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INTERNET OF THINGS BASED SMART AGRICULTURE FOR LEAF DISEASE CLASSIFICATION USING OPTIMIZATION INTEGRATED DEEP CONVOLUTION NEURAL NETWORK

[1]L. Subash and [2]Dr. G. Arulselvi

[1]Ph.D. Research Scholar, Department of Computer and Information Science, Faculty of Science, Annamalai University, Annamalainagar, Tamil Nadu, India

[2]Associate Professor, Department of Computer Science and Engineering, Faculty of Engineering and Technology, Annamalai University, Annamalai nagar, Tamil Nadu, India

[1]l.subashmenon@gmail.com and [2]arulselvi_ag2004@yahoo.com

ABSTRACT

The smart agricultural business is being revolutionized by the Internet of Things (IoT). This application facilitates the user in gathering real-time data from agricultural fields and transferring it to distant locations for further processing. Automated disease prediction is feasible using the existing sensor data and the captured picture from the fields. A deep neural network is used to classify diseases based on leaf images. Agriculture serves as the fundamental support of our nation; yet, our productivity falls short in comparison to worldwide benchmarks owing to the inadequate utilization of technological advancements in agriculture. The study presents a method for classifying leaf diseases in plants using deep learning methods, with the use of Internet of Things (IoT) technology. This strategy aims to monitor the health of various plants. At first, the network nodes in the simulated environment take images of plant leaves and send them to the sink node for disease categorization. Upon receiving the plant images at the sink node, the image undergoes preprocessing using a Gaussian filter. After preprocessing, the segmentation procedure is carried out utilizing the Information Gained Farthest First Clustering (IGFFC) technique. Subsequently, the segmented image outcomes undergo data augmentation, followed by illness classification using an Allied Layered Deep Convolutional Neural Network (ALDCNN). The ALDCNN is trained using the suggested Red Panda Optimization (RPO) method. The suggested technique achieves enhanced accuracy in detecting leaf diseases within a short time frame. PYTHON serves as the implementation tool for assessing the proposed system. Furthermore, the suggested approach achieves superior performance in terms of measures such as accuracy, precision, and recall, with values of 98.06%, 98.11%, and 98.06% correspondingly.

Keywords: Internet of Things (IoT), preprocessing, segmentation, feature selection (FS), feature extraction, classification, Information Gained Farthest First Clustering (IGFFC), Allied Layered Deep Convolutional Neural Network (ALDCNN) and Red Panda Optimization (RPO)

1. INTRODUCTION

The use of Internet of Things (IoT) technology in the agricultural industry has facilitated the development of inventive and effective methods, especially in addressing issues pertaining to foliar diseases. The capacity of IoT-based smart agricultural transformation to detect, track, and control the impact of low fog on crops [1, 2]. The integration of IoT sensors, data analytics, and agricultural practices has the potential to revolutionize the improvement and mitigation of illnesses in agricultural goods, enhancing their quality, and promoting sustainability. This paper explores the significance of IoT-enabled systems, emphasizing their ability to gather, analyze, and provide real-time data, allowing farmers to make well-informed choices promptly. The detrimental effects of these hazardous variables on crops directly contribute to the decrease in both the quality and quantity of crops. The name "pesticides" was created to address the need to battle, regulate, and limit the impact of biological organisms and illnesses [3]. The diagnosis of plant pests and diseases is often conducted by visual examination, which involves analysing the look, morphology, and other properties of the leaves. It is recommended that this visual inspection be conducted and evaluated only by a highly skilled biologist, since an incorrect diagnosis might result in irreversible reduction in crop production [4]. Pest and disease control research often incurs significant costs and need the involvement of a specialised biologist to promptly detect and prevent the dissemination and transmission of any diseases. This study attempts to determine the basic direction of IoT technology in influencing the future of agriculture, particularly in terms of large-scale production and environmental protection. It does so by analysing the present landscape and researching the prospective uses of IoT in impoverished regions [5].

IoT-enabled smart agriculture offers a solution that effectively addresses many long-standing issues encountered in conventional agricultural conservation methods [6, 7]. A major obstacle in traditional agriculture is the prompt and precise identification of illnesses that impact plant foliage. In the absence of proactive surveillance, these diseases often remain unnoticed until they progress to advanced stages, leading to substantial reductions in agricultural yield. Moreover, the absence of precise and geographically specific data on illness trends adds extra complexity to the implementation of efficient disease management techniques [8]. In addition, the manual inspection approach may involve a significant amount of labour, use a lot of time, and be subjective. It is crucial to identify foliar diseases early and respond quickly in order to prevent their spread [9, 10]. Moreover, the presence of many environmental variables that impact the development of diseases adds to the intricacy, emphasising the need for more appealing and data-driven methods [11]. Limited availability of dependable, up-to-date information undermines farmers' capacity to make well-informed choices and affects the well-being and total productivity of crops. The presence of these difficulties emphasises the need for creative solutions facilitated by IoT technology in the domain of smart agriculture, namely in the detection and prevention of foliar diseases that impact agricultural systems globally [12].

In recent times, AI has been extensively used in many aspects of daily life, resulting in the emergence of the phrases "machine learning" (ML) and "deep learning" (DL). These terms refer to the ability of computers to acquire a vast array of patterns and then make decisions or perform actions [13]. Machine learning and deep learning enable a software programme to enhance its prediction accuracy without requiring explicit design for that purpose. The extent of crop loss caused by illness varies between 10% and 50%, depending on the severity of the disease. Therefore, it is crucial to promptly identify illness signs and promptly implement suitable actions to avoid the advancement or transmission of the diseases [14]. An accurate and immediate diagnosis will undoubtedly decrease crop loss in the sugar beet field. The progress in computer vision provides an opportunity to improve and broaden the precision in plant protection methods and to promote precision agriculture. Various research has presented the technology of image processing for the purpose of recognising and classifying crop diseases. The feature extraction approach in image processing was used to determine if it is infected or not [15]. The identification of infected regions and the classification of disease severity may be achieved by analysing the colour and form characteristics using a direct image processing technique on diseased leaf pictures. Alternatively, disease classification may be achieved by using machine learning (ML) techniques such as support vector machine (SVM) and K-means clustering. DL approaches were used to categorize the disorder, including artificial neural networks (ANN) and convolutional neural networks (CNN). There has been much research in recent years on the use of deep learning methods for the identification of pests and diseases in plants. Despite the introduction of many methods and methodologies, there is still scope for further enhancements.

Major Contribution of Research work:

- To classify various diseases affecting different types of plant leaves, such as apple, banana, mango, and groundnut leaves, we utilised an advanced abnormality Internet of Things (IoT), preprocessing technique, segmentation, deep feature extraction, and an improved classification model. Our goal is to develop a hybridised optimization-based algorithm for this purpose.
- To carry out leaf segmentation, the Information Gained Farthest First Clustering (IGFFC) method will be used. It enhances the quality of the segmented images.
- To enhance the classification performance, a new RPO model will be created. This model will optimize the hidden neurons of DCNN to extract important features from the pooling layer. Additionally, it will optimize the hidden neurons of Allied Layered to classify several diseases in plant leaves.

- To assess the efficiency of the multi-disease classification model for plant leaves, training dataset was used and various performance metrics were utilized to compare it with standard classifier techniques.

The subsequent sections of the paper are organised in the following manner: Section 2 presents a comprehensive analysis of the current research scenario regarding plant diseases, emphasising the existing challenges and indicating areas that need further investigation. Section 3 provides an overview of the planned plant disease system, while Section 4 includes the findings and comments focused on improving performance metrics. Section 5 provides a summary of the system and its main discoveries, ultimately concluding the article.

2. LITERATURE REVIEW

To make efficient advancement in this field, it is necessary to have a thorough understanding of previous research. Diagnosing plant leaf diseases has proved to be a formidable undertaking. Deep learning algorithms are crucial in accurately categorizing pictures in this important scientific field. This is an overview of the commonly used methods described in the relevant body of research. Manually monitoring important agricultural activity is a laborious effort. Minimising human labour in monitoring plant health is a cost effective way of crop production. As a result, this work has become very important, drawing the attention of many researchers towards the topic. The literature has a multitude of publications that discuss plant diseases, emphasising the importance of this study effort.

The authors Nirmal *et al.* [16] have introduced a categorization of illnesses affecting pomegranate leaves using image processing and machine learning methods. This framework employs image processing methods, including capture, resizing, enhancement, segmentation, ROI extraction, and feature extraction, to accurately detect and categorize illnesses affecting pomegranate plants. The framework is constructed by using a training set and a test set of pictures that are linked to pomegranate leaf disease. Image enhancement and image segmentation are often used in the implementation phase to detect regions of interest (ROIs) and distinguish characteristics. Utilising machine learning (ML) might potentially provide a feasible solution to address this issue. The issues are resolved by using machine learning methods such as linear discriminant analysis (LDA), K-Nearest Neighbour, Naive Bayes (NB), and ensembles (LDA–NB). The integration of Latent Dirichlet Allocation (LDA) with Naive Bayes (NB) enables the framework to get a classification accuracy of 96.49% while identifying illnesses on pomegranate leaves.

Abhilasha *et al.,* [17] have used deep learning approaches to analyse oil seed leaf diseases. Soybeans, groundnut, and rapeseed/mustard are the primary oilseeds. Fungal, viral, and bacterial pathogens may induce diseases in oilseed leaves. Disease incidence lead to a decrease in output, which has a negative impact on the economy. Early detection of illnesses may lead to the preservation of crops. They have used a convolutional neural network (CNN) to get dependable and verifiable outcomes. The necessary images for this procedure should be gathered from internet sources as well as an agricultural research centre.

Gaur *et al.* [18] have created a very efficient device for detecting disease incidence in bananas using compressed sensing. This device utilises a foreground-based segmentation approach and a two-step feature extraction strategy to accurately identify and categorize two of the most significant diseases affecting bananas. A database is established to document the occurrences of banana bunchy top and sigatoka leaf spot diseases. This was achieved by capturing real-time images from various locations in the southern regions of Tamilnadu, specifically Thadiyankudisai and Thandikudi in Dindigul district, KC Patti, Muthalapuram, Suruli Patti, and Kambam in Theni district, as well as ICAR NRCB in Tiruchirapalli. The performance of the suggested device has been assessed based on the proportion of infected regions, detection accuracy, decrease in features, and classification accuracy.

Gautam *et al.,* [19] proposed an ensemble stacked deep learning model to address the issue of automatically identifying mango-leaf disease. The suggested methodology involves segmenting the pictures to isolate the area of interest, which is then fed into a series of deep neural networks. The results obtained from the deep neural networks are combined with a machine learning model to accurately detect leaf disease. This model was used for the detection and classification of several mango leaf diseases, including Powdery mildew and Anthracnose. The work involved the integration of deep learning models with machine learning techniques to accurately detect and classify illnesses affecting mango leaves.

Hosny *et al.,* [20] proposed a compact deep convolutional neural network (CNN) architecture to extract high-level latent feature representations. The profound characteristics are then combined with conventional manually designed local binary pattern (LBP) characteristics to capture the local texture details in plant leaf images. The proposed model undergoes training and testing using three publically accessible datasets, namely Apple Leaf, Tomato Leaf, and Grape Leaf. The suggested technique obtains validation accuracies of 99%, 96.6%, and 98.5% on the three datasets, respectively. Similarly, it achieved test accuracies of 98.8%, 96.5%, and 98.3% on the same datasets, respectively.

The authors Suresh *et al.* [21] had introduced a method for detecting and classifying groundnut leaf disease in real-time using a combination of machine learning algorithms. This method is based on the Internet of Things (IoT) and is referred to as GLD-HML. To begin, use the improved crow search (ICS) algorithm to separate the illness region from the leaf. This step is crucial for accurately classifying the condition. Furthermore, provide a multi-objective sunflower optimization (MSO) technique to achieve optimum feature selection from a set of multiple extracted features during the feature extraction stage. They have explained the use of moth optimization based deep neural network (MO-DNN) for classifying diseases in Groundnut leaf with several categories.

Deep learning has revolutionized the field of plant disease detection by providing high accuracy and efficiency. However, there are some possible drawbacks to using deep learning models for plant disease detection. Firstly, deep learning models [17] require a large amount of labeled data to train and generalize well, which may not be available or easy to obtain for some plant diseases or species. Secondly, deep learning models [18] are often complex and computationally expensive, which may limit their deployment and application in resource-constrained settings or real-time scenarios. Thirdly, deep learning models [19] are often seen as black boxes, which may reduce their interpretability and explainability, especially for the end-users such as farmers or agronomists who may need to understand the rationale behind the diagnosis and the recommended actions. Lastly, deep learning models [20] may not be robust or adaptable to changes in environmental conditions, such as lighting, weather, or background, which may affect the quality and consistency of the plant leaf images.

3. PROPOSED METHODOLOGY

In this study, leverage an array of sensors like as humidity, pH level, temperature, and soil moisture sensors—in agricultural fields to capture real-time data. These sensors, strategically positioned across diverse farm locations, are centrally managed by a Raspberry Pi 3 module (RPI3). Concurrently, an RPI3-connected camera observes plant leaf diseases. Initially, network nodes simulate the environment, capturing plant leaf images directed to a sink node for disease classification. Upon image reception, preprocessing steps, including data augmentation and Gaussian filtering-based noise removal, are executed. Subsequent segmentation employs the Information Gained Farthest First Clustering (IGFFC) mechanism. The process then includes data augmentation on segmented images, followed by disease classification utilizing an Allied Layered Deep Convolutional Neural Network (ALDCNN). Crucially, ALDCNN training is facilitated through the proposed Red Panda Optimization (RPO) algorithm. The block diagram for the proposed research methodology is shown in Figure 1,

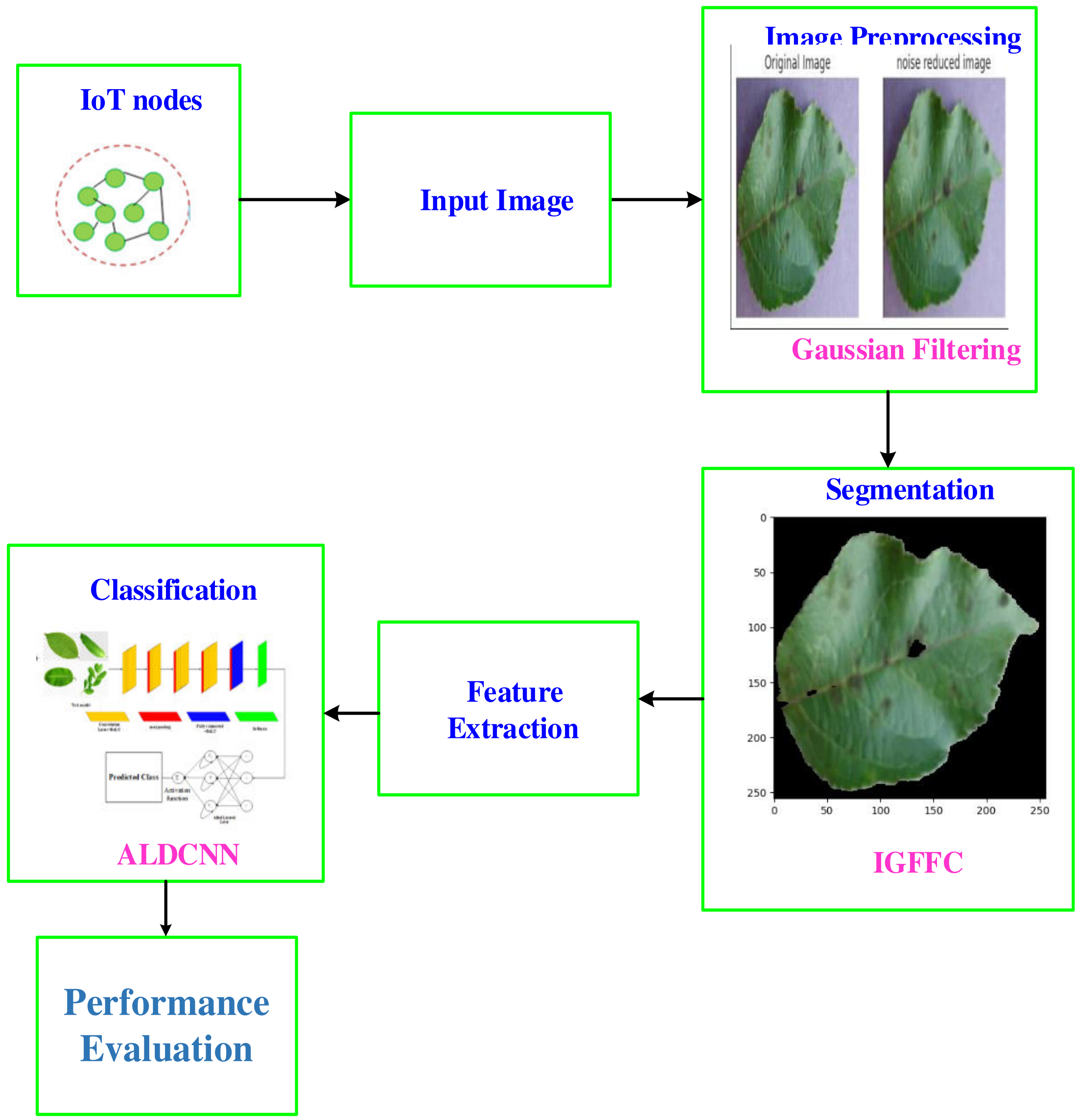


Figure 1: Block diagram for the proposed research methodology

The proposed algorithms are explained as follows,

3.1. Internet of Things (IoT) in Smart Agricultural Monitoring System

In this research endeavor, a comprehensive approach is adopted for real-time data collection in smart agricultural fields, employing a diverse set of sensors. The IoT technology by using various sensors include humidity, pH level, temperature, and soil moisture sensors. The sensors are strategically placed in different locations across the farms to ensure comprehensive data collection. All the sensors are controlled by a central Raspberry Pi 3 module (RPI3), which serves as a common controller for overseeing the data collection process. The RPI3 module collects data from the sensors and manages the communication between the sensors and the central system [22]. The IoT aspect is further enhanced by the integration of a camera connected to the RPI3 module, which captures images of plant leaves for disease observation. In addition to the sensors, a camera is also connected to the RPI3 module. The camera is specifically used to capture images of plant leaves in order to observe signs of diseases.

Initially, network nodes, which are simulated within the environment, capture images of plant leaves. These images are then sent to a central sink node, which acts as a central point for receiving and processing the images. The sink node is likely equipped with a disease classification model, which is used to analyze the images and identify any potential diseases affecting the plant leaves. The disease classification model categorizes the diseases based on the analysis of the images. This integrated approach of using both sensor data and image analysis provides comprehensive insights into the health and conditions of various plant leaf disease in real-time. By combining sensor data and image analysis through IoT, the agricultural monitoring system enables proactive agricultural management practices, facilitating early detection and prevention of diseases in plant.

3.2. Preprocessing and Augmentation using Gaussian Filtering

The initial step involves the simulation of network nodes within a designated environment. These network nodes are designed to capture images of plant leaves. As the simulation progresses, the captured plant leaf images are then directed or routed to a central node known as the sink node. The primary function of the sink node is to carry out disease classification based on the received plant images. Upon arrival at the sink node, the plant images undergo a series of preprocessing steps to ensure optimal quality and reliability for subsequent analysis. Two specific processes are applied during this preprocessing stage: data augmentation and Gaussian filtering-based noise removal.

Data Augmentation:

Data augmentation is a technique used to diversify the dataset by applying various transformations to the plant images. The goal is to increase the variability of the dataset, enabling the model to better generalize and improve its performance. The data are transformed into a standard classification format after pre-processing the images. The images are first converted into RGB, and the pixel resolution is kept constant at 224 × 224 pixels. As part of the image augmentation process, an open-source Keras ImageDataGenerator class is used to enhance the dataset size by recreating images using various pre-processing techniques, including random rotation (15°), horizontal and vertical flips, width and height shifts, shear ranges, fill modes, and transpositions. The Keras normalization function is used to normalize the images of plant leaf diseases, which transforms the input images' floating pixel values [23]. Before augmentation, each class contains 320 images, but only 296 healthy banana images are utilized for improvement. Through augmentation, the number of healthy banana images is increased to almost 320.

Gaussian Filtering-Based Noise Removal:

Gaussian filtering is employed as a method to reduce noise in the plant images. Noise, such as random variations in pixel intensity, can interfere with the accuracy of disease classification. The application of Gaussian filtering helps smooth out these variations, resulting in cleaner and more reliable images for analysis [24]. The Gaussian filter is mostly used to enhance picture quality by reducing noise and achieving a smoother appearance. The convolutional operator refers to the Gaussian operator, which is used to achieve Gaussian smoothing by convolutions. The 1-D Gaussian operator may be defined as follows:

$$G_{1D}(K) = \frac{1}{\sqrt{2\pi s_f}} e^{-\left(\frac{K^2}{2(s_f)^2}\right)} \tag{1}$$

The most effective smoothing filter s_f for pictures is determined by analysing the spatial and frequency domains, therefore satisfying the uncertainty connection described below:

$$\delta K \delta \alpha \geq \frac{1}{2} \tag{2}$$

The 2D Gaussian operator may be expressed as:

$$G_{2D}\left(K,L\right)=\frac{1}{2\pi\sigma^2}e^{-\left(\frac{K^2+L^2}{2\sigma^2}\right)} \qquad (3)$$

The symbol σ (Sigma) represents the standard deviation of the Gaussian function. When the value of σ is increased, the picture smoothening effect also increases. Additionally, K, L'stands for the Cartesian coordinate points that indicate the dimensions of a picture depicting the window.' The process involves performing addition and multiplication operations on the kernel and pictures. The image may be represented as a matrix with values ranging from 0 to 255.The kernel is a square matrix that has been normalised and may be defined using multiple bits. When doing a convolutional job, each kernel bit and each picture component is multiplied and divided by a power of two.

3.3. Segmentation using Information Gained Farthest First Clustering (IGFFC)

Segmentation of diseased regions is useful to extract discriminative features. In this study, the diseased region is extracted for texture feature calculation as it contains the most discriminative portion of the plant disease. For clustering the obtained feature from different locations this research methodology uses the Information Gained Farthest First Clustering (IGFFC) algorithm. In this algorithm the initial centroid point is selected randomly and the farthest point from the initialized centroid is considered as the next centroid point. But directly selection of the centroid attains poor clustering performance. So that the information gain is calculated for the input features based on the information gain the centroids are chosen. Farthest-First operates in two steps of process:

- Information gains the centroids selection
- Cluster assignment

In the first stage, a random data location is chosen as the first cluster centre. Then, during the cluster assignment step, the second centre is identified as the data point that is furthest from the first centre. The subsequent centres are selected based on their maximum distance from the first set of centres. After determining the suitable X number of centroids, the method allocates all remaining data points to the cluster that has the nearest centroid and executes them. Thus, IGFFC required a single step to categorize a sequence of data points. The FFC technique distinguishes itself from IG clustering by not identifying common attribute locations to modify centroids. Additionally, all centroids in FFC are real data points rather than geometric centres of clusters [25]. The optimal centroids, which minimise the distance between clusters, may be found using approximation technique 2, c--ommonly known as the X centre issue. This algorithm employs a single iteration and starts with a random selection; however, it is more suitable for doing bulk selection. Put simply, the IGFFC algorithm selected centroids that were twice the ideal distance $\left[W_i X_i\right]$.

Input: Obtained cluster feature sets

Output: Selected disease region

Begin

Initialize population, fitness, iteration I_t and maximum iteration MI_t

Compute fitness

Set iteration $I_t = 1$

While $\left(I_t \leq MI_t\right)$ **do**

Finding a third point which is the farthest point from the first two existing points $\left[W_i X_i\right]$

Henceforth $i = 1,2,3....,X$

Calculate fitness

Set $I_t = I_t + 1$

$P_1, P_2......, P_X$ are points or objects of dataset belongs to cluster

End while

Return segmented region

End

As a result, the centroids are selected based on the information gained as follows:

$$Min\left\{Max\left[Dis\left(P_i, P_1\right), Dis\left(P_i, P_2\right)....P_n\right]\right\} \tag{4}$$

Where, Dis defines the distance cluster feature sets and P_i defines the i-number of points from the selected cluster extract feature centroids.

3.4. Feature Extraction

Feature extraction is an essential stage in classification algorithms, since the accuracy of the algorithm is greatly affected by the selected feature set. This procedure entails reducing the number of dimensions in order to accurately depict the pertinent characteristics of an affected area in a more succinct manner. The leaves provide various categorization criteria based on their shape, colour, and texture. Although form parameters are useful for distinguishing between healthy and diseased leaves, their effectiveness decreases when it comes to diagnosing diseases because of the significant differences in shape within and across different classes of segmented sick regions. Conversely, the colour of the affected area consistently shows distinct variations compared to the healthy area within the same category and also differs across other categories. Likewise, the consistency of the affected area, which is affected by the particular kind of sickness, becomes an important indicator. This talk explores the parameters involved in computing these feature sets, clarifying their significance in characterising plant leaves for disease detection.

Colour Characteristics: The two primary categories of colour characteristics are colour histograms and colour moments. In the current context, the significance of colour as a predictor of illness categories has diminished. Colour histograms provide an extensive range of features that are not really necessary in this situation. Colour moments are used to characterise colour information, serving as a concise method for representing colour data.

Mean The mean value of the two-dimensional image matrix may be computed to represent the initial colour moments. The colour picture is decomposed into its three RGB channels, and the average value is computed for each channel.

Variance: The second colour moment refers to the standard deviation, which quantifies the dispersion of colour data from the average value. The calculation is performed for three RGB layers inside a two-dimensional picture matrix. The sick picture area is characterised by six colour information characteristics, consisting of three measures for the mean and three measures for the standard deviation of the red, green, and blue layers of the RGB image.

Texture Features: The texture plays a crucial role in illness detection since it contains a wealth of information about the affected area. In this case, 7 texture features have been derived from the Gray-Level Cooccurrence Matrix (GLCM) of a grayscale leaf picture. The reason for employing the GLCM is because the colour information has already been stored using colour moments. The GLCM is computed over a grayscale picture that has been resampled to eight grey levels [26, 27, 28]. It computes the frequency at which a pixel with a certain gray-level is located next to a pixel with the value y. The elements (x, y) of the GLCM matrix of 8 × 8 correspond to the frequency of occurrences when a pixel with value x is close to a pixel with value y.

The GLCM GY of size 8 × 8 is defined over $u \times v$ an image Im with 8 distinct gray-level intensities. The offset parameter $(\Delta i, \Delta j)$ is described by the formula in equation (5).

$$GY_{\Delta i,\Delta j}(x, y) = \sum_{i=1}^{u}\sum_{j=1}^{v}\begin{cases} 1 \text{ if } & \mathrm{Im}(i, j) = x(i+\Delta i, j+\Delta j) = y \\ 0 & otherwise \end{cases} \quad (5)$$

Where: x and y represent the pixel values; x and y represent the spatial coordinates in the picture matrix Im; $(\Delta i, \Delta j)$ offset refers to the spatial relation of the matrix; and $\mathrm{Im}(i, j)$ denotes the pixel values at a certain place (i, j). The specific characteristics of these textural features are outlined below:

Uniformity (angular second moment)

$$U = \sum_{x=1}^{n_g}\sum_{y=1}^{n_g} Pl(x, y)^2 \quad (6)$$

Entropy

$$E = -\sum_{x=1}^{n_g}\sum_{y=1}^{n_g} Pl(x, y)\log\left[Pl(x, y)\right] \quad (7)$$

Contrast

$$C = \sum_{x=1}^{n_g}(x-y)^2\left\{\sum_{x=1}^{n_g}\sum_{y=1}^{n_g} Pl(x, y)\right\} \quad (8)$$

Dissimilarity

$$D = \sum_{x=1}^{n_g}(x-y)\left\{\sum_{x=1}^{n_g}\sum_{y=1}^{n_g} Pl(x, y)\right\} \quad (9)$$

Inverse Difference Moment (Homogeneity)

$$Homogeneity = \sum_{x=1}^{n_g}\sum_{y=1}^{n_g}\frac{Pl(x, y)}{1+(x-y)^2} \quad (10)$$

Inverse Difference (ID)

$$ID = \sum_{x=1}^{n_g}\sum_{y=1}^{n_g}\frac{Pl(x, y)}{1+|x-y|} \quad (11)$$

The segmented diseased area of the leaf picture is represented by a set of 7 texture features that capture the texture information.

3.5. Classification using Allied Layered Deep Convolutional Neural Network with Red Panda Optimization

The ALDCNN with RPO is a hybrid model specifically developed for feature classification problems. This novel method integrates the capabilities of a layered convolutional neural network (CNN) architecture, which leverages deep learning, with the optimization skills of the Red Panda Optimization algorithm. Within the realm of feature categorization, this model uses its deep learning layers to autonomously acquire hierarchical representations from input data, facilitating efficient feature extraction. By incorporating Red Panda Optimization, an additional layer of optimization is introduced to optimize the training process of the model, perhaps leading to improved convergence and performance. The combination of these elements enhances the strength and effectiveness of the system for categorizing characteristics, making the Allied Layered Deep Convolutional Neural Network with Red Panda Optimization a very favourable option for applications that need precise and automatic categorization of data.

The attributes obtained at this stage are offered as a contribution to the Allied Layered based deep CNN classifier. The image is categorized into two groups: healthy and ill. The DCNN (Deep Convolutional Neural Network) idea employs many layers of representation. The complex architecture of DCNN enables it to effectively extract and isolate valuable information. Nevertheless, the Allied layer has a little superior level of presentation compared to the default classifier, known as the softmax classifier, which possesses a fundamental capacity for generalisation. Hence, it is essential to complete the study on these two methods, with the AL-DCNN classifier being recommended. The deep convolutional process is implemented with the aim of enhancing the efficiency of the proposed system. The concepts of "parameter sharing" and "local connectivity" are used in DCNN. The convolutional layer is used to acquire feature representations of the inputs. Each individual neuron inside a component map is directly connected to a specific group of neighbouring neurons in the preceding layer. This area is referred to as the neuron's response field by the preceding layer. The new feature map may be produced by convolving the input with a learning kernel and applying an element-wise nonlinear activation.

Many different kernels are used to produce the whole feature maps. The feature value in the layer's r^{th} feature map fm^{th} , Ω_r^{fm} is determined mathematically by,

$$\Omega_r^{fm} = Wt_r^{fm} I^{fm} + Bs_r^{fm} \tag{12}$$

Where, I^{fm} is the input data for the fm^{th} layer, Wt_r^{fm} and Bs_r^{fm} are the weight factor and bias term of the fm^{th} layer's filter r^{th}, respectively. Keep in mind that the feature map is Ω_r^{fm} generated by a common kernel Wt_r^{fm} . DCNN becomes nonlinear because to the activation function. Let the nonlinear activation function be $L_N^x(\bullet)$ represented. Convolutional feature Ω_r^{fm} activation value $\left(L_N^x\right)_r^{fm}$ may be calculated as:

$$\left(L_N^x\right)_r^{fm} = L_N^x\left(\Omega_r^{fm}\right) \tag{13}$$

By lowering the resolution of the feature maps, the pooling layer seeks shift-invariance. Normally, it is placed in the middle of two convolutional layers. Each component guide of a pooling layer is connected to the first convolutional layer's corresponding feature map [29].

For each feature map $\left(L_N^x\right)_r^{fm}$, the pooling functions $PF(\square)$ are shown as follows:

$$Y_r^{fm} = PF\left(L_N^x\right)_r^{fm} \tag{14}$$

Average pooling and maximum pooling are the two most used pooling processes. The Allied layered neural network is then provided the characteristic of the filtered mixture as input. The suggested DCNN-AL's structural architecture, which is seen in Fig. 2, clarifies the function of Allied Layered. Allied layered is implemented as a position layer. The following is an explanation of the RBF's fundamental operating idea:

Modeled as a vector of real values $I \in \mathrm{Re}_{num}$ is the input. Equation (15) illustrates how the output is then treated as a scalar function of the input vector $\phi : \mathrm{Re}_{num} \to \mathrm{Re}$.

$$\phi(I) = \sum_{x=1}^{NR} Wt_x^{NR}\, \omega\left(\left\| I - c_x^{NR} \right\|\right) \tag{15}$$

where Wt_x^{NR} is the weight of neuron x, NR hidden layer neurons, and c_x^{NR} center vector for neuron x. Each buried neuron is connected to essentially all inputs. The Euclidean distance is often assumed to be the norm, and the AL is assumed to be Gaussian.

$$\omega\left(\left\| I - c_x^{NR} \right\|\right) = \exp\left[-\alpha \left\| I - c_x^{NR} \right\|^2\right] \tag{16}$$

In that they are close to the center vector, the Gaussian basis functions,

$$\lim_{\|I\| \to \infty} \omega\left(\left\| I - c_x^{NR} \right\|\right) = 0 \tag{17}$$

In other words, changing the parameters of a single neuron has a negligible impact on input values encoded distant from the neuron's position.

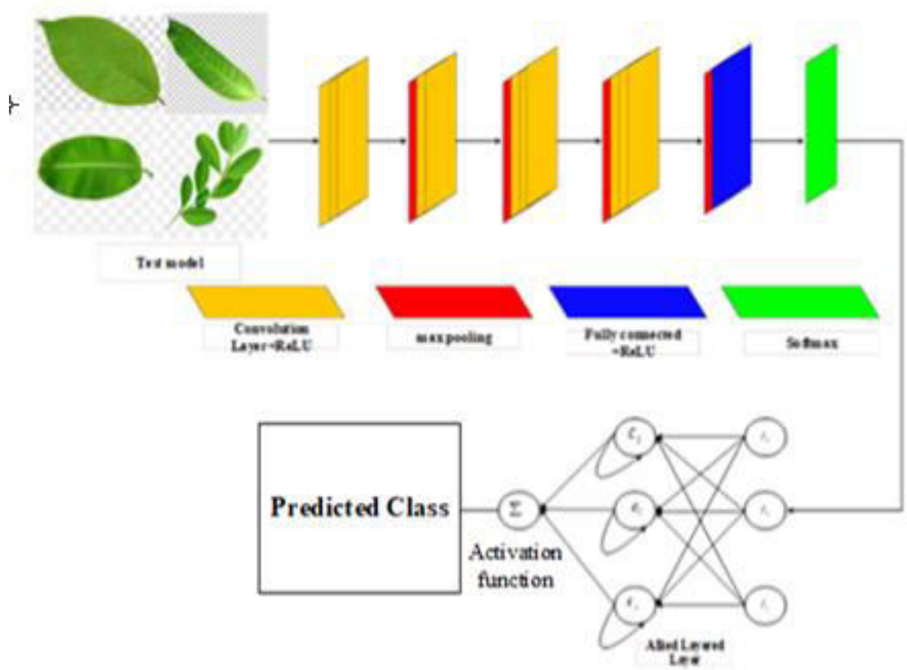


Fig.2: Architecture of AL-DCNN classifier

Figure 2 depicts the architecture of the classification of disease images in which the AL-DCNN is efficiently classify the disease leaf and also show what kind of disease its occurred in the input leaf.

3.5.1. The Training Process of ALDCNN using the Red Panda Optimization

The process of training an ALDCNN for plant leaf disease classification using the Red Panda Optimization (RPO) algorithm involves several key steps. First, a dataset comprising labeled images of healthy and diseased plant leaves is collected and preprocessed through resizing and augmentation. The ALDCNN architecture, tailored for leaf disease classification, is designed, incorporating convolutional layers for feature extraction. The RPO algorithm is then integrated into the training process to optimize model parameters, minimizing the chosen loss function. Hyperparameters are fine-tuned, and the model is trained on the dataset, with monitoring on a validation set to prevent overfitting. After achieving satisfactory performance, the final model is evaluated on a test set, and if successful, it can be deployed for real-world use, potentially aiding in timely and accurate plant disease diagnosis. The proposed RPO (Red Panda Optimization) approach is a population-based metaheuristic algorithm, where the members of the population are represented by red pandas [30]. In the design of RPO, each red panda serves as a candidate solution to the given problem, suggesting specific values for the problem variables based on its position in the search space [23]. The red pandas within the algorithm's population can be mathematically modeled using a matrix, as described in equation (18). In this matrix, each row corresponds to a red panda (i.e., a candidate solution), and each column represents the suggested values for the respective variable of the given problem. At the initiation of RPO execution, the positions of red pandas in the search space are randomly initialized using equation (19).

$$P = \left[P_1 \dots P_k \dots P_n\right]_{n\times m} = \begin{bmatrix} P_{1,1} & \cdots & P_{1,y} & \cdots & P_{1,m} \\ \ddots & \ddots & \vdots & \iddots & \iddots \\ P_{x,1} & \cdots & P_{x,y} & \cdots & P_{x,m} \\ \vdots & \iddots & \vdots & \iddots & \vdots \\ P_{n,1} & \cdots & P_{n,y} & \cdots & P_{n,m} \end{bmatrix}_{n\times m} \tag{18}$$

$$P = \left[P_1 \dots P_k \dots P_n\right]_{n\times m}$$
$$P_{x,y} = Lb_y + Rand_{x,y} * \left(Ub_y - Lb_y\right), x = 1,2,...,n \;\; y = 1,2,....,m \tag{19}$$

where, P is the population matrix of red pandas' locations, P_x is the xth red panda (i.e., candidate solution), $P_{x,y}$ is its yth dimension (problem variable), N is the number of red pandas, m indicates the number of problem variables $Rand_{x,y}$ are random numbers in the interval [0, 1], Lb_y and Ub_y are the lower bound and upper bound of the yth problem variable, respectively

The set of evaluated values for the objective function can be represented using a matrix according to (20).

$$OF = \left[OF_1 \;\; \cdots \;\; OF_x \;\; \cdots \;\; OF_n\right] = \left[OF\left(P_1\right) \;\; \cdots \;\; OF\left(P_x\right) \;\; \cdots \;\; OF\left(P_n\right)\right]_{n\times 1} \tag{20}$$

where OF is the objective function values vector and OF_x denotes the value of the objective function obtained by the xth maximum accuracy.

The assessed values for the objective function of the problem serve as the primary criteria for gauging the quality of candidate solutions. Simply put, the optimal value obtained for the objective function signifies the best candidate solution, while the poorest value corresponds to the worst candidate solution. Given that candidate solutions are updated in each iteration, it is essential to update both the best and worst candidate solutions accordingly. The updating process of candidate solutions in the proposed RPO involves two phases: exploration and exploitation. To simulate the foraging behavior of red pandas, the first step involves computing a new position for each red panda, guided by movement towards the location of the food source (the best candidate solution), as detailed in equation (21). Subsequently, if the objective function value improves at the new position, the red panda's location is updated to the position calculated during the exploration phase, as outlined in equation (22).

$$P_x^{Q1} : P_{x,y}^{Q1} = p_{x,y} + Rand * \left(fs_{x,y}^{s} - G\square p_{x,y} \right) \tag{21}$$

$$P_x = \begin{cases} P_x^{Q1}, OF_x^{Q1} < OF_x \\ P_x, \qquad else \end{cases} \tag{22}$$

where, P_x^{Q1} is the new position of the xth red panda based on the first phase of RPO, P_x^{Q1} is its yth dimension, OF_x^{Q1} represents its objective function value, fs_x^s is the selected food source for xth red panda, $fs_{x,y}^s$ denotes its yth dimension, $Rand$ is a random number in the interval [0, 1], and G is a random number selected from the set {1, 2} randomly.

Approaching the tree and ascending it results in little changes in the red pandas' location, hence enhancing the effectiveness of the suggested RPO method in exploiting and conducting local searches in favourable regions. To mathematically simulate the natural climbing behaviour of red pandas, the location of each red panda is determined using equation (23). Subsequently, in the event that the value of the goal function is enhanced, this updated location supersedes the old position of the related red panda using equation (24).

$$P_{x,y}^{Q2} : P_{x,y} + \frac{Lb_x + Rand * \left(Ub_y - Lb_x \right)}{I} \tag{23}$$

$$P_x = \begin{cases} P_x^{Q2}, OF_x^{Q2} < OF_x \\ P_x, \qquad else \end{cases} \tag{24}$$

Where P_x^{Q2} is the current location of the xth red panda, $P_{x,y}^{Q2}$ yth dimension , OF_x^{Q2} represents the objective function value in the second phase of RPO. The variable $Rand$ is a random integer between 0 and 1, and "I" is the maximum number of iterations. During the training process, the model continuously attained high levels of accuracy, demonstrating strong learning capabilities and efficient pattern identification. Integrating the RPO method has been advantageous in optimizing the network's parameters, enabling quicker convergence, and improving the overall training efficiency. The results of the suggested technique are assessed in the next section.

4. RESULTS AND DISCUSSION

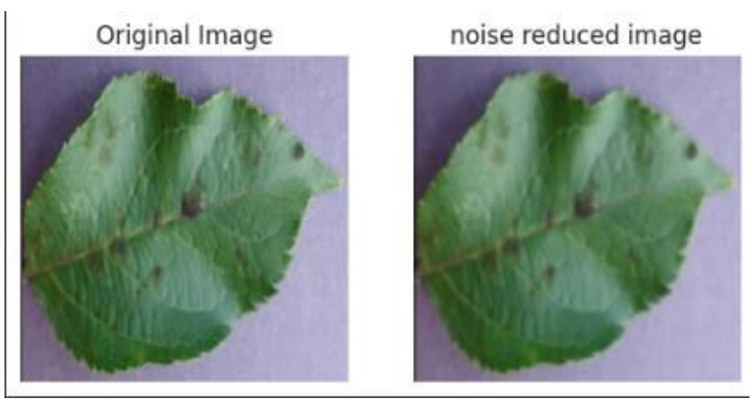
In this outcome part, the assessment of the suggested research is examined. The Python tool workbench is used to implement the suggested research technique.

4.1. Dataset Collection

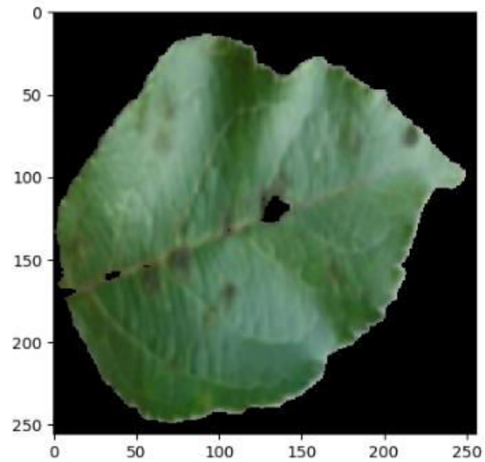
A consolidated dataset including several sets of data, namely Apple leaves, Banana leaves, Mango leaves, and Groundnut leaves, has been merged into a unified dataset. This consolidated dataset may be accessed on platforms such as Kaggle and UCI. The dataset consists of 21 distinct categories, totaling 8,731 images. To enhance computational efficiency, the images are first reduced to 6,696 images during preprocessing. Subsequently, augmentation techniques are employed. The dataset includes both healthy and damaged leaves, illustrating a range of plant illnesses. Table 1 presents the analysis of several leaf disease classifications in our dataset. The Apple dataset [31] has four diseases: apple scab, black rot, and cedar apple rust. Furthermore, a robust class is included for the purpose of categorization. The mango dataset [32] consists of eight selected disease classes: anthracnose, bacterial canker, cutting weevil, die back, gall midge, powdery mildew, and scooty mould. Additionally, a nutritious class is also included. The banana dataset [33] has three distinct classes: Healthy, Segatoka, and Xamthomonas. The groundnut dataset [34] has six distinct classes: Early leaf spot, Early rust, Healthy leaf, Late leaf spot, Nutrition deficit, and Groundnut rust.

Table.1: Various leaf disease classes in our dataset

Classes	Leaf Disease	No of Images
Apple	Apple Scab	320
	Black Rot	320
	Cedar Apple Rust	320
	Apple Healthy	320
Banana	Healthy	296
	Segatoka	320
	Xamthomonas	320
Groundnut	Early leaf spot	320
	Early rust	320
	Healthy leaf	320
	Late leaf spot	320
	Nutrition deficiency	320
	Groundnut rust	320
Mango	Anthracnose	320
	Bacterial Canker	320
	Cutting Weevil	320
	Die Back	320
	Gall Midge	320
	Healthy	320
	Powdery Mildew	320
	Scooty Mould	320
Total class	21	



(a)



(b)

Fig.3: (a) Preprocessed image and (b) Segmented Image

In Figure 3(a), the preprocessed image is obtained through Gaussian filtering, a common technique in image processing. Gaussian filtering involves convolving the image with a Gaussian function, which helps to smooth out noise and enhance important features. This preprocessing step aims to create a more refined and noise-resistant version of the original image. In Figure 3(b), the segmented image is achieved using IGFFC. Unlike traditional clustering methods, IGFFC employs information gain criteria to guide the clustering process, ensuring that clusters are formed based on the most informative features in the data. This segmentation approach is particularly useful in scenarios where the emphasis is on capturing the most relevant and distinctive information within the image. The combination of Gaussian filtering and IGFFC provides a comprehensive image processing pipeline, enhancing the image quality and extracting meaningful segments for further analysis or applications like object recognition.

4.2. Performance Evaluation

According to the precision, recall, accuracy, and F-Measure metrics, the proposed ALDCNN for plant leaf disease classification is compared to the existing Convolution Neural Network (CNN) and Gated Recurrent Unit (GRU).

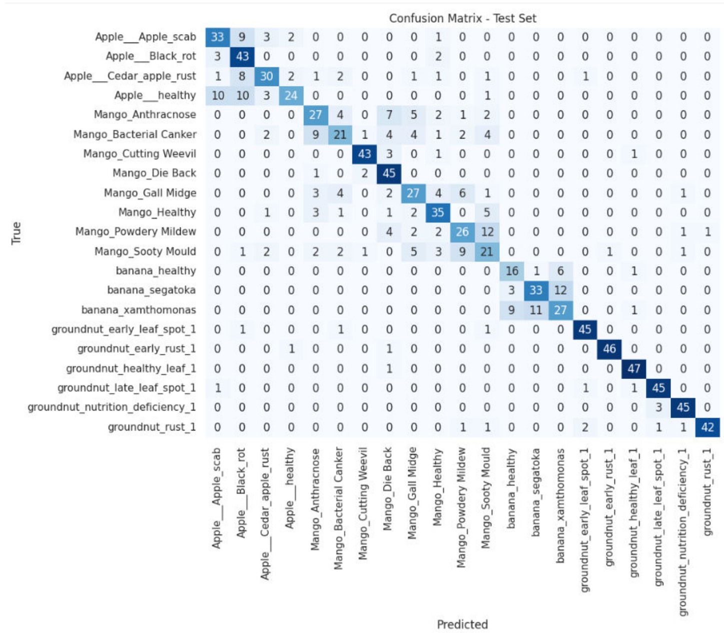
$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{25}$$

$$\text{Recall} = \frac{\text{TN}}{\text{TN} + \text{FN}} \tag{26}$$

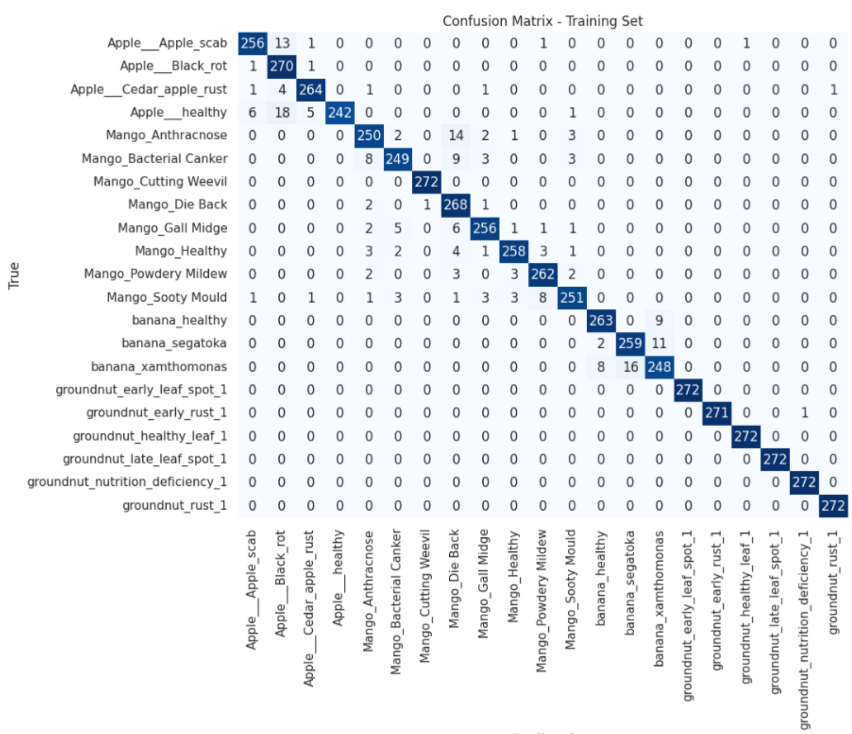
$$\text{Precision} = \frac{1}{Q} * \left[(TP) \cdot (TP + FP) \right] \tag{27}$$

$$\text{F - Measure} = \frac{(\alpha^2 + 1) P \times R}{\alpha^2 (P + R)} \tag{28}$$

Where Q describes the class count, α is set to 1 to make it an F1-score, P and R the values of accuracy and recall are TP-True Positive, FP-False Positive, TN-True Negative, and FN-False Negative. Upgrade best practices should now be more precise.



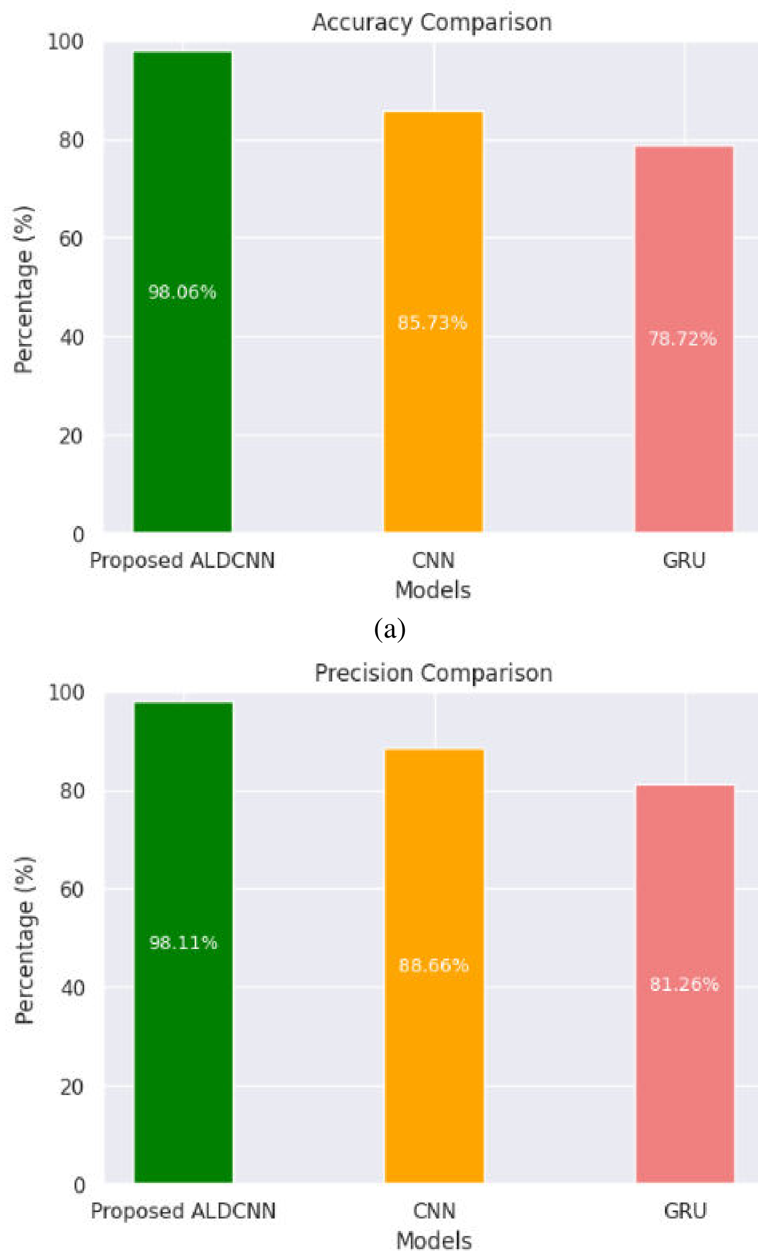
(a)



(b)

Fig.4: Simulation Output of Confusion Matrix (a) Test and (b) Training dataset

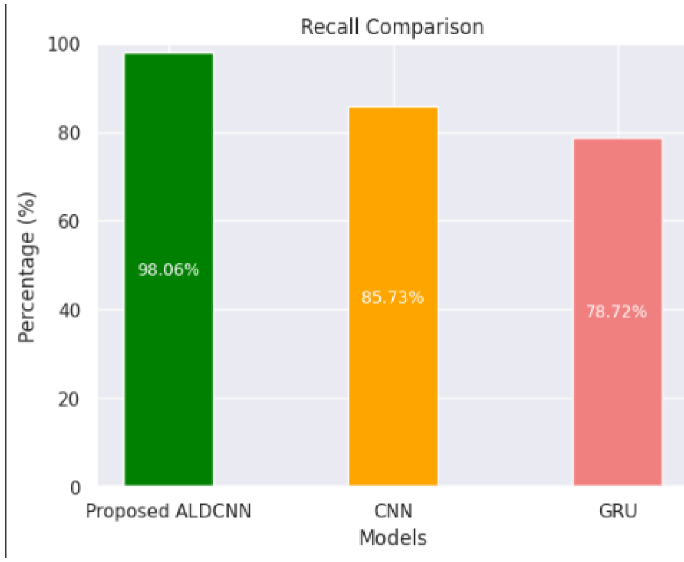
In Figure 4, the simulation output is visually represented through two confusion matrices: (a) for the test dataset and (b) for the training dataset in the context of plant leaf disease classification. The test dataset confusion matrix provides a detailed breakdown of the model's performance on previously unseen data, offering insights into true positives, true negatives, false positives, and false negatives. On the other hand, the training dataset confusion matrix illustrates how well the model has learned from the data used during its training phase. Discrepancies between these matrices can signal potential issues like overfitting or underfitting, guiding researchers and practitioners in refining the model for improved accuracy and generalization to real-world scenarios. The information contained in these confusion matrices is instrumental in assessing the robustness and reliability of the plant leaf disease classification model.



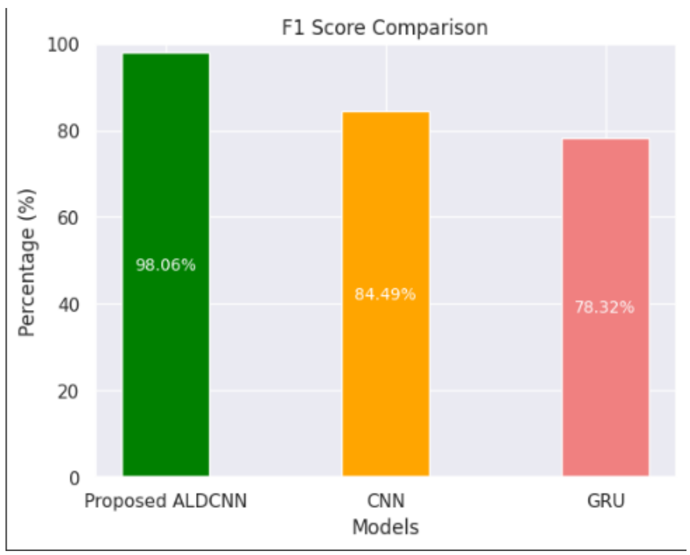
(b)

Fig.5: Simulation Output of (a) Accuracy and (b) Precision

Figure 5 presents the simulation output for plant leaf disease classification, showcasing key metrics such as accuracy (a) and precision (b). Accuracy reflects the overall correctness of the model's predictions, capturing its ability to correctly identify both healthy and diseased plant leaves. Precision, depicted in (b), emphasizes the accuracy of positive predictions, specifically the model's ability to correctly identify plant leaves affected by diseases. The accuracy and precision values of the suggested technique are higher than 98%. The suggested methodology's accuracy and precision also produces superior results compared to existing CNN and GRU. Considering that the suggested technique has greater activation function.



(a)



(b)

Fig.6: Simulation Output of (a) Recall and (b) F1 score

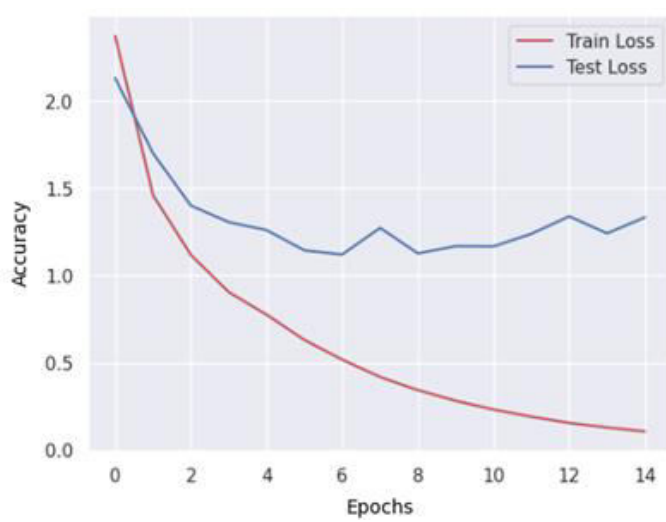
In figure 6 shows that comparison analysis of recall and F1- score measures. The recall value of the proposed method is 97.06% but the CNN and GRU recorded the recall value of 85.73% and 78.72%. Both CNN and GRU recorded less recall values when compared to the proposed research approach. Because the suggested study approach employs an allied layered function-based output layer and a superior activation function in the plant leaf disease classification. The F1- score value of the proposed method is 97.06% which is higher than the existing methodologies such as CNN (84.49%), and GRU (78.32%) techniques. The graphical representation supports these findings, visually demonstrating the superior performance of the proposed technique over existing approaches in the context of plant leaf disease classification.

Table.2: Comparison analysis of statistical measurement

Methods	Accuracy	Precision	Recall	F1-score
Proposed ALDCNN	97.06%	97.11%	97.06%	97.06%
CNN	85.73%	88.66%	85.73%	84.89%
GRU	78.72%	81.26%	78.72%	78.32%

Table 2 provides a detailed comparison of statistical measurements for different plant leaf disease classification methods, namely the Proposed ALDCNN, CNN, and GRU. The Proposed ALDCNN method exhibits superior performance across multiple metrics, boasting an accuracy of 97.06%, precision of 97.11%, recall of 97.06%, and an F1-score of 97.06%. In contrast, the CNN method achieves an accuracy of 85.73%, precision of 88.66%, recall of 85.73%, and an F1-score of 84.89%. Similarly, the GRU method yields an accuracy of 78.72%, precision of 81.26%, recall of 78.72%, and an F1-score of 78.32%. These results highlight the effectiveness of the Proposed ALDCNN method in plant leaf disease classification, emphasizing its superior performance compared to the CNN and GRU methods across various evaluation metrics [35-36].

(a)



(b)

Fig.7: Comparison analysis of (a) Classifier accuracy and (b) Loss rate

Figure 7 provides a visualization of the training process, showcasing the accuracy and loss metrics over time. Throughout the training, the accuracy consistently reached approximately 0.99, indicating a high level of correctness in the model's predictions. Simultaneously, the loss rate stabilized at around 0.1, signifying a low level of error in the model's classification. These results affirm the successful training of the ALDCNN model, suggesting that it has effectively learned the patterns and features necessary to classify and identify diseases in apple, mango, banana, and groundnut plants. The robust accuracy and minimal loss demonstrate the model's readiness for practical applications, instilling confidence in its ability to provide accurate and reliable disease identification for diverse plant species. Even as epoch 14 goes up, its accuracy values remain at the same level, so it stops with epoch 14.

5. CONCLUSION

This work presents a very effective method for classifying plant leaf diseases using an ALDCNN model, which is facilitated by the Internet of Things (IoT). The suggested model encompasses a series of operations, including IoT-based picture collecting, preprocessing, segmentation, feature extraction, and classification using the ALDCNN-RPO method. The GF methods and scaling techniques were used to preprocess the original images of different types of plant leaves. Subsequently, the IGFFC approach was used to segment the leaf area from the pre-processed pictures. The categorization of plant leaves was carried out using ALDCNN-based optimum features and supplemented by the RPO method to improve the Allied layer classification approach. The improved classification model has yielded more accurate categorization of plant leaves. The comprehensive evaluation of the ALDCNN-RPO model has shown encouraging outcomes compared to standard models like CNN and GRU. The ALDCNN-RPO model has achieved a plant leaf disease detection performance with a precision of 98.11%, recall of 98.06%, F1-score of 98.06%, and accuracy of 98.06%. In the future, the ALDCNN model may be used in real-time agricultural settings to support farmers in the intelligent detection of plant diseases for smart agriculture. In addition, we will explore the implementation of computer vision and other advanced deep learning frameworks. We will use a substantial dataset consisting of diverse farmed plants, namely in the form of photographs.

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