of iterations
- Select the best optimum level of accuracy

The insect travel measures are calculated by deriving the following equation,

$$Npop^{i+1} = Pollination\left(H^{best+h}, \eta\right) \; - \left(q^{i+1}.H^{insects+h} + q^{i-2}\,x\,Npop^{i+1}\right) \tag{3}$$

where, $Npop^{i+1}$ denotes insects travelled spots are selected for distance calculation and the optimum level is reached to classify the spots and diseases for the next process. In this research work, the upgraded IFPA-GA with mutation pool is recommended for selecting the most practicable and compact function subset. The conditional shared knowledge measure is used to find function subsets. After convergence, each dataset is input into a stochastic search-based feature selection algorithm, which generates a subset of features that are examined before the non-dominated feature subset is picked. In IFPA-GA several techniques are employed for data augmentation includes image rotation transformations, horizontal and vertical changes, intensity adjustments, brightness, sharpness and contrast. A GNP Gaussian Noise Process operation is also applied for better object detection in leaves.

Improvised Flower Algorithm IFPA -GA with SVM-SVI

1. Input: Initialize the datasets
2. Objective min f (x) and f (n)
3. Initialize a population of n insects /pollen with random solutions for iterations
4. Find the best solution b* in the insect population and pollination
5. Calculate all f (x) and f(n)for randomsolution
6. Object detection time t=0
7. while t $\leq$MaxGeneration do
8. for i= 1to n do
9. if t$\leq$ then
10. Global search method (Biotic)b(search) is implemented for b*
11. else
12. Local search method (Abiotic)a(search) is implemented for b*
13. 14: Randomly choose a and bamong all iterative solutions
14. Do repeat global and local pollination via gt+1 15. end if
16. Calculate all new f (gt+1) by applying RGA and SGDM
17. if f (gt+1) $\leq$f (gt) then
18. gt= gt+1
19. end if
20. end for
21. Find the new best solution g* among all gt
22. Repeat the steps
23. Find the maximum accuracy level
24. end while

2.3 MC-SVM and SVI Machine Learning for Classification of apple leaves

The Multi Class-Support Vector Machine, or MC-SVM, is used to classify and separate image points (data points) found in areas where pollinated insects have not traveled. Two search methods are combined and use the same strategy to identify the solution. The one-versus-all method using the winner-takes-all strategy and the one-versus-one method implemented by max-wins voting is popularly used for this purpose. SVI is used in IFPA-GA in terms of sensing the deep points in the images and providing an approximate measure as an output. This method is used for early prediction where it points out the complete apple leaves in a robust manner. Optimum image classification is done using the SVM technique to experiment with the deep sensing of images extracted from the datasets. Multiclass SVM uses SVM to assign labels to samples, with the labels derived from a finite collection of multiple items (augmented apple leaves). The most common method is to divide the single multiclass problem into numerous binary classifications where MC minimizes the error rate and maximizes the accuracy levels.

2.4 RGA and SGDM for colour segmentation

RGA is used as a combinational algorithm along with IFPA-GA SVM-SVI to set the threshold value and to identify the deep pixel region where the disease occurs. The Stochastic Gradient Descent Method (SGDM) is used to detect leaf colour segments and identify the disease at an early stage based on shape, texture, and colour features. The RGB and HSI models are used to derive the colour characteristic of apple leaf disease spot. During the insect pollination, the colour of the leaf is also spotted where the insect will not travel in the decomposed area. In that case the maximum infected spots are identified in apple leaves with the minimum time by deriving the below equation,

$Minimum^{t} = 1 - (1 - (\mathrm{TP}))\, N^{time\ and\ speed}(\mathrm{nj}/\ TP^{speed}\, x \frac{R^{closest*h-1}}{Total\ Infections} R^{ij}$ (4)

where, TP is true positive value, and the speed of object detection is calculated $N^{time\ and\ speed}$. Total infected areas in the apple leaf are identified by RGA and time is measured for full detection.

2.5 Early Prediction of apple leaf disease with Deep Search and Spotting Method in Pollination

After the feature extraction, classification, and accuracy detection, the deep sensing object detection is applied in real time to test the captured images in real time and measure the performance whether the pollination works or not in terms of detecting the disease at an early stage. The functional and non-functional object detection is done with the help of SGDM where the pixel levels are fixed prior to deep scanning. The frequency S-Level is denoted by the below equation. SGDM measures the grey spot levels in a robust manner at the insect pollination travel distance. Selecting the finite solutions for crossover mutation using the cross function randomly based on insect pollination and the mutation process allows us to create new solutions by performing different iterations. The frequency level of mutation is derived by using the equation,

$IP1 - Level^{frequency} = \sum_{i=0}^{p-i\,(insect)} (G2)\, n^{k} l^{n-1} + AM - minimize(\,Xi))$ (5)

The frequency level is chosen and the object is ready for deep scanning to ensure that all the preprocessing stages are completed. However, the states of IP1 and AM are calculated in the process of deep search with biotic and abiotic processes.

2.6 Disease Level Classification and Identification of Disease

The colour segmentation approach, which employs RGA and SGDM, is used to classify illnesses. The pollinator notices the colour difference and stops travelling. The disease stages and subtypes are determined in this case. All five diseases are identified as Class 1 and Class 2 sets for further extraction, and the findings are used to assess performance.

The following are the different states of performance and accuracy:

- G_1 - G_n state - to detect the disease at early stage
- Eliminate the duplicate values
- Derive the colour segments in apple leaves for early prediction
- Choose the correct level for diagnosis
- Measure the performance and accuracy levels

3 About Implementation Process in MATLABR2020a Tool

The Matlab R2020a research analysis tool, one of the most popular tools for analyzing image datasets integrating machine learning and deep learning techniques, is used to compare the proposed novel research work with the IFPA-GA technique to baseline versions. In terms of image processing, data mining, and convolutional neural networks, MATLAB has high user-friendliness and is employed in a variety of supporting IT and engineering applications, medical centres, and research fields. Matlab was designed to provide a wide number of integrated and built-in math functions for handling scientific problems in general. The majority of the time, Matlab is utilised to tackle iteration-based challenges since the results are accurate.

4 Performance Analysis Measures

The following are the performance analysis measures that are used in this paper to compare the performance of the proposed algorithm IFPA-GA with SVM-SVI to the existing methods R-SSD [25], Faster R-CNN [26] and INAR-SSD [27] in terms of detecting apple leaf disease. These were chosen as the baseline techniques for implementation.

- **Accuracy**-Measures the amount of accuracy in identifying plots at the highest level in order to diagnose the disease in apple leaves
- **Detection Speed**- Calculates the dataset's object detection speed and time for better performance
- **Sensitivity and Specificity** - It is a statistical method of comparing finite samples between TP and FN and TN and FP
- **Precision and Recall** - Recall the measurements of acceptable finite examples using a continuous determination analysis ratio of the provided datasets or samples
- **F-Score Analysis** - Used to classify datasets as positive or negative by eliminating noise and determining the level of accuracy
- **True Positive Rate and True Negative** - Accuracy classification in tested samples or in the given datasets

5 Results and Discussions

This section illustrates the implementation results obtained by the novel algorithm IPFA-GA with SVM-SVI against R-SSD [20],Faster R-CNN [21]and INAR-SSD [22].The proposed IPFA-GA with SVM-SVI outperforms the baseline versions in terms of object detection with deep sensing, early prediction of leaf disease, feature extraction, prediction accuracy evaluation, and easy identification of infected and noninfected leaves. Figures 6 to 11 indicate the X axis plotted with performance efficiency metrics and the Y axis plotted with final output values.

5.1 Accuracy in Detection Analysis

Figure 2 clearly showcased the performance analysis of the accuracy level of detecting apple plant leaf disease at an early stage of the proposed IPFA-GA with SVM-SVI against R-SSD [20], Faster R-CNN [21] and INAR-SSD [22]. As IFPA-GA utilized both the biotic and abiotic search methods with the deep scanning object detection method, it resulted in high accuracy in identifying the infected leaves at an early occurrence in all climatic conditions. Also, the accuracy level was met up to 94%, outperforming the baseline versions.

Table 1. Detection Accuracy Performance Values

Metrics / Schemes	R-SSD [20]	Faster R-CNN [21]	INAR-SSD [22]	IFPA-GA with SVM-SVI
Accuracy IT-1	81.02	79.01	85.07	94.01
Accuracy IT-N	82.05	76.01	87.04	94.09

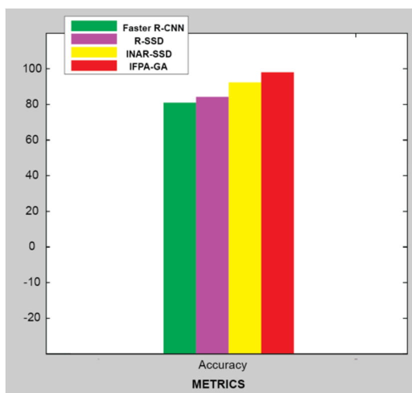

Fig 2. Accuracy Analysis

5.2 Detection Speed Analysis

Figure 3 compares and analyses the plant leaf disease detection speed and time of IPFA-GA with SVM-SVI against R-SSD [20], Faster R-CNN [21] and INAR-SSD [22]. It is observed that IPFA-GA with SVM-SVI gives significant performance with enhanced results. The process of pollination and insect travel speed is measured in the proposed method to increase the detection speed and the outcome is achieved. Due to perfect object detection and classification, the proposed algorithm works well in terms of predicting the disease at an early stage.

Table 2. Detection Speed and Time Analysis Performance Values

Metrics / Schemes	R-SSD[20]	Faster R-CNN[21]	INAR-SSD[22]	IFPA-GA with SVM-SVI
Speed	71.02	62.03	79.14	93.07
Time (in seconds)	79	98	76	51

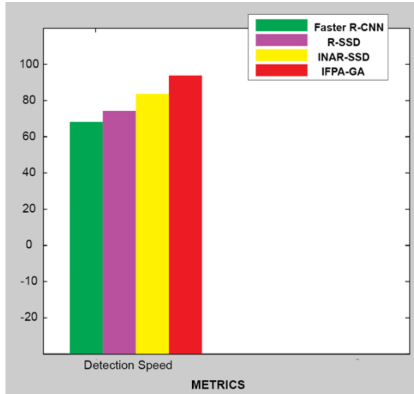

Fig 3. Detection Speed Analysis

5.3 Sensitivity and Specificity Analysis

Figure 4 portrayed the sensitivity and specificity performance analysis of IPFA-GA with SVM-SVI against R-SSD, Faster R-CNN and INAR-SSD. It is noted that IPFA-GA with SVM-SVI gives outstanding performance with enhanced results. The procedure of selecting the appropriate functions to perform classification and detection of disease is done by spotting the colour difference in leaves with the help of deep sensing and object scanning method. Due to considerable classification and data extraction, the proposed DL method works well in terms of differentiating the infected and non-infected leaves.

Table 3. Sensitivity and Specificity Performance Values

Metrics / Schemes	R-SSD[20]	Faster R-CNN[21]	INAR-SSD[22]	IFPA-GA with SVM-SVI
Sensitivity	82.08	80.07	83.64	94.01
Specificity	80.17	79.13	83.76	93.38

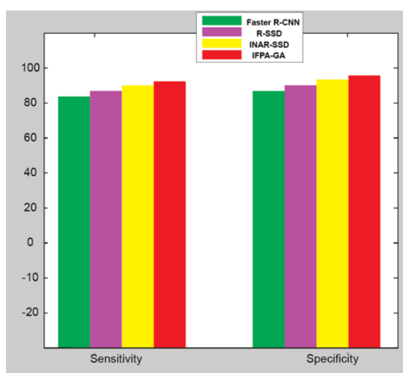

Fig 4. Sensitivity and Specificity Analysis

5.4 Precision and Recall Analysis

The analysis of precision and recall of the proposed IPFA-GA with SVM-SVI against R-SSD [20], Faster R-CNN [21] and INAR-SSD [22] is shown in Figure 5. The novel IPFA-GA with SVM-SVI delivers the expected output in terms of data processing and classification using combinational algorithms and outperforms the existing methods. Due to its local and global search method adoption, the speed and time are improvised and the overall performance is increased.

Table 4. Precision and Recall Performance Values

Metrics / Schemes	R-SSD [20]	Faster R-CNN [21]	INAR-SSD [22]	IFPA-GA with SVM-SVI
Precision	87.03	84.08	90.01	95.01
Recall	83.08	80.02	89.07	93.17

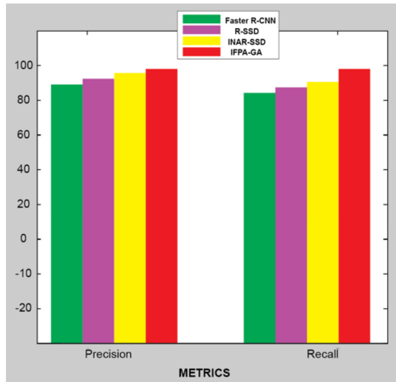

Fig 5. Precision and Recall Analysis

5.5 F-Score Analysis

Figure 6 reveals the detailed analysis of True Positive and True Negative of the proposed IPFA-GA with SVM-SVI against R-SSD [20], Faster R-CNN [21] and INAR-SSD [22]. On the chosen images in the datasets, the IPFA-GA with SVM-SVI outperforms the existing algorithms. The novel method performs well in prediction and optimization of images by removing the noise due to its efficient object detection model and does with outstanding extraction and classification. Even for large number of iterations, the performance and accuracy level is good compared to the existing methods.

Table 5. Performance Values F-Score Analysis

Metrics / Schemes	R-SSD [20]	Faster R-CNN [21]	INAR-SSD [22]	IFPA-GA with SVM-SVI
F-Score (It 1)	81.02	79.08	88.08	92.07
F-Score (It N)	80.01	77.11	87.04	91.09

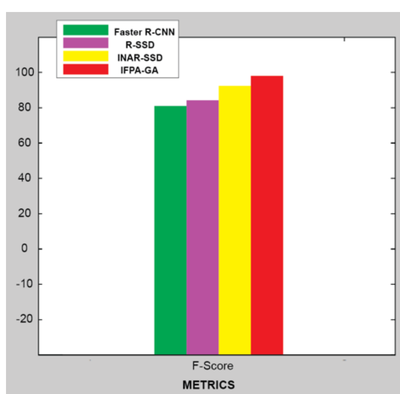

Fig 6. F-Score Analysis

5.6 True Positive and True Negative Rate Performance Analysis

Figure 7 clearly shows the performance analysis of True Positive and True Negative of the novel method IPFA-GA with SVM-SVI against R-SSD [20], Faster R-CNN [21] and INAR-SSD [22]. The IFPA-GA with SVM-SVI performs better than the existing algorithms on the selected datasets. With the help of RGA and SGDM, the phenomenal search method and colour segmentation detection are done to increase the performance measures. The TP and TN show that the accuracy level is improvised in IFPA-GA with SVM-SVI.

Table 6. Performance Values of TP and TN Analysis

Metrics / Schemes	R-SSD [20]	Faster R-CNN [21]	INAR-SSD [22]	IFPA-GA with SVM-SVI
True Positive	169	150	180	190
True Negative	140	130	120	110

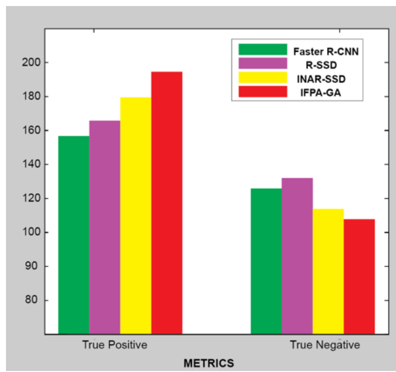

Fig 7. True Positive and True Negative Analysis

6 Conclusion

This paper proposes the IFPA-GA with SVM-SVI deep learning algorithm for object detection and apple leaf disease detection to detect the disease early and increase the level of accuracy up to 94.09% with a detection speed of 93.07% in 51 seconds, where the existing algorithms reach only up to 87% with a speed of 79.14 with a speed of 76 seconds. For testing and implementation, IFPA-GA with SVM-SVI uses an apple leaf dataset collected from the Apple Experiment Station of Northwest A&F University, China for testing and implementation. A Flower Pollination Genetic algorithm (GA) is used to select the set of feature values, and Spectral Vegetation Indices (SVI) are used to separate the image points where the disease is detected. RGA is also used as a combinational algorithm to set the threshold value and to identify the deep pixel region where the disease occurs. The Stochastic Gradient Descent Method (SGDM) is used to detect leaf colour segments and identify the disease at an early stage based on shape, texture, and colour features. The trained and test data extracted are compared to the available datasets to check the detection level with a large number of iterations. The results show that the IFPA-GA with SVM-SVI is superior to the other detection models. A few limitations in IFPA-GA with SVM-SVI are that it is only based on apple leaf disease prediction, though prediction and accuracy levels may differ in various plant leaves such as guava, vegetable leaves, and so on. The algorithm may be improved in the future to identify leaf disease in real time in all types of plants with greater stability and accuracy to contribute to the fields of computer science and agriculture.

References

1) Nagasubramanian K, Jones S, Singh AK, Sarkar S, Singh AK, Ganapathysubramanian B. Plant disease identification using explainable 3D deep learning on hyperspectral images. *Plant Methods*. 2019;15(1). Available from: https://doi.org/10.1186/s13007-019-0479-8.
2) Hasan RI, M YS, L A. Review of the state of the art of deep learning for plant diseases: a broad analysis and discussion, Plants. *Plants*;2020:1302–1302. Available from: https://doi.org/10.3390/plants910130233019765.
3) Khan KRU, Khan W, Albattah AM, Qamar F, Ullah. Image-Based Detection of Plant Diseases: From Classical Machine Learning to Deep Learning Journey. *Wireless Communication and Mobile Computing*;2021:1–15. Available from: https://doi.org/10.1155/2021/5541859.

4) Khan AI, Quadri S, Banday S, Shah JL. Deep diagnosis: A real-time apple leaf disease detection system based on deep learning. *Computers and Electronics in Agriculture*. 2022;198:1–15. Available from: https://doi.org/10.1016/j.compag.2022.107093.
5) Zhang S, You Z, Wu X. Plant disease leaf image segmentation based on superpixel clustering and EM algorithm. *Neural Computing and Applications*. 2019;31(S2):1225–1232. Available from: https://doi.org/10.1007/s00521-017-3067-8.
6) Kurmi VY, Gangwar S. A leaf image localization based algorithm for different crops disease classification. *Information Processing in Agriculture*;p. 1–23. Available from: https://doi.org/10.1016/j.inpa.2021.03.001.
7) Soyer MS, Yilmaz C, Ozcan IM, Cogen F, Yildiz TC. LeafLife: Deep Learning Based Plant Disease Detection Application. *2021 13th International Conference on Electrical and Electronics Engineering (ELECO)*. 2021;2021:1–10. Available from: https://doi.org/10.23919/ELECO54474.2021.9677785.
8) Yunong T, En L, Zize L, Min T, Xiongkui H. Diagnosis of Typical Apple Diseases: A Deep Learning Method Based on Multi-Scale Dense Classification Network. *Frontiers in Plant Science*. 2021;12:1–21. Available from: https://doi.org/10.3389/fpls.2021.6984742020.
9) Guo Y, Zhang J, Yin C, Hu X, Zou Y, Xue Z, et al. Plant Disease Identification Based on Deep Learning Algorithm in Smart Farming. *Discrete Dynamics in Nature and Society*. 2020;2020:1–11. Available from: https://doi.org/10.1155/2020/2479172.
10) Zhang S, Huang W, Zhang C. Three-channel convolutional neural networks for vegetable leaf disease recognition. *Cognitive Systems Research*. 2019;53:31–41. Available from: https://doi.org/10.1016/j.cogsys.2018.04.006.
11) Turkoglu M, Hanbay D, Sengur A. Multi-model LSTM-based convolutional neural networks for detection of apple diseases and pests. *Journal of Ambient Intelligence and Humanized Computing*. 2022;13(7):3335–3345. Available from: https://doi.org/10.1007/s12652-019-01591-w.
12) Sujatha R, Chatterjee JM, Jhanjhi NZ, Brohi SN. Performance of deep learning vs machine learning in plant leaf disease detection. *Microprocessors and Microsystems*. 2021;80:103615–103615. Available from: https://doi.org/10.1016/j.micpro.2020.103615.
13) Liang Q, Xiang S, Hu Y, Coppola G, Zhang D, Pd2se-Net SW. Computer-assisted plant disease diagnosis and severity estimation network. *Computers and Electronics in Agriculture*. 2019;157:518–529. Available from: https://doi.org/10.1016/j.compag.2019.01.034.
14) Gargade A, Khandekar SA. A Review: Custard Apple Leaf Parameter Analysis and Leaf Disease Detection using Digital Image Processing. *2019 3rd International Conference on Computing Methodologies and Communication (ICCMC)*. 2019;p. 267–271. Available from: https://doi.org/10.1109/ICCMC.2019.8819867.
15) Nithyanandh S, 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. Available from: https://doi.org/10.35940/ijrte.b2271.078219.
16) Duralija B, Putnik P, Brdar D, Markovinović AB, Zavadlav S, Pateiro M, et al. The Perspective of Croatian Old Apple Cultivars in Extensive Farming for the Production of Functional Foods. *Foods*. 2021;10(4):708–708. Available from: https://doi.org/10.3390/foods10040708.
17) Machine Learning for Plant Leaf Disease Detection and Classification - A Review. *2019 International Conference on Communication and Signal Processing (ICCSP)*. 2019;p. 538–542. Available from: https://doi.org/10.1109/ICCSP.2019.8698004.
18) Kour VP, Arora S. Particle Swarm Optimization Based Support Vector Machine (P-SVM) for the Segmentation and Classification of Plants. *IEEE Access*. 2019;7:29374–29385. Available from: https://doi.org/10.1109/ACCESS.2019.2901900.
19) Chao X, Sun G, Zhao H, Li M, He DM. Identification of Apple Tree Leaf Diseases Based on Deep Learning Models. *Symmetry*;12(7):1065–1065. Available from: https://doi.org/10.3390/sym12071065.
20) Jeong J, Park H, Kwak N. Enhancement of SSD by concatenating feature maps for object detection. *Procedings of the British Machine Vision Conference 2017*. 2017;p. 1–20. Available from: https://arxiv.org/abs/1705.0958720.
21) 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*. 2017;39(6):1137–1149. Available from: https://doi.org/10.1109/TPAMI.2016.2577031.
22) Jiang P, Chen Y, Liu B, He D, 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. Available from: https://doi.org/10.1109/ACCESS.2019.2914929.
23) Eldho KJ. Impact of Unbalanced Classification on the Performance of Software Defect Prediction Models. *Indian Journal of Science and Technology*. 2022;15(6):237–242. Available from: https://doi.org/10.17485/IJST/v15i6.2193.