International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

An Optimized Machine Learning Model for Tomato Leaf and Fruit Disease Detection using Kernel Extreme Learning Machine (KELM) Model with Firefly Optimization

Mrs. M. Sharmila[1*], Dr. M. Natarajan[2]

Submitted: 08/05/2023 **Revised**: 14/07/2023 **Accepted**: 08/08/2023

Abstract: Tomato, botanically called Solanum Lycopersicum is a profoundly cultivated cash crop. It is a very common plant which has wide usage across the globe because of its pharmacological properties. Tomato plants are prone to many diseases triggered by various organisms like virus, fungus, bacteria, nematodes, and sometimes environmental conditions also. It is impossible for the farmer to visually identify them. Hence, this research work presents a classification system that automatically recognizes diseases of tomato leaves and fruits. In this study, an optimized machine learning classifier is proposed to classify disease types in tomato leaves and vegetables. The presented technique uses adaptive histogram equalization Contrast Limited AHE (CLAHE) to enhance the input images. In addition, the two-level nested U-structure architecture is employed for segmentation so that the affected diseased portions are identified in the pre-processed images. Besides, LBP, Gary-Level Co-occurrence Matrix (GLCM) are utilized for feature extraction process. For disease detection and classification, the proposed model uses kernel extreme learning machine (KELM) model with firefly optimization (FFO) based parameter optimizer. The performance validation is done using dataset from Haggle repository and our own dataset. The proposed model leverages the power of machine learning algorithms to automatically analyse and classify diseases based on digital images of tomato leaves and fruits.

Keywords: *Tomato, Disease Detection, Firefly optimization, Kernel extreme learning machine.*

1. Introduction

Tomatoes are globally grown with simple agricultural procedures being followed, accounting for 15% of global vegetable consumption [1]. A database of Food and Agricultural Organization shows that1, 86,821 million tons of tomatoes are produced every year across the globe [2]. Plant diseases are unavoidable factors in agriculture that mitigate the production of crops to a great extent. Statistics says that pest losses for crops like wheat are around 50% and 26 to 29% for soya beans. This is alarming as the contribution of agriculture towards GDP is 17.5%. There is no absolute way to avoid plant diseases. Using pesticides is not always a good solution as it will affect the soil, water and cause biological pollution. Therefore, it is necessary that we fight them in an appropriate way and help farmers attain sustainable development of agriculture. As population keeps rising year by year, the United Nations Food and Agricultural Organization says that we must increase the overall agricultural production by 70% in order to meet the food demand in the year 2050[3].Hence, we need to shift to precision farming which is defined as the type of agriculture that utilizes the growth of technology and improves productivity, yield, and agricultural economy [4]. The goal of precision farming is to make the best use of real time data for the betterment of farmers and agriculture.

Tomato is a cash crop that is grown in huge hectares of land where manual supervision of plants becomes tedious. Even if a farmer locates a diseased plant, he cannot identify the exact disease that has affected the plant and hence cannot take proper preventive measures. He would need the help of an expert like a plant pathologist or a botanist or an agriculture specialist [5]. Availability of these experts in rural farms is very low. It is said that 80% of farmers have rural background and hence cannot be expected to be aware of upcoming science and technologies. Hence, automatic classification of diseases from crop image is essential. Plant diseases crash almost half of a farmer’s yield every year if left untreated. Hence, it becomes essential to identify field crop diseases as early as possible and take appropriate preventive actions immediately before the disease starts spreading to the neighboring plants.

[1*]*Research Scholar, Department of Computer and Information Science, Annamalai University, Annamalai Nagar, 608002, Tamil Nadu, India*
[1*]*Email: sharmi.mca12@gmail.com*

[2]*Assistant Professor and Programmer, Department of Computer and Information Science, Annamalai University, Annamalai Nagar, 608002, Tamil Nadu, India*
[2]*Email: mnid2004@gmail.com*

2. Tomato Leaf and Fruit Diseases

A plant can acquire a disease at any stage of its life. Tomato diseases pose a real threat to tomato supply chain globally. In 1950, the disease triangle theory was proposed which says that there are three important agents for a disease to develop. They are the environment, the host (plant) and the causative agent (bacteria/virus). If these three are present, then the spread of a disease is inevitable, according to biologists. A disease not just affects the leaves and fruits; it affects all the vital functions of a plant such as photosynthesis, fertilization, germination, and pollination.

Diseases in plants can be widely classified into two categories, such as abiotic and biotic, based on the factor causing the diseases. Figure 1 will best explain the classification of diseases.

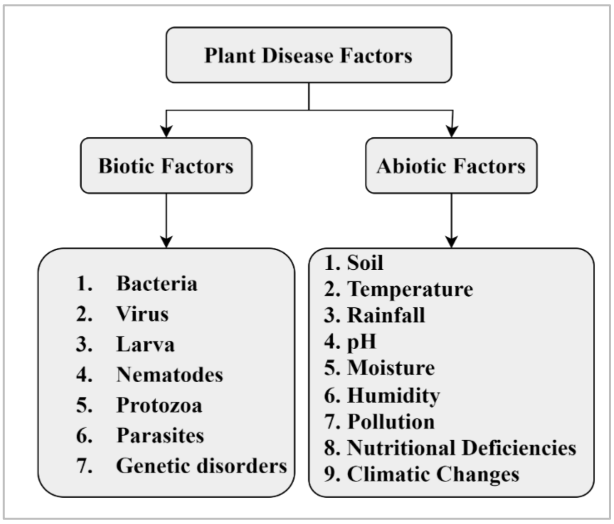


Fig 1: Biotic and abiotic causatives of plant diseases.

Biotic factors are external organisms that cause a particular disease. They could be bacteria, viruses, viroid's, different types of fungus, small microorganisms like larva and protozoa, nematodes, parasites, and sometimes even certain genetic disorders present in the plant [6]. Abiotic factors causing plant diseases are majorly attributed to environmental conditions like rainfall, temperature, nature of the soil, humidity, air, and water pollutants. Certain diseases are caused due to the lack of minerals like nitrogen, potassium, calcium, and magnesium. Narrowing down our research into tomato diseases, we find that there are more than twenty types of different diseases that affect various parts of tomato plants like leaves, fruits, stem, and root [7]. Most diseases attack tomato leaves and fruits. Hence, this paper concentrates on the diseases of tomato leaves and fruits alone. Table 1 below shows the detailed list of tomato leaf and fruit diseases.

Table 1: List of Common Tomato Plant Diseases

S.No.	Disease Name	Part Affected	Causative Agent	Symptoms	Sample Image	Prevention/ Treatment
1.	Septoria Leaf Spot	Leaves	Septoria lycoperscici	Small round to irregular spots with grey center and dark edges. Starts on lower leaves and advances up.		Eliminating spores and cleaning up the farm, using fungicides.
2.	Bacterial Stem and Fruit Canker	Leaves and Fruits	Clavibacter michiganens is	White blister like spots on leaves, stems, and fruits. Vascular discoloration of stems.		Good seeds, crop rotation and drip irrigation will reduce chances of this disease

3.	Early Blight	Leaves and Fruits	Alternaria solani	Small black spots and concentric rings appear. Surrounding part may turn yellow.		Fungicide will help
4.	Late blight *(This initiated the Great Irish Potato Famine)*	Leaves and Fruits	Phytophthora infestans	Associated with potatoes, indefinite patches on older leaves. Spots enlarge and produce white fuzzy growth. Dark greasy lesion on green fruit. Then the whole fruit turns black.		Remove infected plants properly.
5.	Bacterial leaf spot	Leaves and Fruits	Xanthomonas. Campest is	Small brown water-soaked spots surrounded by yellow halo. Scabby surface on green fruit.		Crop rotation
6.	Leaf curl	Leaves	White fly	Stunted plants, downward rolling, crinkling of leaves. New leaves emerge yellow and later curl.		Avoid high temperatures and nitrogen exposure. Maintain soil moisture to prevent dryness
7.	Tomato mosaic virus disease	Leaves	Mosaic virus	Mottling on leaves. Leaves become small and resemble fern leaves		Buy resistant seed varieties as it lives up to 100 years in soil.
8.	Tomato Spotted Wilt disease	Leaves and Fruits	Trips	Chlorotic rings form on the leaves, bronzing of young leaves, drooping leaves, pale yellow areas on fruit, discoloration of seed.		Planting resistant tomato varieties will help.
9.	Anthracnose disease	Ripe Fruits	Colletotrichum coccodes	Water-soaked spots enlarge to ¼ of diameter, black fungal structure in center		Well drained soil

				of ripe fruits.		
10.	Buckeye rot	Green Fruits	Phytophthora parasitic	Green fruits that lay on soil develop black rings. Over time it becomes soft and mushy.		Keep moisture constant and avoid fluctuations. Good drainage is a solution.
11.	Black mold	Ripe Fruits	Alternaria alternata	Sunken lesions decay the fruit. This is a serious disease.		Fungicides
12.	Powdery mildew	Leaves	Oidiopsis Taurica	White spores on upper and lower surfaces of leaves.		Neem oil, organic spray, Bacillus pumilus fungicide will help.

Apart from this list, there are several physiological disorders like blossom end rot, Cat facing, fruit cracking, tomato big bud etc. It is essential that these diseases are identified very early and precisely so that proper preventive measures can be taken to avoid loss of productivity, time, and money [8].

3. Literature Survey

In this section, research related to current tomato plant diseases and their recognition ideas are discussed. Yahya and Kocamaz [9] utilizes 18,835 images and classifies 7 diseases using Support Vector Machine (SVM) as classifier and Convolutional Neural Networks (CNN) architectures such as Alex Net, Google Net and Resnet50 as feature extractors. The accuracy achieved is 96.99% and the author says that SVM has shown high performance in the classification of agricultural images.

Hemalatha and Kailasam [10] uses MATLAB 2017A for the identification of six tomato fruit diseases such as late blight, blossom end, rot, anthracnose, bacterial spots, sunscald, and fungal disease. Median filter, watershed algorithm, K means clustering technique were used for preprocessing, segmentation, and classification purposes.

Singh et al., [11] makes use of images from Plant Village datasets containing images of rice plants, tomato, potato, corn, and apple. Histogram of Oriented Gradients (HOG) and SVM classifiers are used for the purpose of disease detection. It underlines the fact that machine learning does well in pattern learning and classification and is believed to produce good results in various research fields. It is also suitable for multi label classification with good accuracy and great speed.

Qimei Wang et al uses Recurrent CNN model for classifying 286 images. Data is annotated in processing stage itself which finally scored an accuracy of 99.64 %.Lingeswari et al classifies 10 tomato fruit diseases using 1201 images acquired from android camera. The images were cropped, median filtered and segmented using K means algorithm.

Mohammad Chowdury et al opines that incessant supervision of farm crops would be a laborious job for a farmer and prone to human errors too. He applies Efficient net to 18,161 tomato leaves. The mosaic virus and yellow leaf curl virus diseases were detected. The original image is normalized and resized to 224 * 224 size. Modified U net algorithm was used for segmentation which achieved an accuracy of 99.95%.

Saeed Alzahrani employed 11,000 images of tomato leaves and fruits for tomato disease detection. The input images were initially preprocessed using normalization and resizing technique. Two trivial architectures of CNN namely Dense Net 121 and Reset 50V2 are used for classification.

Cengil and Cinar [12] have used 10,000 images from Taiwan tomato field and concentrated majorly on bacterial wilt disease. The initial input image needed for this system can be a single leaf or even contain multiple leaves. Using SVM they attained an accuracy of 96.1%.

Sampoorna and Rasadurai[13] have made use of SVM and K means and achieved an increase in accuracy of 15% when compared to the existing work. In yet another paper published by the same authors, they have proposed an automatic disease detection system. Here they have mentioned about the usage of various sensors to aid farmers in the sustainable development of agriculture [14]. K means algorithm was used for segmentation, Gray Level Co-occurrence Matrix (GLCM) for feature extraction and SVM is used as a classifier. This method improved the accuracy of the existing system by 11.0165 %.

Attalah [15] had acquired input images from Plant village dataset comprising 54,309 images. Images were initially augmented, and CNN was used as feature extractor. Six classifiers were used such as Naives Bayes, Linear discriminant Analysis, Decision tree,K Nearest neighbor, SVM and Quadratic discriminant analysis. The highest yielding accuracy was 99.92% given by SVM.

Vijay Kumar Trivedi made use of 73 images, 15 of which were healthy, and others were diseased. Rank order fuzzy filter was employed for preprocessing and K means was used for segmentation to classify diseases such as bacterial blight, Alternaria, cercospora spot and anthracnose. The Jaccard coefficient value finally obtained in this classification was around 0.7747.

Rahman et al., [16] had proposed a software solution for Tomato disease detection. Dataset was obtained from the fields in Pakistan using an android based digital camera. The obtained images were resized to the size of 512*512. Otsu’s method was used for segmentation, GLCM for feature extraction and SVM for classification purposes. A total of 400 images were captured and the accuracy obtained was 100% for healthy leaves and 90% for other diseases.

Monu Bhagat takes into consideration 200 tomato, potato and bell pepper leaf images, resizes them and converts them to gray scale for better clarity. Speeded Up Robust Features (SURF) technique was used for feature extraction. K means and SVM were employed for segmentation and classification achieving an accuracy of 97 %.

Jagadeesh and Arlene Anthony [17] describes the old techniques that were used for disease detection such as gas chromatography, polymerase chain reaction, mass spectrometry, thermography, hyper spectral techniques etc. For experimental purpose he considers mosaic, bacterial spot, tomato yellow curl, Septoria diseases. It was found that the yellow curl virus is capable of living in the soil for 50 years. This has been considered as the utmost damage causing virus to tomato plants. Jagadeesh used 300 images which were resized to 500*500 and features were extracted using Linear Binary Pattern. The decision tree was used as a classifier which gave an accuracy of 90 %.

Bora et al., [18] signifies that tomato is a very important economic crop and had tried new different algorithms for Tomato disease detection. During preprocessing stage, images were converted from RGB to HIS color space and for segmentation; Rectilinear K means clustering algorithm was used. Random Motion Squirrel Search Optimization algorithm was employed for feature extraction and Multivariate Normal Deep Learning Neural Network algorithm was used for classification. The results finally obtained were accuracies of 93.6%, 96.8%, 95.2%, 99.84%, and for root disease detection, fruit, stem, and tomato leaf, respectively.

Abbas et al., [19] also has used Plant Village data set which is one of the benchmark datasets for plant leaf diseases. 16,012 images of tomato leaves were utilized. The obtained images were resized to 244*244 size and synthetic images are generated using CGAN algorithm to prevent the problem of over fitting. Dense net 121 was used as a classifier for decision making. The accuracy obtained is 99.51% in the case of five classes, 98.6% for seven classes and 97.11% for ten classes.

Ananda Natarajan et al acquired 1090 tomato images from the farms of Kallur, Andhra Pradesh. Images were labeled using a tool called LabelImg and Recurrent CNN was used for feature extraction and Resnet50 for classification. The overall accuracy achieved by the system was 80.952%. As the authors were disappointed with the results, they conducted a failure analysis. This revealed that the symptoms of Septoria leaf spot were confused with the symptoms of early blight and bacterial spot as they were similar in nature [20-24].

4. Proposed System

The proposed system workflow has been depicted in Figure 2.What makes the proposed system easier for farmers is that they need not pluck the diseased fruits or leaves and seek the help of an agricultural professional every single time. It is enough that the farmer takes a picture of the diseased plant and gives it as an input to the classifier which will identify the disease that has affected the plant and the farmer can take proper corrective measures.

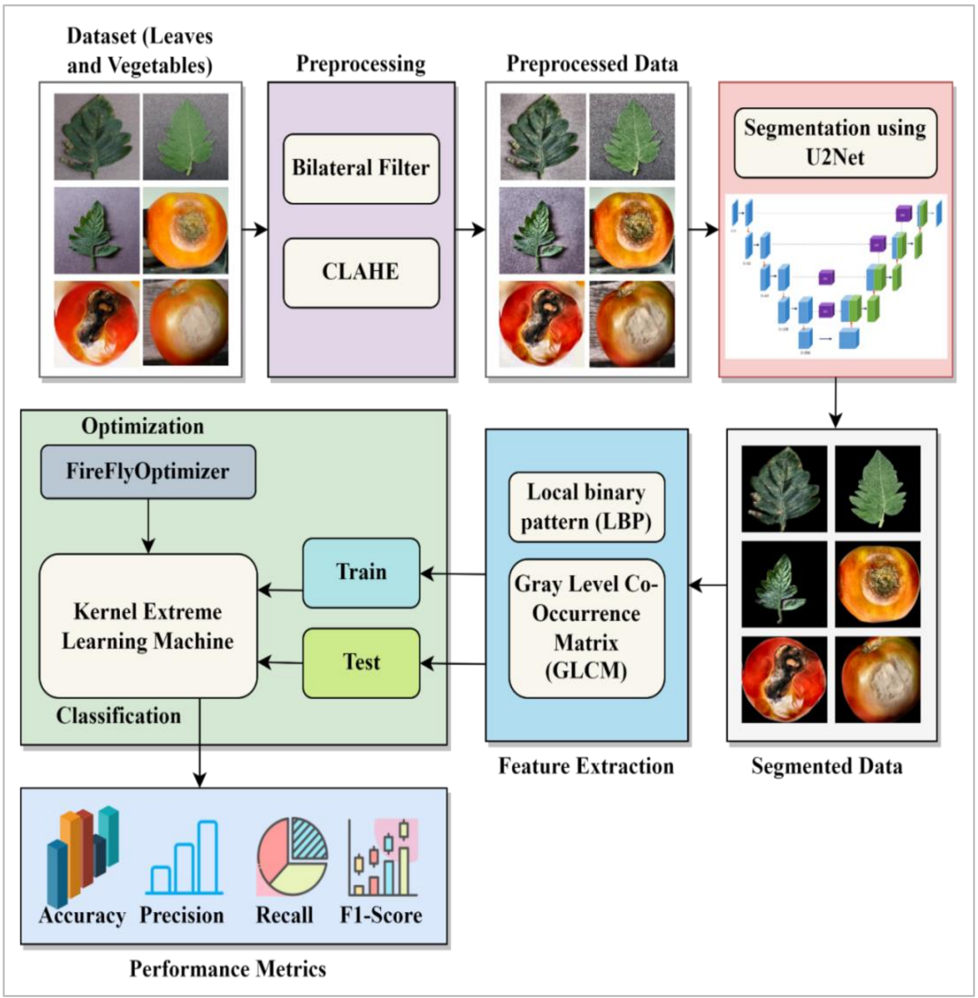


Fig 2: Proposed model overview

4.1 Preprocessing

Here, noises are removed using bilateral filter and contrast enhancement is made through Contrast Limited adaptive histogram equalization (CLAHE).

4.1.1. Bilateral Filter

Bilateral filter is a familiar denoising filter which considers local neighborhood pixels weighted sums. Weight is defined based on the intensity distance and spatial distance. Due to this, noises are reduced, and the edges are preserved. Mathematically the filter is formulated as follows.

$$\check{I}(x) = \frac{1}{c}\sum_{y\in N(x)} e^{\frac{-\|y-x\|^2}{2\sigma_d^2}} e^{\frac{-\|I(y)-I(x)\|^2}{2\sigma_r^2}} I(y) \quad (1)$$

where spatial negihborhood is indicated as $N(x)$ and c indicates the normalization constant which is mathematically formulated as

$$c = \sum_{y\in N(x)} e^{\frac{-\|y-x\|^2}{2\sigma_d^2}} e^{\frac{-\|I(y)-I(x)\|^2}{2\sigma_r^2}} \quad (2)$$

where the parameters which controls the spatial and intensity domain weights are indicated as σ_d and σ_r respecitively. Using bilateral filter the noises in the input normal and disease affected leaves, vegetables are removed.

4.1.2 CLAHE

In the second step of preprocessing CLAHE is used for contrast enhancement. The noise removed image is further contrast enhanced using CLAHE. CLAHE derives the transformation function using a contrast enhancement function which is applied over neighborhood pixels. Unlike conventional histogram methods which has contrast limitations, CLAHE overcomes the contrast enhancement limitations over gray scale and colored images. The contrast enhancement process obtains the clip limit, number of regions in row and column direction, distribution parameter type and dynamic range of an input image. Further the image is split to rectangular window and then for each block a histogram is calculated. Meanwhile excess portions are redistributed, and cumulative distributive function is computed. Finally, the pixel values are interpolated to obtain the final image. Mathematically the histogram is formulated as

$$h(n) = \sum_{i=0}^{xx-1}\sum_{j=0}^{yy-1} g(n,i,j) \text{ for } n = 0,1,\ldots,N-1 \quad (3)$$

$$g(n,i,j) = \begin{cases} 1 & if\ I(i,j) = n \\ 0 & otherwise \end{cases} \quad (4)$$

Where grey level is indicated as n, number of histogram bins are indicated as N, nth bin histogram value is indicated as $h(n)$. xx and yy is indicated as image block dimensions, i,j indicates the pixel coordinates. $I(i,j)$ indicates the pixel value coordinates (i,j). The function which evaluates the pixel value coordinates which are equal to n is represented as $g(n,i,j)$.

4.2 Image Segmentation using U2Net.

After preprocessing, the enhanced input image is next subject to the process of segmentation. It helps reduce the processing time since the algorithm works on the needed segments of the image rather than processing the entire image. There are many methods available for segmentation such as region growing, edge-based segmentation, thres holding or Otsu method, watershed-based segmentation etc. The proposed work includes U2Net for background removal. The U2Net is a familiar background removal model which is widely used in various medical image processing application. The segmentation model generates a mask of region of interest for the input image. Further U2Net performs a bitwise operation to produce the mask. The general architecture of U2Net is depicted in figure 3. The twofold interlaced U-Structured architecture has six stage encoder and five stage decoder units. A residual U-Block (RSU) is used in the encoder stage to extricate the local features. A convolutional layer which is used in the input generates the intermediate activation map $fm(x)$. Encoder-decoder in the next step takes $fm(x)$ as input and encodes the multi-scale contingent attributes $U(fm(x))$. Combining all the complete formulation that represents RSU is given as follows.

$$h_{RSU} = U(fm(x)) + fm(x) \quad (5)$$

Figure 3 shows the architecture of U-Net. The loss in the RSU needs to be minimized during up sampling by extracting the multi scale attributes. Activation maps perform concatenation, up sampling and convolution during the encoding process. Finally, the local and multi scale attributes are combined using the residual connection.

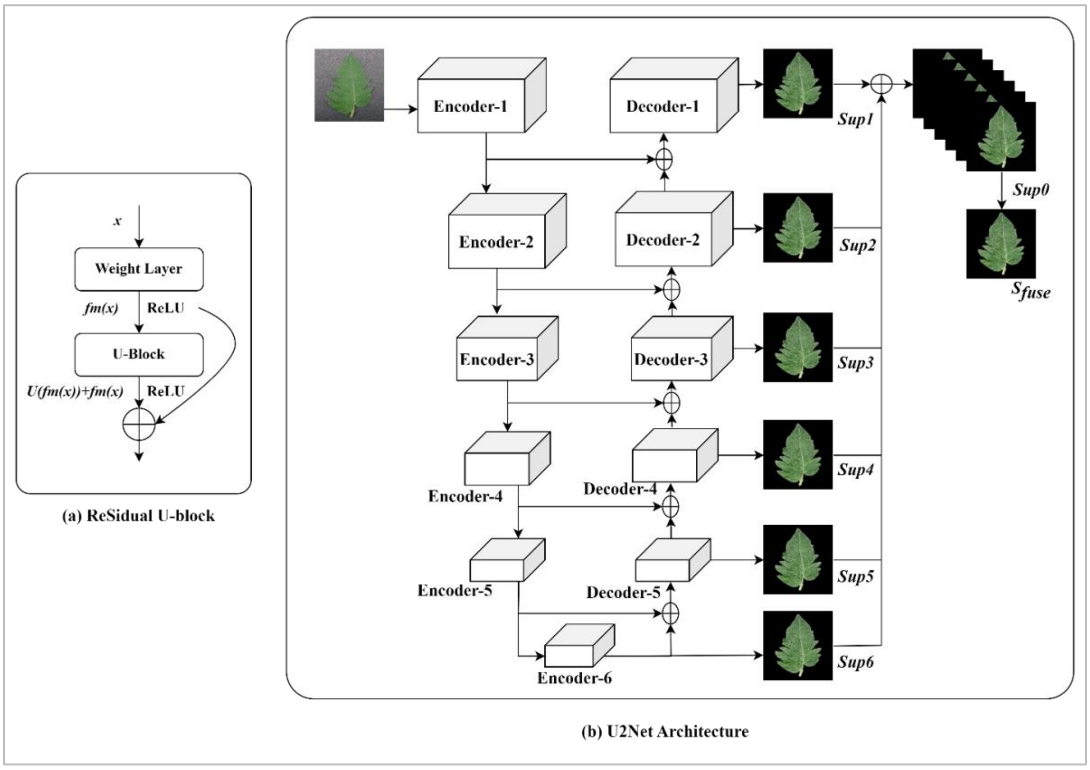


Fig 3: (a) Residual U-Block (b) U2Net Architecture.

The second stage of architecture includes five decoder units which is a dilated version of RSU. Complete architecture of U2Net encoder and decoder is depicted in figure 3(b). It can be observed that for each stage decoder generates a saliency probability map considering the encoder inputs. The saliency maps define the image pixel quality, and it helps to differentiate background and interesting area. To obtain the loss function in the fusion process, deep supervision is employed so that the loss is minimized for the learned features. mathematically the loss function is formulated as

$$L = \sum_{n=1}^{N} w_{side}^{n} l_{side}^{n} + w_{fusion} l_{fusion} \quad (6)$$

where the saliency maps is indicated as N, side saliency map loss is indicated as l_{side}^{n} and its weight is indicated as w_{side}^{n}. The fusion of saliency map loss is indicated as l_{fusion} and its weight is indicated as w_{fusion}. Further, the essential features from the segmented image are extracted for classification.

4.3 Feature Extraction

Once the image has been segmented, the next job is to extract the relevant features from the image. This can be done in this step called Feature Extraction or Feature selection. Features relating to texture and shape are very important for plant pathology as plant diseases usually affect the leaves texture and shape properties. Texture features may be related to uniformity, correlation, contrast, roughness, and entropy, whereas shape features show the area, perimeter, centroid, orientation of the leaves. Researchers suggest that using more than one type of feature will yield more accurate results than relying upon a single feature.

Feature extraction techniques available in image processing are Principal Component analysis, GLCM, HOG, SURF, Linear Binary Pattern, Scale Invariant Feature Transform (SIFT) etc. In the proposed model, the shape features are extracted using local binary pattern (LBP), GLCM is employed for texture feature extraction and color feature like entropy and variance are extracted and fed into the classifier.

4.3.1.Local Binary Pattern (LBP)

The local binary pattern (LBP) is a familiar texture extractor for images which is widely used in various image processing applications. The feature extraction procedure considers central and neighbor pixels. A window which has specified neighborhood value is traversed over the image. In this process, a central pixel is selected and labeled. Considering the pixel values which are adjacent to central pixel a threshold is applied. Based on this a matrix is calculated. A simple illustration of local binary pattern is depicted in figure 4. In this process, 8 neighbor pixels with single central pixel is considered. The neighborhood pixel value is compared with center pixel and if the value of center pixel is larger than neighbor pixel then the pixel value is changed into zero otherwise it is changed into one. From left to right all the pixel values are compared and replaced with binary numbers. Finally, all the pixels are combined from left to right to convert the binary into decimal.

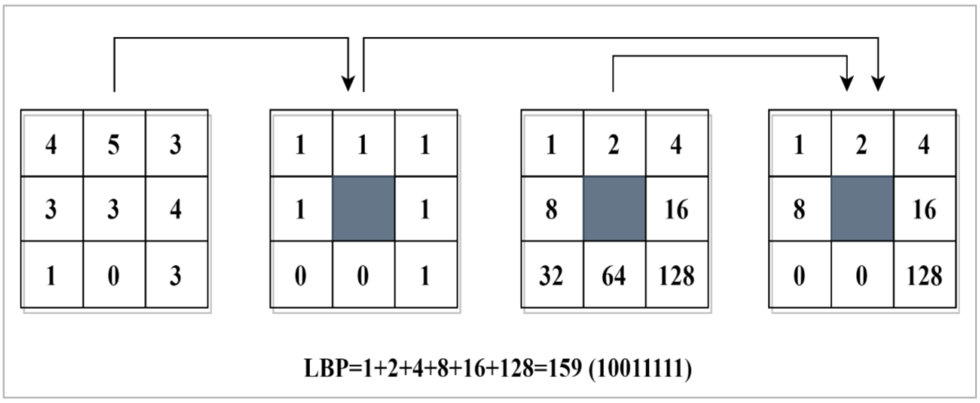


Fig 4: Local Binary pattern calculation

The major features of LBP are its resistance to gray level changes and simple computation process. Due to this, LBP is used in the numerous real time applications. The essential formulation which describes the pixel labeling in LBP is given as follows.

$$LBP_{p,r} = \sum_{p=0}^{p-1} s(g_p - g_c)2^p \quad (7)$$

$$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \quad (8)$$

where central pixel gray value is indicated as g_c and the neighbor pixel values are indicated as g_p. The total number of neighbors is indicated as p and radius of neighborhood is indicated as r.

4.3.2GLCM

GLCM is usually used to extract the statistical texture features from an image. The low-level features which describe the image textures are extracted. The major features that can be extracted by GLCM from an image are inverse difference moment (IDM), energy, entropy, homogeneity, sum variance, contrast, correlation, autocorrelation, maximum probability, dissimilarity, IDM normalized and many more. The interconnected pixels from a gray scale image spaced with moderate angle of 0°, 45°, 90° and 135° are calculated by GLCM. Some of the essential mathematical formulations for the features that can be extracted by GLCM are given as follows.

- **Angular second moment** is defined as the total of square of entries in the GLCM matrix. Image homogeneity is measured in the angular second moment and it will be high if the image has better homogeneity or similar pixel values. mathematically it is described as follows.

$$Energy\ or\ ASM = \sum_{i,j=0}^{N-1} (p_{i,j})^2 \quad (9)$$

Where the spatial coordinates are indicated as i, j, N indicates the number of grey levels in an image.

- **Contrast** defines the intensity which links contrast between pixel and its neighbors in the entire image. Mathematically it is described as follows.

$$Contrast = \sum_{i,j=0}^{N-1} p_{i,j}(i-j)^2 \quad (10)$$

- **Correlation** defines the linear dependency of neighbor pixels grey levels. The gray tone linear dependencies are measured in the correlation process. The pixel correlation is mathematically formulated as

$$Correlation = \sum_{i,j=0}^{N-1} p_{i,j} \frac{(i-\mu)(j-\mu)}{\sigma^2} \quad (11)$$

where μ indicates the calculated mean, σ indicates the variance of pixel intensities.

- **Entropy** defines the randomness of the image. The amount of information which is required for image compression is defined as entropy function. The information loss is measured using the entropy which is mathematically formulated as

$$Entropy = \sum_{i,j=0}^{N-1} - \ln(p_{i,j})\, p_{i,j} \quad (12)$$

- **Homogeneity** defines the local homogeneity of an image and is computed as shown below.

$$Homogeneity = \sum_{i,j=0}^{N-1} \frac{p_{i,j}}{1+(i-j)^2} \quad (13)$$

The mean and variance used in the above formulation is mathematically expressed as

$$mean\ \mu = \sum_{i,j=0}^{N-1} i p_{i,j} \quad (14)$$

$$varaince\ \sigma^2 = \sum_{i,j=0}^{N-1} p_{i,j}(i-\mu)^2 \quad (15)$$

4.4 Classification using Kernel Extreme Learning Machine with Firefly Optimizer

The proposed model includes an optimized classifier for plant leaf and vegetable disease classification. An optimized kernel extreme learning machine (KELM) is used in the proposed work as classifier and the network parameters of KELM is optimized using firefly optimization algorithm. Compared to conventional learning machines the learning speed of KELM is high and it provides better generalization with minimal human intervention. Due to this major feature merits KELM is used in the proposed classification process. Similarly, the firefly optimization algorithm used to optimize the network parameters is a simple and efficient optimization algorithm suitable for parallel operations.

4.4.1 Kernel Extreme Learning Machine

Extreme learning machine (ELM) is a kind of feed forward neural network. For the given training data (x_i, t_i), ELM composes N-dimensional input layers and L nodes of hidden layers. where $x_i = [x_{i1}, x_{i2}, \dots, x_{in}]^T$ and $t_i \in R^m$, $i = 1,2, \dots, N$. The output function

$$\sum_{i=1}^{L} h_i(x)\beta_i = t_i \quad (16)$$

In the above equation $h_i(x)\beta = t_{i_i}$ can be rewritten as $H\beta = T$, where $\beta = [\beta_1, \beta_2, \beta_3, \dots, \beta_L]^T$ and

$$H = \begin{bmatrix} h(x_1) \\ \vdots \\ h(x_n) \end{bmatrix} = \begin{bmatrix} h_1(x_1) & \cdots & h_L(x_1) \\ \vdots & \ddots & \vdots \\ h_1(x_n) & \cdots & h_L(x_n) \end{bmatrix} \quad (17)$$

where the output weights vector which connect hidden layer is indicated as β and hidden layer is indicated as H. To train the network, it is essential to obtain the essential method to attain the following objective.

$$minimize: \|H\beta - T\| \quad (18)$$

In the classification process using ELM, there will be a small training error and smallest norm of output weights. The norm least square solution in ELM is formulated as

$$\tilde{\beta} = H^+T \quad (19)$$

where the Moore Penrose generalized inverse is indicated as H^+. Based on this the ELM constraint which need to be optimized are formulated as

$$minimize: L_{P_{ELM}} = \frac{1}{2}\|\beta\|^2 + C\frac{1}{2}\sum_{i=1}^{N}\|\xi_i\|^2 \quad (20)$$

$$subject\ to: h(x_i)\beta = t_i^T - \xi_i^T, i = 1,2, \dots, N \quad (21)$$

In order to attain the desired objective function, a firefly algorithm is incorporated in the proposed work.

4.4.2 Firefly Algorithm

The firefly optimization algorithm is an intelligent method which is formulated on the basis of behavior of fireflies. The fireflies have the characteristics to move towards high luminescence and it is related to real time application to obtain optimal solution. Compared to other optimization algorithms, the global optimization ability of firefly is better so that it is widely used in path planning, scheduling, and numerous image processing applications. The algorithm considers individual firefly which has low intensity luminescence and high intensity luminescence firefly for formulation. The degree of attraction and individual brightness of fireflies differs from each other. In the formulation few assumptions are made such as: All the fireflies are considered as same gender and have tendency to attract each other. The attraction is purely based on luminous intensity and distance. Flies which have strong luminescence will attract fireflies with weak luminescence. However, when the distance increases, the attraction rate decreases due to surrounding light. The illumination intensity is defined by the objective function. The search process in the optimization is defined based on brightness and mutual attraction factors of fireflies. The bright fireflies indicate an optimal result for the optimization problem. The three factors of fireflies are mathematically formulated as follows.

The fluorescence brightness is mathematically formulated as

$$I = I_{ini} e^{-\gamma r_{i,j}} \quad (22)$$

where bright firefly brightness is indicated as I_{ini}, light absorption coefficient is indicated as γ and the distance between two fireflies is indicated as $r_{i,j}$. The mutual attraction degree is mathematically formulated as

$$\varphi(r) = \varphi_{ini} e^{-\gamma r_{i,j}} \quad (23)$$

where maximum attractiveness is indicated as φ_{ini}. The optimal target iteration is mathematically formulated as

$$x^{(i)}(t+1) = x^{(i)}(t) + \varphi\left(x^{(j)}(t) - x^{(i)}(t)\right) + \alpha(rand - 1/2) \quad (24)$$

where the position of firefly i and j is indicated as $x^{(i)}(t)$and $x^{(j)}(t)$ respectively. The step length factor is indicated as α and random factor which defines the random distribution of fireflies is indicated as $rand$. The optimization model optimizes the network function and enhances the classification accuracy.

5. Results and Discussion

The proposed model performance evaluation is verified through simulation analysis performed in python tool. Two sets of datasets are used in the proposed model. The first data set is “Tomato leaf disease detection dataset” which is a benchmark dataset publicly available in Kaggle data repository [1]. The tomato leaf dataset has 10 different types of tomato leaf images including health images and 9 disease attacked images. For each category 300 images are present in the dataset and a total of 3000 images are used in the experimentation.

The second dataset used in the proposed work is a vegetable dataset which is prepared by us. The images are collected from open repositories and categorized into three types as “Anthracnose,” “Blossom End Rot” and “Sunscald.” 10 different images are collected for each category and then the number of images is increased through data augmentation. The augmentation step includes image rotation by 90 degrees, Zoom range of 0.15, width shift, height shift, shear change, horizontal flip, fill model. After data augmentation the number of sample images for Anthracnose is increased from 10 to 260 images. The number of images for Blossom End Rot is increased from 10 to 234, and for Sunscald the number of images is increased from 10 to 182. The total images in the dataset after data augmentation is 676.Table 2 depicts the essential details of dataset used in the experimentation.

Table 2: Tomato diseases selected for classification.

Dataset	Leaf/Fruit disease	No. of sample images
Tomato leaf dataset	Bacterial Spot	300
	Late Blight	300
	Early blight	300
	Mosaic Virus	300
	Leaf Mold	300
	Septoria Leaf Spot	300
	Healthy	300
	Yellow Leaf Curl Virus	300
	Target Spot	300
	Two Spotted Spider Mite	300
Fruit Diseases	Anthracnose	260
	Blossom End Rot	234
	Sunscald	182

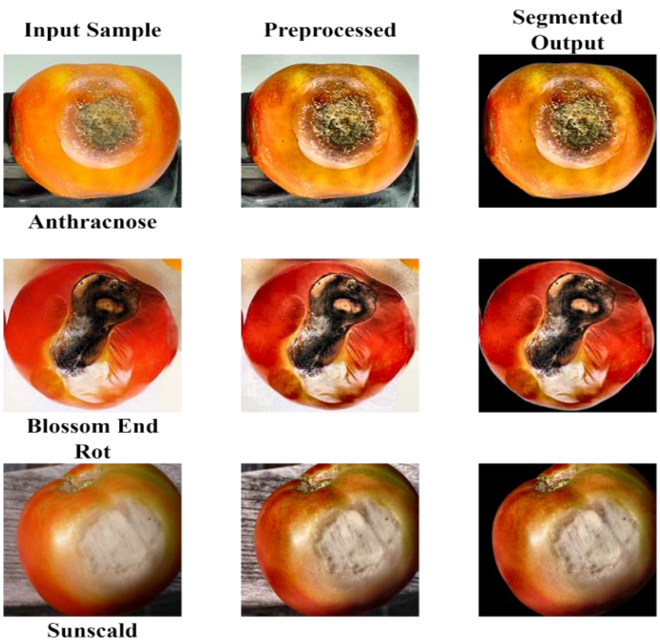


Fig 5: Sample image from tomato leaf dataset

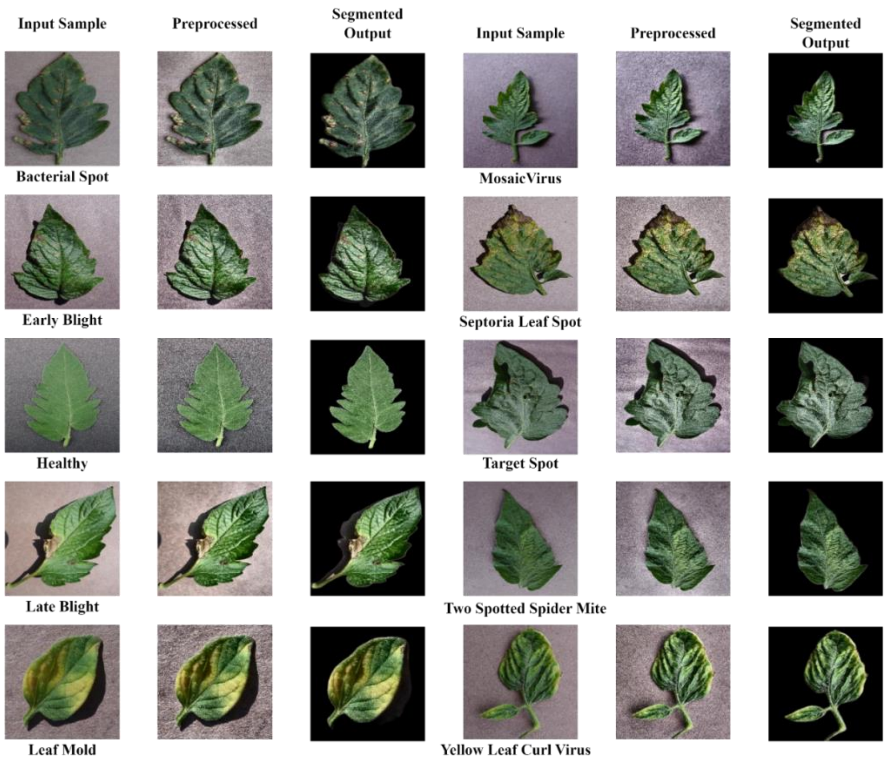


Fig 6: Sample image from tomato leaf dataset

Figure 5 and 6 depicts the outputs of proposed model experimentation. The input samples from leaf dataset and vegetable dataset are presented in the first column. The second column is the preprocessed input sample where bilateral filter is used to remove the noise and CLAHE is used to enhance the contrast. The Third column provides the segmented output where U2Net is used for background removal. In the following section, the confusion matrix is formed for both datasets and the classification results are presented.

5.1 Confusion matrix

It is defined as a form of matrix that describes the performance of the classifier when testing is performed. The confusion matrix obtained by the proposed model tomato leaf dataset and vegetable dataset is depicted in figure 7 and 8. The different classes in tomato leaf dataset are mentioned as different classes. “Bacterial Spot” is assigned with class 1, “Early Blight is assigned with class 2”, “Healthy” is assigned with class 3, “Late Blight” is assigned with class 4, “Leaf Mold” is assigned with class 5, “Mosaic Virus” is assigned with class 6, “Septoria Leaf Spot” is assigned with class 7, “Target Spot” is assigned with class 8, “Two Spotted Spider Mite” is assigned with class 9, and “Yellow Leaf Curl Virus” is assigned with class 10.

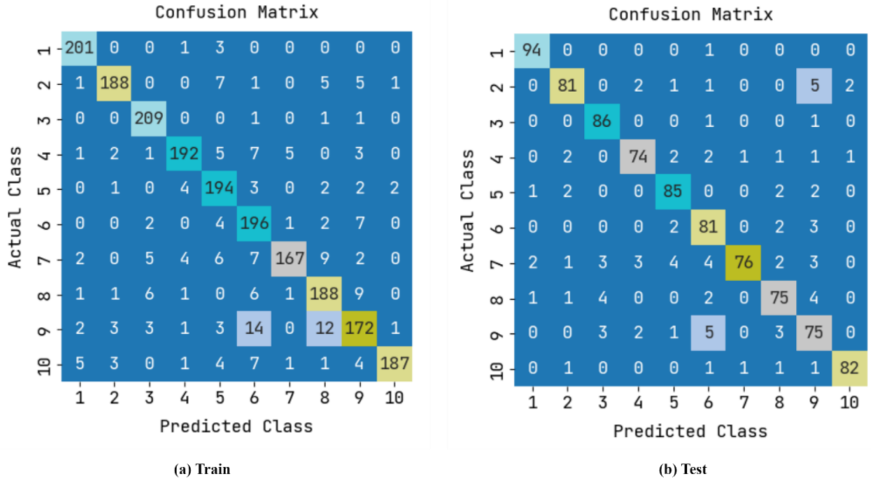


Fig 7: Confusion matrix for tomato leaf dataset

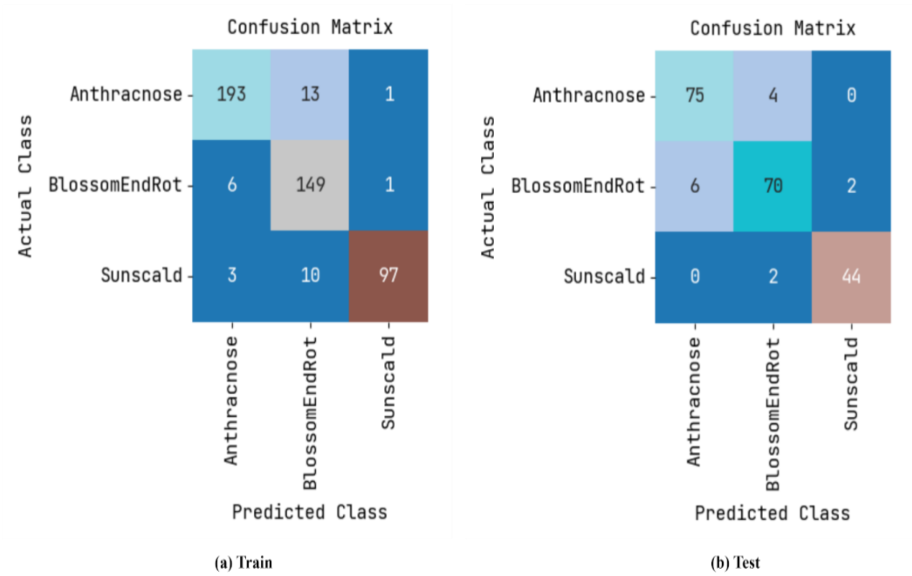
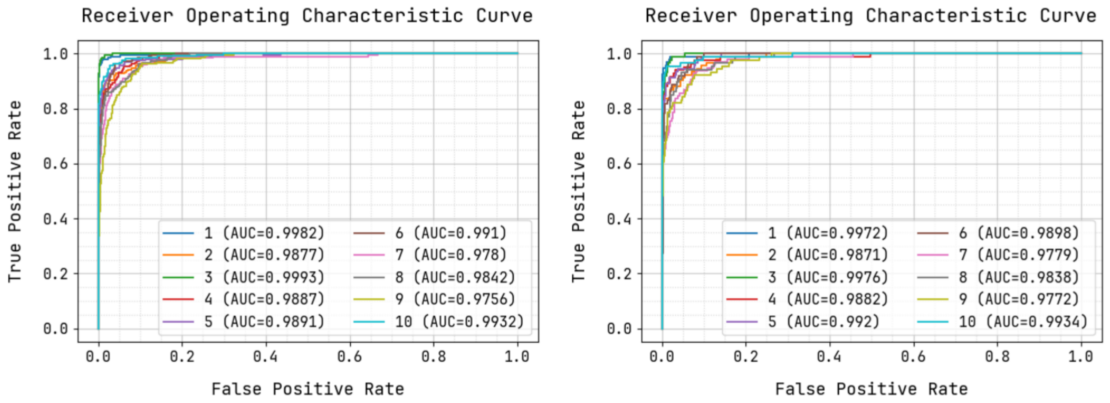


Fig 8: Confusion matrix for vegetable dataset

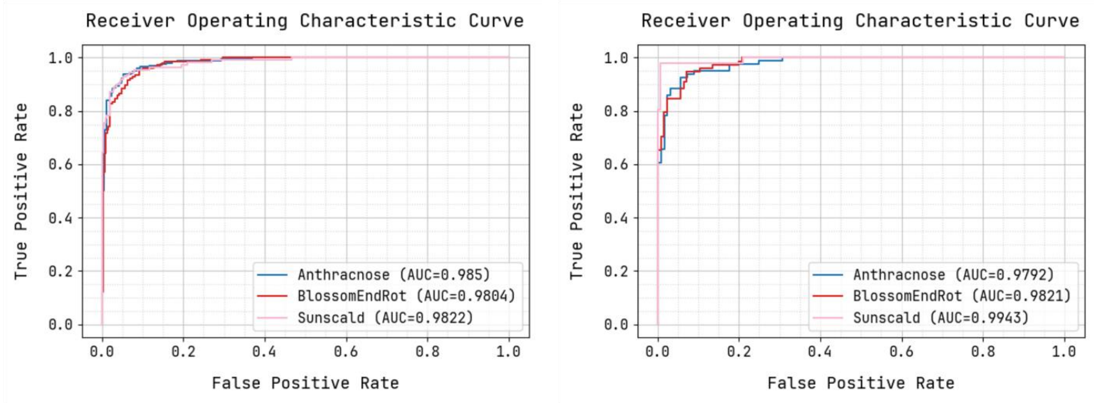
5.2 ROC curve analysis

The receiver operating characteristics obtained by the proposed model is presented in figures 9 and 10 for tomato leaf disease dataset and vegetable dataset, respectively. Figure 9(a) depicts the training process ROC curve and figure 9(b) represents the testing process ROC curve for 10 different classes. Results clearly depicts that the AUC score attained by the proposed model for all the classes are above 0.9 which reflects the better performances. Similarly in figure 10(a) and (b) the AUC value attained by the proposed model is above 0.9 for all the classes.



(a) Train (b) Test

Fig 9: Receiver operating characteristics for tomato leaf dataset



(a) Train (b) Test

Fig 10: Receiver operating characteristics for vegetable dataset

5.3 Performance Metrics

From confusion matrix, we can arrive at various performance metrics. The true performance measure of the classifier is described in terms of accuracy. Its formula is given below in equation 25. It is calculated from the values of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN).

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

Precision indicates the success rate of the prediction of the classifier and the formulation for precision is metric is presented in equation 26.

$$\text{Precision}=\frac{TP}{TP+FP} \tag{26}$$

Recall is otherwise called a sensitivity or hit rate. The formula for calculating recall is given in equation 27.

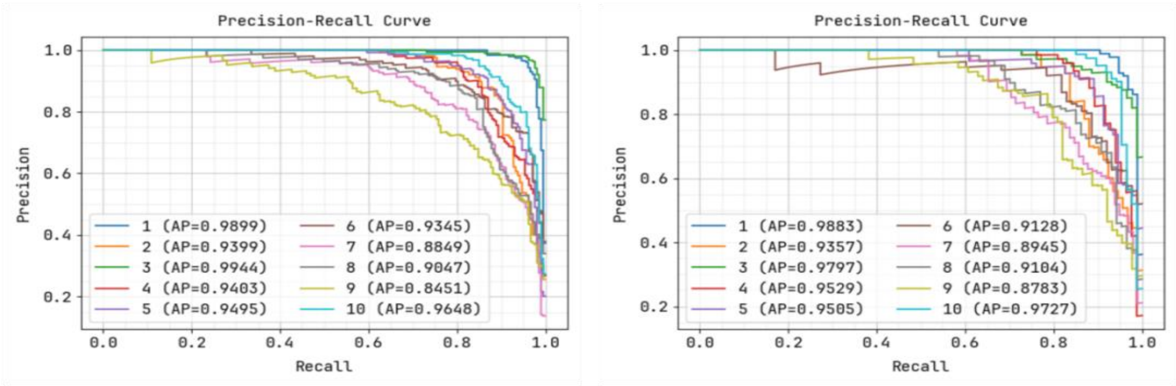
$$\text{Recall}=\frac{TP}{TP+FN} \tag{27}$$

F_1 score indicates the classification performance of the chosen classifier. It includes both precision and recall in its calculation as indicated in equation 28.

$$F_1\, score=\frac{2*Precision*Recall}{Precision+Recall} \tag{28}$$

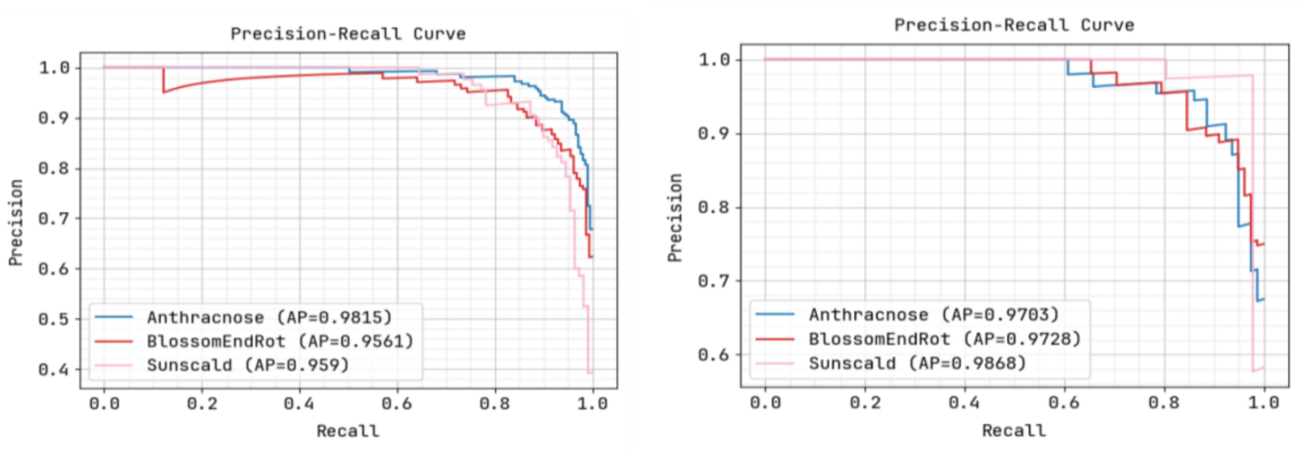
5.4 Precision – Recall analysis

The precision recall curve attained for tomato leaf dataset is depicted in figure 11. The average precision is measured for all the classes. The proposed model attained better AP values for all the classes. Similarly, the precision recall curve depicted in figure 12 for training and testing process clearly validates that proposed model attained better AP values for all the classes.



(a) Train (b) Test

Fig 11: Precision-Recall curve for tomato leaf dataset



(a) Train (b) Test

Fig 12: Precision-Recall curve for vegetable dataset

The overall performance metrics is presented in table 3 for training and testing process for all the metrics. The maximum accuracy attained by the proposed model for tomato leaf dataset is 94.42% and for vegetable dataset the attained accuracy is 94.9%.

Table 3: Performance metrics of proposed model for tomato and vegetable dataset

S. No	Metrics	Tomato leaf dataset		Vegetable Dataset	
		Train	Test	Train	Test
1	Accuracy	0.9455	0.9442	0.9429	0.949
2	Precision	0.9054	0.9011	0.9338	0.9345
3	Recall	0.9891	0.9888	0.9627	0.9636
4	F1-Score	0.9021	0.8985	0.9268	0.9344
5	MCC	0.8922	0.8884	0.8913	0.8982

5.5 Performance comparative analysis

To validate the proposed model performance, existing research work which utilizes the same to mato leaf dataset is considered for comparative analysis. Research work of Agarwala et al., [24] presented a CNN model for tomato disease detection and attained accuracy of 91.2%. For comparative analysis, research work includes Mobile Net, VGG16 and Inception V3 models. The comparative analysis of accuracies for all the models are presented in figure 13. The better performance of the proposed model is visible in figure 13. The maximum accuracy attained by the proposed model for tomato leaf dataset is 94.42% which is 3% better than CNN model, 30% better than Inception V3 and Mobile Net models, and 17% greater than VGG16 model.

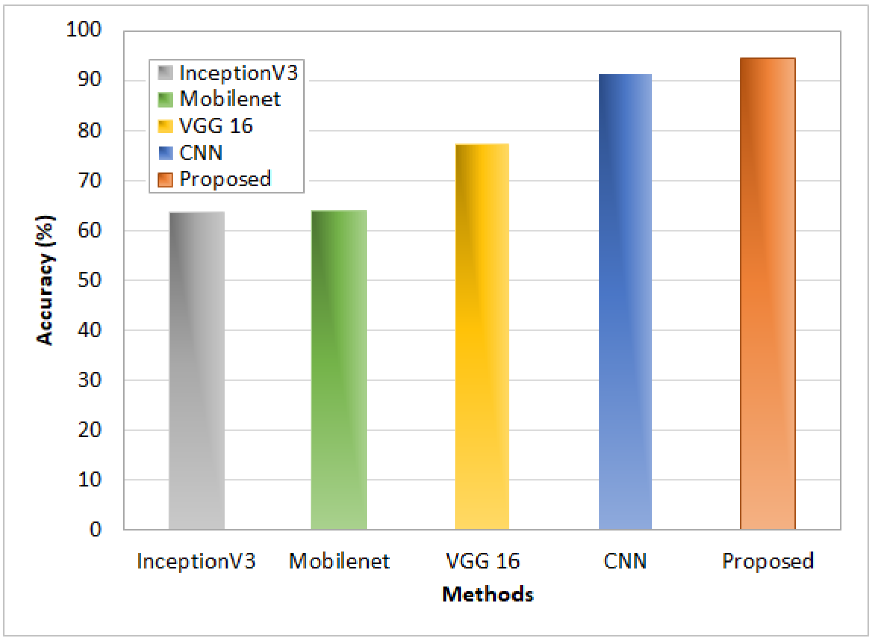


Fig 13: Comparative analysis with existing research work

5.6 Preventive Measures

This section describes the list of preventive measures that can be taken. Though plant diseases are unavoidable, we can always take some precautions in order to avoid them. Some of the preventive measures to be taken by the farmers are listed below.

1. Periodic health testing of plants.
2. Avoiding monoculture i.e., cultivating the same plant species over and over [25].
3. Adopting crop rotation.
4. Proper removal of debris after harvesting.
5. Proper sanitation of field.
6. Good drainage system and sunlight.

5.7 Factors affecting classifier.

The structure of tomato leaves is not plain in general, and it has several curves in nature, which makes tomato leaf disease detection even more critical. However good the classifier may be, sometimes there are several factors that affect the performance of the classifier some of which are listed below [26]. If we consider these factors while training the classifier, then we may improve the performance of the classifier even more to attain full accuracy.

1. Similar disease symptoms.
2. Irregular structure of affected leaves.
3. Lower number of inputs for a particular class.
4. Lack of large data set.
5. Wrong self-annotation of diseases.
6. No specific shapes for certain diseases.
7. Geographical effects on the disease which is hard to interpret.

6. Conclusion

Plant losses because of plant diseases are estimated to be 20 to 40 % of total agricultural production every year and this rate will keep increasing if appropriate measures to control it are not taken. The proposed model of this work will provide an improved artificial intelligence solution for farmers to automatically identify the plant diseases and act accordingly to combat the disease and will ensure them with a better yield. This is evident from the results attained by the proposed system where accuracy is 94.42%, precision is 90.11%, rate of recall is 98.88% and F1 Score is 89.85% for tomato leaf dataset. Similarly, the proposed system attained accuracy is 94.9%, precision is 93.45%, rate of recall is 96.36% and F1 Score is 93.44% for vegetable dataset. Compared to existing classification models like Inception V3, Mobile Net, VGG16 and CNN, the proposed model attained better classification accuracy.

Pest and disease risk assessment analysis before the strike of a disease can be added as an enhancement to this project in future.

Declaration

- Funding – The author did not receive support from any organization for the submitted work.
- Conflicts of Interest - The author has no relevant financial or non-financial interests to disclose.
- Availability of Data & Material – The author hereby declare that no specific data sets are utilized in the proposed work.
- Code Availability – Since future works are based on the custom codes developed in this work, the code may not be available from the author.
- Author's contribution – The author is solely responsible for the experimental works conducted in this paper, drafting of the paper and presentation of all the sections.

References

[1] M.S. Alzahrani, and F.W. Alsaade,2023. "Transform and Deep Learning Algorithms for the Early Detection and Recognition of Tomato Leaf Disease". *Agronomy*, *13*(5), p.1184.

[2] M.E. Chowdhury, T. Rahman, A. Khandakar, M.A. Ayari, A.U. Khan, M.S. Khan, N. Al-Emadi, M.B.I. Reaz, M.T. Islam, and S.H.M. Ali, 2021. "Automatic and reliable leaf disease detection using deep learning techniques". *AgriEngineering*, *3*(2), pp.294-312.

[3] I. Ahmad, M. Hamid, S. Yousaf, S.T. Shah, and M.O. Ahmad, 2020. "Optimizing pertained convolutional neural networks for tomato leaf disease detection". *Complexity*, *2020*, pp.1-6.

[4] V.A. Natarajan, M.M. Babitha, and M.S. Kumar. 2020 "Detection of disease in tomato plant using Deep Learning Techniques". *International Journal of Modern Agriculture*, 9(4), pp. 525-540.

[5] S. Khatoon, M,M. Hasan, A. Asif, M. Alshmari, and Y.K. Yap. 2021 "Image-based automatic diagnostic system for tomato plants using deep learning". *Computers, Materials and Continua*. 67(1), pp. 595-612.

[6] V,S. Dhaka, S,V. Meena, G. Rani, D. Sinwar, M,F. Ijaz, and M. Woźniak. 2021 A survey of deep convolutional neural networks applied for prediction of plant leaf diseases. *Sensors*, 21(14).

[7] Q. Wang, F. Qi, M. Sun, J. Qu, and J. Xue, 2019. "Identification of tomato disease types and detection of infected areas based on deep convolutional neural networks and object detection techniques". *Computational intelligence and neuroscience*, *2019*.

[8] G. Longer, P. Jain, and N. Panchal. 2020 "Tomato Leaf Disease Detection Using Artificial Intelligence and Machine Learning". *International Journal of Advance Scientific Research and Engineering*.5(7).

[9] Y. Altuntaş, and F. Kocamaz,. 2021 "Deep feature extraction for detection of tomato plant diseases and pests based on leaf images". *Celal Bayar University Journal of Science*. 17(2) pp. 145-157.

[10] T. Hemalatha, and S.P. Kailasam. 2022 Study of Solanum Lycopersicum L. Disease Detection using Watershed Segmentation Technique. Dogo Rangsang Research Journal. 13(3).

[11] A.K. Singh, S.V.N. Sreenivasu, U.S.B.K. Mahalaxmi, H. Sharma, D.D. Patil, and E. Asenso, 2022. "Hybrid feature-based disease detection in plant leaf using convolutional neural network, bayesian optimized SVM, and random forest classifier". *Journal of Food Quality*, *2022*, pp.1-16.

[12] E. Cengil, and A. Çınar. 2022 "Hybrid convolutional neural network-based classification of bacterial, viral, and fungal diseases on tomato leaf images". *Concurrency and Computation: Practice and Experience*. 34(4).

[13] C.K. Sampoorna, and K. Rasadurai, K. 2020 "Tomato Leaf Disease Detection using K-Means, SVM Classifier & Neural Networks". *International Journal of Recent Technology and Engineering*, 8(5), pp. 461-466.

[14] C. Sampoorna, and D.K. Rasadurai. 2019 Tomato plantleaf disease detection using k-means and svm classifier. Journal of Emerging Technologies and Innovative Research, 6(6).

[15] O. Attallah, 2023. "Tomato leaf disease classification via compact convolutional neural networks with transfer learning and feature selection". *Horticulturae*, *9*(2), p.149.

[16] S.U. Rahman, F. Alam, N. Ahmad, N. . 2023 "Image processing-based system for the detection, identification, and treatment of tomato leaf diseases". *Multimed Tools Appl*. 82 pp. 9431–9445.

[17] J. Basavaiah, A. Arlene Anthony. 2020 "Tomato Leaf Disease Classification using Multiple Feature Extraction Techniques". *Wireless Pers Commun*. 115, pp. 633–651.

[18] R. Bora, D. Parasar, and S. Charhate. 2023 "Detection of tomato plant diseases using deep learning MNDLNN classifier". *Springer - Signal, Image, and Video Processing*. 2023. 18, pp.1-9.

[19] A. Abbas, S. Jain, M. Gour, and S. Vankudothu. 2021 "Tomato plant disease detection using transfer learning with C-GAN synthetic images". *Computers and Electronics in Agriculture*, 187.

[20] S. Lingeswari, D.P. Gomathi, and S.P. Kailasam. 2021 "A Study of tomato fruit disease detection using RGB color thresholding and K-Means clustering". *International Journal of Computer Science and Mobile*". 10(8), pp.51 – 59.

[21] V.K. Trivedi, P.K. Shukla, and A. Pandey. 2022 "Automatic segmentation of plant leaves disease using min-max hue histogram and k-mean clustering". Multimed Tools Appl 81, pp.20201–20228 .

[22] V.K. Vishnoi, K. Kumar, and B. Kumar. 2021 A comprehensive study of feature extraction techniques for plant leaf disease detection. Multimedia Tools and Applications. 81, pp.367–419.

[23] M. Bhagat, and D. Kumar. 2023 "Efficient feature selection using BoWs and SURF method for leaf disease identification". *Multimed Tools Appl*. pp.1-25.

[24] M. Agarwal, A. Singh, S. Arjaria, A. Sinha, and S. Gupta, 2020. "ToLeD: Tomato leaf disease detection using convolution neural network". *Procedia Computer Science*, *167*, pp.293-301.

[25] J.O. Oladokun, M.H. Halabi, P. Barua, and P.D. Nath. 2019 "Tomato brown rugose fruit disease: current distribution, knowledge, and future prospects". *Plant Pathology*, 68(9), pp. 1579-1586.

[26] R. Thangaraj, S. Anandamurugan, P. Pandiyan, and V.K. Kaliappan. 2021 "Artificial intelligence in tomato leaf disease detection: a comprehensive review and discussion". *Journal of Plant Diseases and Protection*. 129(3), pp. 469-488.

[27] Ms. Nora Zilam Runera. (2014). Performance Analysis On Knowledge Management System on Project Management. International Journal of New Practices in Management and Engineering, 3(02), 08 - 13. Retrieved from http://ijnpme.org/index.php/IJNPME/article/view/28

[28] Khem, D. ., Panchal, S. ., & Bhatt, C. . (2023). An Overview of Context Capturing Techniques in NLP. International Journal on Recent and Innovation Trends in Computing and Communication, 11(4s), 193–198. https://doi.org/10.17762/ijritcc.v11i4s.6440

[29] Mrs. Monika Soni. (2015). Design and Analysis of Single Ended Low Noise Amplifier. International Journal of New Practices in Management and Engineering, 4(01), 01 - 06. Retrieved from http://ijnpme.org/index.php/IJNPME/article/view/33

[30] Srivastava, A. ., & Kumar, A. . (2023). Secure Authentication Scheme for the Internet of Things. International Journal on Recent and Innovation Trends in Computing and Communication, 11(4s), 182–192. https://doi.org/10.17762/ijritcc.v11i4s.6368