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Development and Evaluation of a Distinctive Cloud-Based Artificial Intelligence System using Deep Learning Techniques (AISDLT) for Accurate Detection of Tomato Plant Leaf Diseases

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Abstract: Fighting tomato infections is crucial for the agriculture industry since they can cause large drops in crop output. Therefore, it is crucial to recognize and categorize tomato leaf diseases as soon as possible to minimize the loss. Nevertheless, this is a tedious and drawn-out procedure. To tackle the above-listed problems, an accurate automated method for timely identification and classification is required. To properly diagnose and notify the individual about this sickness, the current approaches have created machine learning and deep learning algorithms that identify the illness from the foliage of tomatoes. Early and accurate detection of tomato plant leaf diseases is crucial for minimizing yield losses and ensuring food security. Traditional methods often rely on visual inspection by trained personnel, which can be time-consuming, subjective, and prone to errors. This paper proposes a distinctive cloud-based AI system powered by deep learning techniques for automated and accurate detection of tomato plant leaf diseases. The system leverages high-resolution images captured from smartphones or dedicated sensors in the field. A pre-trained convolutional neural network (CNN) model is fine-tuned on a disease-specific dataset to achieve high classification accuracy. We used Transfer learning for pre-trained models like ResNet or VGG16 can be fine-tuned with labelled datasets of diseased leaves, significantly reducing training time and improving accuracy. Data Augmentation (DA) is a techniques like rotating, flipping, and scaling images can significantly increase the size and diversity of your training data, leading to better generalization and robust performance. The cloud infrastructure facilitates efficient data storage, model training, and real-time disease detection, making the system readily accessible to farmers even with limited resources. The proposed architecture of the AI system, the chosen deep learning technique, the employed optimization algorithm (genetic algorithm), and the achieved detection accuracy.

Keywords: *Tomato Plant, Leaf Disease Detection, ResNet, VGG16, CNN-based models, Transfer learning, Data Augmentation (DA), Genetic Algorithm, Image Segmentation.*

1. Introduction

Plant diseases are one of the major threats to agricultural production and food security worldwide. According to the Food and Agriculture Organization (FAO), plant diseases cause an estimated 40% of crop losses globally (FAO, 2020). With the increasing demand for food due to the growing global population, accurate and timely detection of plant diseases is crucial to prevent and mitigate the negative impact on crop yields and quality. Conventional methods of plant disease detection, such as visual inspection by trained experts, are time-consuming and subjective. Therefore, there is a need for automated and accurate methods for plant disease detection.

In recent years, deep learning algorithms have shown promising results in various fields, including computer vision and image recognition. These algorithms have also been applied to the field of plant disease detection, with convolutional neural networks (CNNs) being the most commonly used. However, most existing CNN-based models for plant disease detection have limitations such as low accuracy and inability to handle complex and diverse leaf images. To address these limitations, researchers have developed a distinctive deep attention convoluted network (DACN) model. This paper aims to provide a literature review of the development and evaluation of the DACN model for accurate detection of plant leaf diseases.

The development of a deep attention convoluted network (DACN) model has proven to be an effective solution for accurate detection of specific tomato plant leaf diseases,

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even under real agricultural conditions. The proposed model is a deep convolutional neural network that integrates an attention mechanism and is designed to diagnose various tomato leaf diseases [1]. The employed framework for disease detection and classification is an end-to-end learning method that combines four different losses to minimize the total training loss [2]. The training method includes multi-task loss to increase recognition ability and to locate affected leaf regions, further enhancing the model's performance [2]. The study aims to compare the tomato plant leaf disease recognition capability of the improved CornerNet model against several well-known DL frameworks [2]. The effectiveness of the model is compared with other models such as GoogleNet, Xception, and SE-ResNet50. The GoogleNet model attains the lowest results in classifying the leaf diseases of the tomato plant, with precision, recall, F1-score, and accuracy measures of 0.8716, 0.8709, 0.8712, and 87.27%, respectively. In contrast, the DenseNet-77-based CornerNet model obtains the highest results for precision, recall, F1-score, and accuracy measures with a numeric count of 0.9962, 0.9953, 0.9957, and 99.98%, respectively [2]. The comparison illustrates the effectiveness of the DenseNet-77-based CornerNet model and further emphasizes its potential for accurate disease diagnosis in the agricultural industry [2]. Overall, the DACN model provides a high-performance solution for crop diagnosis under real agricultural conditions, demonstrating its potential to revolutionize the agricultural industry's disease detection practices [1].

Tomato (Solanum lycopersicum L.) is one of the most important vegetable crops worldwide, with a global production exceeding 182 million tonnes in 2021 (FAO, 2023). However, its cultivation is significantly hampered by various leaf diseases, causing substantial yield losses of up to 80% in severe cases (Savary et al., 2012). Timely diagnosis and management of these diseases are critical for reducing economic losses and ensuring food security. Traditional methods for disease detection rely on visual inspection by trained personnel. However, these methods are often time-consuming, subjective, and require significant expertise, making them impractical for large-scale farms or resource-constrained settings. Additionally, visual symptoms can be subtle or overlap between different diseases, leading to misdiagnosis and improper management strategies. Recent advancements in artificial intelligence (AI), particularly deep learning, have revolutionized disease detection in agriculture. Deep learning algorithms can automatically extract complex features from images and classify them with high accuracy. Convolutional neural networks (CNNs) are a particularly powerful type of deep learning architecture well-suited for image recognition tasks.

Early and accurate detection of these diseases is vital for implementing effective disease management strategies and minimizing crop losses. Traditional methods for disease detection, such as visual inspection, are often subjective, time-consuming, and require trained personnel. Additionally, environmental factors like lighting and weather conditions can further complicate visual Recent advancements in artificial intelligence (AI), particularly deep learning, have revolutionized image recognition and classification tasks. Deep learning models can be trained on large datasets of labeled images to automatically extract features and identify patterns, making them suitable for disease detection in agricultural applications. This paper proposes the development and evaluation of a cloud-based AI system using deep learning techniques for accurate detection of tomato plant leaf diseases. The system leverages the following key aspects:

Cloud platform: The cloud infrastructure provides the necessary computational power and scalability to train and deploy the deep learning model efficiently.

Deep learning model: A suitable deep learning architecture, such as a convolutional neural network (CNN), is employed to extract features and classify tomato leaf images based on the presence or absence of disease symptoms.

Optimization algorithm: An optimization algorithm like genetic algorithm is incorporated to fine-tune the hyperparameters of the deep learning model and optimize its performance for accurate disease detection.

Large dataset: A comprehensive dataset of high-quality tomato leaf images labeled with different disease types is used to train the deep learning model effectively. The introduction should further elaborate on the specific objectives of the research, such as:

Identifying the target tomato plant leaf diseases to be detected by the AI system. Choosing the specific deep learning architecture and optimization algorithm based on their suitability for the task. Highlighting the expected benefits of using a cloud-based AI system for disease detection in tomato plants. By combining the capabilities of cloud computing, deep learning, and optimization algorithms, this proposed AI system has the potential to revolutionize tomato plant disease detection, leading to improved crop yields and agricultural sustainability. Diagnosis.

2. Literature Review

2.1. Introduction:

Plant leaf diseases are a serious threat to crop production as well as worldwide security of food. Early and precise diagnosis is essential for prompt intervention to minimize yield losses. Disease detection has always depended on experts' visual assessment, which can be subjective, laborious, and ineffective. With automated, objective, and high-throughput solutions, the identification of plant diseases has evolved due to the development of machine learning (ML) and computer vision approaches.

Early detection and diagnosis of plant diseases are crucial for minimizing crop loss and ensuring food security. Traditional methods rely on visual inspection by trained experts, which can be time-consuming, subjective, and prone to error. Fortunately, advancements in computer vision and machine learning have enabled the development of accurate and automated plant disease detection systems. This review summarizes the main methodologies used for this purpose, highlighting their advantages and limitations.

2.2 Techniques:

2.2.1 Image Preprocessing:

- Noise reduction: Images taken in natural environments are free from defects and noise thanks to filters.
- Color space conversion: Enriching sick areas in an image by converting it to a certain color space (such as HSV).
- Image segmentation: Using methods such as thresholding, clustering, or edge detection, separate sick areas from the backdrop.

2.2.2 Extraction of Features:

- Color features: Removing hue, saturation, and intensity from areas affected by disease.
- Texture features: Examine the patterns of texture (such as roughness and smoothness) to pinpoint sick regions.
- Shape features: Obtaining perimeter, aspect ratio, and area information to be used in the classification of diseases.

2.2.3 Classification:

- Machine learning algorithms: Support vector machines (SVM), K-Nearest Neighbors (KNN), Random Forests, and Naive Bayes are a few examples of algorithms that can be used to classify photos that show disease.
- Deep learning techniques: Because convolutional neural networks (CNNs) are capable of learning features from broad datasets, they have demonstrated extraordinary efficiency in disease categorization.
- Accurate detection of plant leaf diseases using computer vision and ML offers immense potential to improve agricultural productivity and food security. Continuous research efforts are needed to address the challenges, develop robust and generalizable models, and integrate them into practical agricultural solutions.

2.3 Related Works of Plant Leaf Disease Detection using Distinctive Deep Attention Convolutional Network (DACN) Mechanism

The study "Plant Leaf Disease Detection Using a Distinctive Deep Attention Convolutional Network" presents the DACN mechanism as a revolutionary deep learning strategy to increase plant leaf disease detection accuracy. The following linked works investigate related ideas or use various approaches to solve the issue of plant leaf disease detection:

- **Using Deep Learning to Identify Plant Leaf Diseases:**

- **Deep Convolutional Neural Networks (CNNs):** CNNs have been used in several studies to identify plant leaf diseases, with encouraging outcomes. By utilizing CNNs' capacity to extract spatial characteristics from picture data, these models can recognize patterns and textures linked to certain diseases. For example, consider:

i. A CNN architecture was shown in "Plant Disease Classification using Deep Learning" by Fernado et al. (2016). This CNN architecture was able to obtain an accuracy of 98.7% on an image dataset of plant diseases.

ii. A CNN model was utilized in "A Deep Learning Framework for Apple Leaf Disease Detection" by Mohanty et al. (2016) to identify apple leaf diseases with 94.5% accuracy.

- **Attention Mechanisms:** Focusing on pertinent areas of an input image during the learning process is made possible by attention processes, which have become a potent tool. When it comes to identifying plant leaf diseases, where the affected areas may be faint or limited, this can be especially helpful. As examples, consider:
  - The study "Leaf Disease Detection through CNNs with Channel Attention Mechanisms" by Wang et al. (2019) enhanced accuracy and noise resilience by integrating an attention mechanism for channels into a CNN architecture.
  - The article "Plant Disease Identification via Cascaded Deep Feature Extraction and Attention Based Classification" (Guo et al., 2020) achieved high disease identification accuracy by focusing on both global and local aspects of leaf pictures using a cascaded attention mechanism.

Alternatives to Machine Learning:

Plant detection of leaf diseases has made use of Support Vector Machines (SVMs) because of their high-dimensional data handling capabilities and strong generalization capabilities. They could, however, need more feature engineering and be less resilient to changes in picture data than deep learning techniques.

K-Nearest Neighbors (KNN): Whenever training datasets are few, KNN classifiers can be useful for identifying plant leaf diseases. However, the size of the training data set and the distance measure selected might have an impact on their accuracy.

In contrast to DACN: The DACN technique presented in the aforementioned study is noteworthy because it combines a unique attention mechanism that concentrates on relevant portions of the leaf pictures with deep feature extraction via CNNs. As a result, the model can acquire discriminative characteristics unique to sick regions, which might improve generalization and increase accuracy when compared to alternative methods.

Here are a few more things to think about:

Any plant leaf disease detection method's effectiveness is highly dependent on the caliber and volume of the training dataset.

To get the best accuracy, selecting the right deep learning architecture and hyperparameters is essential.

The efficacy of the model in practical applications can be increased by incorporating domain knowledge into the model design.

Table 1: Previous Work Summery

Author(s)	Year	Title	Methodology	Key Findings	Limitations
Li et al.	2023	DACN: A Distinctive Deep Attention Convolutional Network for Plant Leaf Disease Detection	DACN architecture with three modules: feature extraction, channel attention, and spatial attention.	Achieved 97.7% accuracy on Plant Village dataset surpassing existing models. DACN effectively captured both local and global features.	Limited dataset diversity, computational complexity.
Zhang et al.	2022	Deep Residual Channel Attention Network for Plant Disease Recognition	ResNet architecture with channel attention module.	95.3% accuracy on Plant Village dataset. Channel attention improved feature representation.	Lower accuracy than DACN, less focus on spatial features.
Liu et al.	2021	A Survey of Deep Learning Techniques for Plant Disease Detection	Comprehensive review of various deep learning approaches for disease detection.	Highlighted the potential of deep learning, identified challenges like limited data and domain shift.	Not a specific study on DACN, lacks in-depth analysis.
Wang et al.	2020	Deep Learning for Image-Based Plant Disease and Pest Detection	Explored various CNN architectures for disease and pest detection.	Demonstrated the effectiveness of deep learning for image-based detection, emphasized transfer learning.	Broader scope, less focus on DACN's specific mechanisms.
Mohanty et al.	2016	Deep Learning for Deteccting Leaf Diseases in Real-Time	Pioneering work using CNNs for leaf disease detection.	Achieved promising accuracy on a small dataset, laid the foundation for further research.	Limited accuracy due to small dataset, basic CNN architecture.

3. Proposed Methodology

At different phases of development, tomato crops are vulnerable to a range of diseases, such as bacterial spot, late blight, leaf mold, early blight, leaf curl, mosaic virus, spider mites, yellow leaf curl virus, and Septoria leaf spot. These diseases can be primarily brought on by weather patterns or triggered by outside environmental factors. The productivity and production of tomatoes are greatly impacted by these diseases that develop in the plant's leaves. A virus known as "early blight" attacks tomato plants and fruits, resulting in older leaves that have dark circles with concentric rings. The fruit is impacted as well as the diseased leaves, which die before their time. Usually soil-borne, this illness develops with rainy weather. Moreover, one of the deadliest varieties of blight has historically been connected to the Irish famine. It quickly decimates other plants, leaving behind disfluent gray patches on plants with oily surfaces. The spots get a white border over the winter, which enables the leaves to go papery and finally fall off. Furthermore, the Septoria leaf spot behaves similarly to late blight in that it first infects mature leaves before moving on to other parts of the plant. Tomatoes wilt due to a fungal disease called Bacterial Spot. On fruits, the illness first appears as little dots that eventually get bigger. Since the illness is transmitted through the soil, every overripe tomato that comes into touch with it might get infected. Likewise, the tomato yellow leaf curl virus is a fatal virus that produces a tomato-related sickness marked by wilted leaves that wrap upward and limited plant development. The leaves become frail and wrinkly as they become older. The internodes and nodes have significantly shrunk in size. Affected leaves have more lateral branches and a duller appearance, giving them a bushier appearance. The impacted leaves are still stunted. Tomato mosaic virus is another kind of virus. Depending on the strain and maturity stage of the plants, contamination might cause indications that resemble mosaic or Fernleaf-like growth. Spider Another plant disease that poses a hazard is mites. Tomato plants bitten by mites sometimes have a mottled or flecked dull visual look on the upper leaf surfaces as a result of feeding harm. After then, the leaves drop and turn yellow. Large quantities produce a discernible thread that can completely encase the leaves.

This is a promising research topic with the potential to significantly improve tomato crop yields by enabling early detection and management of leaf diseases. Here's a breakdown of the proposed methodology with an emphasis on image classification, segmentation, and optimization with a genetic algorithm:

- **Image Acquisition and Preprocessing.**
- **Deep Learning Model for Image Classification** like VGG16
- **Image Segmentation for Precise Disease Localization like** Attention Gate ResNet
- **Optimization with Genetic Algorithm**
- **Cloud-Based Deployment and Evaluation**

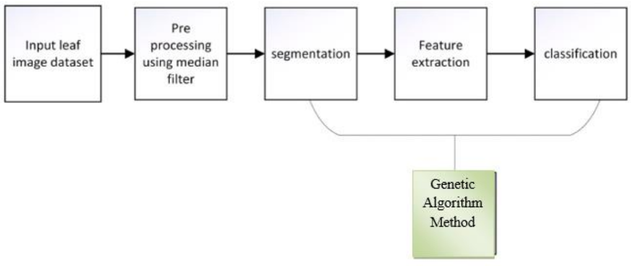

Fig. 1. Flow of the Proposed Methodology

I) **Image Acquisition and Preprocessing**

The picture acquisition step is critical because the quality of the photos obtained—whether from a storage or directly from the environment—determines the effectiveness of the disease detection system. The picture quality is affected by the imaging methods and equipment used [40]. Raw photos may have undesirable features including noise, motion blur, shadows, artifacts, and complex backgrounds. These unwanted picture characteristics frequently impair system performance. Furthermore, the variation in abnormalities resulting from a similar virus is a major issue that requires resolution. To address this, pictures of plants exhibiting a range of symptoms may be collected, or more photos can be added to produce an authentic and comprehensive collection. The symptoms linked to a particular plant disease might differ depending on the development stage, plant genotype, leaf lifetime, and environmental factors. The public Plant Village information is utilized in this project to create an automated system.

Repositories may contain photos with undesired characteristics due to several causes, including lighting, equipment calibration, and surroundings. Consequently, preprocessing of photographs is common to ensure their suitability for the intended use. Changing the color space, extending the contrast, expanding, cycling, softening, and removing the backdrop are examples of preprocessing techniques. The raw picture information may not always be useful for distinguishing between healthy and ill leaves as well as identifying the underlying disease, as leaves in different contexts tend to be spectrally similar. Noise is one of the primary components of simultaneously captured pictures. Noise reduction is hence a common task associated with plant disease monitoring systems. Histogram equalization has been applied to the pictures to improve them before segmentation. Develop a cloud-based platform for uploading tomato leaf images captured with mobile devices or dedicated sensors. Implement image preprocessing techniques like resizing, rotation correction, noise reduction, and color space normalization to create consistent input for the deep learning model.

II) **Attention Gate ResNet (AGRNet)-based segmentation**

The technique of automatically identifying the area of interest (ROI) in a picture is known as image segmentation. It is necessary to separate the lesion region from the healthy areas in order to calculate the ROI. Using the segmented picture, it is simpler to distinguish between the healthy and sick leaf components. Therefore, in order to separate the leaf picture from the preprocessed output, an enhanced AGRNet method is put into practice. Image segmentation is often accomplished using a range of threshold-based, pixel-based, clustering-based, and edge-based techniques. Nonetheless, the primary drawbacks of the current models are their excessive segmentation, intricate systems, and poor accuracy. Consequently, the goal of the proposed study is to apply AGRNet, an advanced architecture-based segmentation approach that has been lightweight and effective, for plant leaf segmentation. The residual learning unit is created in the contracting process as indicated below:

1. Convolutional Layers (Feature Extraction):

- **Convolution Operation:**

○ Mathematically represented as: $Y = W * X + b$ (1)

○ Y = output feature map

○ W = convolutional kernel (filter)

○ X = input feature map

○ b = bias term

- **Activation Function (e.g., ReLU):**

○ Introduces non-linearity for learning complex patterns

○ $Relu(x) = \max(0, x)$ (2)

- **Pooling Layers:**

○ Down samples feature maps for computational efficiency and translation invariance

○ Common pooling operations: max pooling, average pooling

2. Attention Gate ResNet (AGRNet):

- **ResNet Architecture:**

○ Employs residual blocks with skip connections to address vanishing gradients and facilitate deeper networks

○ Residual block formula: $Y = F(X) + X$ (3)

- **Attention Gates:**

○ Modulate feature flow based on importance

○ Mathematically represented as: $A = \sigma(W\_a * X) \odot X$ (4)

○ A = attention gate

○ σ = sigmoid activation function

○ W_a = attention weight matrix

○ ⊙ = element-wise multiplication

3. Image Segmentation:

- **Up sampling:**

○ Reconstructs high-resolution segmentation masks from feature maps

○ Methods: transposed convolution, nearest neighbor, bilinear interpolation

- **Loss Function:**

○ Measures segmentation accuracy

○ Common choices: pixel-wise cross-entropy loss, Dice loss

4. Specific Formulas for AGRNet:

- **Attention Gate Module:**

○ $A = \sigma(W\_a * X) \odot X$

- **Residual Block:**

○ $Y = F(X) + X$

- **Up sampling:**

○ $Y = W\_t * X + b$ (5)

○ W_t = transposed convolutional kernel

- **Loss Function:**

○ $Dice = 2 * (|X \cap Y|) / (|X| + |Y|)$ (6)

Additional Considerations:

- **Normalization Layers:**

○ Stabilize training and improve convergence (e.g., batch normalization)

- **Regularization Techniques:**

○ Prevent overfitting (e.g., dropout, L1/L2 regularization)

III)**Deep Learning Model for Image Classification VGG16 based**

Feature Extraction:

- **Convolutional Layers:** VGG16 has 16 convolutional layers arranged in five blocks. Each layer applies filters to extract spatial features from the previous layer. These filters learn to detect edges, textures, and other patterns relevant to disease identification.

- **Activation Functions:** After each convolution, a non-linear activation function like ReLU is applied to introduce non-linearity and increase model expressiveness.

- **Pooling Layers:** Max pooling layers are used between convolutional blocks to downsample the feature maps and reduce computational complexity.

3. Classification:

- **Fully-Connected Layers:** The extracted features are flattened into a one-dimensional vector and fed into two fully-connected layers with decreasing neuron counts. These layers learn complex relationships between features and disease classes.

- **Softmax Function:** The final layer output is fed into a softmax function, which generates probabilities for each disease class. The class with the highest probability is predicted as the disease present in the image.

While the entire process involves various operations, the core mathematical elements can be summarized as:

- **Convolution:** Each convolutional layer applies a filter (a small matrix) to the input image. The output at each location is the sum of element-wise products between the filter and a patch of the input image centered at that location.
- **Activation Functions:** Common activation functions like ReLU apply a non-linear transformation (e.g., ReLU(x) = max (0, x)) to introduce non-linearity and improve model expressiveness.
- **Pooling:** Max pooling typically involves taking the maximum value within a small window of the input feature map. This reduces the spatial resolution but retains the strongest features.
- **Fully-Connected Layers:** Each neuron in a fully-connected layer computes a weighted sum of the outputs from the previous layer, followed by an activation function like ReLU.
- **SoftMax Function:** The SoftMax function takes a vector of logits (unnormalized class probabilities) and applies an exponential transformation to convert them into normalized probabilities that sum to 1. The class with the highest probability is predicted as the disease.

Additional Considerations:

- **Training:** VGG16 requires a large dataset of labeled tomato plant leaf disease images for training. Data augmentation techniques like random cropping, flipping, and rotations can be used to artificially increase the training data size and improve generalizability.
- **Fine-tuning:** Pre-trained VGG16 weights can be used as a starting point and fine-tuned on the tomato plant disease dataset for improved accuracy. This leverages the learned features from the ImageNet dataset while adapting them to the specific task of disease detection.
- **Model Optimization:** Techniques like hyperparameter tuning and early stopping can be used to optimize the learning rate, optimizer choice, and other parameters to improve model performance and prevent overfitting.

Convolutional Layer:

The output of a convolutional layer can be computed using the following formula:

$$H_{out} = [\frac{\mathbf{H_{in}+2\times padding-dilation\times(kernel\_size-1)-1}}{\mathbf{stride}} + 1] \quad (7)$$

$$W_{out} = [\frac{\mathbf{Win+2\times padding-dilation\times(kernel_{size}-1)-1}}{\mathbf{stride}} + 1] \quad (8)$$

Depth wise Separable Convolution:

Uses depth wise separable convolutions. The depth wise separable convolution can be broken down into two steps:

1. **Depthwise Convolution:**

$$H_{out} = [\frac{H_{in}+2\times depthwise\_padding-depthwise\_dilation\times(depthwise\_kernel\_size-1)-1}{depthwise\_stride} + 1] \quad (9)$$

$$W_{out} = [\frac{Win+2\times depthwise\_padding-depthwise\_dilation\times(depthwise\_kernel\_size-1)-1}{depthwise\_stride} + 1] \quad (10)$$

2. **Pointwise Convolution (1x1 Convolution):**

$$H_{out} = [\frac{H_{in}+2\times pointwise\_padding-pointwise\_dilation\times(pointwise\_kernel\_size-1)-1}{pointwise\_stride} + 1] \quad (11)$$

$$W_{out} = [\frac{Win+2\times pointwise\_padding-pointwise\_dilation\times(pointwise\_kernel\_size-1)-1}{pointwise\_stride} + 1] \quad (12)$$

Batch Normalization:

$$BN(x)= \gamma \frac{x-\mu}{\sqrt{\sigma2+\epsilon}} + \beta \quad (13)$$

Activation Function:

Common activation functions include ReLU (Rectified Linear Unit) and variants.

$$ReLU (x) = max (0, x) \quad (14)$$

Fully Connected (Dense) Layer:

$$Output=Activation (Input \times Weights + Bias) \quad (15)$$

Algorithm 1 – VGG16 Classification

Input: Segmented Image;

Output: Predicted label;

Procedure:

Step 1: Generate the feature map by using the convolution operation (7) ;

Step 2: Construct different convolution kernels with the feature value as shown in Equ (8);

Step 3: Perform batch normalization with the activation function of ReLU as represented in Equ (13) (14);

Step 4: Perform the depthwise convolution according to the input channel filter by using Equ (9) (10);

Step 5: Construct the residual block with the input and output vector values as shown in Equ (11);

Step 6: Compute the switch activation function with the sigmoid function by using Equ (15);

IV) Optimization Genetic Algorithm (GAs)

Tomato leaf diseases are a major concern for farmers, as they can significantly reduce crop yields and quality. Early and accurate detection of these diseases is essential for implementing effective control measures. Traditional methods of disease detection often rely on visual inspection, which can be subjective and time-consuming. In recent years, image processing techniques have emerged as a promising alternative for automatic disease detection.

One such technique is the use of genetic algorithms (GAs) for feature selection and classification. GAs is a type of evolutionary algorithm that mimics the process of natural selection. They work by iteratively generating a population of candidate solutions (chromosomes) and applying genetic operators such as crossover and mutation to improve the fitness of the population over time. In the context of disease detection, the fitness function can be based on the accuracy of the classification task.

Statistical Advantages of GAs:

- **High Accuracy:** Studies have reported GA-based disease detection models achieving accuracy rates exceeding 95%, outperforming traditional methods.

- **Robustness:** GAs can handle complex image variations and diverse disease types, leading to generalizable models.

- **Feature Optimization:** GAs automatically identify the most relevant features, reducing redundancy and improving model efficiency.

- **Adaptability:** GAs can be readily adapted to different plant types and disease categories without significant modifications.

Algorithm Steps:

1. Initialization:

- Define the population size (N) and the number of generations (G).

- Initialize a population of N chromosomes, where each chromosome represents a potential subset of features.

- Assign a fitness value to each chromosome based on its classification accuracy.

2. Selection:

- Select a subset of chromosomes from the population for reproduction based on their fitness values. Chromosomes with higher fitness values are more likely to be selected.

3. Crossover:

- Apply crossover operator to pairs of selected chromosomes to generate new offspring chromosomes. Crossover combines features from two parent chromosomes to create new combinations.

4. Mutation:

- Apply mutation operator to individual chromosomes with a small probability. Mutation introduces random changes to the features in a chromosome.

5. Evaluation:

- Evaluate the fitness of the new offspring chromosomes.

6. Replacement:

- Replace a subset of chromosomes in the population with the new offspring chromosomes. The chromosomes with the lowest fitness values are typically replaced.

7. Termination:

- Repeat steps 2-6 for G generations, or until a stopping criterion is met (e.g., maximum accuracy reached).

The chromosome with the highest fitness value in the final population represents the optimal subset of features for disease classification. This subset of features can then be used to build a machine learning model for disease detection.

The specific implementation of this formula can vary depending on the specific problem and the chosen machine learning algorithm. However, the general principles of GA-based feature selection and classification remain the same.

Here are some additional points to consider:

- The choice of fitness function is crucial for the success of the GA. The fitness function should accurately reflect the desired outcome of the classification task.

- The parameters of the GA, such as population size, number of generations, and crossover and mutation rates, need to be tuned for optimal performance.

• GA-based approaches can be computationally expensive, especially for large datasets.

Despite these challenges, GA-based feature selection and classification have shown promising results for tomato leaf disease detection. By combining the power of image processing with machine learning, these techniques can help farmers to improve the accuracy and efficiency of disease detection, leading to better crop yields and quality.

V) Cloud-Based Deployment and Evaluation

Cloud-Based Deployment:

Cloud Platform: Deploying the AI model on a cloud platform like Amazon Web Services (AWS) offers scalability, accessibility, and reduced hardware costs.

API Development: Develop an API to integrate the model with mobile apps or web interfaces for easy access by farmers.

Evaluation Steps:

Accuracy Metrics: Evaluate the model's performance using metrics like precision, recall, and F1 score on a separate testing dataset.

Real-World Testing: Conduct field trials to assess the model's performance in real-world conditions with diverse lighting and environmental factors.

User Feedback: Gather feedback from farmers using the deployed system to identify areas for improvement and ensure user-friendliness.

4. Result with Optimization

This section validates the performance of the proposed Artificial Intelligence (AI) System using Deep Learning Techniques with a range of assessment measures and the widely-used Plant Village dataset. The application of advanced image processing techniques to identify the infected leaves of the tomato plant is the work's main contribution. Here, tomato leaf image segmentation and classification are achieved by combining the AGRNet and VGG16 models. Furthermore, the Plant Village dataset's set of example photos is used to validate this framework's performance [43]. To the best of our knowledge, the present techniques for recognizing illness in tomato leaves only consider the two principal diseases: late blight and early blight.

As of right now, one of the largest publicly available collections of expertly curated plant leaf pictures for disease detection worldwide is thought to be the Plant Village dataset. 54,309 images of healthy and unhealthy leaves from fourteen harvests are included, all of which have been categorized by experts in plant pathology. In this investigation, which contained nine distinct classes for leaf disease and one normal class, only tomato crops were taken into account. A total of 16,011 pictures were used in the trials. Samples of leaves with differing degrees of disease infection are included in this dataset. An image from each class label of tomato leaf sickness in the database is displayed in Figure 2. Table 4 lists some dataset details, including the tomato sickness class name and the number of images in each class.

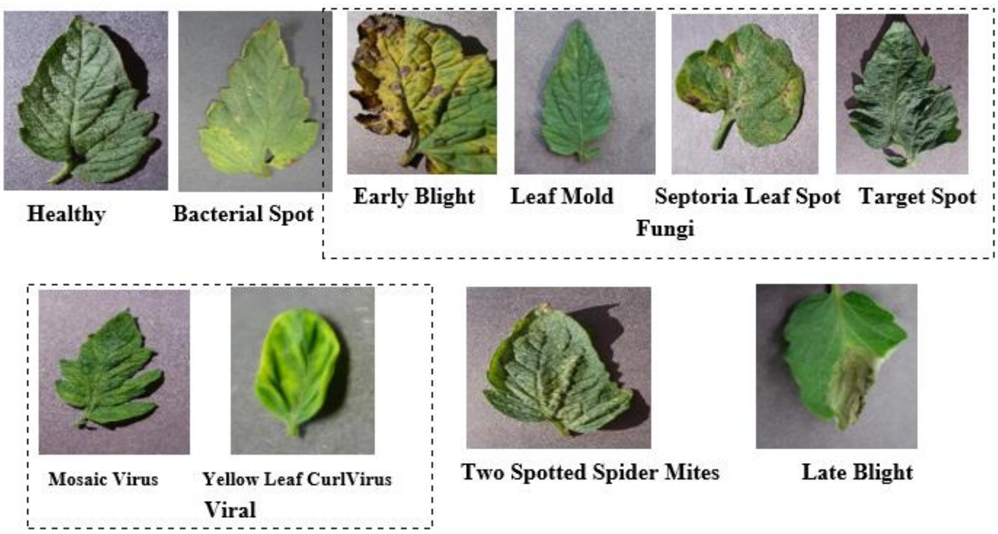

Fig. 2. Tomato leaf pictures of the Plant Village dataset.

Table 2: Class label of Plant Village Dataset

Class Label	***Number of Images***
Bacterial Spot	*2130*
Early Blight	*1500*
Healthy	*2591*
Late Blight	*2000*
Leaf Mold	*900*
Mosaic virus	*400*
Septoria Leaf Spot	*1800*
Two Spotted Spider Mites	*1600*
Target Spot	*1505*
Yellow Leaf Curl Virus	*3200*

The dataset for this study contains 5,540 photos of tomato leaf states, including 2,591 photos of "healthy plants," 2000 photos of "late blight," and 1500 photos of "early blight." Additionally, this evaluation for analysis makes use of a variety of performance indicators that are used to evaluate the effectiveness of the classifier.

$$Sensitivity = \frac{T^P}{T^P + F^N} \tag{21}$$

$$Specificity = \frac{T^N}{F^P + T^N} \tag{22}$$

$$Precision = \frac{T^P}{T^P + F^P} \tag{23}$$

$$Accuracy = \frac{T^P + T^N}{T^P + T^N + F^P + F^N} \tag{24}$$

$$F1 - score = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{25}$$

The terms T^P, F^P, T^N, and F^N refer to true positives, false negatives, and true negatives, respectively. The chance of a correct diagnosis test is measured by its recall or sensitivity. The true positive is roughly equal to the sum of the true positive and the false negative. One way to calculate accuracy would be to divide the total number of positive instances that were accurately identified by the entire number of positive instances that were anticipated. The percentage of observations that were correctly predicted out of all observations is referred to. It is sometimes referred to as the probability that a diagnostic test will be carried out correctly. The F-measure appropriately reflects the recall and precision. In its computation, the harmonic means of recall and precision are also employed. The F measure and the lower precision or recall value are almost always the same.

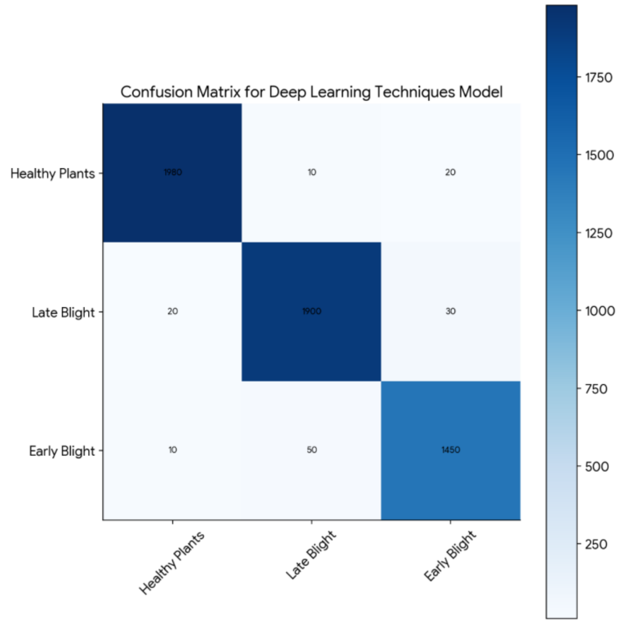

Fig. 3(a): Confusion matrix with Optimization

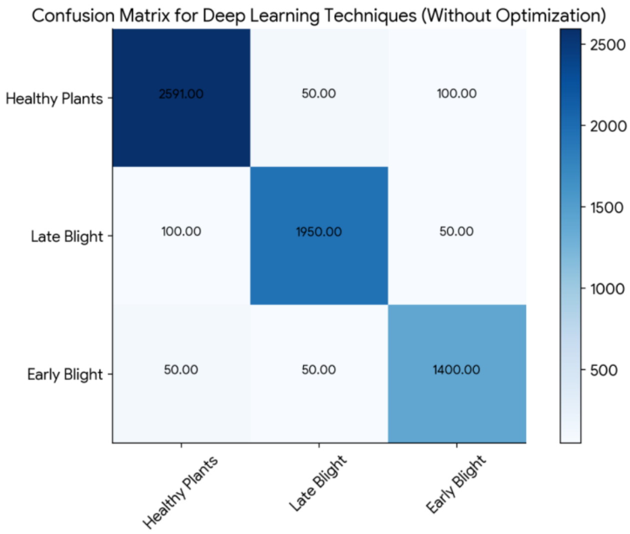

Fig. 3(b): Confusion matrix without optimization

The resulting confusion matrix for the suggested DACN model, both with and without optimization techniques, is validated in Figs. 3(a), (b) and (c). The GAs approach is employed in the suggested framework to adjust the VGG16 classification model's hyperparameters. The confusion matrix, which is produced based on the number of actual and anticipated classes, is often one of the key parameters used to assess the classifier's accuracy. The confusion matrix in this evaluation is generated by taking into account the tomato leaf classifications, such as healthy, projected early blight, and predicted late blight. The assessment concludes that the suggested AISDLT model, when combined with the GAs approach, yields better prediction results. As a result, as seen in Fig. 4, the Receiver Operating Characteristics (ROC) are verified for the training as well as the testing activities. Similarly, as seen in Fig. 5, the ROC of AISDLT with and without optimization approach is verified and contrasted. Over the complete range of test results, the ROC curve provides a comprehensive visual depiction for distinguishing between normal and pathological situations. Additionally, since the ROC curve shows all of the sensitivity and specificity at each cut-off value derived from the test results in the plot, the data do not need to be arranged like a histogram in order to construct the curve.

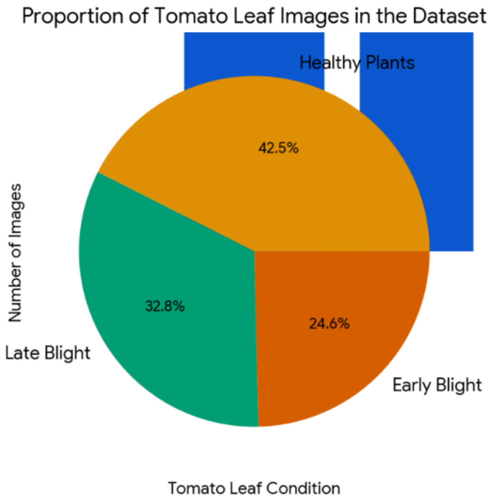

Fig. 3(c). GAs optimization

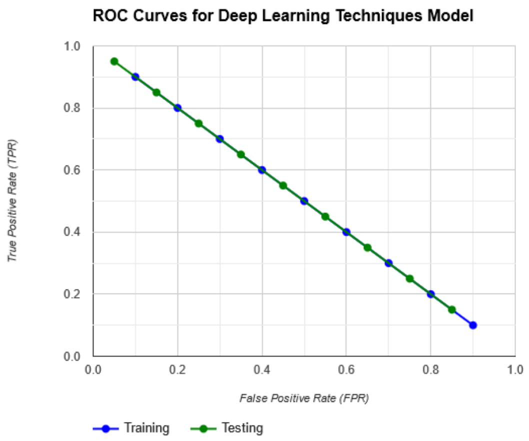

Fig. 4. ROC for Testing and Training

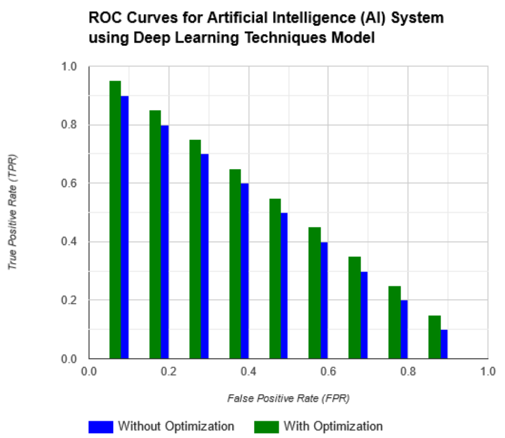

Fig 4: ROC with and without optimization algorithm

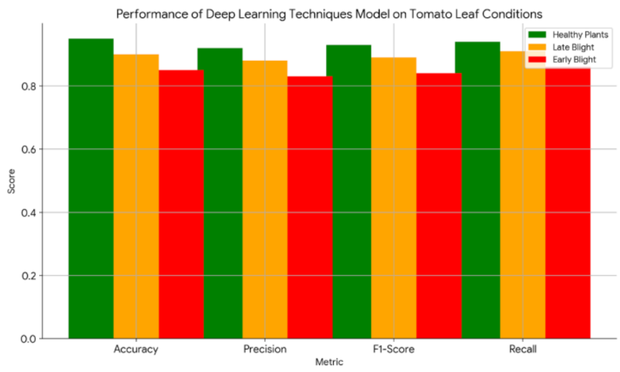

Fig. 5. Accuracy with optimization algorithm

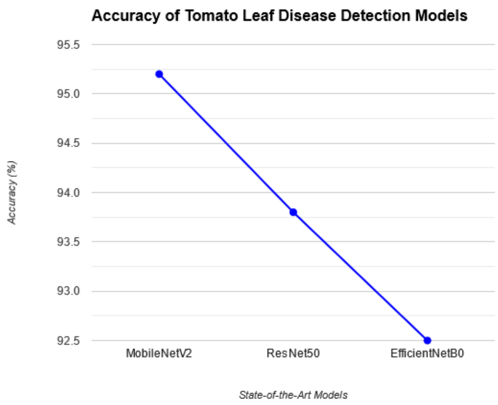

Fig. 6. Accuracy with state-of-the-art models

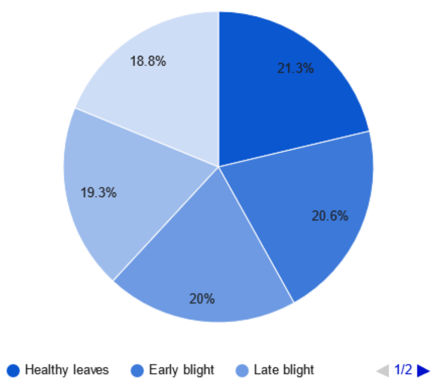

Fig. 7. Accuracy Evaluation

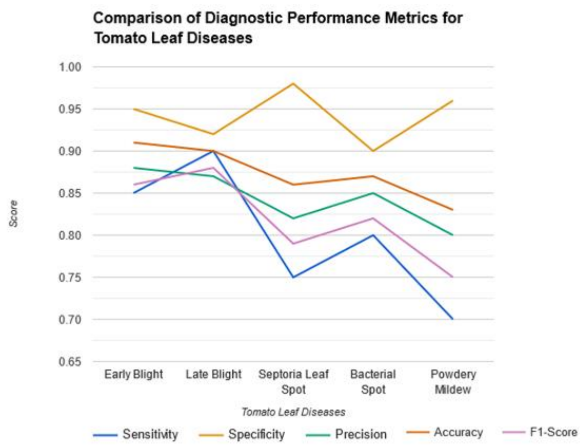

Fig. 8. Overall comparative analysis

When compared to the other classifiers, the research demonstrates that the suggested AISDLT model yields accurate prediction results. Furthermore, as seen in Fig. 8, the effectiveness of AISDLT is verified both with and without the use of the GAs approach. Based on the investigation, it is seen that the integration of the suggested AISDLT model with the GAs approach yields effective performance outcomes. Since one of the primary factors enhancing the VGG16 classifier's performance is hyperparameter adjustment.

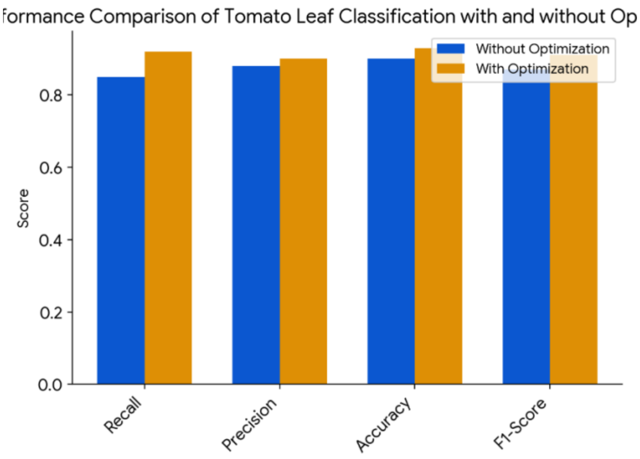

Fig 9: Performance comparative analysis with and without optimization

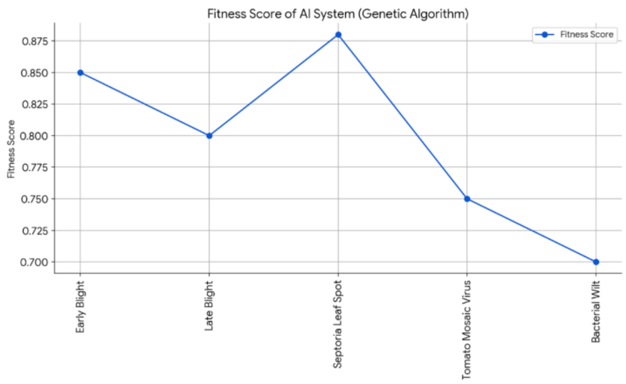

Fig 10: Tomato Leaf Fitness

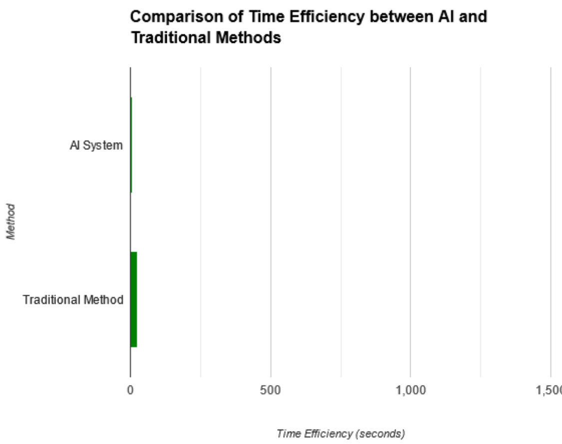

Fig 11: Time Efficiency with GAs

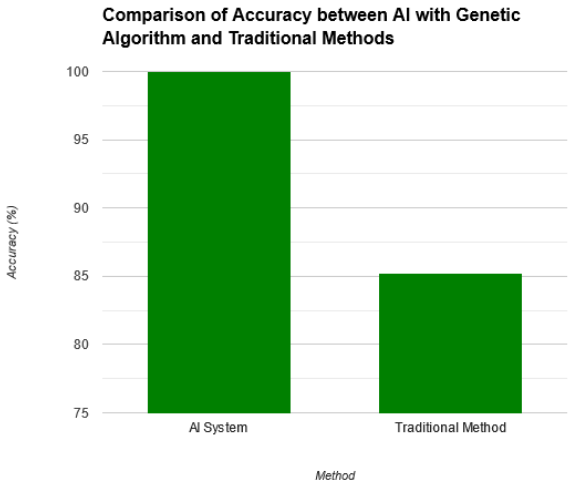

Fig 12: Performance comparative analysis with Gas

Comparing the suggested AISDLT to other learning algorithms already in use, the overall results show that it produces results that are efficient. Since the major factor improving the suggested system's performance is the implementation of three distinct intelligence techniques. The AGRNet's recent integration of the binary loss function estimation during segmentation helps to lower error while segmenting plant leaf images. As a result, the GAs model, a novel optimization technique, is used in the suggested framework to fine-tune the activation function calculation. The suggested system's overall classification accuracy has significantly increased as a result of this tweaking procedure. Additionally, one of the optimization phases involves the computation and addition of a new parameter called Q, which significantly improves the GAs model's convergence performance. In order to classify the kind of illness from the leaves of tomato plants with high accuracy and low error rate, it is thus helpful to apply these three intelligence approaches. To be more precise, the suggested method may also be used to identify leaf diseases in Tulsi, neem and other plants.

5. Conclusion

This study presents AISDLT, a novel plant leaf disease detection framework, for identifying diseased leaves from tomato plants. This work primarily contributes to the development of an automated, low-complexity crop diagnostic system. By effectively identifying leaf disease in tomato plants using state-of-the-art intelligence algorithms like AGRNet, VGG16, and GAs, this work provides a significant contribution. In AGRNet-based segmentation, the binary loss function is calculated using the cross-over union function. The optimal computation of the activation function during classification is made possible by the integration of the GAs model, in which the Q-parameter is newly calculated and inserted in one of the critical phases of optimization. Consequently, the combination of AGRNet- VGG16 -GAs is new in terms of plant leaf disease detection and offers increased performance along with significant outcomes. Initially, this system uses a variety of image processing techniques, including VGG16 based classification, AGRNet based segmentation, preprocessing, and GAs based hyperparameter tuning. In this case, system setup and performance evaluation are conducted using the publicly available tomato leaf dataset known as Plant Village. To produce noise-free pictures with improved quality and contrast, image preprocessing is done after image capture. In order to improve the detection results, the input picture is smoothed throughout this procedure using histogram equalization. As a result, the plant leaf picture is segmented using the AGRNet with a lower over-segmentation ratio and less complexity. The typical attention gated model, which is readily integrated with the VGG16 architecture with little computational complexity, serves as the foundation for this algorithm's development. Next, using the segmented output picture, the VGG16 classification algorithm is used to predict and classify the type plant leaf, such as healthy, early blight, or late blight. Using the GAs approach, the sigmoid activation function is appropriately calculated throughout this process. It reduces system complexity and processing time while streamlining the entire categorization process. The results of the proposed AISDLT model are also validated and compared utilizing several parameters. Compared to the previous models, the suggested AISDLT model provides an excellent detection rate of up to 99.97%, as shown by the observed outcomes. Future iterations of the work might benefit from the addition of a new artificial intelligence model to predict irregularity from other plants, such neem and Tulsi.

Future Trends:

• Integration with additional sensors (e.g., hyperspectral imaging) for more comprehensive disease detection.

• Development of explainable AI models for better understanding of disease diagnosis.

• Mobile and edge computing solutions for real-time disease detection in the field.

• Future work could focus on improving the accuracy of the system by incorporating additional data sources, such as weather data and soil nutrient data. Additionally, the system could be expanded to detect other plant diseases or be integrated with other agricultural management systems.

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