Journal of Advanced Research in Applied Sciences and Engineering Technology 31, Issue 3 (2023) 155-172

SEMARAK ILMU
PUBLISHING
202103268166(003316878-P)

Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage:
https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index
ISSN: 2462-1943

An Effective approach for Plant Disease Detection Using Assessment-Based Convolutional Neural Networks (A-CNN)

Nirmal Jothi Jerome[1,*], Sivasankari Jothiraj[2], Saranya Kandasamy[1], Divya Ramachandran[4], Dineshkumar Selvaraj[5], Poonguzhali Ilango[6]

[1] Department of Electronics and Communication Engineering, Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Avadi, Chennai, Tamil Nadu, 600062, India
[2] Department of Electronics and Communication Engineering, Velammal College of engineering and Technology, Madurai, India
[3] Bannari Amman Institue of Technology, India
[4] Department of Information Technology, PSNA College of Engineering and Technology, Dindigul, 624622, Tamil Nadu, India
[5] Department of Electrical and Electronics Engineering, M.Kumarasamy College of Engineering ,Karur, 639113.Tamil Nadu, India
[6] Department of Electronics and Communication Engineering, Panimalar Engineering College, Poonamallee, Chennai, 600 123, Tamil Nadu, India

ARTICLE INFO

Article history:
Received 11 May 2023
Received in revised form 30 June 2023
Accepted 2 July 2023
Available online 10 August 2023

Keywords:
Plant diseases detection; deep learning; optimized filter; ACNN; segmentation; region; affected leaf; classification

ABSTRACT

Agriculture is crucial in determining land availability and economic productivity in developing countries, where most of the population relies on this sector. Even though plant diseases are common, they are primarily identified in agriculture. Automated disease detection technology is necessary for the timely identification of plant diseases. Detecting plant diseases is crucial in avoiding loss of production and enhancing agricultural produce quality. Lack of proper attention in this area can cause severe damage to plants, resulting in loss of product quality, quantity, or productivity. Diagnosing plant diseases can be a complex process that requires specialized knowledge and hands-on attention. The previous methods didn't find accurate disease in the plant leaves. To combat this problem, this paper presents deep learning (DL) based Assessment-based Convolutional Neural Network (A-CNN) method to detect healthy and unhealthy plant leaves. We first collect the plant image dataset from a Kaggle repository. To enhance the quality of plant images and achieve a smoother appearance, an Optimized Gaussian Wiener Filter (OGWF) can be utilized for image pre-processing. Additionally, the edges of plant leaves can be detected by implementing Sobel and Canny operators. Then we use Otsu's Threshold Fragment (OTF) algorithm to segment the disease-affected region. Additionally, the Spatial Grey-Level Dependence Matrix (SGLDM) algorithm is utilized to identify the most suitable feature of the impacted leaf. The A-CNN method is employed to detect healthy and unhealthy plant leaves accurately. The proposed simulation results have shown higher accuracy, sensitivity, and specificity in predicting plant diseases than other methods.

* *Corresponding author.*
E-mail address: njothijerome@gmail.com

https://doi.org/10.37934/araset.31.3.155172

1. Introduction

Currently, the agriculture sector is growing increasingly to obtain quality food, and the contribution of economic and population growth is the primary source. Later, the detection of plant diseases can prevent yield loss. In plants, disease symptoms usually appear on leaves, fruits, buds and young shoots. Image processing and Machine Learning (ML) models can be applied to detect plant diseases. Also, diseases in these plants can lead to new types of infections, and seasonal factors make diseases more likely to spread quickly. Timely and accurate diagnosis of plant diseases can avoid production loss and can play a significant role in reducing crop yield. Image processing acts as a division and helps to extract image features and valuable data from images [1-2].

Population growth is growing exponentially, and the demand for food is increasing increasingly due to the cultivation of grains and the detection of plant diseases in scientific agriculture. Applying technology to analytical processes can improve diagnostic accuracy while increasing the accuracy and reliability of methods. Plant diseases can be diagnosed by taking photographs of individual parts of plant leaves. Then, the presence of disease can be demonstrated in plants using a diagnostic approach, and the extent of damage can be determined.

With modern technology, the chances of disease control are high and unintended diseases can be analysed. Plant-friendly pesticides and herbicides can prevent diseases and improve yield and quality. Plant diseases can be detected and studied using visual observation methods of plants. Early detection of plant diseases can benefit plant disease control [3-4].

However, agriculture and crop production face significant challenges, such as plant diseases, as each sector has exact problems. As the global demand for food grows, there is a need to focus on crop invention. Natural disasters such as droughts, earthquakes and diseases are challenging to reduce crop yields significantly. However, conditions affect the plant's overall performance and, due to increased defoliation and many other diseases in plants, stunt growth and reduce fruit production [5].

Nevertheless, the impact of plant diseases and insect attacks greatly affects the global economy while reducing the quality of food production. Identifying the types of plant diseases is a critical task, although they are all considered one of fundamental problems. Plant diseases usually appear as isolated spots or spots on stems, fruits, leaves or flowers. In addition, their determination is subjective and time-consuming when examining the type of plant infection. Also, farmers' and experts' predictions of plant disease diagnosis may be wrong [6].

The principle of this method is to collect information for plant disease images into a new plant disease dataset by recommending the Kaggle dataset. Next, image smoothing can preprocess vegetation images using the OWEF method to improve image quality. And Sobel and Ganey operators can be implemented to detect the edges of plant leaf images. Then, the OTF method can use image segmentation to identify regions of diseased plant leaves. Next, plant leaf features such as colour, size and design can be extracted using SGLDM methods. Finally, we propose a new interpretation of the ACNN method for detecting healthy and unhealthy plant leaf diseases detection using DL. Next, the diseased plants can be identified and determined with the help of image processing.

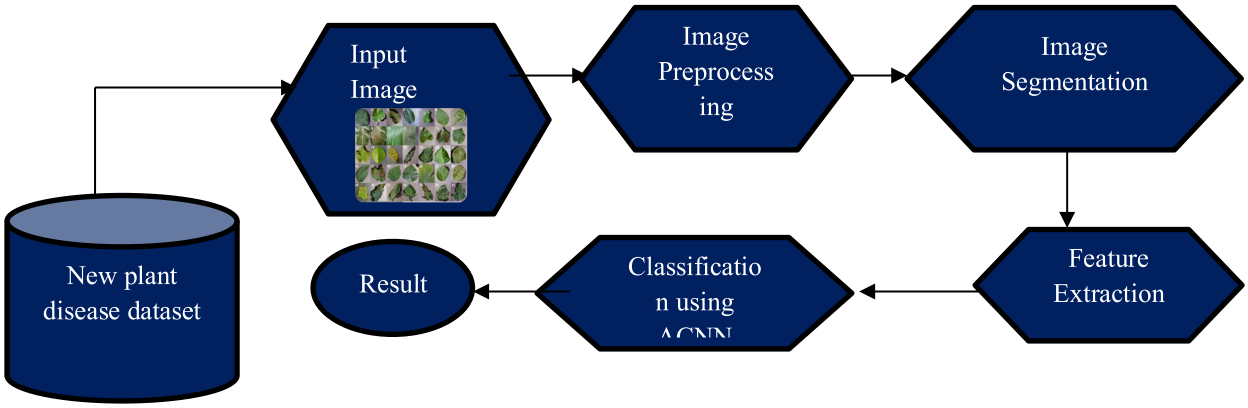


Fig. 1. Basic Architecture of Plant Disease Detection

Figure 1 introduces the basic structure of plant disease diagnosis in this section. They collect and process data based on new plant disease diagnoses identified on Kaggle. Plant disease detection can be done by first inputting an image and applying image preprocessing, image segmentation, feature extraction, and accurate classification to detect plant disease.

2. Literature Survey

The author proposed that DoubleGAN could generate high-resolution images by processing fewer samples of diseased leaves. DoubleGAN can be divided into two stages, which take healthy and diseased leaves as input. Then, a super-resolution generative adversarial network (SRGAN) can extract the corresponding 256 x 256-pixel images and augment the asymmetric dataset [7]. The author proposes removing relevant features from training data with different dimensions with an enhanced Spatial Pyramid Pooling (SPP) layer. These can be combined with multi-level components ranging from small to large sizes. In addition, many advances in plant diseases can cause similar symptoms and are difficult to identify [8].

The author proposed InceptionResNetV2, EfficientNetV2L and Exception based on a new powerful deep ensemble model, then already submitted and called PlantDet. Their performance can solve the planet mismatch problem when applied to sparse datasets with diverse background image datasets [9]. The author proposed a lightweight transfer learning-based approach to detect tomato plant leaf disease. Efficient preprocessing methods can enhance leaf images with illumination corrections for improved classification. The system can extract features for effective prediction using a combined model consisting of a pre-trained MobileNetV2 framework and a classifier network [10].

The author proposed that fusion of multiple patterns is essential for robust and reliable diagnosis, as rice disease diagnosis based on a single pattern needs to be revised. A sample of 3,200 rice health cultivars was collected manually and utilized two methods of the dataset, such as agro-meteorological sensors and cameras [11]. The author proposed that Guan filtering and various features can be used to demonstrate the L1-Extreme Learning Machine (ELM) algorithm after preprocessing. Experiments on a standard plant dataset show in the evaluation phase that L1-ELM outperforms all existing one-class classification algorithms and maintains superior learning and generalization capabilities [12].

The author aims to develop a system to predict plant fungal diseases (powdery mildew, anthracnose, rust, root rot/leaf blight). These methods consist of three main phases: dataset preprocessing, examining data analysis and detection module [13]. The author proposes that Convolutional Neural Networks (CNNs) with fewer layers can be used to reduce the computational burden. Augmentation techniques such as transform, crop, scale, and flip can increase the training set without taking too many images and generating additional samples. [14].

The author proposes developing a single-stream CNN framework to detect plant citrus disease. Four types of data augmentation can be improved using the first functions: shadow removal, pixel intensity adjustment, brightness enhancement, and local contrast enhancement. Next, the second stage can be fine-tuned by selecting a MobileNet-V2 CNN model [15]. The author focuses on an excellent new method of detecting tomato leaf diseases using deep neural networks, which could improve agricultural industries. However, determining yield and quality is challenging in classifying and diagnosing healthy and diseased crops [16].

The author proposed that disease classification, detection of chilling damage, maturity and humidity can be used to solve plant problems related to banana production. In addition, ML implementations can be used to implement the review framework, the sources of data collection, and the detailed results achieved. Furthermore, ML frameworks/techniques can be further evaluated using various performance metrics [17]. The author proposed using FieldPlant, a dataset of 5,170 images of plant diseases collected directly from gardens. The quality of the process can ensure the individual leaves in each image. All of them can be hand-picked under the supervision of a plant pathologist as per the scientific claim. However, the absence of plant pathologists during the annotation process may lead to misclassification [18]. The author proposed that detecting plant leaf diseases using Deep Learning (DL) and advanced imaging techniques can be a valuable resource for researchers studying plant disease and pest diagnosis [19].

The author proposes that the priming block be implemented by replacing the original coil with a deep point-like curve to maximize the priming block. Using a plant extraction tool, a modified inception (M-inception) module can be attached with a pre-trained mobile network to excerpt superior image features [20]. The author proposes an Attention-based Multi-Input Multi-Output Neural Network (A-MIMONN) model to predict disease using self-collected data. Data used to train the model can be collected from three sensor nodes: temperature, humidity and Leaf Wetness Sensor (LWS) [21]. The author proposed that the CNN method can be used for an efficient plant disease symptom classification. These networks are memory efficient and reduce training time, and can be combined with the proposed training configuration to enable the rapid development of industrial applications [22].

The author proposed method is significantly more efficient in processing time and discriminative power, outperforming traditional end-to-end CNN-based methods and reducing the available dataset for precision agriculture [23]. The author notes that early symptoms allow growers to quickly diagnose diseases in tomato leaves and process samples of damaged tomato leaves to treat them [24]. The author describes that various plant diseases can be manipulated with DL models used for visualization. In addition, many research gaps can be used to identify plant diseases before disease symptoms appear and improve their transparency [25]. The author proposes that three aspects can be studied based on DL to detect plant diseases and pests. Additionally, the function of plant disease diagnosis is a classification, detection, and segmentation network [26].

2.1 Describe the problem

- However, the number of unhealthy leaf images collected from different plants is generally challenging to determine accurately.
- However, the systems are fast, accurate and computationally limited when providing solutions for low-end devices.

- However, generalization ability and learning cost, time and cost consumption have been challenging in previous research.
- Plant diseases are a significant cause of global agricultural crop loss, and diagnosis of diseases is difficult due to lack of expertise.
- Plant diseases reduce the yield of fruits and cause significant losses to the national economy.
- However, a well-organized imaging plan can effectively simplify the design process of conventional methods while increasing the overall implementation cost.

3. Proposed Methodology

In this category, they implement various methods to detect plant diseases and achieve their exact accuracy. Then, we collect the necessary data from the Kaggle to identify diseases in plants. Next, the OGWF method can be used in image preprocessing to smooth the leaves of plant images, improve image quality, and perform edge detection. Next, the OTF method can segment diseased areas on plant leaves. Next, features can be extracted in plant leaves by implementing SGLDM methods. Finally, the DL technique proposes a new A-CNN method to detect healthy and unhealthy plant leaf diseases accurately. With the help of image processing, the accuracy of diseased plants can be detected and determined.

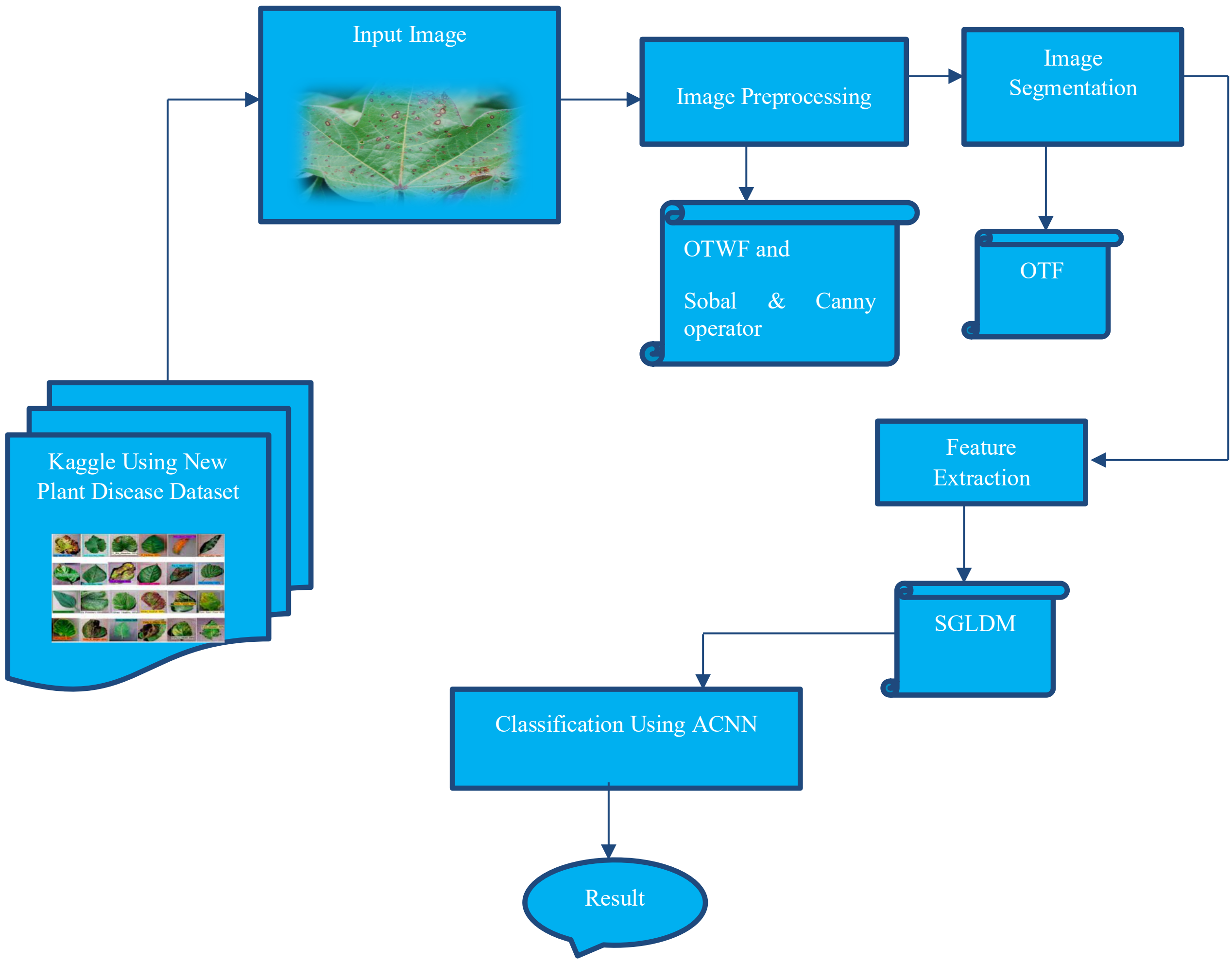


Fig. 2. The Proposed Diagram for Plant Diseases Detection

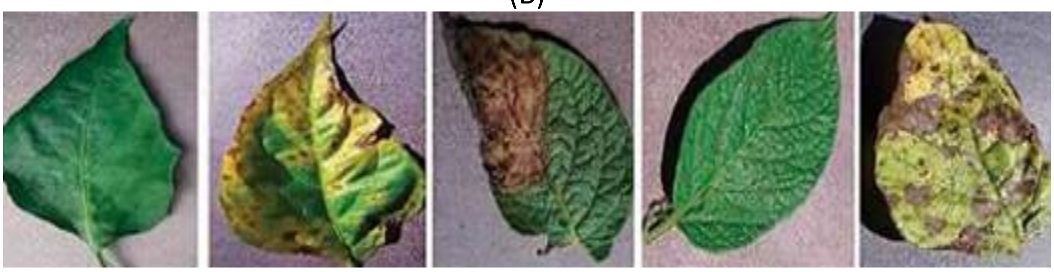
Data is collected from a new plant disease dataset to diagnose plant diseases in this category, and plant images are inputted. Then, the image of that plant disease can be pre-processed to improve its quality. Next, image segmentation was performed using the OTF algorithm to detect plant diseases. Then SGLDM methods were used to extract the feature's colour, size, and shape in plant images. Finally, as illustrated in Figure 2, the accuracy of the proposed A-CNN method can be used to detect healthy and unhealthy plant leaf diseases.

3.1 Data collection

This section will gather the necessary information from the recently discovered new plant disease dataset on Kaggle. The dataset contains images that can identify both healthy and diseased plant leaves. We can enhance this dataset by augmenting the original data from the standard repository. The dataset contains about 87,000 RGB images of healthy and diseased plants grouped into 38 categories. Next, when testing and training using, the value can be split into 80/20 training and validation sets to preserve the directory structure. A new directory containing 33 test images can be created for prediction purposes.

(A)

(B)



(C)

Fig. 3. Sample images of New plant Disease Detection

In this section, we use the dataset to detect plant diseases in pepper, potato, and tomato plants, as shown in Figure 3. The tomato leaf tags observed in this new plant disease detection dataset are bacterial spot, early late blight, late blight, leaf blight, needle blight, two-spotted spider mite, target spot, yellow leaf cigar virus, mosaic virus, and many other plant diseases.

3.2 Image Preprocessing

In this section, we used the OWEF technique to enhance the quality of vegetation images by smoothing the leaves and eliminating noise. Furthermore, we applied Sobel and Canny operators to identify the edges of plant leaves. Image preprocessing techniques are used to analyze plant leaf images to remove noise or artefacts present in the image and extract the region of interest. The OWEF method can enhance the quality of plant leaf images by smoothing them and eliminating noise. These methods are effective in reducing errors and preserving frequency content. Additionally, the filter can quickly remove additive noise and double image blur inversion.

A. Image smoothing

In this category, image quality can be improved by reducing pixel intensity variations in an image using an intuitive and straightforward technique, as stated in Equation 1.

$$K(u,v) = \frac{1}{A^*B} \sum_{c,d \in p_{uv}} S(c,d) \quad (1)$$

This section is calculated by numerically sorting all the pixel values in a neighbouring window to find their average weight and replacing the pixel of interest with the pixel value (Equation 2).

$$K(u,v) = \underset{(c,d)\in p_{uv}}{median}\{s(c,d)\} \quad (2)$$

In this section, it can be evaluated using the filter method to remove noise from plant disease images and smooth the quality of the images. (Equation 3)

$$L(u,v) = \frac{1}{2\pi\sigma^2} L^{-(u^2+v^2)/2\sigma^2} \quad (3)$$

In this section, the error is reduced by applying a filter for plant disease detection and the noise and double image blur inversion can be immediately removed. (Equation 4)

$$(c,d) = \left[\frac{1}{z(c,d)} \frac{|z(c,D)|^2}{|z(c,D)|^2 + \frac{q_\eta(c,d)}{q_J(c,d)}}\right] s(c,d) \quad (4)$$

Let's assume L- Gaussian mask, u and v- coordinate value, σ-standard deviation, p-represents value, S- Filter, u and v –cantered point, A*B-sub-image of windows size, S- pixel value, c and d- function, K(u, v)- surrounding pixel value, K(u,v)-median filtered image, s(c,d) – represents the image, z (c, d) – degradation function, q- power spectrum, z(c,d)- complex conjugate, $q_\eta(c,d)$-power spectrum of the noise, $q_J(c,d)$-power spectrum of the undegraded image. This section uses preprocessing techniques on plant images to enhance their appearance by smoothing and applying filters to eliminate any noise present.

B. Edge detection

In this section, the curvature of edges caused by abrupt transitions acts on brightness or spatial derivatives. Variations in brightness appear when the orientation of a surface change continuously; where one object obscures another, shadow lines or discontinuities in the surface's reflective properties appear. Edge detection works as a technique that creates pixels only at the boundaries between each region. In addition, edge detection can be used more widely than the Sobel and Caney operators in edge detection.

C. Sobel edge detection

In this respect, the Sobel method can be used in image processing techniques, generation of edge-enhanced images, and edge detection algorithms. In Equation 5, these two kernels represent the vertical and horizontal pixel values of the pixel grid edges to calculate the gradients of the image.

$$|O| = \sqrt{{O_u}^2 + {O_v}^2} \quad (5)$$

In this section, the amount of gradient can be calculated in Equation 6.

$$|O| = |O_u| + |O_v| \quad (6)$$

Calculate the edge angle detection for each pixel in the pixel grid of the Sobel edges in Equation 7 in this section. Let's assume θ -the angle of orientation.

$$\theta = arc/\tan(O_u/O_v) \quad (7)$$

Canny edge detection

In this section, canny edge detection is a simple 2D first derivative operator applied to a smooth image to highlight regions with high first spatial derivatives. The first derivative of the image in each direction is the gradient. That is, non-maximizing suppression is the main difference in calculating slope. (Equations 8 and 9).

$$\text{Edge gradient } O = \sqrt{o_u^2 + O_v^2} \quad (8)$$

$$(\theta) = \tan -1\left(\frac{O_u}{O_v}\right) \quad (9)$$

Let's assume an O- grid, Ou and Ov- values, O_u-horizontal directions, $and\ O_v$-vertical direction. This section employs two operators to detect leaf edges in plant disease image preprocessing. The purpose of this is to minimize noise in frequency and decrease errors.

3.3 Otsu's Threshold Fragment

In this section, plant image segmentation is an image processing application that divides the image into distinct regions, each with a high similarity of pixels and high differences between them. Additionally, it is an essential function in many computer vision applications. Image segmentation methods of plant leaves can be implemented in disease diagnosis and plant identification applications. Grayscale can be used based on features to separate an image into foreground and background. The OTF method can be implemented by examining the pixel values separating the two classes to find the sweet spot and minimize the variance in the histogram. To achieve correct image segmentation of plants, image segmentation can be performed where the variability between classes is maximized, and the probability of misclassification is minimized. Images of plant diseases can be generated using threshold grayscale images. The OTF method converts each pixel in the image to a simple pattern of black pixels.

Equation 10 calculates the weighted sum of variances to reduce conflict within a class.

$$\sigma_T^2(z) = T_0(z)\sigma_0^2(z) + T_1(t)\sigma_1^2(z) \quad (10)$$

Calculate a probability class from the histogram bins (Equations 11 and 12)

$$T_0(z) = \sum_{x=0}^{z-1} Q(x) \quad (11)$$

$$T_1(z) = \sum_{x=z}^{G-1} Q(x) \quad (12)$$

In this category, a class that minimizes within-class variance can be evaluated as equivalent to a class that maximizes between-class variance. (Equations 13, 14, and 15)

$$\sigma_T^2 = T_0\sigma_0^2 + T_1\sigma_1^2 \quad (13)$$

$$\sigma_A^2 = T_0(u_0 + u_z)^2 + T_1(u_1 + u_z)^2 = T_0T_1(u_0 + u_1)^2 \quad (14)$$
$$\sigma_z^2 = \sigma_A^2 + \sigma_T^2 \quad (15)$$

Equation 16, a maximum optimal threshold value can be calculated.

$$E^* = arg_{0\leq+\leq G-1}max_{\eta}(E) \quad (16)$$

In this section, pixels can be segmented according to their intensity values, as shown in Equation 17. In addition, the global limit can be calculated using appropriate limits.

$$F(u,v) = \begin{cases} 1 & if\ f(u,v)>E \\ 0 & if\ f(u,v)\leq E \end{cases} \quad (17)$$

Equation 18 calculates local or regional limit functions for multiple thresholds in this category.

$$F(u,v) = \begin{cases} l \quad if\ w(u,v) > E_2 \\ m\ if\ E_1\, w(u,v) \leq E_2 \\ n\ if\ w(u,v) \leq E_1 \end{cases} \quad (18)$$

Equation 19 is divided based on this model's lightest and darkest pixels. Calculate the average strength of the new threshold value.

$$E_{new} = \frac{\boldsymbol{c_1+c_2}}{\boldsymbol{2}} \quad (19)$$

Let's assume T- weight, T_0 and T_1- the probability of the two classes, σ-variance, σ_0^2 and σ_1^2-variance of two categories, u-class, Q-class probability, G-bins, E- threshold value, E^*-Best threshold value obtained, σ_T^2- statistical characteristic based first order, σ_A^2- statistical feature based second order, E- threshold, F-global threshold, w- function, u, v- Local and regional threshold. In this sense, thresholding is a simple segmentation method that can segment pixels according to their intensity values. A new strength can be calculated using a suitable threshold for the global threshold.

3.4 Spatial Grey-Level Dependence Matrix (SGLDM)

In this section, the feature extraction method can be applied in many image processing applications and detect plant diseases using their features such as colour, texture, shape and edges. Recently, most researchers have implemented textual features in plant disease diagnosis. These can be used to identify parts of diseased plants. Various feature methods can be used to extract features from plant disease images

In this section, SGLDM is a statistical technique in addition to generating a co-occurrence matrix to represent the spatial distribution of grey levels within the region of interest. The SGLDM method works based on second-order conditional probability density estimates. The angle can be used to evaluate texture orientation, and using some distance value reveals a meaningful description of the size of periodic textures. The parameters to be focused on in this study can be divided into six types of features,

- Contrast
- Homogeneity
- Energy
- Entropy
- Mean
- Variance

A. Contrast

In this category, images with significant differences between adjacent grey groups correspond to high contrast. Further, it quantifies the local variation of the grey levels present in the image. This parameter can also be calculated by classifying the variance of the matrix values from the main diagonal, as shown in Equation 20.

$$cont = \sum_u \sum_v (u-v)^2 F(u,v) \quad (20)$$

B. Homogeneity

In this section, the parameter is used to measure the local uniformity of the image. Small grey-level differences within a pair of pixels can be assigned large values. These include parametric, contrast, anti-behaviour, highly uniform system regions, and highly parametric regions. This integral can be found in Equation 21.

$$hom = \sum_{u,v} \frac{1}{1+(u-v)^2} F(u,v) \quad (21)$$

C. Energy

Image similarity can be measured by re-evaluating pixel pairs in these parameters. Equation 22 clearly illustrates that a smooth image has significant grayscale transitions as its energy is high.

$$Ener = \sum_{u,v} \big(F(u,v)\big)^2 \quad (22)$$

D. Entropy

In this context, feature entropy estimates the diversity within an image or region of interest. Many elements in the co-occurrence matrix will have small values if the images are viewed as multi-dimensional. Entropy is negatively related to energy and is given in Equation 23.

$$ent = \sum_u \sum_v F(u,v) \log\big(F(u,v)\big) \quad (23)$$

E. Mean

In this case, the average value is based on the uniform lightness or darkness of the image. If the image's brightness is more consistent, the average will be higher and more positive (Equation 24).

$$Mean = \sum_u \sum_v F(u,v) \quad (24)$$

F. Variance

It is a measure of heterogeneity and is closely related to standard deviation. Additionally, it depends on the distribution of grey levels around the average calculated above. Thus, as the variance in Equation 25 increases, the grey value deviates from its mean value.

$$var = \sum_u \sum_v (u-mean)^2 F(u,v) \quad (25)$$

Let's assume F- grey level matrix, $F(u,v)$ –element of co-occurrence matrix, u and v- element of grey value position. In this category, the local variation of the grey levels of the images can be calculated, and the parameters can be estimated by characterizing the interpretation of the matrix values. Then, small grey-level differences within a pair of pixels can be assigned large values. Next, the distribution of grey levels around the calculated mean can be evaluated.

3.5 Assessment-based Convolutional Neural Network (A-CNN)

This section proposes an Assessment-based Convolutional Neural Network (ACNN) method based on the DL approach to detect healthy and unhealthy plant leaf diseases. The proposed ACNN method can be trained on images from a new plant disease dataset, and image processing can be used to identify diseased plants accurately. ACNN outperforms traditional image processing methods in specific applications such as classifying plant disease images. These commonalities are also observed in the automatic detection of plant diseases. Different numbers and sizes of convolution and pooling layers have been developed to compare their performance using the ACNN method. In this respect, ACNN provides better training performance than other developed models. The proposed ACNN method for plant disease images consists of input, hidden and output layers. Among them, the input layer is the layer that accepts features as input and plant disease images can be passed as input through this layer. The middle layer contains many nodes required by the application. Next, the output can be generated in the output layer for plant disease images. In this category, we used five layers to handle plant disease images which are,

- Convolutional Layer
- Max Pooling Layer
- ReLU Activation Function
- Soft max function
- Fully Connected Layer

i. Convolutional Layer

This section determines values by performing a convolution operation on the kernel matrix and its pixel values and sliding the kernel matrix over the pixel matrix.

Calculate the dimensions of the output of the Conv layer. (Equation 26). Let's assume D-dimension, c- width, G- height, I_c- input width, I_G-input height, a-stride, z-kernel filter, and F- filter conv layer.

$$D\big(conv(I,Z)\big) = \left(\left[\frac{I_c - F_c}{A} + 1\right], \left[\frac{I_G - F_G}{A} + 1\right], F_a\right) \tag{26}$$

ii. MaxPooling Layer

In this model, a filter can be applied to the graph to reduce the final size and prevent over-complications. A first max pooling layer is introduced to try to reduce the dimensionality of the output values of the conv layer.

Computes the output dimensions of the maximum pooling layer and calculates the output dimension (Equations 27 and 28).

$$D(Pooling(I,Z)) = \left(\left[\frac{I_c - F_c}{A} + 1\right], \left[\frac{I_G - F_G}{A} + 1\right], I_a\right) \tag{27}$$

$$H_{out} = \left\lfloor\frac{H_{in} + 2q - z}{A}\right\rfloor + 1 \tag{28}$$

Let's assume H- number, H_{out}-no of input feature, H_{in}- no of output feature, q- padding size, A-stride size, and z- convolutional kernel layer.

iii. ReLU Activation Function

This model replaces negative values with zero (0) in the output matrix in adjusted linear units and evaluates all positive values. Implement the kernel using a single stride value for the input data from the Conv layer.

Compute the ReLu activation functions on all Conv layers and calculate the dense layer of the input and output range (Equations 29 and 30).

$$ReLu\,(u) = max(0, u) \quad (29)$$

$$T_y = ReLu\left(0, \sum_x^{512} B_y + u_x c_x\right) \quad (30)$$

Let's assume u- the value, the weight, the x and y- no of the input and output dense layer, T_y-individual neuron output, and B- bias value.

iv. Softmax function

In this section, calculate the number of input and output values using the Softmax activation function to classify plant leaves. The softmax function value of a neuron in the dense layer can be calculated. Let us assume the f- softmax activation function, σ-sigma. (Equation 31)

$$Softmax\left(\sigma(T_x)\right) = \frac{f^{T_x}}{\sum_{y=1}^{59} f^{T_x}} \quad (31)$$

v. Fully Connected Layer

In this region, nodes with dense FC layers may have as many nodes as needed in the FC layer. All layers can be connected before and after using edges between existing neurons in the computational results.

Calculate the nonlinear transformation using the nonlinear processing function (Equation 32). Let's assume v- nonlinear function, z-kernel value, c- the weight of the matrix, c_0-bias term, I_G-input height, and f- activation function.

$$v_{xz}(u) = f\left(\sum_{x=1}^{I_G} c_{yz} u_x + c_{x0}\right) \quad (32)$$

The output category estimates for input images of healthy and unhealthy plant leaves can be found using Equation (33). Where, T- output neuron, T_1 to T_{59}- no of output values.

$$outputclass(T_{out}) = max(T_1, T_2, \ldots, T_{59}) \quad (33)$$

In this category, the output value reflects the number of leaf and non-leaf classes for diseased and healthy plant leaves in the new plant disease dataset. The total number of training parameters for the ACNN model was 5,424,583.

Figure 4 in this section displays that the weight matrix columns have distinct values and are optimized during the model's training.

4. Result and Discussion

This section has two criteria for detecting plant diseases: training and testing. A model of laboratory conditions can be specified using plant images from the same dataset used for training and testing. Among these, the proposed method to detect diseases of plant images can be used to find accurate models using the Jupiter tool in Python.

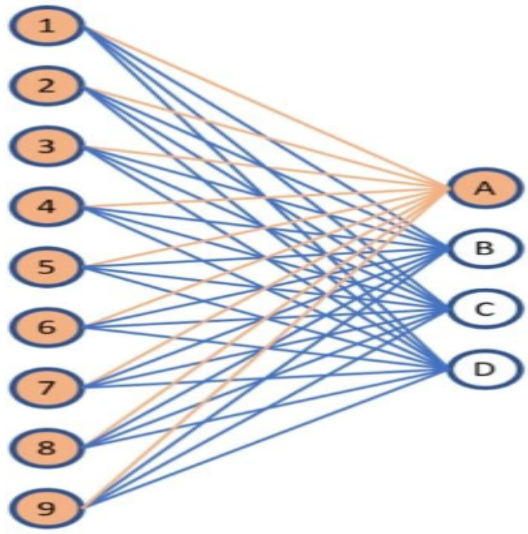


Fig. 4. Fully Connected and Convolutional Layer

Table 1
Simulation Parameters

category	Variables
Dataset name	New plant disease dataset
No of dataset	87000
Tool	Juypter
Language	Python
Training	80
Testing	20

In this section, the accuracy of plant disease detection can be evaluated using the simulation parameters introduced in Table 1. Then, these are seeded for training and testing on datasets for plant disease diagnosis.

4.1 Evaluation matrix

In this category, the accuracy of plant disease diagnosis may vary depending on the research centre and evaluation criteria. Standard measures include precision, recall, mean average precision (mAP) and F1 score.

- $Precision = \frac{T_P}{T_P+F_P}.100\%$ (34)
- $Recall = \frac{T_P}{T_P+F_N}.100\%$ (35)
- $P_{avg} = \sum_{i=1}^{n(class)} P(i).R(i).100\%$ (36)
- $mAP = \frac{p_{avg}}{n(class)}$ (37)

A. Sensitivity

In this section, sensitivity analysis can be performed to determine the accuracy of plant disease images. Then, the accuracy of the rest of the method will be lower when comparing the ELM, SPP, and LWS models with the proposed method in the sensing function. High accuracy can be obtained with the proposed ACNN method. Thus, the accuracy of plant disease images by applying sensitivity analysis in image processing is increased to 69% by the proposed method, as presented in Figure 5.

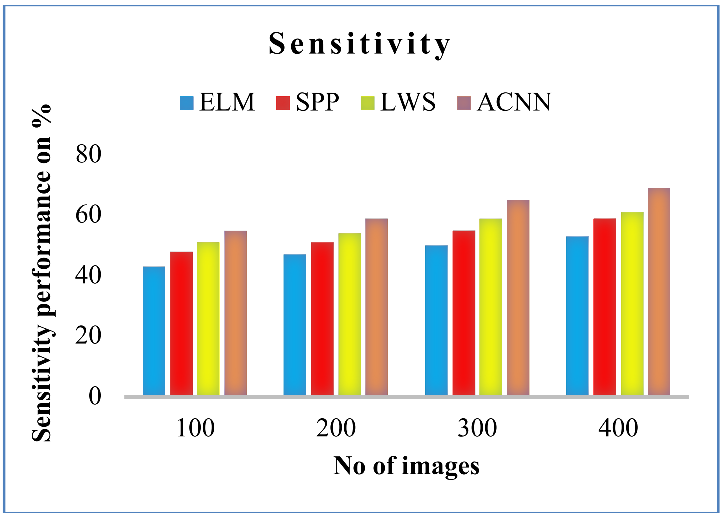


Fig. 5. Performance of Sensitivity

B. Specificity

In this section, specific performance analysis can be used to determine the accuracy of plant disease images, as shown in Figure 6. Then, the accuracy of this method is rated lower when comparing LWS, ELM, and SPP models in specific performance. The proposed ACNN method can achieve high accuracy for plant images. Therefore, the proposed method can increase the accuracy of plant disease images to 74% by exploiting specific efficiency in image processing.

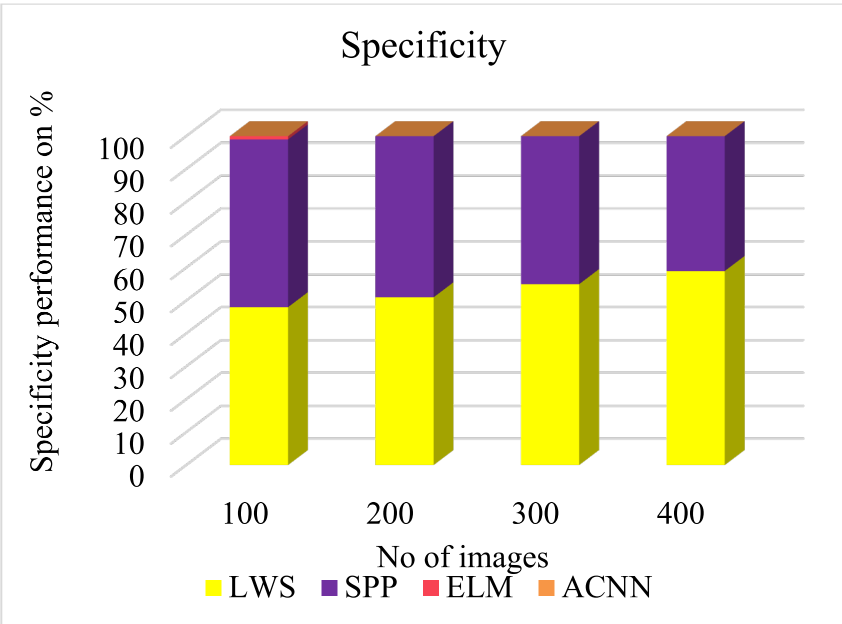


Fig. 6. Performance of the Specificity

C. Precision

In this category, the calculation of plant disease images can be determined using accurate performance analysis, as shown in Figure 7. Then comparing the SPP, LWS, and ELM models, the accuracy of this method is less than 55%. The proposed ACNN method can achieve high accuracy for plant images. Therefore, the proposed method increases the accuracy of plant disease images to 77% by exploiting the accuracy efficiency in image processing.

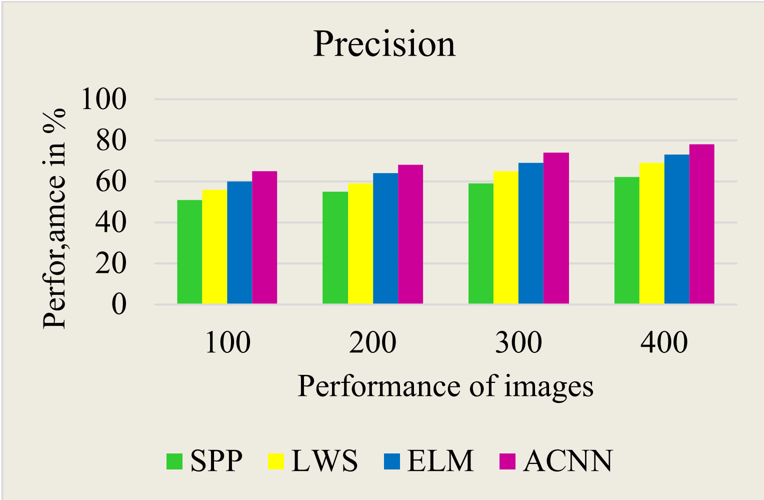


Fig. 7. Performance of Precision

D. Recall

In Figure 8, this method can obtain the correct accuracy for plant disease detection using the introduced recall performance. Then, SPP, ELM and LWS three models are presented in these methods to evaluate the recall performance and achieve less accuracy in plant images. Comparing the three methods through image processing, the proposed ACNN method achieves the highest accuracy of 82% on plant disease images.

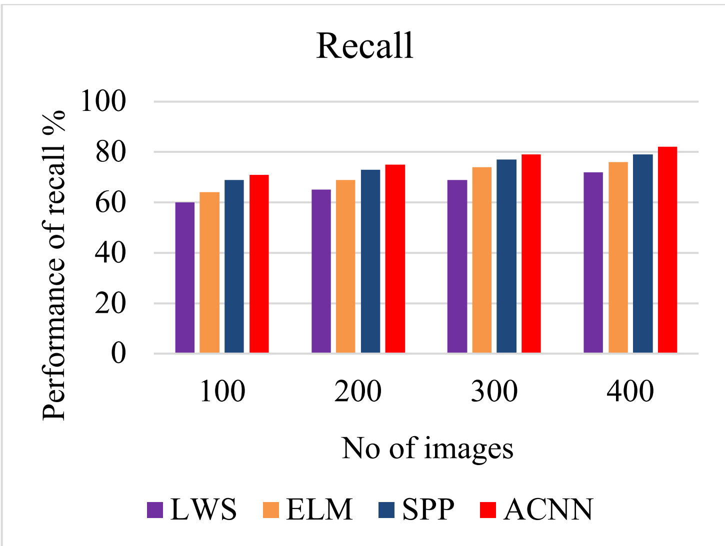


Fig. 8. Performance of Analysis in Recall

E. Accuracy

In this section, figure 9 illustrates that the proposed ACNN method achieves a high accuracy of 91% compared to the other three methods to obtain the correct accuracy for plant disease diagnosis. Then, reasonable accuracy can be obtained in feature analysis for plant disease images by the ACNN method.

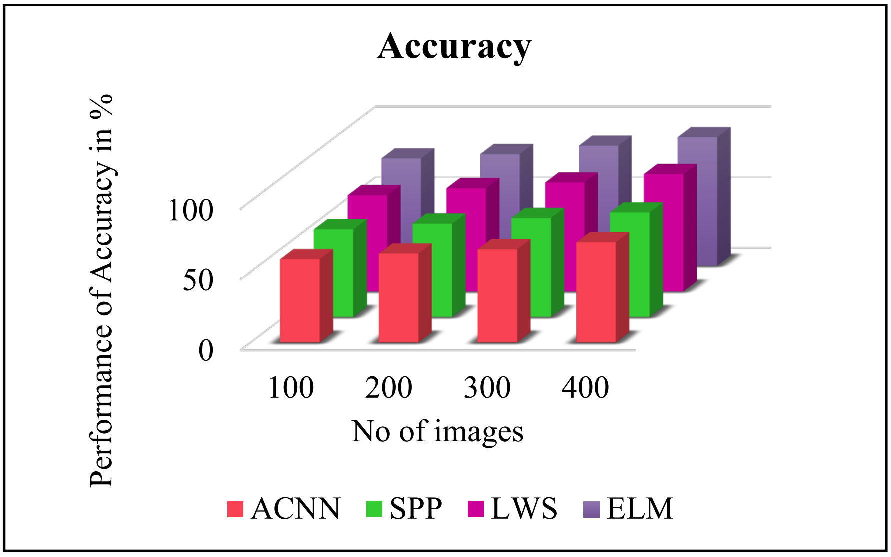


Fig. 9. Performance of Accuracy

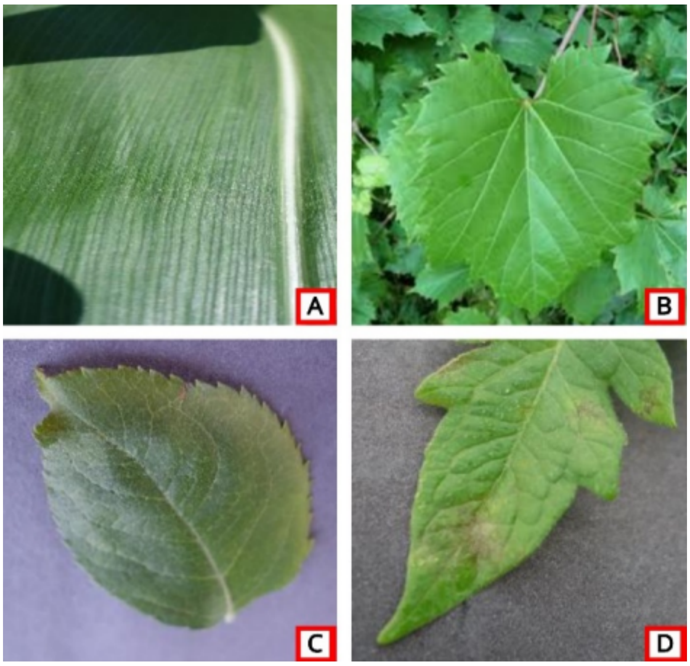


Fig. 10. Sample Plant Disease Dataset Used For Training Model

In this section, the dataset can be used to identify different types of plants and their diseases. Later, images can be manually added to other fields to use this model in real-time situations. As shown in Figure 10, corn, grapes, apples, and tomatoes can be collected from the database and marked in image processing.

5. Conclusion

This section introduces a new ACNN technique that utilizes several methods to detect plant leaf diseases accurately. Later, new plant disease data can be collected from image processing to detect plant disease images. Then, plant disease can be detected using image preprocessing, image segmentation, feature extraction and classification. It can detect plant leaf diseases and automatically identify subsequent classifications. So everyone tries to identify the diseases associated with these plants. Next, when using existing procedures to test plant leaves, their accuracy reaches 52%. Then the proposed ACNN method is compared with the other three methods, and their highest accuracy leads to better results with less computational effort. The ACNN algorithm proposed for plant leaf disease detection is known for its speed and accuracy, making it a beneficial method. This section includes techniques such as precision, recall, and others to ensure accurate plant disease detection. Therefore a novel ACNN method can be proposed and implemented to detect widespread plant diseases and achieve a high accuracy of 92% with the proposed classification.

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