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An Efficacious Deep Fusion based Tomato Leaf and Fruit Classifier using Convolutional Gated Recurrent Unit and Bonobo Optimizer

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Abstract— Agriculture is suffering a drastic blow because of sudden changes in environmental conditions and novel pathogenic attacks. These attacks have brought in heavy disruptionto the integrity of the food supply chain. In order to meet the growing global food demand,an automated system is needed for early identification of diseases and to enable smart farming with the advent of upcoming technologies. This paper proposes such an expert system that augments farming returns both economically and productively. Tomato leaf images are obtained from Kaggle repository and fruit images are self- captured, both making a total of 3676 images. Data is augmented using techniques like rotation, zooming, width shift, height shift, horizontal flip etc.Under preprocessing block, Wiener filter and Contrast Limited Adaptive Histogram Equalization model are used for noise smoothing and contrast enhancement.The U2Net architecture of convolutional neural networks is used for image segmentation after whichfeatures are extracted from a fusion layer based on InceptionV3 and EfficientNetB2 models. The final stage involves aConvolutional Gated Recurrent Unit classifier along with Bonobo optimizationfor obtaining optimal results.Evaluation metrics like accuracy, precision, recall, F1 score,Matthew's correlation coefficient are calculated to find the effectiveness of the proposed system. The proposed algorithm is compared with currently prevailing algorithms like InceptionV3, MobileNet, VGG16, CNNandKernel Extreme Learning Machine and is found to produce promising results with an astounding accuracy of 96.90%.

Keywords- Tomato Diseases, Bonobo Optimizer, CLAHE, InceptionV3, U2Net, EfficientNetB2

I. INTRODUCTION

The study of plant diseases called phytopathology is becoming a very hot topic in today's research world because of the direct impacts it has on food supply chain and national economy. It is predicted that the global population will reach 10 billion by the year 2025 and this will increase the food demand by almost 70% of what is being produced and cultivated today [1]. This fact presents to us the need for mass agricultural revolution. But the sad reality is that we have been losing 20 to 40% of annual production of any crop that is cultivated in any part of the world [2]. This will create a huge food insecurity which will threaten the global population in the upcoming years as food products are very essential for necessitating human living. It was because of this underlying reason that the United Nations had announced the year 2020 as International Year of Plant Health to alert farmers and agriculturists all around the world to pay attention to this issue [3].

In this alarming scenario, we cannot still rely on simple visual techniques that were used in previous days for identification of crop diseases which affect both yield and quality of plants. With a plethora of modern technologies available, it is high time that we go in search of alternatives that boost production so that we are able to meet the market demand. In a subtropical climated country like India, it is not possible to control the development and spread of diseases as they keep changing with seasons [4].Rather on the other hand, a modular approach is required to monitor and manage crops in an efficient manner and identify any shortcomings to the plant be it a nutrient deficiency, any issues related to soil or water or the onset of a pest or a disease at the earliest. This can be done with the aid of many techniques that are available such as robotics, artificial intelligence, deep learning, machine learning, image processing, smart engineering etc. Among these, deep learning techniques have continuously assured reliable performance and results when it comes to classification. The advantage of deep learning models compared to that of a traditional or a machine learning model is that it is optimal in all ways with minimized computation and time.

Concentrating now on the particular crop of this paper's interest i.e., Tomato (Solanum Lycopersicum) is broadly cultivated vegetable crop which gets very easily affected by certain diseases. These diseases often end up detrimental towards tomato fruit production because the diseases interrupt the process of photosynthesis [5]. Tomato is a sensitive commodity which has positioned itself in a prominent place of the vegetable market since it is one of the immensely eaten vegetables. Statistics say that 180.64 million metric tonnes of tomatoes are being cultivated globally on an average every year and the export value of tomato is approximately around 8.81 billion U.S. dollars [6]. These figures remind us of the importance that has been gained by the plant tomato in the vegetable market.

Tomato diseases can lead to losses of several billions if left untreated and not identified in an earlier stage. Agriculture in today's world has become a critical field of business so much that it is also called as agribusiness. It is possible for any plant disease to grow up to an epidemic state which can cause detrimental damage to the whole family of crops worldwide, thereby leading to food scarcity of the particular crop under threat. Hence it is essential that any disease is identified in the very beginning stage so that proper treatment for eradication can be taken to avoid further spread of the disease to the nearby farms or other plants. There are several diseases that affect tomato plants caused by a variety of pathogens and sometimes even abiotic factors can contribute to such diseases. The biotic factors contributing to the diseases can be bacteria, virus, larva, nematodes, protozoa, parasites, and sometimes genetic disorders whereas the abiotic factors could be nutritional deficiencies, climatic changes, pollution of water, pesticidal allergy, changes in pH, rain fall, soil, and temperature.

Conventional diseases by which tomato plants are usually affected are Leaf Spot, Early Blight, Late Blight, Anthracnose, Black Mold, Powdery Mildew, White Mold,Fusarium Wilt, Necrosis, Tomato Big Bud, Root Rot,Gray Leaf Spot Gray Mold, Tomato Fruit Wormetc. These diseases often attack the leaves and fruits part of the plant while sometimes the stem and root can also be attacked. The problem with the identification of diseases is the similarity of symptoms for certain diseases. Therefore, we need state-of-the-art classifiers for identifying the exact disease so that proper medicinal treatment can be given to control the disease.

Some of the major symptoms are small round irregular spots on the leaves and roots, indefinite patches on the leaves, water-soaked spots surrounded by yellow halo, fungal growth in tomato fruits. Some proven techniques for prevention could be proper cleanup of the farm after each harvest, choosing good and resistant variety of seeds, annual crop rotation, drip irrigation, controlling soil moisture in the appropriate level, limited use of fungicides and pesticides, maintaining nitrogen levels of soil, keeping the land well drained, usage of organic sprays like neem oil etc.

II. LITERATURE SURVEY

Abhishek Sharma and Satyajit Mahato employ Convolutional Neural Network (CNN) classifying 54,306 tomato leaf images. Diseases identified are early blight, late blight, bacterial spot, leaf mold, septoria leaf spot, target spot, yellow leaf curl virus, mosaic virus and two spotted spider mite. The proposed system uses images from Kaggle platform. For preprocessing, the image is converted into a Numpy array and label binarizer library is used for labeling the data. The data is further augmented before classification to achieve better results. InceptionV3 algorithm is used for extracting features, then deep neural nets are employed for classification along with Adam optimizer which achieves an accuracy of 90%.

Sobia Sadiq et al. deploys four deep learning models such as VGG16, EfficientNetB4, InceptionV3 and Inception ResnetV2 to classify potato leaf diseases such as early blight and leaf blight. Healthy leaves are also identified using the proposed models. The highest accuracy achieved was EfficientNetB4 with a score of 100 %, followed by VGG16 with an accuracy of 99%. InceptionV3 and ResnetV2 secured 98% and 94% of accuracy, respectively. The input images were obtained from Plant Village data sets with 20,000 images containing both healthy leaves and diseased potato leaves. The data were initially preprocessed and augmented and finally the proposed scheme was trained and then tested. Performance was calculated for all the four models to study the comparative analysis among the four models.

Zubin Quinn et al. proposes a new methodology for object detection called U2Net. The architecture resembles that of nested U and hence the name. The prime advantage of the proposed model is being able to grab extra information from different angles without adding any extra cost. The U2net model can also be used for training models from the beginning. This can also be used for effective image segmentation in various applications. It has got nested U structures has said previously, with each layer containing 11 stages of encoding and decoding. To validate the proposed architecture, DUTS-TR dataset containing 10,553 images are used. Performance indices such as precision, recall, f-measure, mean absolute error are calculated. For preprocessing, the images were resized, vertical flip operation was performed, and the models are trained using convolutional layers.

Thomkaew and Intakosum [7] present a new classification technique for tomato leaf disease detection by combining VGGnet and InceptionV3 algorithms. The proposed model operated on Plant village data set that contained 10 classes of tomato leaves and achieved an accuracy of 99.27%. The input image is in RGB color channel with the dimension of 256*256 pixels which is reduced to 224*224 sized images. The preprocessed images are then given to the compiled classifiers and finally Adam optimizer is used to obtain the optimal solution.

Sabir Ahmed et al. propose a new deep neural network for tomato disease classification. The data set used was sought from the Plant Village data set consisting of 54,319 images. The images were preprocessed using CLAHE for contrast enhancement and data augmentation techniques were applied. For preprocessing, mobilenetV2 architecture was used. Transfer learning classifier was used for classification and its performance was compared with densenet 121, EfficientnetB0, Mobile Net, Nas Net, Resnet and VGG19.The Argmax layer is used in the classifier instead of SoftMax layer. The proposed system was executed in Python environment with the help of Tensor Flow and Keras libraries. Experimental setup needed was Intel Xeon CPU and Nvidia Tesla T4 GPU. Metrics such as accuracy, parameter count, model size, FLOPS count, precision, F1 score, Recall, AUC, and ROC score etc. were calculated. The accuracy obtained by the proposed transfer learning base classifier was around 99.3%.

Rasim Alguliyev uses input images from plants that are gained from drones and cameras. Preprocessing is done using color space conversion and image resizing operations. Features are then extracted using convolutional neural network and classification is done using Gated recurrent model. The input data set contains 87,867 images comprising 14 different fruit crops including tomato. 26 diverse types of bacterial, viral, and fungal diseases were classified.

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Performance is evaluated on the basis of accuracy, precision, recall, and F1 score. Tensorflow and Keras library were used for the implementation of the proposed model in Python 3.7.4. language. The parameters of training for the proposed model are batch size of 100.The overall accuracy of the GRU classifier was 91.19%.

Patel and Sharaff [8] proposed incremental learning-based rice plant disease identification. For preprocessing, the input images were obtained from Rice Knowledge Bank which contained real time images captured by smartphones during preprocessing. After preprocessing, the images are given as input to Resnet101 and VGGNet based CNN models for pre-training. Gated Recurrent units is employed as a classifier which achieves a final accuracy of 99%.

Haleem Farman et al. suggest a new efficient net based expert system for identification of peach plant diseases. Input data needed was acquired from the Khyber province of Pakistan. A total of 2500 images were used for this purpose including healthy fruits and peach fruits that were affected by diseases such as brown rot, gummosis, shot hole, nutritional deficiency etc. The input data was augmented using label preserving transformation techniques like rotations, horizontal and vertical flips and non-label preserving transformations like manual cleaning and fruit cropping. After augmenting the images, they are given as input to frozen fine-tuned CNN model called Efficient net which achieves an accuracy of 96.6% precision and sensitivity score of 90% and 98% specificity.

Pavithra, Kalpana and Vigneshwaran [9] propose a deep learning-based classification system that supports precision agriculture.U2Net architecture is used for removing the background as it might interfere with the classifier. Squeeze net model is used for feature extraction and Xgboost classifier is used for classifying plant diseases. Adam optimizer is also used along with the proposed classifier. Two datasets containing potato leaf diseases and citrus fruit diseases are utilized for executing the proposed model containing 5702 samples which achieved an accuracy of 95.45%.

III. PROPOSED SYSTEM

The proposed system exploits the finest of techniques that give rigorous performance and aspiring results. It is mainly based on deep learning techniques as they have yielded improved results over other techniques and seem to be efficient in many decision support systems employed in various fields [10].The tomato leaf images required for processing are obtained from the Kaggle repository and tomato fruit images are self-acquired. The obtained tomato leaf and fruit images are put though the process of data augmentation to increase the amount of input data so that the problem of under-fitting can be avoided. Data augmentation methods chosen are rotation, zooming, width shift, height shift, shearing and horizontal flip**.** Wiener filter and CLAHE algorithm is used for preprocessing. Segmentation is done using U2net model and feature extraction is done by combining inceptionV3 and efficientnetB2 algorithms using layer fusioning of both the models. Classification is done using Convolutional Gated Recurrent Unit (CGRU) which is followed by Bonobo optimizer for better results. Figure 1 below shows the proposed system workflow.

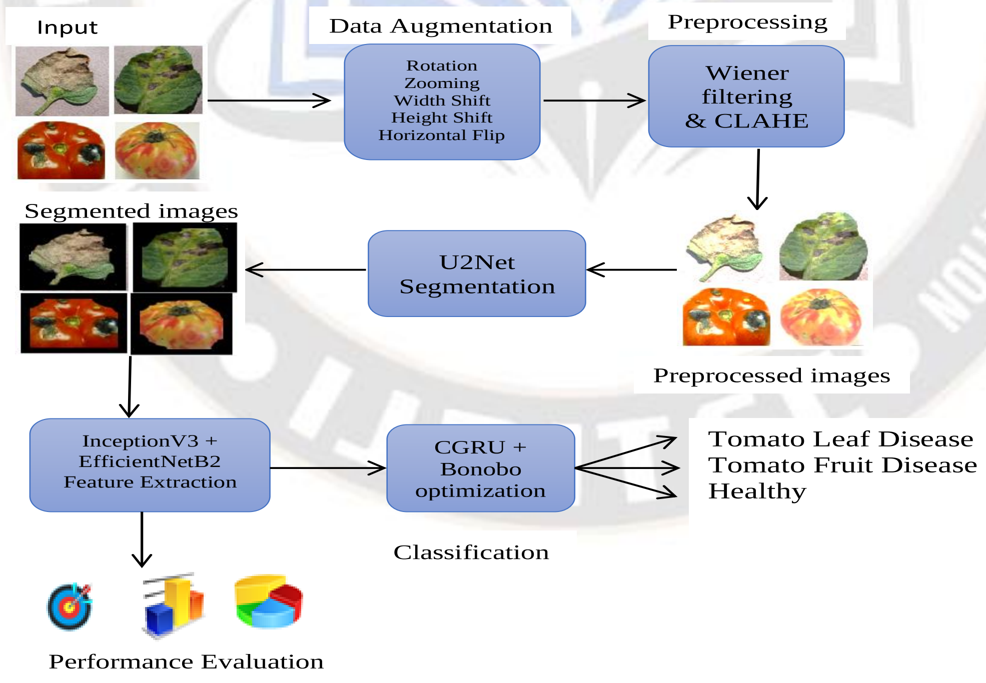

Figure 1. Proposed system workflow depiction

3.1 Image Acquisition

A total of 3676 tomato leaf and fruit images containing 12 diseases like Septoria Leaf Spot, Early Blight, Late Blight, Bacterial Spot, Yellow Leaf Curl virus, Tomato Mosaic Virus Disease, Target spot, Two Spotted Spider mite, Anthracnose, Blossom Endrot, Sunscald, Leaf Mold and healthy tomato leaves are used for carrying out the proposed model execution.3000 tomato leaf input images are obtained from

Kaggle library and tomato fruit images of 676 are obtained from self-dataset.

3.2 Data Augmentation

It is defined as the process of expanding the dataset in order to avoid under-fitting problem and also achieve better performance measures. There are two types of methods available for augmenting a dataset namely data warping and oversampling. Data warping techniques chosen here are rotation, zooming, width shift, height shift, shearing and horizontal flip [11]. This process also eliminates the imbalance learning issue where a certain class has many inputs, and some classes of diseases have very fewer images for the classifier to learn. Data augmentation is applied to tomato fruit dataset alone as they are less in number when compared to tomato leaf images.

3.3 Data Preprocessing

Preprocessing approaches will not be essential to laboratory images which are captured in a controlled background. But it is very essential that the images obtained from the farms are preprocessed as they will evidently contain background interferences [12]. If these background structures are not eliminated from the image, obviously this will lead to misdiagnosis and cause discrepancies in the further processing states.

3.3.1 Wiener filter

Wiener filter, which is a linear filter, is the one chosen here for smoothing the image. These filters by the way are optimal, time invariant and stationary in nature that is well suited for images that could possibly be blurred by a potential noise [13]. This filter is a kind of restoration filter that is mainly used in frequency domain. To obtain the spectrum of the filtered image, discrete Fourier transform of the input images is initially calculated which is then multiplied with the wiener filter. To arrive at the image back from its spectrum inverse discrete Fourier transform is applied. The below equation 1 shows the formula of wiener filter.

$$W(u,v) = \frac{H^{*}(u,v)P_s(u,v)}{|H(u,v)|^2 P_s(u,v) + P_n(u,v)} \quad (1)$$

where,
W (u, v) – Wiener filter
H (u, v) – Fourier transform
$P_s(u,v)$ – Power spectrum of the image
$P_n(u,v)$ - Power spectrum of noise

The prior condition that is required to make the wiener filter work is to assume that the image and noise are second order stationary. It simultaneously removes the noise and also deblurs the image. In this entire process the mean square error is also reduced. This is the commonest form of deconvolution filter and mathematically more appropriate filter which supports excellent noise removal that is based on a stochastic approach.

3.3.2 CLAHE Algorithm

Contrast is an especially crucial factor that plays a vital role in image classification. Hence the proposed algorithm utilizes a contrast enhancement method called the Contrast Limited Adaptive Histogram Equalization (CLAHE). This method improves the contrast between the affected areas of the plant and other normal parts thus enabling better classification accuracy [14]. It is a modification of Adaptive Histogram Equalization (AHE)that imposes a threshold for contrast amplification. This algorithm splits the image into subdivisions called tiles and calculates the histogram of each tile. The calculated histograms are then assessed for their contrast values and if any of them is seen to possess a higher value than the set threshold, the extra luminance values are given to the neighboring tiles. Once this process of histogram calculation and luminance redistribution is done for all the tiles, the tiles are merged using bilinear interpolation in order to eliminate false edges created by the division. Scaling and mapping operations are also performed using cumulative distribution function. The two parameters which are majorly involved in the working process of this algorithm are the clip limit and tile grid size. The equation for CLAHE algorithm is given below.

$$h(n) = \sum_{i=0}^{xx-1} \sum_{j=0}^{yy-1} g(n,i,j) \text{ for } n = 0,1,\ldots,N - \quad (2)$$

$$g(n,i,j) = \begin{cases} 1 & if\ I(i,j) = n \\ 0 & otherwise \end{cases} \quad (3)$$

where
n – gray level indicator
N - no. of histogram bins
$h(n)$ - n^{th} bin histogram value
xx, yy- image block dimensions
i, j- pixel coordinates
$I(i,j)$- pixel value coordinates (i,j)
$g(n,i,j)$ – Evaluating function

Figure 2 shows the working process of the CLAHE algorithm.

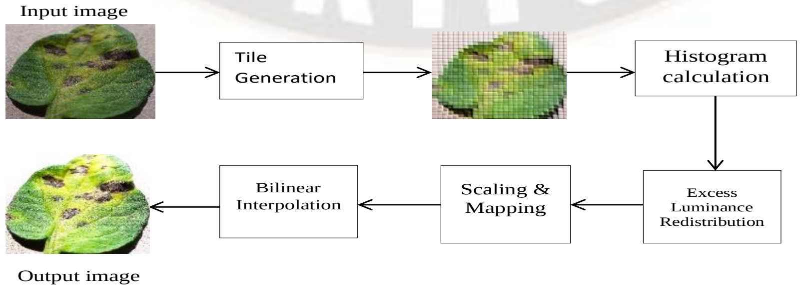

Figure 2. CLAHE Algorithm

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3.4 Image Segmentation

After the application of Wiener filter and CLAHE algorithm, the image is then passed to the next stage of processing called image segmentation. During segmentation, the background is removed to gain a fine-grained observation of what is contained in the image. The method chosen for segmenting the images here is U2net architecture of CNN. It is an advancement of UNet architecture that is nested and has two levels of encoding and decoding. This architecture is much deeper than any other segmentation algorithms and hence can obtain high resolution of the segmented images but incurs no additional cost or memory which is considered as the biggest advantage [15].

Of late U2Net is the most preferred algorithm for image segmentation as it has revolutionized segmentation performance in various fields. Similar to that of a structure of UNet, this architecture also possesses an encoder decoder format. It is to be noted that U2Net won the ISB challenge with its extraordinary performance in 2015. The encoder and decoder are each composed of four blocks containing 2 convolutional layers. The output of which is passed to the ReLu activation function and a max pooling layer. Once the encoder part is completed, the feature map is obtained at the bottommost layer called the bottleneck layer after which the process of decoding begins. This also consists of four blocks where each block contains a transpose convolution with the kernel size of 2*2 and a final ReLu activation function. Figure 3 below shows the architecture of U2Net.

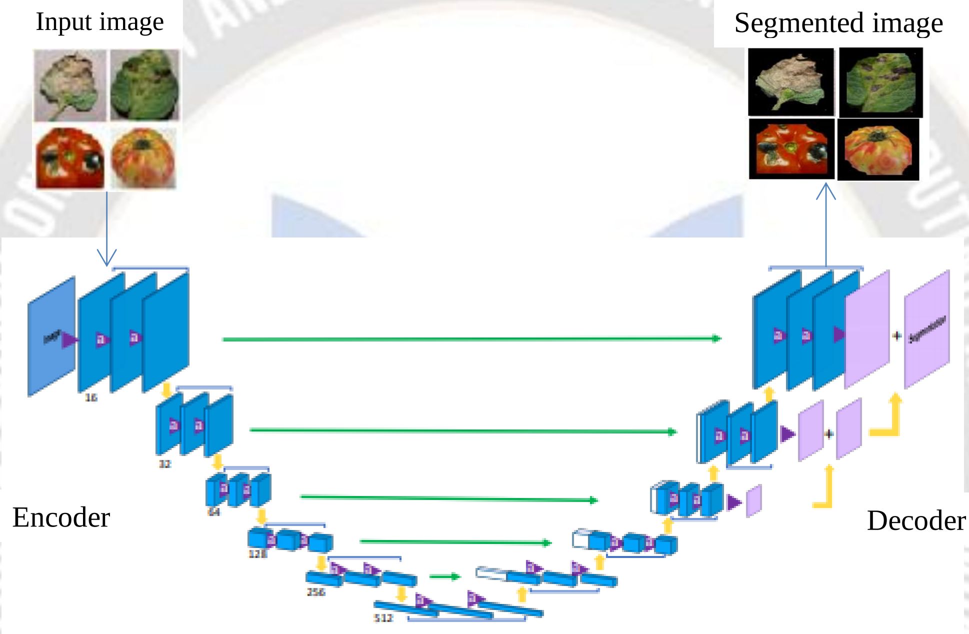

Figure 3. U2Net Architecture

3.5 Feature extraction and Fusion

The relevant features needed for classification are extracted from the segmented images using InceptionV3 and EfficientnetB2 fusion layer. Instead of using a single feature extractor the proposed system opts to use fused features from two different but efficient feature extractors in order to maximize the classification accuracy.

3.5.1 InceptionV3

InceptionV3 is one of the most impressive and unique deep learning models that produces commendable accuracy in its task. It was proposed by Christian Szegedy in 2015 and it bagged many awards since its introduction [16]. With each addition, the aim is to heighten the efficiency attained and simultaneously reduce cost and time of parameters. It consists of 48 layers where the layers are parallel to each other making the model wider instead of making it deeper.

It consists of convolution and pooling operations where convolution is the process in which an image is transformed with the application of a kernel on each and every pixel of the image. Pooling on the other hand is a technique that is employed for reducing the dimensions of the feature map produced by the convolution layer.InceptionV3 is more advanced in terms of time and efficiency than its predecessor models and forms better then V1 and V2 models. Though it is deeper it does not take more time. It is less expensive when compared to other feature extractors and the error rate is also comparatively low. It makes use of auxiliary classifiers which are also called as regularizers and RMS prop optimizer. The convolution operations performed here are smaller and efficient in terms of grid size resolution and spatial factorization.

3.5.2 EfficientNetB2

This is yet another architecture of convolutional neural network that uses scaling process. It uses a progressive model of learning which can alter the value of regularization based on the input image that is given to the model. It utilizes a method called compound efficient for identical distribution of parameters [17]. The advantage of Efficient NetB2 is that it performs uniform scaling rather than random scaling. It is a particularly good transfer learning method that achieves good accuracy and is well suited for feature extraction. There are many versions, and each version was developed with an aim to reduce the size of parameters involved and number of flops used. It is based on auto ML and MNAS framework and it is a very fine-tuned network which auto penalizes if the network is slow or heavy which makes it the most powerful architecture of CNN prevailing today. Inverted mobile bottleneck convolutions are made use of in executing the model of EfficientnetB2. The output of inceptionV3 feature extractor and EfficientnetB2 feature extractors are fused together to form a single feature vector that is used for further processing. Figure 4 shows the layer fusioning of InceptionV3 and EfficientNetB2 models.

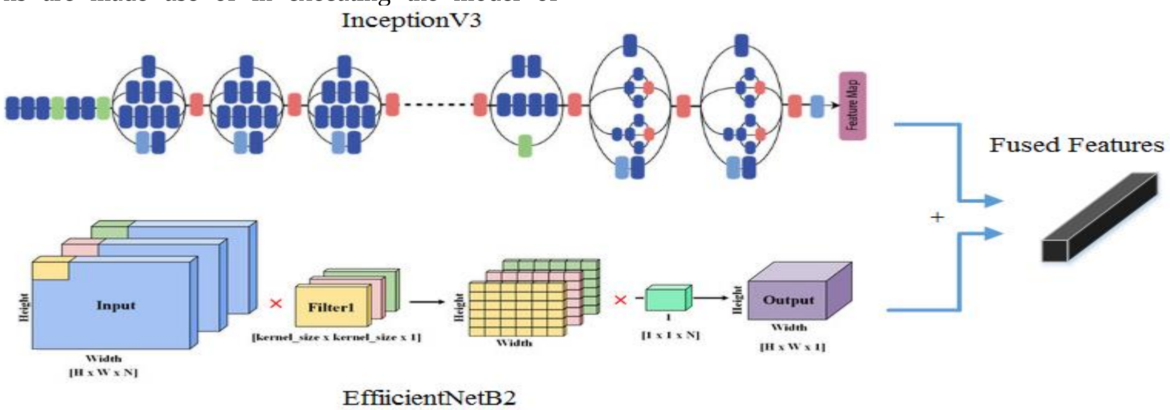

Figure 4. Layer Fusioning of InceptionV3 and EfficientNetB2

3.6 Image Classification

From the fused features obtained, the proposed system aims to classify the input tomato leaf and fruit images into its corresponding diseases using classifier called as convolutional gated recurrent unit which is then optimized using a Bonobo optimizer.

3.6.1 Convolutional Gated Recurrent Unit (CGRU)

It is the blend of recurrent neural networks (RNN) and long short-term memory. More properly it is a type of gated recurrent network that uses the process of convolutions to achieve impressive results on small dataset [18]. It is easier to train, needs less memory and makes the whole lot processing of the underlying network amazingly fast. It comprises of three blocks namely the original recurrent unit block g(t) and two gates called the reset gatez (t)and update gate r(t). Gated recurrent unit solves the problem of gradient vanishing. This problem arises due to the usage of multiple images at various times employing the same quadrant with an aim to improve accuracy. While RNN uses one spectral measurement for prediction or classification CGRU uses multivariate time series images that overcomes the problem of RNN.

The job of reset gate is to forget unwanted details and make the network remember only the valuable information that is needed. The update gate on the other hand performs the work of determining what previous state should be used as input for the next state. CGRU basically takes two inputs: the training data x(t) and previous state of the cell h(t-1). Similarly, it produces two outputs which is the current state of cell h(t) and a prediction value for the current cell y(t). To put it in simpler words a gated recurrent unit simply uses gates to update the network state selectively rather than updating all of the gates. It is used to extract information from hidden states most of the time which contain exclusive information when compared to the other states. The basic idea is to just control the information that gets in and goes out of the network. The reset gate also determine what information and how much of information from the previous stage should be removed from the network and the update gate gives an indication of what and how much new input should be stored in the upcoming hidden state. The final output is derived from the lastly updated hidden state of the network. Figure 5 shows the unit of CGRU.

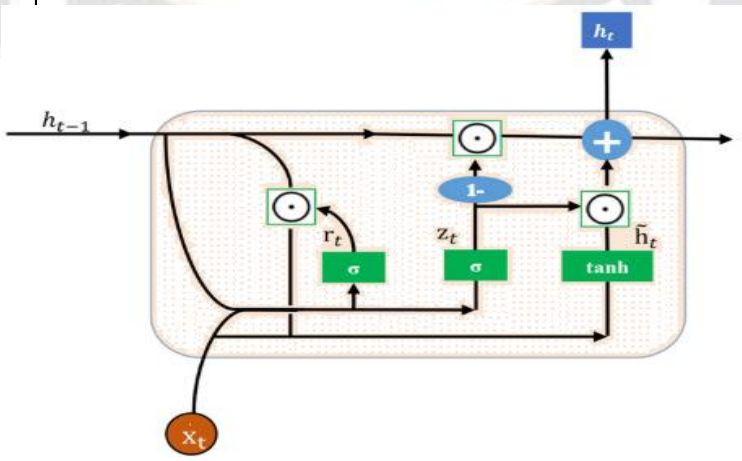

Figure 5. A Simple unit of CGRU

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3.6.2 Bonobo optimizer

It is a population-based optimization algorithm which produces many viable solutions. The best solution is called the alpha Bonobo. It is based on the societal and reproductive behavior of bonobos which is a type of monkeys belonging to the family *Hominidae.* An interesting fact is that bonobos belong to the same family of human beings and have many natures in common with us. It is in fact the closest relative of the human race as of now. The bonobos are scattered throughout the region and follow four types of reproductive patterns such as restrictive mating, promiscuous mating, extra group meeting and consort ship mating [19]. It undertakes a different mechanism of social evolution called the fission fusion technique. In the process of fission, the bonobos split into smaller groups for certain tasks and in the process of fusion they combine together for performing certain tasks which is believed to be the success strategy of the bonobos.

Inspired from the characteristics of bonobos which are otherwise called as pygmy chimpanzees, Bonobo optimizer is highly intelligent and adaptive in terms of adjustable parameters. There are two phases called the positive phase and negative phase in the Bonobo optimization cycle. A positive phase is considered as one that improves the value of alpha Bonobo and negative phase is one that does not alter the alpha Bonobo. The parameters involved in the Bonobo optimization technique are probability of phase (P_p), positive phase count, negative phase count, probability of extra group mating, change in phase, sub group size and directional probability value [20]. The working process of the global optimization algorithm is given below.

Bonobo Optimization Algorithm

Step 1: *Initialize you should define parameters*
Step 2: *Conduct fission fusion strategy and select bonobos*
Step 3: Perform different mating strategies and create bonobos
Step 4: *Evaluate fitness values*
Step 5: *Set the values of boundary limits*
Step 6: *Accept a new Bonobo which will from now onwards be called as the alpha Bonobo*
Step 7: *Choose a random number and check if it is less than the probability of phase*
Step 8: *If yes, build new Bonobo using promiscuous or restrictive mating strategies*
Step 9: *If no, then create bonobos using consort ship or extra group meeting strategies*
Step 10: *Again, assess the fitness scores*
Step 11: *Update the parameters.*

The below figure 6 shows the sequential flow of processes in a Bonobo optimizer. It outperforms standard evolutionary algorithms like evolution strategy cultural algorithm and differential evolution.

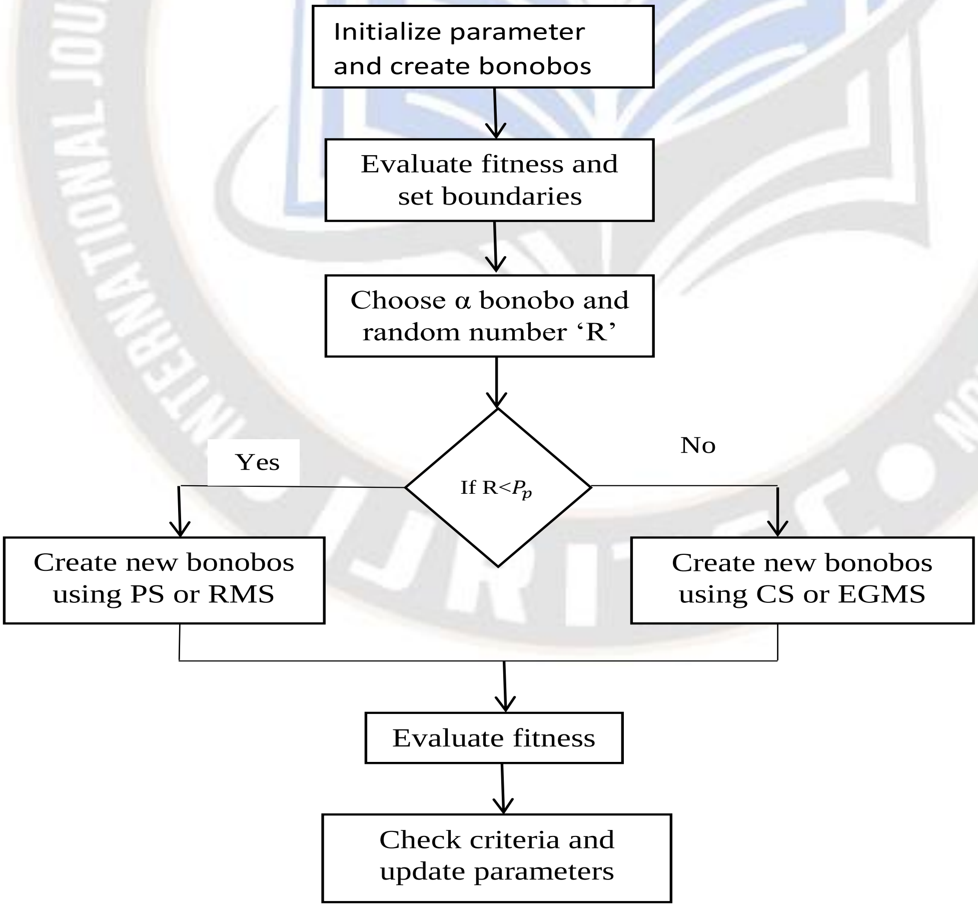

Figure 6. Workflow of Bonobo Optimizer

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IV. RESULTS AND DISCUSSION

Classification of diseases from an image is actually a more complicated process than visual inspection method. But since the visual methods cannot be performed on a large-scale basis, we opt for automatic detection systems that identify crop diseases at an early stage so that timely treatment can be implemented to stop the further spread of diseases [21]. When it comes to development of automatic expert systems, it is of utmost importance that each and every individual block of the proposed model is managed with absolute care and precision as the output of one block serves as the input to another block. It is with that central idea in mind that the proposed system uses finest techniques with high learning speeds for each process. All the techniques employed here come under the circle of deep learning making them more efficient and trustworthy.

4.1 Image Acquisition

3676 images are used for executing the proposed framework, out of which 3000 images are tomato leaf disease images obtained from repository of Kaggle. The remaining 676 images depict tomato fruit diseases and were self-captured. 12 diseases like Septoria Leaf Spot, Early Blight, Late Blight, Bacterial Spot, Yellow Leaf Curl virus, Tomato Mosaic Virus Disease, Target spot, Two Spotted Spidermite, Anthracnose, Blossom Endrot, Sunscald, Leaf Mold and healthy tomato leaves are classified. Table 1 shows the list of images belonging to each disease.

TABLE 1. TOMATO DISEASES SELECTED FOR CLASSIFICATION

Tomato Dataset	Diseases	No. of images
Tomato leaf images (3000)	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
Tomato fruit images (676)	Anthracnose	260
	Blossom End Rot	234
	Sunscald	182

Figure 7 shows the sample of input images used.

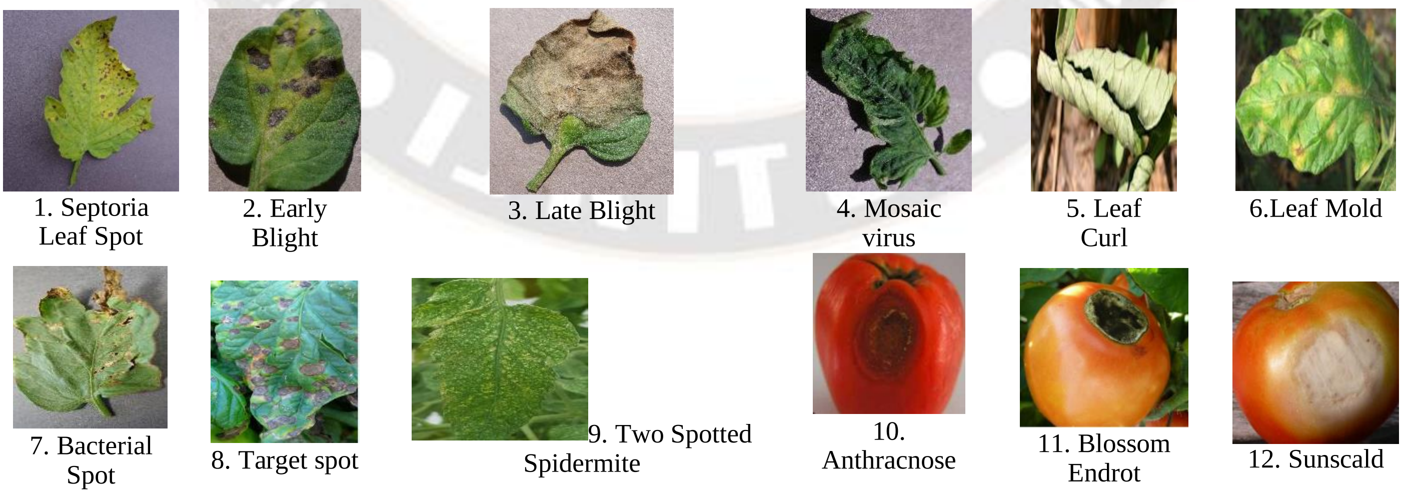

Figure 7. Sample input images for each disease

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4.2 Data Augmentation

This step is executed in order to expand the tomato fruit dataset before further processing. It contains a variety of methods like rotation, zooming, shearing, flipping, filling, width and height shifting etc. Table 2 below shows the parameter range details of augmentation techniques used here.

TABLE 2. DATA AUGMENTATION PARAMETERS

S.No.	Augmentation method	Range Values
1.	Rotation	90
2.	Zoom	0.15
3.	Horizontal Shift	0.2
4.	Vertical Shift	0.2
5.	Shearing	0.15
6.	Horizontal Flip	True
7.	Fill Mode	Nearest

4.3 Preprocessing and Segmentation

This section shows the result of preprocessing and segmentation techniques. Figure 8 and figure 9 show the output of preprocessed and segmented images.


1. Septoria Leaf Spot


2. Early Blight


3. Late Blight


4. Mosaic virus


5. Leaf Curl


6.Leaf Mold


7. Bacterial Spot


8. Target spot


9. Two Spotted Spidermite


10. Anthracnose


11. Blossom Endrot


12. Sunscald

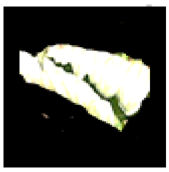
Figure 8. Preprocessed images


1. Septoria Leaf Spot


2. Early Blight


3. Late Blight


4. Mosaic virus


5. Leaf Curl


6.Leaf Mold

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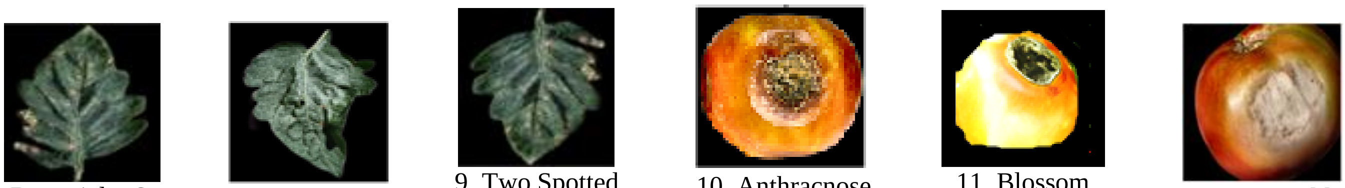

7. Bacterial Spot 8. Target spot 9. Two Spotted Spidermite 10. Anthracnose 11. Blossom Endrot 12. Sunscald

Figure 9: Segmented images

4.4 Confusion Matrix

It shows the result of correct and incorrect classification. It forms the base from which various evaluation metrics can be calculated [22]. Figure 10 portrays the confusion matrix of tomato leaf disease classification for training and testing datasets.

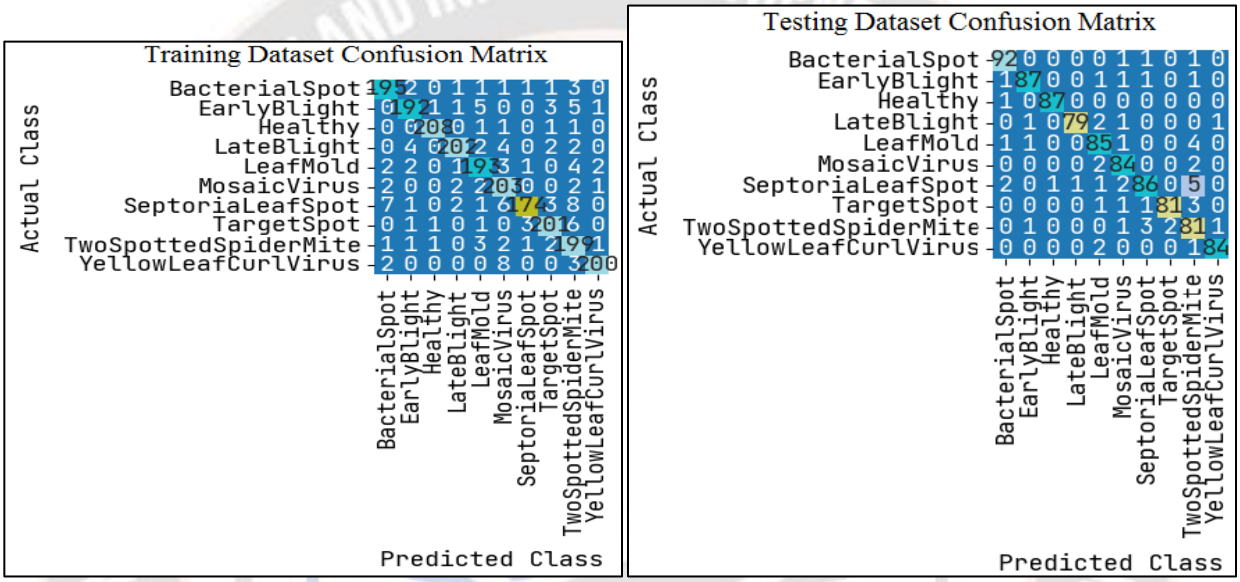

Figure 10. Tomato Leaf Disease Confusion Matrix

Figure 11 shows the confusion matrix of tomato fruit disease classification for training and testing datasets.

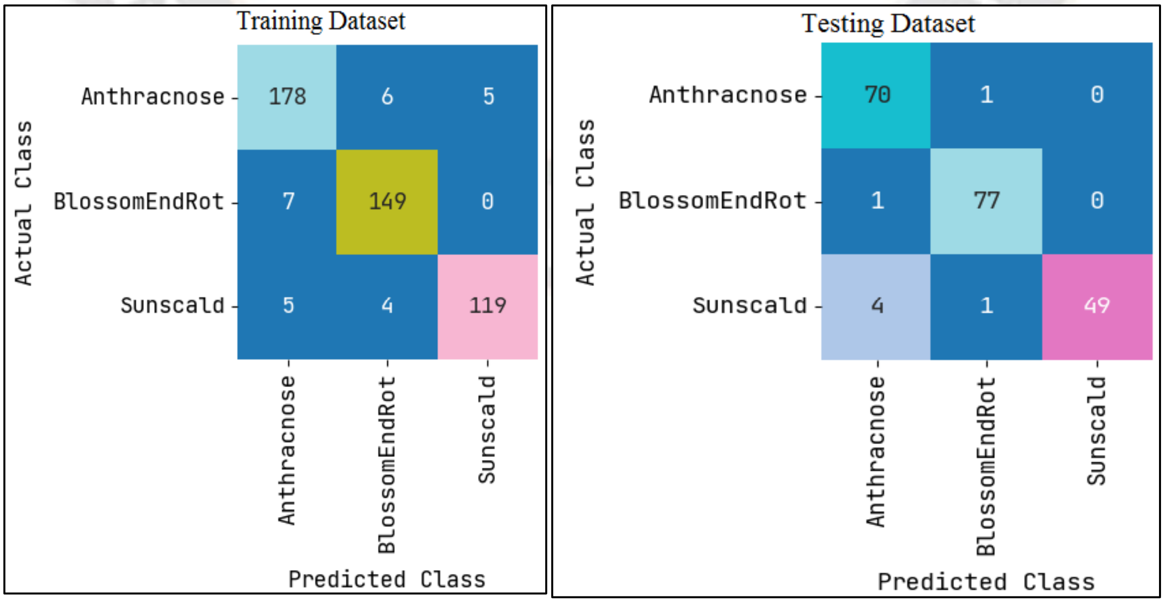

Figure 11. Tomato Fruit Disease Confusion Matrix

4.5 Evaluation Metrics

Performance evaluations like precision, accuracy, recall, F1 score, and Matthews Correlation Coefficient (MCC) are calculated for the proposed system. They are estimated from True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) values. The formula for all of the calculated performance metrics are presented here [23].

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad (4)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (5)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (6)$$

$$F_1\ score = \frac{2*Precision*Recall}{Precision+Recall} \quad (7)$$

$$\text{MCC} = \frac{(TP*TN-FP*FN)}{\sqrt{(TP=FP)(TP+F)(TN+FP)(TN+FN)}} \quad (8)$$

While precision, accuracy, recall, F1 score are all standard measures which indicate a particular class of correct classification, MCC is an excellent measure which indicates the overall statistical performance of all the four classes such as TP, TN, FP, and FN [24]. Table 3and 4 shows the performance metrics of tomato leaf and fruit disease classification in both the training and testing datasets.

TABLE 3. TOMATO LEAF CLASSIFICATION PERFORMANCE

S. No.	Metrics	Training dataset Values	Testing dataset Values
1.	Accuracy	0.9646	0.967
2.	Precision	0.9385	0.9423
3.	Recall	0.993	0.9933
4.	F1-Score	0.9367	0.9409
5.	MCC	0.9301	0.9346

TABLE 4. TOMATO FRUIT CLASSIFICATION PERFORMANCE

S. No.	Metrics	Training dataset Values	Testing dataset Values
1.	Accuracy	0.9564	0.9711
2.	Precision	0.9445	0.9693
3.	Recall	0.9706	0.982
4.	F1-Score	0.9433	0.9638
5.	MCC	0.9141	0.9475

4.6 Performance curves

This section shows the analysis of performance curves such as the precision-recall curve, Receiver Operating Characteristic (ROC) curve etc. These curves are a direct reflection of the classification performance exhibited by the proposed model [25]. Figure 12 shows the training and validation accuracy and loss curves of tomato leaf disease. Similarly figure 13 displays the training and validation accuracy and loss curves of tomato fruit disease.

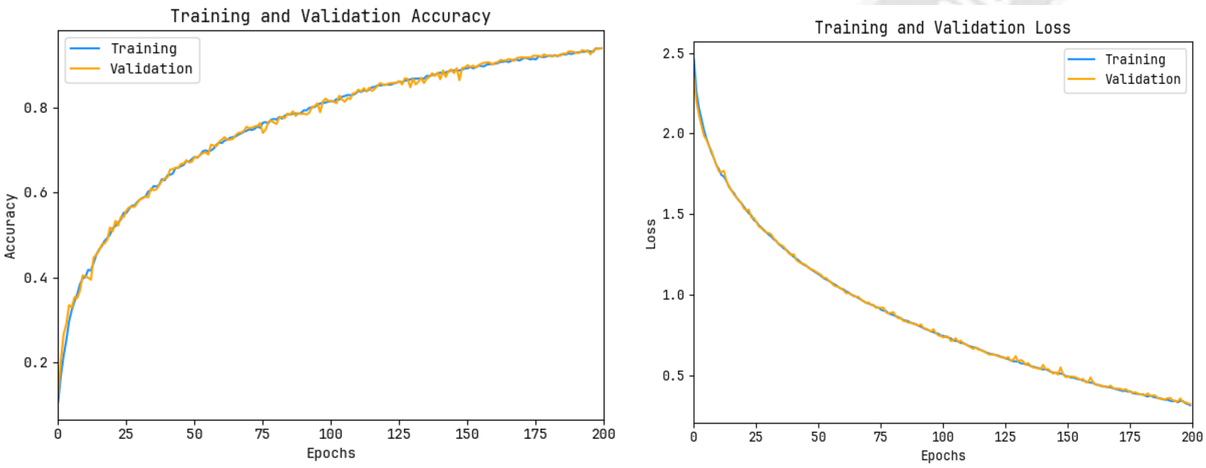

Figure 12. Training and validation accuracy and loss for tomato leaf classification

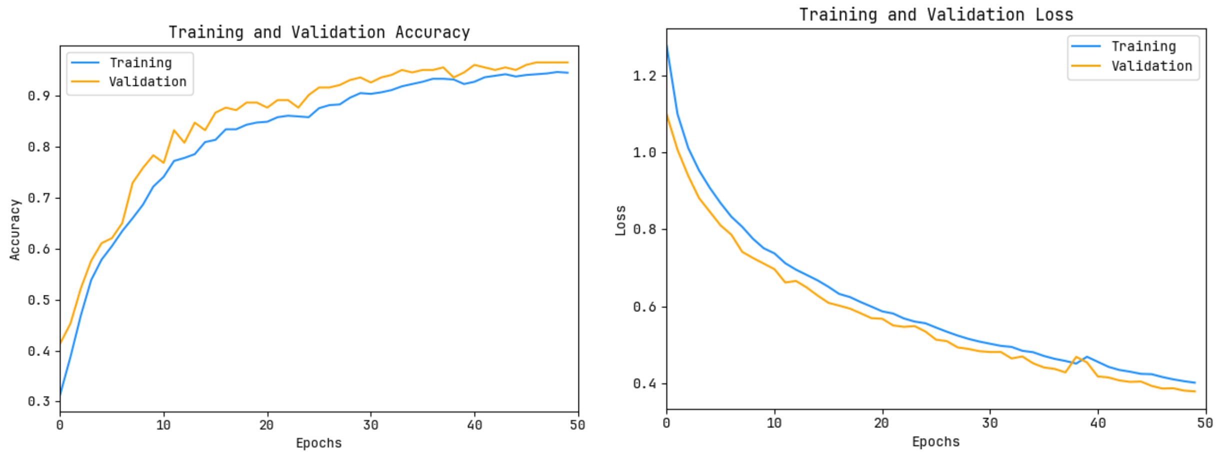

Figure 13. Training and validation accuracy and loss for tomato fruit classification

Figure 14 shows the precision recall curve and ROC curve analysis of tomato leaf disease classification. It is evident from the curves that for all the diseases, the value is higher than 0.95 which indicates high classification accuracy.

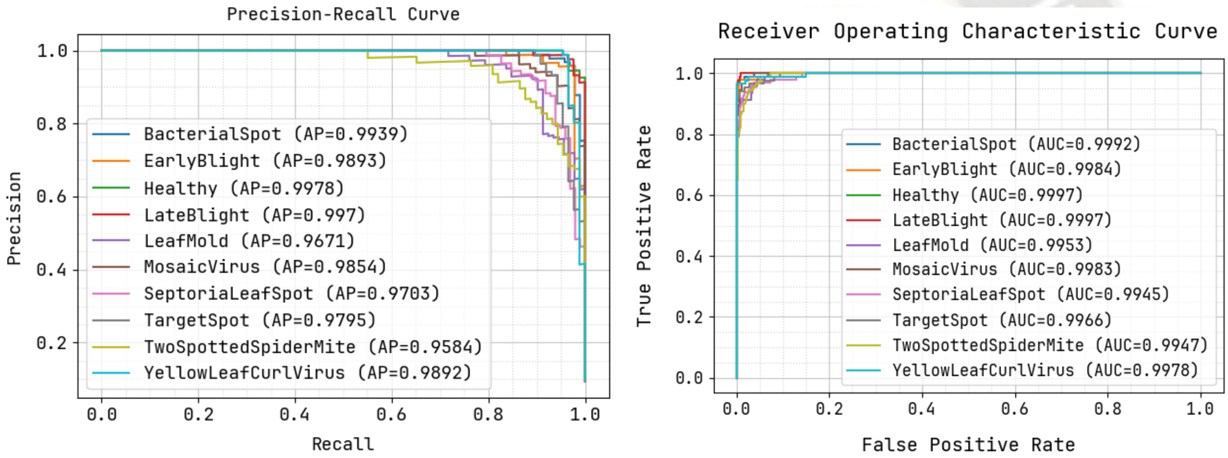

Figure 14. Tomato Leaf Precision – Recall curve analysis and ROC curve analysis

Figure 15 shows the precision recall curve and ROC curve analysis of tomato fruit disease classification. For all the three fruit diseases classified, values are higher than 0.99. This indicates superior performance of the proposed CGRU classifier along with Bonobo optimizer.

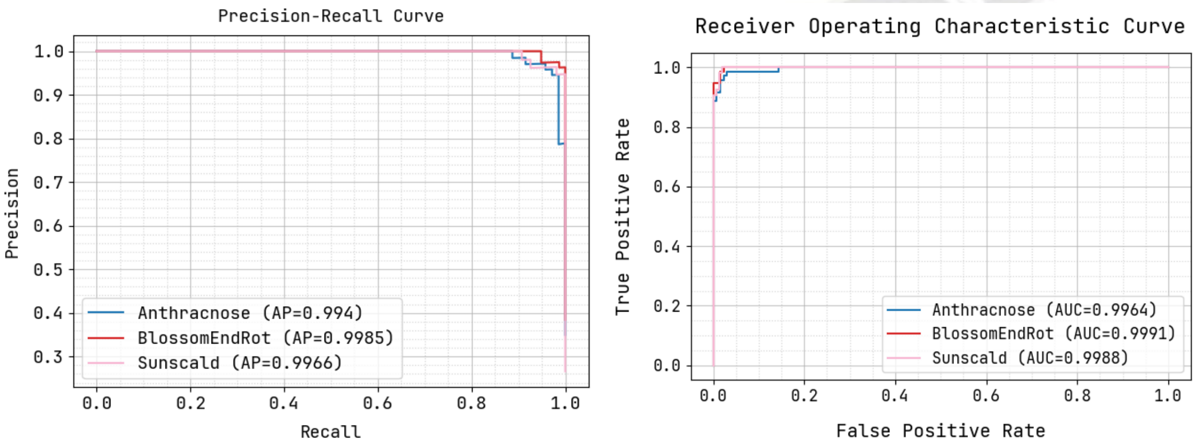

Figure 15. Tomato Fruit Precision – Recall curve analysis and ROC curve analysis

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4.7 Comparative Analysis with Existing Algorithms

This section shows the performance of other existing methods such as InceptionV3, MobileNet, VGG166, CNN, Kernel Extreme Learning Machine (KELM) and the proposed CGRU method. Table 5 shows the accuracy achieved by all of these algorithms for tomato leaf and fruit disease classification.

TABLE 5. PERFORMANCE COMPARISON WITH EXISTING METHODS

S.No.	Methods	Accuracy
1.	InceptionV3	63.4
2.	MobileNet	63.75
3.	VGG16	77.2
4.	CNN	91.2
5.	KELM	94.42
6.	Proposed system	96.90

InceptionV3 returned an accuracy of 63.4%, MobileNet was able to score only 63.75%, VGG16 yielded an accuracy of 77.2%, CNN produced 91.2% accuracy, Kernel Extreme Learning Machine (KELM) generated a good accuracy score of 94.42 and the proposed convolutional gated recurrent unit has achieved an outstanding accuracy of 96.90%. Hence it can be concluded that our proposed work is better and more efficient than the other previously existing techniques. Figure 16 below shows the comparative performance of the above said methods in a graphical format.

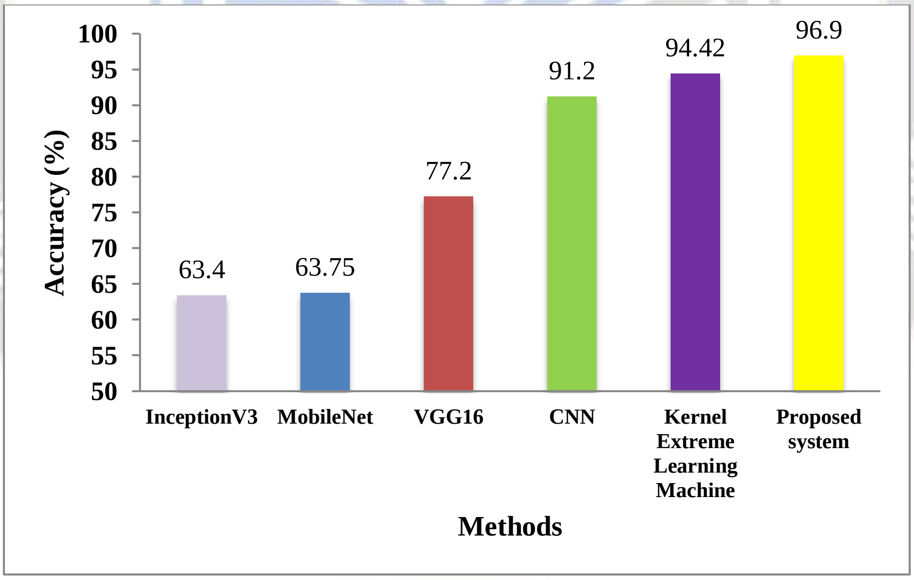

Figure 16. Comparative analysis of algorithms

V. CONCLUSION

Agriculture has become very unstable due to the emergence of many natural impediments. It is predicted that 10 to 15% of crop harvest goes useless due to the dreadful impact caused by pests and plant diseases all around the world. This has made the field of crop disease detection a forerunner of today's research whose ultimate aim is to create decision support systems that regularize farming management practices that make agriculture self-sufficient and quality rich and helps farmers achieve better yield and quality of crops. The proposed system has developed such a promising solution to classify tomato leaf and fruit diseases. The future development of this paper could possibly be a mobile assisted crop disease identification system which will help farmers enable the process of marketing, weather analysis, soil analysis and farm management much easier.

Declaration

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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.

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