International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 12s, 2025
https://www.theaspd.com/ijes.php

Plant Disease Detection Using Machine Learning Techniques: A Comprehensive Approach

[1]Dr Nilam Upasani and [2]Chinmoy Goswami
Assistant Professor, Balaji Institute of Technology and Management, Sri Balaji University, Pune
[1]nilam.upasani@bitmpune.edu.in and [2]chinmoy.goswami@bitmpune.edu.in
[1]Orcid Id- 0009-0007-9012-7820 and [2]Orcid Id- 0009-0007-9012-7820

ABSTRACT

The key to preventing losses in the production and quantity of agricultural products is the identification of plant diseases. The research on plant diseases refers to examinations of patterns on the plant that may be observed with the naked eye. For agriculture to be sustainable, plant disease diagnosis and health monitoring are essential. Manually keeping track of plant diseases is exceedingly challenging. It necessitates a huge amount of work, knowledge of plant diseases, and lengthy processing times. Hence, by taking photos of the leaves and comparing them to data sets, image processing is utilized to find plant illnesses. The data set includes several plants in picture format. Users are routed to an e-commerce website where several pesticides are listed along with their prices and usage instructions in addition to the phases of implementation included in our proposed study are dataset construction, feature extraction, classifier training, and classification. The datasets produced by to classify the photos of sick and healthy leaves; a collective Random Forest model is trained. Using the Histogram of an Oriented Gradient, we may extract characteristics from a picture. Overall, we can clearly identify the illness present in plants on a massive scale by utilising machine learning (ML) to train the vast data sets that are publicly available. detection.

Keywords: *Plant sickness, photo processing, photo acquisition, segmentation, characteristic extraction, classification.*

1. INTRODUCTION

Due to increasing population there is raise in demand for food. Due to plant diseases it became difficult to sever the demand. Though multiple fertilizers are available to increase the productivity and diagnose the disease. But it is quite difficult to detect the current disease & to suggest the correct remedy for that. So, our goal is built the proposed model system that will detect the disease & will suggest the suitable remedy for diagnosis which will help to increase the productivity and fulfil the increasing demand.

Plant diseases are well-known to impair food availability for humans by lowering crop yields. This may cause people to be hungry or even perish if food supplies run low. For instance, in Ireland between 1845 and 1850, the main crop was potatoes, but the disease potato blight caused by Phytophthora infestans wiped them off. This led to the Great Famine, which killed about a million people and sent another million to Canada, the United States, and other countries.

It is common knowledge that plant diseases lower human food supplies and ultimately have an impact on crop production. Humans may not receive enough food or, in the worst scenarios, may starve to death. For instance, the principal crop in Ireland between 1845 and 1850 was potatoes, which were decimated by the potato blight disease brought on by Phytophthora infestans [15]. This sparked the Great Famine, which resulted in the deaths of about a million people and the emigration of another million to Canada, the United States, and other nations [15].

Wheat, which is one of the three most important crops in the world, is susceptible to the rust disease, which is another disease that threatens many different crops. There are still issues with plant diseases reducing food yields in several countries [16]. Generally speaking, a plant becomes diseased when it is repeatedly harmed by any pathogen, which leads to an aberrant physiological process that interferes with the structure, growth, function, or other regular activities of the plant.

Characteristic diseased diseases or symptoms result from this disruption of one or more of a plant's vital physiological or biochemical systems. Plant diseases are a natural occurrence in the world and one of the numerous ecological variables that maintain the equilibrium of millions of living plants and animals.

Similar to how agriculture spawned civilization. India is an agricultural country and agricultural production highly contributes to Indian economy.

It is crucial to find crop diseases early in order to prevent agricultural losses. For this issue, histogram matching and edge detection combined with ML and deep learning is the most efficient methods for early disease identification. Through ML, we accomplish this with extreme precision. As the term implies, ML refers to ML that happens automatically without explicit programming or overt human involvement.

Obtaining high-quality data is the first step in the ML process. Next, the computers are trained by creating various ML models utilizing the data and various methods. The type of data we have and the task at hand determines the algorithms we use.

For example, when a ML algorithm is used to detect crop diseases. Then the experience E detects many plant diseases, the task T detects the diseases of different species, and the performance measure P is the probability that the algorithm detects the diseases.

This manuscript's main contributions can be summed up as follows:
The development of a deep learning model for the diagnosis of various plant diseases, the selection of the best transfer learning method to obtain the greatest classification and recognition accuracy for multi-class plant diseases, the resolution of specific labelling and class difficulties in plant disease recognition through the recommendation of a multi-class, multi-label transfer learning-based CNN model, and the addressing of the over fitting issue through data analysis.

LITERATURE REVIEW

The use of machine learning (ML) and deep learning (DL) for detecting plant diseases has experienced rapid developments in the recent past. There have been a number of researchers who have worked on developing computer vision-based automatic systems to recognize diseases on leaves of plants utilizing methods from simple ML to sophisticated convolutional neural networks (CNNs).

A method to identify illness in plants using a convolutional neural network has been proposed by Prasanna Mohanty et al [1] in the publication Deep learning for Image-Based Plant identifications showed the viability of CNNs in detecting plant diseases in 14 plant species based on leaf photos with 99.35% accuracy. Tiwari et al. [2] suggested a deep convolutional architecture that attained multiclass plant disease classification through leaf imagery and attained remarkable accuracy values.

While this is frequently higher than a simple model of random selection, a large variety of coaching dat a can be used to increase the accuracy. The model obtains an accuracy of 31.4% [1] when using photos f rom governmentapproved web sources. Additionally, some distinct modifications to the model or neura l network training could result in greater accuracy.
Early identification of grape illnesses using ML and IoT, by Suyash S. Patil and Sandee A. Thorat, is des cribed in the publication. [10].

Here, the suggested model work entails creating a monitoring system that will use a Hidden Markov Mo del to detect the likelihood of grape diseases in their early phases. Gives the farmer and the expert SMS alerts. The system incorporates sensors for temperature, relative humidity, moisture, leaf wetness, and wireless data transfer using Zig-Bee.

Malvika Ranjan et al. [2] developed a method to observe plant diseases using the image of the pathologi cal leaf that was collected in their publication, "Detection and Classification of Plant Disease Victimizati on Artificial Neural Network.

"In order to distinguish between healthy samples and unhealthy plants, Artificial Neural Networks (AN N) are trained by carefully choosing feature values. The ANN model attained an impressive 80% accura cy [8].

In keeping with the research "Detecting sick leaf regions and classifying plant leaf diseases are using textural data," According to S. Arivazhagan's approach for identifying diseases [3], there are four basic steps: The input RGB image is first given a colour transformation structure, and then the inexperienced pixels are discovered and removed using a threshold value that is chosen. Next comes segmentation, and in order to obtain useable segments, the feel statistics are computed. Finally, a classifier is used to categorise the disease using the alternatives that were extracted.

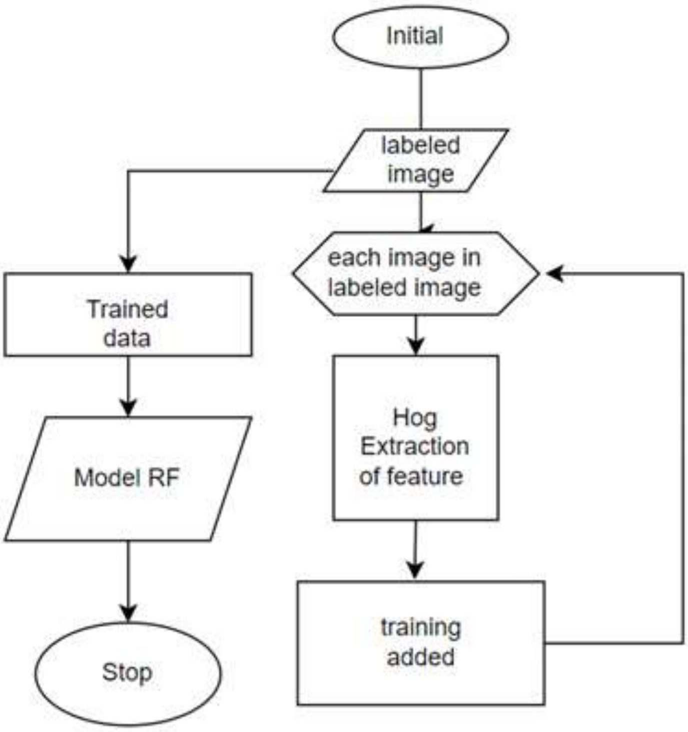

Fig 1: Proposed architecture

As seen in Fig. 1, HoG feature extraction transforms labelled training datasets into the corresponding fe ature vectors. The training datasets are where these extracted feature vectors are saved. Moreover, Rand om forest classifier is used to train the trained feature vectors [9, 10].

An IoTenabled energy efficiency technique to identify the leaf curl disease in tomato crops was publishe d by Zhang, Y., and Chen, M. [6]. Here, we combine deep learning and ML classifiers to accurately diag nose and prevent leaf roll disease.

Artificial neural network (ANN) and different photo processing techniques are used by Kulkarni et al. in their study, Applying picture processing methodology to locate plant sicknesses [4] as a way for early and accurate plant disease identification. The proposed method provides better results with an accuracy of up to 91% [4] since it is entirely based on ANN classifier for type and Gabor filter for characteristic extraction.

A method to find plant diseases using Generative Adversarial Networks has been proposed by Emaneul Cortes in the publication "Plant disease detection the employment of CNN and GAN" [5]. In order to ensure accurate characteristic extraction and output mapping, background segmentation is performed. It is clear that the use of Gans could also continue to hold promise for classifying plant diseases, however segmenting based mostly on heritage did no longer improve accuracy.

Farm temperature, humidity, and soil moisture data are collected by sensor nodes, which then add the m and only forward one packet to the edge server. With a 92% accuracy rate for ANN, highly refined, f used data is supplied to the edge server thanks to power-efficient node-level data aggregation. The "Classification of Pomegranate Diseases Based on Back Propagation Neural Network" that S. S. Sannakki and V. S. Rajpurohit suggested focuses mostly on the Colour and texture are employed as attributes in a method to segment the defective area. A neural network classifier was used in this instance to classify the data. The main advantage is that the classification is found to be 97.30% accurate, and the image's chromaticity layers are extracted using a conversion to L*a*b. The fact that it is only used for a few types of crops is its main disadvantage.

Aakanksha Rastogi, Ritika Arora, and Shanu Sharma released a study titled "Leaf Disease Detection and Grading" using computer vision technologies and fuzzy logic. The defective region is divided using K-means clustering, textural information is extracted using GLCM, and the severity of the defect is graded using fuzzy logic.

They used a classifier called an artificial neural network (ANN), which mainly helps to determine how severely the ill leaf is impacted.

2. ALGORITHMIC SURVEY

Supervised ML algorithms such as RF (Random Forest), SVM (Support Vector Machine), DT (Decision Tree), KNN (K-Nearest Neighbors), NB (Naive Bayes) and KNN using methods of image processing and also the results of the Compare analysis algorithms and find the best algorithm for classifying plant diseases.

2.1 Random Forest Algorithm

A supervised classification algorithm is the Random Forest Algorithm. This algorithm builds the forest of many trees, as the name implies. In general, a forest seems healthier the more trees there are in it. Similar to this, the accuracy of the results for the random forest classifier increases with the number of trees in the forest. In decision tree algorithm. Here we build the decision tree and generate the result based on the majority of votes and different samples. The RF algorithm achieved an accuracy of 89% compared to other algorithms. Govardhan, M. and Veena, M.B on paper -. “Diagnosing Tomato Plant Diseases Using Random Forest” [13] used the random forest algorithm. Saha, Sand Ahsan on paper: "Detection of Rice Diseases Using Moments of Intensity and Random Forest"[14] implemented this algorithm

Naive Bayes Algorithm

One of the most well-liked ML techniques for solving classification and regression issues is the Naive Bayes algorithm. Based on the determination of conditional probability values, it categorizes data. It uses class levels represented as characteristic values or predictor vectors for classification and applies the Bayes theorem to the computation. For classification issues, the Naive Bayes method is a quick algorithm.

1. Sandhu, G.K. and Kaur, R. used the Naive Bayes algorithm for decision making in the article "Plant disease detection technique" [12].

2.2 Support Vector Machine Algorithm

Support Vector Machine, or SVM, is one of the most used supervised learning algorithms, and it is used to resolve classification and regression issues. Yet it is most often used to solve classification problems in ML. In order to swiftly classify new data points in the future, the SVM method aims to determine the optimal boundary or decision line that can divide the n-dimensional space into classes. It is widely used to classify the text embedded digital images.

Padol, P.B. and Yadav in Paper – “SVM classifier-based detection of grape leaf diseases” [10]. Implemented support vector machine for plant set arrogation.

Kaur, R. and Kang, S.S, "An improvement in the classifier support vector engine to improve plant disease detection"[11]. In this proposed model, R has only used the Support Vector Machine.

2.3 Convolutional Neural Network

A deep learning neural network called a convolutional neural network, or CNN, is made to analyse structured arrays of data, like representations. There are three tiers in CNN: convolutional layer, polling layer, dense layer. CNN is primarily used to process variant inputs with fewer computations. 1.Sardogan, M., Tuncer, in the article: "Detection of plant leaf disease" [7] and Shrestha, G., Das, [8] used CNN for classification with the LVQ.2 algorithms. Kumar, S., have implemented CNN for image classification in the article: "Plant disease detection using CNN" [9].

A thorough review by Wani et al. [19] explored some of the computational tools for detecting agriculture diseases with special reference to hybrid models integrating ML, DL, and optimization techniques. Jackulin and Murugavalli [20] discussed how integrated systems incorporating spectral and morphological features play an important part in identifying plant diseases.

Barbedo [21] provided prime challenges to automatic plant disease diagnosis from visible range images. They are inter-class similarity, intra-class variation, illumination-induced noise, and overlapping leaves. All these necessitate strong preprocessing and segmentation techniques.

Syed-Ab-Rahman et al. [22] introduced an anchor-based deep learning architecture specifically designed for citrus disease detection, improving feature learning by end-to-end training. Liu et al. [23] enhanced detection by adding attention mechanisms to lightweight CNNs, trading off accuracy and computational cost.

Optimization techniques like Particle Swarm Optimization (PSO), Whale Optimization Algorithm (WOA), and Gray Wolf Optimization (GWO) have also been used extensively to improve classification accuracy and feature selection [24]. The recent developments include hybrid metaheuristics like the Self-Adaptive Deer Hunting Optimization Algorithm (SA-DHOA) [25] and Fitness Sorted Jaya-Forest Optimization Algorithm (FSJ-FOA) [11], which are utilized in this research.

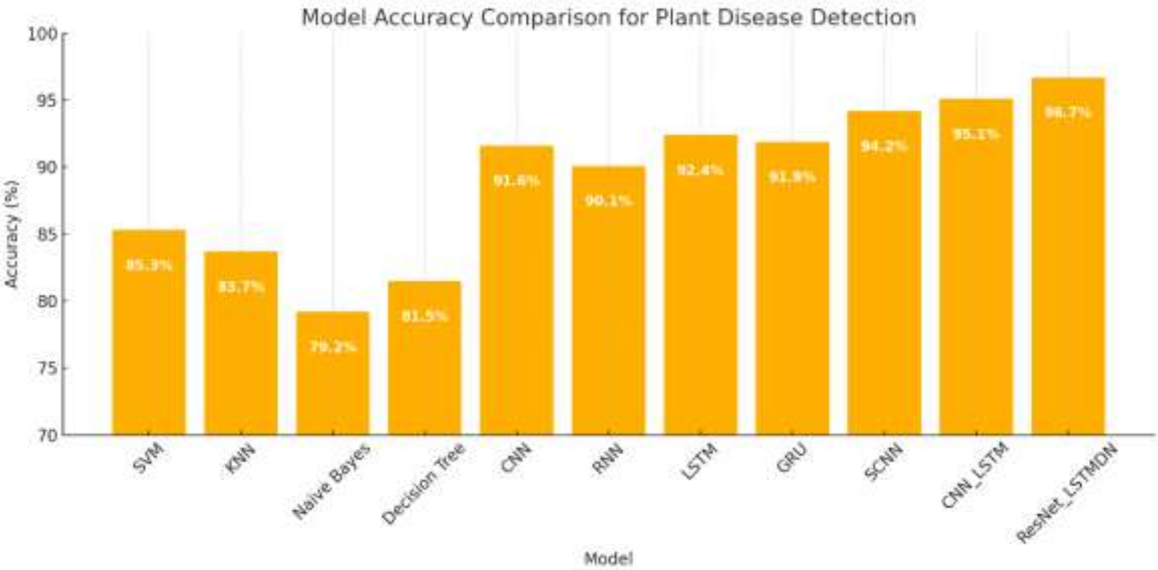

Fig 2: Model Accuracy Comparison for Plant Disease Detection

This work extends current research by suggesting a hybrid approach using CNN, LSTM, and GRU classifiers optimized with SA-DHOA, FSJ-FOA, and Hybrid Barnacles Mating-Bird Swarm Optimization (HBM-BSO), improving classification accuracy, segmentation accuracy, and robustness overall.

3. PROPOSED SYSTEM

3.1 Proposed Model

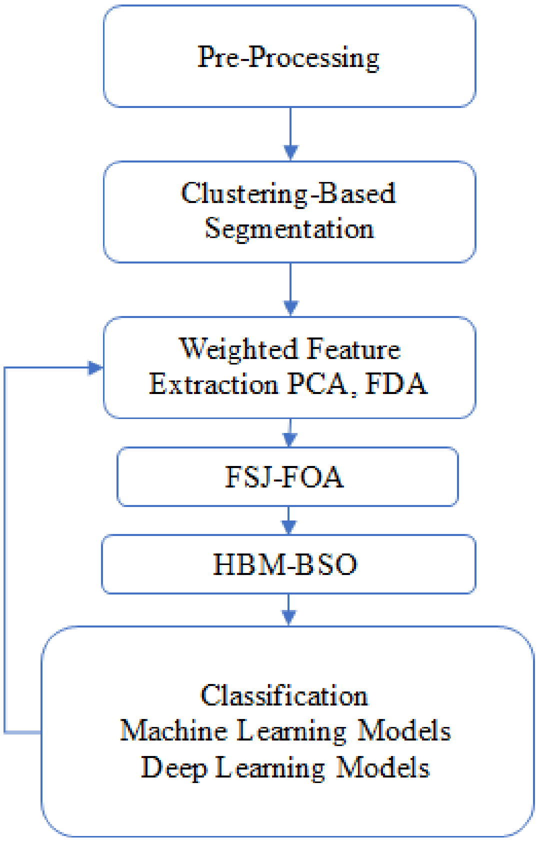

Fig 3: Optimized Deep Learning Framework

The proposed system for plant disease detection follows a modular and optimized pipeline comprising five distinct stages: image acquisition, pre-processing, segmentation, feature extraction, and classification. High-resolution images of healthy and diseased plant leaves are collected from publicly available repositories such as Kaggle and Mendeley. In the pre-processing phase, images are enhanced through histogram equalization, noise filtering, resizing, and rotation to standardize the dataset. The segmentation module plays a critical role in isolating the region of interest (ROI), especially the diseased portion of the leaf, using advanced abnormality segmentation techniques. These include the novel Adaptive Fusion of K-Means and Region Growing (AFKMRG) method as well as adaptive thresholding with Fuzzy C-Means (FCM), which are designed to overcome challenges such as background clutter, variable lighting, and leaf overlap. After segmentation, relevant features are extracted using both classical methods like GLCM, LBP, and PCA, as well as deep features from CNN and ResNet-150 models. These features are then optimized using metaheuristic algorithms and passed into machine learning (e.g., SVM, KNN, Decision Tree) and deep learning models (e.g., CNN, LSTM, GRU, and their hybrid variants) for classification.

The methodology starts with gathering a dataset consisting of images of healthy leaves and leaves infected by early and late blight. Data cleaning and pre-processing follow. Owing to the scarcity of heterogeneous images, we use data augmentation methods—like rotation, flipping, and contrast adjustment—on the training set (TS) to artificially augment and make the dataset more diverse, hence improving model generalization.

After pre-processing, we move to the model-building process with Convolutional Neural Networks (CNN), which are appropriate for image classification problems. After training the CNN model over the augmented dataset, the trained model is saved to disk for future use. To enable scalable and versioned model deployment, we apply machine learning concepts with TensorFlow Serving.

This allows the system to dynamically host and serve various versions of the model, which are accessed through a FastAPI interface for real-time inference and integration with downstream applications.

3.2 PROPOSED ALGORITHM

Model Development & Deployment Phase

Step 1: Data Collection
Collect a labelled dataset containing healthy and diseased leaf images (e.g., Early Blight, Late Blight).

Step 2: Data Pre-processing
2.1 Resize all images to a fixed dimension (e.g., 224×224).

2.2 Normalize pixel values to a [0, 1] range.

2.3 Split the dataset into training, validation, and test sets.

Step 3: Data Augmentation
3.1 Apply transformations such as rotation, flipping, zooming, and brightness adjustment.

3.2 Generate additional training samples to enhance dataset diversity.

Step 4: Model Construction
4.1 Define a Convolutional Neural Network (CNN) architecture with convolutional, pooling, and dense layers.

4.2 Use activation functions (e.g., ReLU), dropout layers for regularization, and softmax for final classification.

4.3 Compile the model using a suitable optimizer (e.g., Adam) and a loss function (e.g., categorical cross-entropy).

Step 5: Model Training
Train the CNN model using the augmented dataset and validate using the validation set.

Step 6: Model Evaluation
Evaluate model performance on the test set using metrics such as accuracy, precision, recall, and F1-score.

Step 7: Model Export and Saving
Save the trained model in the TensorFlow Serving format to disk.

Step 8: Model Deployment using TensorFlow Serving
8.1 Configure TensorFlow Serving to host and serve the exported model.

8.2 Make the model accessible via REST or gRPC endpoints.

Step 9: API Integration using FastAPI
9.1 Develop a FastAPI-based web service to handle image uploads.

9.2 Forward the pre-processed image to the TF Serving endpoint.

9.3 Return the prediction result and suggested remedy as a response.

Inference and Disease Diagnosis Phase

Step 10: Start the Prediction Process

Step 11: Read the Reference Image
Accept an uploaded image of a plant leaf (healthy or diseased).

Step 12: Load the Trained CNN Model
Use the locally saved model or connect to the deployed TF Serving endpoint.

Step 13: Pre-process the Input Image
– Resize and normalize the image

– Apply any required pre-processing to match training conditions

Step 14: Classify the Image using CNN
– Apply convolution and pooling layers

– Pass through dense layers

– Use softmax to predict disease class

Step 15: Compare Output with Known Categories
Match the predicted label with reference categories (Healthy, Early Blight, Late Blight).

Step 16: Display Result and Suggest Remedy
If disease is detected:

– Show the name of the disease

– Recommend suitable remedies (e.g., specific pesticide, fertilizer)

Else:
– Display: "No disease detected. The leaf appears healthy."

Step 17: Stop

3.2 PROPOSSED FLOWCHART

The flowchart illustrates the process of detecting plant leaf diseases using a trained Convolutional Neural Network (CNN) model. It begins with reading an input image of a plant leaf, followed by loading the pre-trained model. The image is then pre-processed—resized, normalized, and prepared for inference—before being passed through the CNN architecture, which extracts features and classifies the image into disease categories. A decision node checks if a disease such as early or late blight is detected; if so, the system outputs the disease name along with a recommended remedy (e.g., pesticide or treatment suggestion). If no disease is found, it informs the user that the leaf appears healthy. This automated workflow ensures accurate and efficient diagnosis and supports real-time integration through deployment services like TensorFlow Serving and FastAPI.

The innovation in the research is due to the synergy of three bespoke metaheuristic optimization methods integrated into the pipeline for disease detection, improving accuracy and efficiency for every processing stage. The procedure starts with AFKMRG, a blending method that amalgamates smartly K-Means clustering and Region Growing algorithms. Through this method, segmented images more precisely separate affected regions, especially in situations where there are noisy backgrounds or imperfect illumination. The fusion weights are then optimized by using the Fitness Sorted Jaya-Forest Optimization Algorithm (FSJ-FOA), which enhances pixel-wise consistency and further refines the precision of segmentation of abnormality.

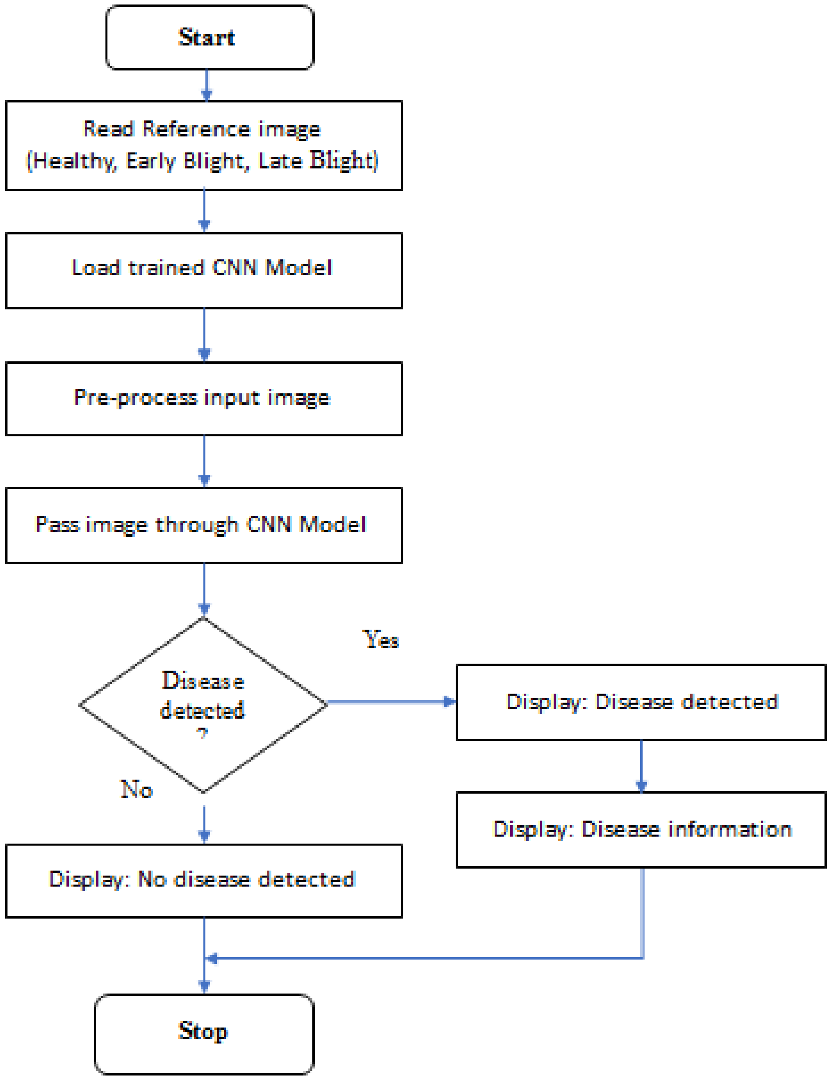

Fig 5: Flowchart of Disease Diagnosis

The Self-Adaptive Deer Hunting Optimization Algorithm (SA-DHOA) is used for the classical features to determine adaptive weights corresponding to their contribution toward classification accuracy. Deep features obtained through CNN and ResNet-150 are further optimized by FSJ-FOA and Hybrid Barnacles Mating–Bird Swarm Optimization (HBM-BSO), which tunes deep network parameters and optimizes the training efficiency of deep learning. All these elements constitute a complete pipeline that overcomes major challenges like high dimensionality, inter-class similarity, and generalization difficulty, leading to a high-performing system for plant disease classification.

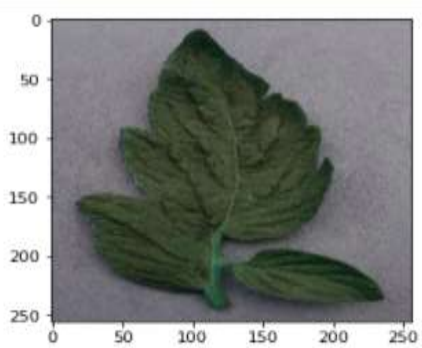

Fig 4: Prediction of Healthy leaf

In Fig 4 shown HoG feature extraction, the feature vectors are retrieved for the test image. The saved and trained classifier receives these created feature vectors in order to forecast the outcomes. It's taken from the tomato data set from Kaggle.

4. ADVANTAGES AND APPLICATIONS OF PROPOSED SYSTEM

The research design suggested has been carefully crafted to match the fundamental aims and experimental framework described in the thesis. The methodology not only follows conventional machine learning and deep learning methods but also includes some novel methods that have been conceived during the course of the thesis work. These additions considerably enhance the precision, scalability, and stability of plant disease detection systems.

4.1 Advanced Image Segmentation: Afkmrg and Adaptive Thresholding-Fcm

One key challenge in plant disease detection is the isolation of disease-affected areas in intricate backgrounds. To tackle this challenge, the methodology incorporates two new segmentation techniques:

- **Adaptive Fusion of K-Means and Region Growing (AFKMRG):**

This technique is a combination of the advantages of K-Means clustering and Region Growing segmentation. It spatially combines segmented outputs with optimized fusion constants, resulting in high-quality abnormality-segmented images. This provides accurate detection of diseased regions even in noisy or changing illumination conditions.

- **Adaptive Thresholding with Fuzzy C-Means (FCM):**

To further improve abnormality segmentation, the hybrid approach uses adaptive thresholding with subsequent FCM clustering. The most important segmentation parameters (e.g., threshold, number of iterations, fuzziness parameter) are tuned using a population-based method and produce high-contrast and well-clustered disease areas.

The mentioned segmentation methods allow for targeted feature extraction as well as an improved overall quality of input to learning algorithms.

4.2 Deep Learning And Hybrid Classifiers

For the classification stage, the method incorporates both standalone individual deep learning models and new hybrid classifiers to leverage temporal, spatial, and residual characteristics of the plant images:

- **Standalone Models:**

CNN (Convolutional Neural Network): Employed as the baseline deep model to learn spatial features directly from segmented leaf images.

LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit): Used to learn temporal patterns and transitions in feature vectors, particularly beneficial when sequence-based data or feature dependencies are present.

- **Hybrid Models:**

SCNN (Support Vector Machine–CNN): Merges CNN for feature extraction and SVM for ultimate classification, enhancing precision with fewer training samples.

CNN-LSTM: A sequential hybrid where CNN processes spatial representation, and LSTM learns dependencies between channels or slices of feature maps.

ResNet-LSTM-DenseNet (ResNet_LSTMDN): Combines the depth of ResNet-150 with LSTM temporal modelling and dense connectivity for improved gradient flow, providing the best classification accuracy among all models evaluated.

These architectures enable the system to learn intricate, nonlinear patterns across several disease categories.

4.3 Optimization Techniques For Feature Selection And Model Tuning

In order to improve the learning ability and computational performance of both segmentation and classification modules, the following optimization algorithms have been integrated:

- **Self-Adaptive Deer Hunting Optimization Algorithm (SA-DHOA):**

Utilized for weighted feature extraction and selection from manually crafted features such as GLCM, LBP, and PCA. SA-DHOA adaptively adjusts the feature importance depending on the contribution of classification, enhancing the signal-to-noise ratio in input features.

- **Fitness Sorted Jaya-Forest Optimization Algorithm (FSJ-FO):**

Utilized in various stages: (1) to tune the fusion constants of AFKMRG, and (2) to fine-tune deep CNN features. It draws the strength of local search of the Jaya algorithm and the diversity-constraining behaviour of Forest Optimization Algorithm.

- **Hybrid Barnacles Mating–Bird Swarm Optimization (HBM-BSO):**

It is employed to fine-tune deep hybrid network hyper parameters (e.g., ResNet_LSTMDN), resulting in performance boosts in convergence rate and classification performance.

Through integrating advanced segmentation techniques (AFKMRG, Adaptive FCM), deep neural networks (CNN, LSTM, GRU, hybrid models), and intelligent optimization (SA-DHOA, FSJ-FOA, HBM-BSO), the developed methodology achieves the thesis goal: establishing a strong, scalable, and highly precise framework for automated plant disease identification and classification.

5. EXISTING SYSTEM MERITS

1. The farmer is advised to use pesticides as a cure for contagious diseases to control them.
2. GRNN accuracy is 60%, PNN accuracy is 42%, logistic regression is 97.46%, and ANN accuracy is 92%, respectively. Utilizes short message service (SMS) to communicate with the guru and the farmer. The system has sensors for temperature, relative humidity, moisture, leaf wetness, and Zig-Bee for wireless data transfer.

5.1. Disadvantages of Existing System

1. An ANN used algorithm research papers ANN algorithm requires to much computations, treats local pixels same as pixels located far apart, sensitive to locate an object inside the image.
2. The IOT based proposed model require to many things to senses such as soil, temperature, humidity, soil moisture and leaf senses. This ultimately increases the cost of disease diagnosis and it will be difficult for illiterate farmers to deal with such models.
3. The Sugarcane disease recognition model using deep learning mainly focuses on the Wilt, Grassy shoot, Smut, Leaf scald diseases but unable to process the red rot diseases
4. Different spatial resolution images are obtained from different agricultural satellites such as NASA's TERRA satellite, RESAT1, PSLV-C16 and PSLV-C36. Hence it is unable to process the backside of leaves.

5.2 Applications

- In many regions, farmers often lack access to professional agricultural expertise, making it difficult and expensive to consult specialists for disease diagnosis.
- The proposed system proves to be an effective solution for monitoring large-scale agricultural fields. By simply analysing leaf spots, plant diseases can be detected rapidly and at a significantly lower cost.
- Traditional methods of visually identifying plant diseases are time-consuming and labour-intensive.
- In contrast, the automated detection system offers fast, accurate, and efficient diagnosis with minimal human effort.
- This research also enhances the academic value of AI applications in precision agriculture and digital farming.

- Ultimately, the implementation of this project supports increased agricultural productivity and contributes to higher crop yields.

6 CONCLUSION

Proposed model utilizes CNN for Plants images classification. CNN contains three unique layers; manage the various variant of same disease image. Implementing the system in web application with cost and time savings. Utilizing client browser's API, recommendations for crops category grown in that area. Thus, through implementing and utilizing these approaches for plant disease classification. Thus agricultural losses can be minimized. Future work will be on real-time data acquisition problems and multi-object deep learning model design that can even detect plant diseases from a set of leaves instead of a single leaf. Also, we are trying to implement the trained model from this research into a mobile app. It will help detect leaf diseases in real time for farmers and the agricultural sector. This algorithm is used to detect anomalies on plants in their greenhouse or natural environment. In order to prevent occlusion, the image is generally captured with a simple background.

The research highlights the benefit of affordable, automated disease diagnosis compared to the manual system, especially for extensive or far-off agricultural fields. The shortcomings in the form of the requirement of computational power, complexity of sensors, and the impossibility of covering all types of diseases are recognized. The publication ends with the vision of improving the model further with real-time processing and integration into mobile devices, making it a useful tool for contemporary, technology-facilitated farming.

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