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A TECH SAVVY TOMATO LEAF AND FRUIT DISEASE CLASSIFICATION SYSTEM BASED ON ENSEMBLE DEEP LEARNING MODEL AND SHUFFLED SHEPHERD OPTIMIZATION ALGORITHM

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ABSTRACT

Deep learning based artificial intelligent solutions are proving to be very successful in many different fields. It shows promising results in precision agriculture as well. Hence in this article, disease classification model based on deep learning has been proposed for identifying and classifying tomato leaf and fruit diseases. The proposed system acquires data set from Kaggle image repository and augments them using data warping techniques. The augmented data is preprocessed using median filter and contrast enhanced using dynamic histogram equalization. U2 net architecture is used for background removal and Segnet algorithm is used for disease region segmentation. Features extraction is achieved through Nasnet Large model and classified using ensemble model. The obtained results are optimized using shuffled shepherd optimization algorithm and the proposed system is tested against existing classifiers like and is proved to work efficiently and accurately than the previous models.

Keywords: *Tomato Diseases, U2Net, Dynamic Histogram Equalization, Segnet, Nasnetlarge, Ensemble Model.*

1. INTRODUCTION

Tomato is a remarkable and substantial component of agricultural sector all around the world. Its existence can be traced from very old ancient days and no replacement for tomato fruit has ever been found so far [1]. It is a commonly grown vegetable crop that gets affected very easily by various diseases caused by several biotic and abiotic reasons. While abiotic conditions can be kept under control by constant monitoring and close surveillance of the field, managing biotic agents of diseases and preventing them entirely is quite hard. Hence there is a need for automatic disease management in the agricultural industry right now. We are running low on agricultural experts and plant pathologists are becoming rare. Also, the farmer is not equipped with appropriate information regarding all possible diseases that could possibly affect the tomato farms. Any misjudgment or wrong identification of diseases will result in heavy economic loss both to the farmer and to the nation as a whole. Timely and accurate identification of diseases becomes essential in this case. Reports indicate that 22% of crop losses are due to infections and disease caused by external organisms [2]. Since tomato is a largely grown vegetable, its diseases are also frequent and repetitive in nature.

21.2 million metrictonnes of tomatoes are procured all over the globe every year among which India is the second largest producer of tomatoes. For a nation like India, where 70% of its people are dependent upon agriculture for the basic needs, the impact that agriculture and its related processes create on the national growth and Gross Domestic Product (GDP) is quite significant thus making agriculture a very crucial layer of existence [3]. No compromise can be made on any crop disease especially tomatoes as it is a commercialized agricultural product which needs good grades for its business. It is considered as a highly valued crop in agriculture which is segregated into several grades based on its goodness and properties. The quality of tomato fruits will definitely be affected in case of any disease that goes untreated or unidentified. China being the biggest producer of tomato in the world has got a separate committee and specification for tomato grading such as NY/T 940 –2006 [4]. Not only the seller, but the end consumer also is very much considerate about the quality of these products, because of which the wellness of tomato crops are considered highly important.

There are several advantages for all the stakeholders in this scenario when employing an automated disease classification system because it aids the farmers in his work without the need for an agronomist. A computerized system will be able to handle complex situations in a way better manner such as multi biotic or dual biotic disease conditions. While there are many artificial intelligence based techniques proposed for this purpose ,deep learning has always been a good performer and has typically revolutionized agriculture over the past few years. A recent survey by the World Bank states that for a developed nation, agriculture contributes to only four percentage of their GDP whereas in a developing nation, the contribution of agriculture is as high as 1/4 of their GDP that is greater than 25%[5]. India being a developing nation until today, the impact that agriculture has on our GDP and national income is of utmost importance to all of us especially the farmers and economists.

2. LITERATURE SURVEY

Kaur et al. [6] have presented a review paper which describes various ways that are available to segment tomato leaves for appropriate classification of diseases. The authors have made use of plant village data set and experimented a new segmentation Convolutional Neural Network(CNN)which has been compared with usual segmentation algorithms like UNet, MSegnet and modified UNet. Various performance measures have been calculated for 1004 images which achieved a segmentation accuracy of 98.24%

Saravanan and Karthigaivel [7] in their paper together have brought out the advantages of dynamic histogram equalization method which is used widely for contrast enhancement nowadays. The authors have stated that while there are many techniques available for contrast enhancement, dynamic histogram equalization performs better in various angles of performance such as entropy, texture preservation, Hausdorff distance etc. They have also compared the proposed algorithm with existing techniques like fuzzy histogram equalization and spline based methods.

Radhika et al. [8] along with her co-authors has analyzed the performance of NasNet as a feature extractor in various domains. The authors have compared the performance of Nasnet with other architectures of convolutional neural networks that are popular like VGGnet, inceptionnet, resnet, mobile net etc. The authors have also presented a chronological evolution of various architectures of CNN along with the advantages and disadvantages for each of these architectures. This paper brings before the readers a detailed description of the above said algorithms from many perspectives.

Abdel Zaher and Eldeib along with Ayman [9] has presented a paper on the classification performance of deep belief networks. A medical data set has been chosen as input for proving the efficiency of the chosen deep learning model which produced an accuracy of 99.68%, showing that it is capable of giving promising results in other domains like agriculture and image processing too. The authors have presented a time series of neural network development right from back propagation technique up to the beginning of the deep belief network. Other performance metrics such as sensitivity and specificity were calculated for the proposed deep belief network.

Sunil et al. [10] have proposed U2net architecture of CNN for background removal and efficientnetB2 as classification model for identification of plant diseases. They have made use of the plant village datasets containing 54,284 images whose background have been removed using tournament algorithm for accurate classification of diseases. This paper projects the importance of preprocessing techniques that are involved in disease classification especially that of background removal as it can interfere with the classification process. The background may not be always useful in real time form setup because of overlapping and under lighting conditions. Background removal is not of much importance in laboratory based dataset as the input images are captured according to various norms and conditions. But rather in a plant field which contains many disturbances in the background such as soil, other plants and part of the same plant etc., background removal plays a very vital role.

Ulutaş and Aslantaş [11] proposed a classification model based on ensemble network and convolutional neural network for detecting tomato leaf disease. 18,160 images were used for this purpose for identification of nine tomato plant diseases and healthy leaves as well. After the classification process, the results were put through particles swarm optimization algorithm which resulted in an accuracy of 99.60%.The Images were resized and cross validated before the features were extracted. An ensemble classifier comprising mobile net V3 small, efficient net V2 large and inception V3 has been utilized to carry out the experiment. The authors have also stated the pros and cons of using the ensemble model classifier in agricultural limits.

Li Liu et al. has presented a tomato grading system based on the shape ,feature, color and morphological properties of the tomato fruit to enable buyers and sellers buy quality food. Among the various properties of the fruit considered, the hue value distribution plays a considerable role in this grading system. In order to grade the tomatoes, the original images are transformed into a gamma platform and filtered using median filter. Otsu segmentation is performed and morphological features are extracted such as contours, shape, colors etc based on which the fruits are classified. This paper explains the importance of image processing and artificial intelligence techniques and the applications of such techniques in agricultural field for enabling better crop management and achieving good economy resulting from agriculture.

Kaveh and Zaerreza [12] have explained the process of shuffled shepherd optimization metaheuristic algorithm based on the behaviors of shepherds and sheep. The first process is to select the number of sheeps and allot them to some herds. The next is to assign a shepherd for each herd and initialize them using the objective function. This paper also explains the in-depth process of shuffled shepherd optimization algorithm and compares it with other such evolutionary algorithms.

Bandi et al. [13] have come up with a research article based on explainable artificial intelligence that has been applied to the field of leaf disease detection for various plants. They have suggested a deep learning model called Yoloversion 5 for classification and U2 net is chosen for background removal. The experiment has been conducted in two ways containing images with background and without background for apple leaves with the F1 score of 0.57 with the background image.

Pavithra et al. [14] have presented an article for achieving precision agriculture using deep learning. They have proposed an automatic plant leaf disease identification system based on extreme gradient boosting classifier. The input images are preprocessed using U2 net architecture of convolutional neural networks and features are extracted using squeeze net model. Adamoptimization is used for tuning the parameters and finally classification is done using xgboost algorithm. The proposed model classified a total of eight diseases using 5775 leaf and fruit images.

Kumar et al. [15] along with his co-authors has presented a review article for detecting different diseases that affect the plant. The authors compare and study the performance of Densenet201, Densenet121, Nasnet large, exception, Resnet 142, Inception V3, Efficientnet B7, VGG19, MobilenetV2 and a hybrid model combining Efficient net and Resnet. Training and validation phases are conducted for all the chosen classifiers to detect various diseases among which dense net emerged as the best performing classifier. Nasnet secures the second place with good accuracy and precision skills.

Maheshwari et al. [16] has presented a paper on tomato plant segmentation with the help of segnet architecture. For training the chosen segmentation model, images were obtained from Manapparai village of Trichy district in India comprising 672 real time images and given as input to segnet deep learning based semantic segmentation. The proposed segnet model has achieved good test results of 89.7% precision, 72.55% of recall and 80.22% of F1 score with good disease segmentation capability for tomatoes. The data was annotated and augmented before it was segmented using the proposed model. This model was executed in Matlab2021A with the help of NVIDIA GeForce GTX 1080 GPU with the memory speed of 10 GBPS.

3. PROPOSED SYSTEM

The input tomato leaf data required for carrying out the experimentation is obtained from Kaggle data repository and fruit images are self-acquired from the farms directly using a smart camera. The acquired tomato leaves and fruit images are augmented before preprocessing in order to attain better accuracy as there are only a few images in the fruit data set. Augmentation techniques were carried out on the input image to increase the number of images. After the data has been augmented, it moves to the preprocessing stage where the background is removed using U2Net model, noise is removed using median filter and contrast is enhanced using Dynamic Histogram Equalization (DHE).

Preprocessed images are then segmented using SegNet disease region segmentation algorithm and features are extracted using NasNetLarge model. Ensemble model containing Deep Belief Networks (DBN), Long Short Term Memory(LSTM) and Convolutional Auto Encoders(CAE)is used as classifier whose result is further optimized by Shuffled Shepherd Optimization Algorithm(SSOA). The proposed system contains various phases as shown in Figure 1.

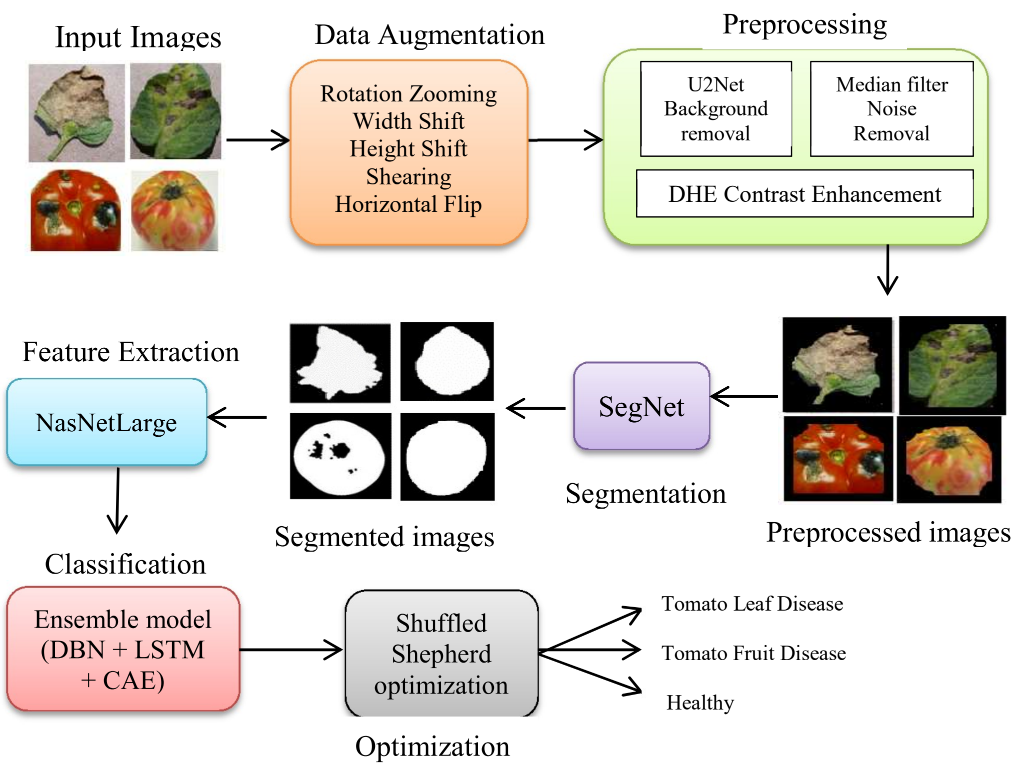

Figure 1. Proposed system workflow

3.1 Data Augmentation

It is a process of escalating the input images to possess enough data for each class of disease. This is done to eliminate the problem of under-fitting and over fitting. The proposed system uses methods of zooming, width shift, rotation, height shift, shearing and horizontal flipping. Data augmentation is not needed for tomato leaf dataset as it contains enough no. of images in each class of disease. It is ample that we apply the augmentation process to tomato fruit dataset.

3.2. Preprocessing

Preprocessing itself contains 3 sub stages such as background removal, filtering and contrast enhancement. Hence this stage of preprocessing becomes very essential for the proposed classification system because it removes all the unwanted details and preserves only the useful information that is required for classifying the disease output. It also segregates the components of the image into desirable and undesirable regions.

3.2.1 Background Removal

A background of plant usually contains other neighboring plants, other parts of the plant, soil, water, overlapping leaves etc. Background removal step proves to be very useful as it removes the undesirable information present in the background which may possibly interfere with the disease symptoms and hinder the classification process. This is because real time farm images are very much different from that of laboratory images which are captured under proper conditions such as good lighting, no background with good resolution. When capturing an image of the plant that grows in

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a farm, we have no control of the lighting or background. Hence the background of a plant image contains more information than the actual part of interest [17].It is because of this reason that background removal is highly advised so that no misclassification happens. For efficient background removal, here we use U2Net model of convolutional neural network.

3.2.1.1 U2Net

It is a state-of-the-art background removal algorithm that has promising results in many areas of its application. It has a simple encoder decoder structure but yet is it is a very powerful tool for background removal [18]. It is usually used for object detection and unlike other CNN models this is not a pre-trained one and makes use of residual blocks for its working. It has a U-shaped structure because of which it has been named so. There are three main components of a U2Net architecture such as the encoder, decoder and a fusion unit which is used for concatenation. There are 11 blocks in total, out of which six blocks are encoder blocks and five blocks are decoders.

U2Net achieves good performance because of two main advantages such as low cost and reduced memory. There's also a possibility of training the architecture according to the user needs because of which it has got a wide range of application. There is a fusion module present at the end which performs the operation of bilinear interpolation which combines the saliency maps produced by each of the decoder and the last encoder and give rise to the final saliency probability map. It is to be noted that no degradation of the object present in the image occurs during this process of background removal. Figure 2 describes the architecture of U2Net that is employed for background removal.

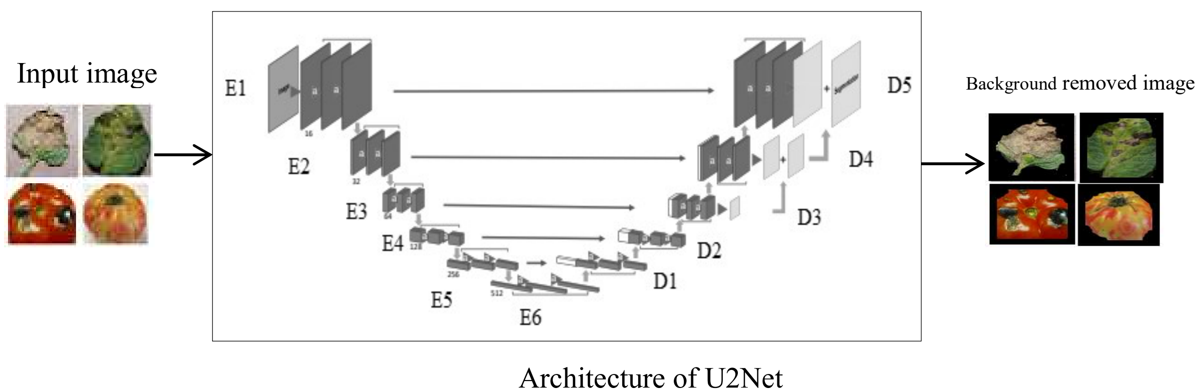

Figure 2. Background removal using U2Net algorithm

3.2.2 Noise Removal using Median Filter

There are a variety of filters available such as Local Filter, Global Filter, Median Filter, Gaussian Filter, Bilateral Filter, Box Filter and Laplacian filter for removing noise in an image. The filter chosen for the proposed system is Median filter. It is a nonlinear filter that replaces the middle pixel by the median value of the corresponding neighborhood values [19]. The process of median filter is shown in Figure 3.

42	38	90	22	14
20	34	15	70	66
55	08	**39**	45	18
12	21	67	33	50
32	45	77	93	112

Figure 3. Median filter working

The 3*3 matrix that has been given in bold is the window under consideration. The values in these windows are arranged in ascending order as given below and the middle value in this list is chosen as the median value and this new value will replace the exact middle value of the window.

08,15,21,33,**34**,39,45,67,70

Therefore 39 will be replaced by 34. Median filter is very easy to implement and takes less computational time. It is said to perform better for agricultural images as it preserves edges better than other filters. The only disadvantage is that the time and space complexity involved.

3.2.3 Contrast Enhancement using DHE

Similar to background removal, contrast enhancement gains importance in identifying the disease exactly because of the poor lighting conditions that is insufficient to highlight the actual symptoms of the disease present in the leaf or fruit image. Farm images captured in real time are usually of low contrast because of the above said reason and it is inevitable that the obtained image is contrast enhanced for further processing [20]. It is a very common process of image processing that can be divided into two major types such as local contrast enhancement and global contrast enhancement. The basic process of enhancing the contrast is to equalize the intensity distribution using histograms. It is identified to be the most effective and standard operation for enhancing the contrast in any type of image.

Simple enhancement techniques have many drawbacks like losing details, enhancing the noise levels or over enhancement of histograms which affects the quality and look of the output image. In order to resolve these issues, we choose to use dynamic histogram equalization method in our proposed technique for enhancing the contrast of tomato leaf and fruit images that are captured from the tomato fields directly. A histogram is nothing but a basic representation of the intensity levels that are present in an image in a graphical format and histogram equalization is a process where this intensity is distributed across the entire image and equalizes its frequency value.

Dynamic histogram equalization contains 3 tasks such as splitting the histogram, gray level range allocation and standard histogram equalization [21].This division is iterated until no domination of a particular intensity is found in any of the histograms after subdividing. Gray level allocation is done with the purpose of achieving a linear cumulative histogram as the output. While allocating the gray levels, it is to be ensured that gray levels in the input are maintained in the same order as the gray levels found in the output.

After this, regular histogram equalization is performed to each of these sub histograms that has been created. This dynamic process allows small features from being washed out and prevents the domination of big features. The whole idea behind dynamic histogram equalization is to make sure that the contrast of each of the sub histograms are moderate in nature and uniform throughout the whole image. After allocating the gray levels, a transformation function is applied to each of the sub histograms and contrast of the input image is thereby enhanced. Figure 4 shows the whole process of dynamic histogram equalization.

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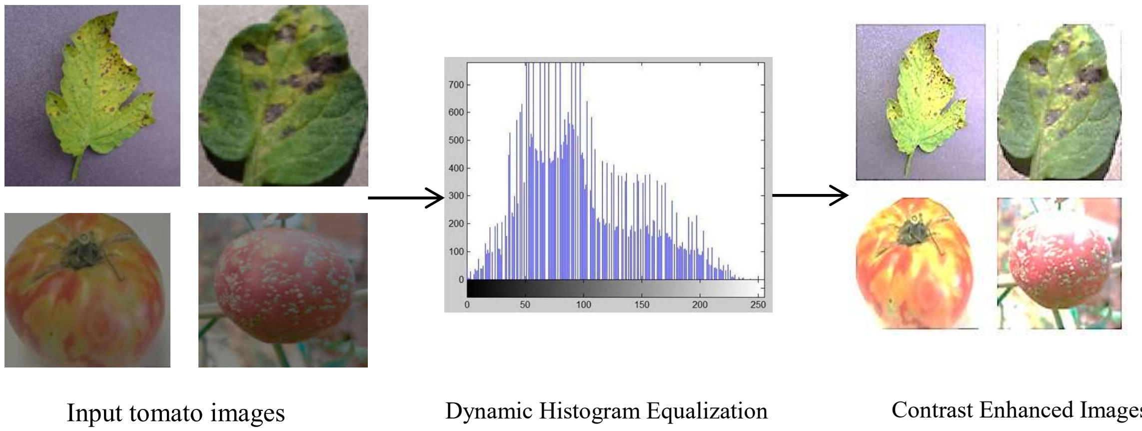

Figure 4. Dynamic Histogram Equalization

3.3 Segmentation

After the acquired input image has been preprocessed, we need to segment the image using a semantic segmentation called the SegNet. The biggest advantage of SegNet is its pixel based segmentation. The components of SegNet include an encoder, decoder and a classification layer[22]. The encoder performs operations like convolutions and max pooling and the architecture of a SegNet encoder is similar to that of the convolutional layers of VGG16 architecture containing 13 layers of convolution which produces the feature maps. The feature maps generated are then put through batch normalization after which a ReLu(Rectified Linear Unit) function is applied.

Finally max pooling and subsampling are done in the encoder stage. The decoder does up sampling in a reverse manner and the classification layer attached to the end of the decoder classifies the pixels and creates a segmented image. SegNet is usually used in images that contain spatial information and temporal information. Also they do not contain the fully connected layers and hence has less than number of parameters. It is the responsibility of the decoder to produce the feature map which is then convoluted to produce a dense feature map which is given as input to the softmax classifier which is present at the end of the SegNet architecture. The pictorial representation of segnet based tomato leaf segmentation is given in figure 5 below.

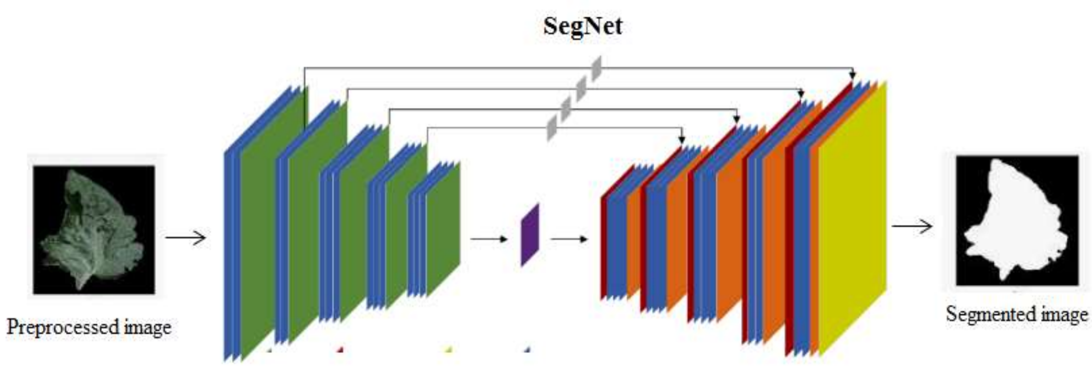

Figure 5. SegNet based semantic segmentation

3.4 Feature extraction

Once the image has been segmented, features are extracted using a very efficient architecture of convolutional neural network called as the NasNetLarge model. It is one of the recently introduced finely performing architecture of CNN models that is based on auto machine learning. Nasnet stands for Neural Architecture Search Network and the building blocks of this architecture is different from that of the others as it contains two types of cells called as normal cells and reduction cells. This architecture was introduced by Google in the year 2017 and it has got the best power for computing. The central idea behind this architecture is not to classify things but it is used to find out the best parameters that could possibly suit the underlying problem. It is considered to be successful in feature extraction as it makes use of reinforcement learning and automates its task of learning and engineering. There are three major components of NasNetLarge like search space, search strategy and performance estimation strategy. The standard size of NasNetLarge model is 331*331. It is a very well trained model that is able to classify over a million of images into thousand different categories of various objects. It possesses a very rich feature map consisting of a wide range of classification knowledge.

The smallest unit of a NasNetLarge architecture is called blocks and concatenation of blocks is called as cells [23]. The number of cells and blocks is not defined for this model and it can be customized based on the needs. Block is considered to be the smallest performing operational unit which is capable of a variety of convolutions and different types of pooling and identity mapping. Element wise addition is also performed and the worst performing cell is removed from the network with the help of tournament selection algorithm.

It has got a very wide search space that could be global or cell based in nature. A normal cell is designed to produce a feature map as present in the input whereas a reduction cell produces a feature map whose dimensions are reduced by a factor of two depending upon the condition. The input size of both the cells is 224*224*3 and the algorithm works in a very fast manner in spite of its huge search strategy. NasNetLarge model is depicted in figure 6 below.

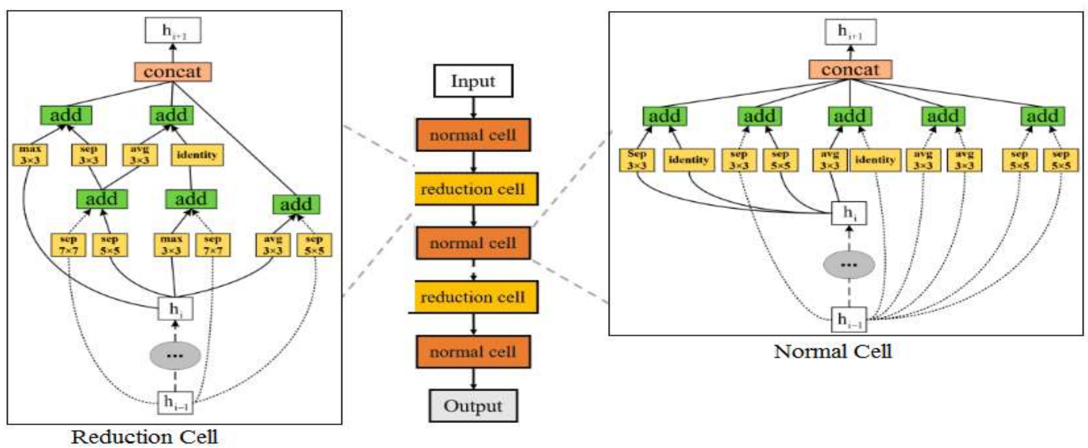

Figure 6. NasNetLarge Architecture

3.5 Classification

The classification system chosen to be of use here is the ensemble model which is nothing but a combination of two or more classifiers that work together. In our ensemble model we have chosen to use DBN, LSTM and CAE as components of the ensemble classifier. Figure 7 presents the proposed ensemble model below.

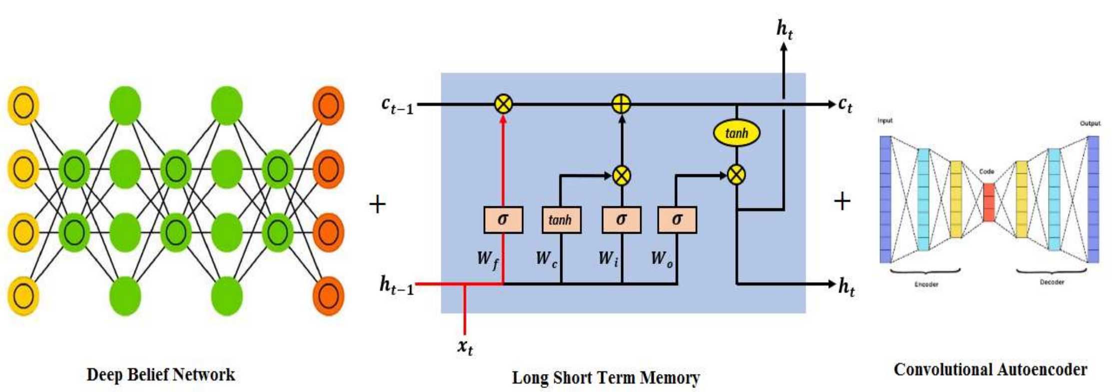

Figure 7. Proposed Ensemble Classifier

3.5.1 Deep Belief Network (DBN)

It contains many hidden layers which act as disease detectors. Deep belief network is basically a combination of neural network and Restricted Boltzmann Machine (RBM) both of which use unsupervised learning method [24]. It has many units of RBM which are stacked one over the other. The output of one machine is given as input to the next and the final output is used for classification purpose. The major advantage of deep belief network is that it does not operate on the input as it is done in auto encoders or RBMs, rather the inputs are processed and used in each layer. It is to be noted that each of the individual RBMs undergo training separately using a method called as contrastive divergence. DBN is a simple graphical network that contains multiple hidden layers with secret connections among them. Though the learning process of deep belief network is considered to be computationally intensive, it has got various advantages like good performance, predefined nature, the capability of fine tuning its parameters etcetera.

3.5.2 Long Short Term Memory (LSTM)

It is producing promising results in recent times. It uses back propagation technique and it resolves the problem of vanishing gradient that has been unaddressed in RNN. It is capable of remembering the output of the previous cells for a long duration and hence it's considered to generate better classification outputs than its predecessor RNN. It is able to reserve long term temporal dependency better than any other model. The major components of long short term memory network are input gate, output gate, forget gate and a softmax layer at the end. The input and output gate control the data entering the system respectively and the forget gate regulates the memory information that should be remembered or forgotten for the next state.

3.5.3 Convolutional Auto Encoders (CAE)

Auto encoders are unsupervised learning models that depend on the technique of back propagation for generating the output values. The basic idea behind auto encoders is to compress the data that enters system so that less memory and space allocations could be achieved. It transforms the input from one representation to another form without losing any information that occupies lesser space. There are many varieties of auto encoders available such as sparse auto encoders, stacked sparse auto encoders, convolutional auto encoders etc. Here we are about to use convolutional auto encoders as a member of the ensemble classifier. Convolutional auto encoder performs an operation of convolution in the process of data compression. It is considered to be a very successful dimensionality reduction algorithm which is widely used for its effectiveness.

3.6 Shuffled Shepherd Optimization Algorithm (SSOA)

After the tomato leaves and fruit image have been classified as having a particular disease, the obtained classification results is optimized using SSOA. It is very simple in nature that utilizes the nature of shepherd in finding its way so the pasture. It is a well-known fact that many animals possess unique characteristics and skills which they use for their survival. Likewise sheep also have a tendency of following its shepherd who's leading the herd. A shepherd employs a horse for each of its herd which finds the fastest and easiest way. Researchers who were inspired by this characteristic of a shepherd wound it into an algorithm.

The first step here is to divide the sheep into n number of herds and allot an agent for each of them [25]. The step size of the first sheep is 0 which is considered as the best sheep and the last sheep is the worst amongst the herd. During initialization, all the parameters of the algorithm are set to default conditions. The agents are then initialized based on the objective function and the herd is built. A solution is generated by each of the herd and a solution vector is created. As new solutions are generated, the solution vector is updated until the termination condition has been met.

Shuffled Shepherd Optimization Algorithm

Step 1: Divide the sheep into 'n' herds
Step 2: Allot an agent for each herd
Step 3: Arrange sheep based on size.
Step 4: Calculate distance.
Step 5: Initialize agents and parameters
Step 6: Create solution vector
Step 7: Update solution vector with solutions produced by each herd.
Step 8: Repeat this until termination condition is met
Step 9: Merge herds
Step 10: Report the best solution in the solution vector.

4. RESULTS AND DISCUSSION

4.1 Image Acquisition

3676tomato leaf and fruit 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. 9tomato leaf diseases and 3 tomato fruit diseases are classified by the proposed system. Healthy tomato leaves are also included. Therefore 13 classes are identified by the proposed system with 12 tomato leaf and fruit diseases and a healthy class of leaves in total. Table 1 indicates the input details belonging to tomato diseases.

Table 1. Tomato diseases identified by the proposed system

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 8 shows the sample of input images used.

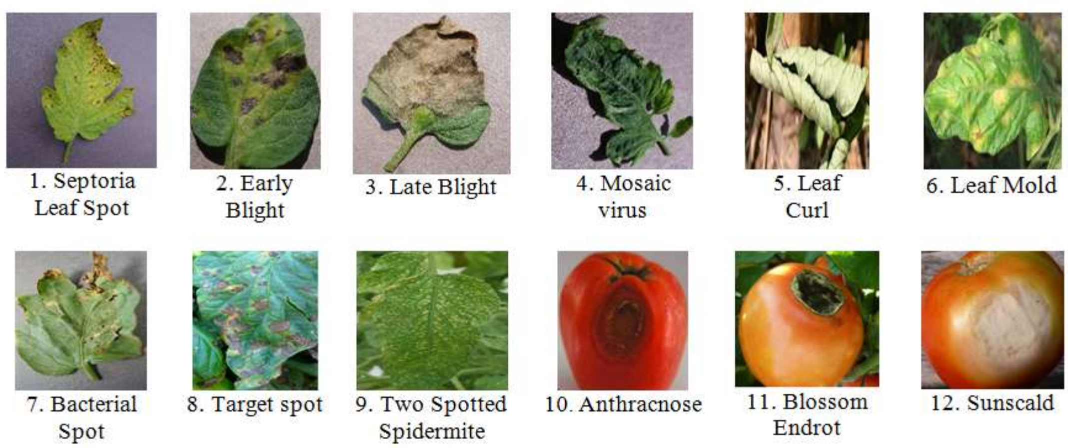

Figure 8. Input images

4.2 Data Augmentation

Data augmentation is done for generalizing the data set and making it a stable one so that it contains enough number of samples for all the categories that are involved in the classification. It becomes very essential for the tomato fruit dataset as it contains only a few samples which will fail terribly in the testing face if not augmented. Table 2 below shows the parameter range details of augmentation techniques used here.

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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

An input image can be of different sizes, dimensions and resolutions which can contain complex background because of which preprocessing becomes necessary. The general task of background removal can itself be complicated if the input images contain soft edges and shadows are present. Dynamic histogram equalization is considered to be computationally very fast and less expensive when compared to other techniques. Figure 9 shows the output of preprocessed images after removing background using U2Net, noise removal using Median filter and contrast enhancement using dynamic histogram equalization.

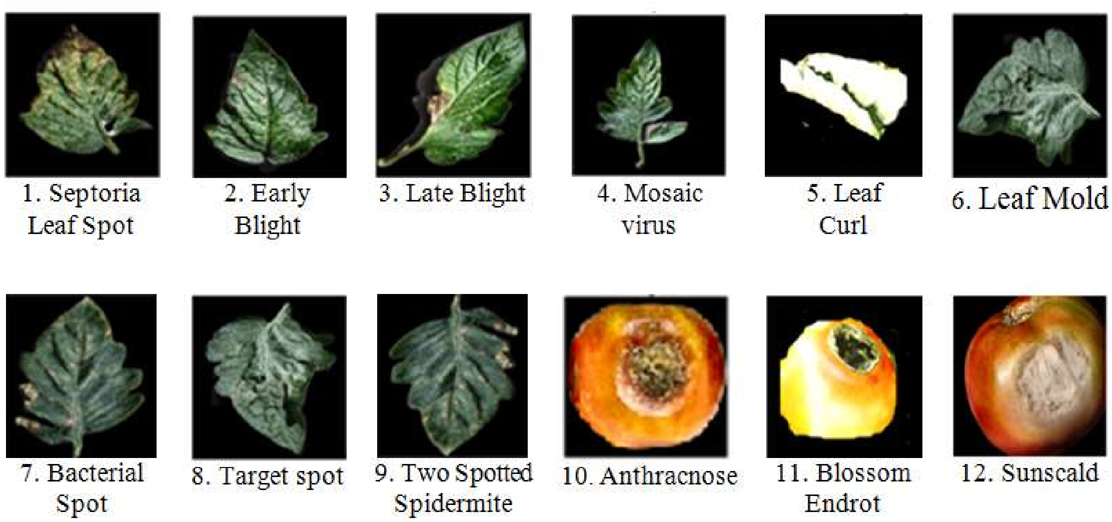

Figure 9. Preprocessed images

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4.4 Segmentation

Figure 10 shows the output of segmented images using SegNet disease region segmentation.

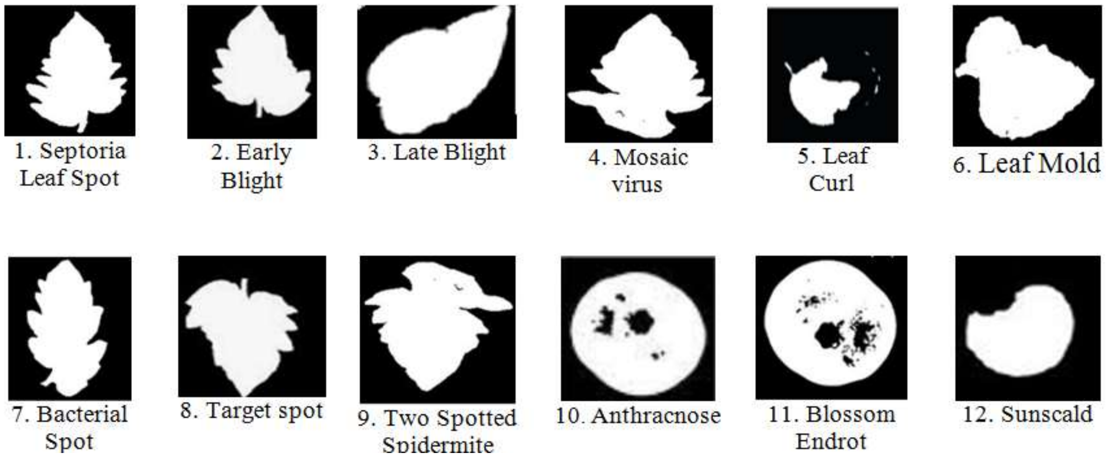

Figure 10. Segmented image

4.5 Confusion Matrix

It is a simple form of matrix that represents the classification result of tomato leaf and fruit diseases. Figure 11 displays the confusion matrix resulting from tomato leaf classification for training and testing datasets.

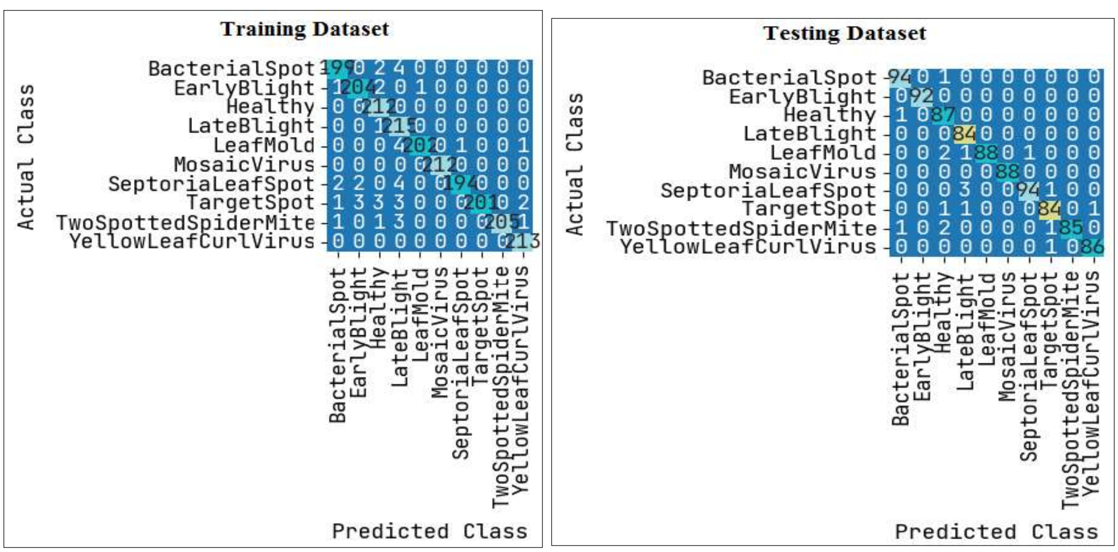

Figure 11. Tomato leaf Confusion matrix

Figure 12 shows the confusion matrix obtained while classifying tomato fruit diseases.

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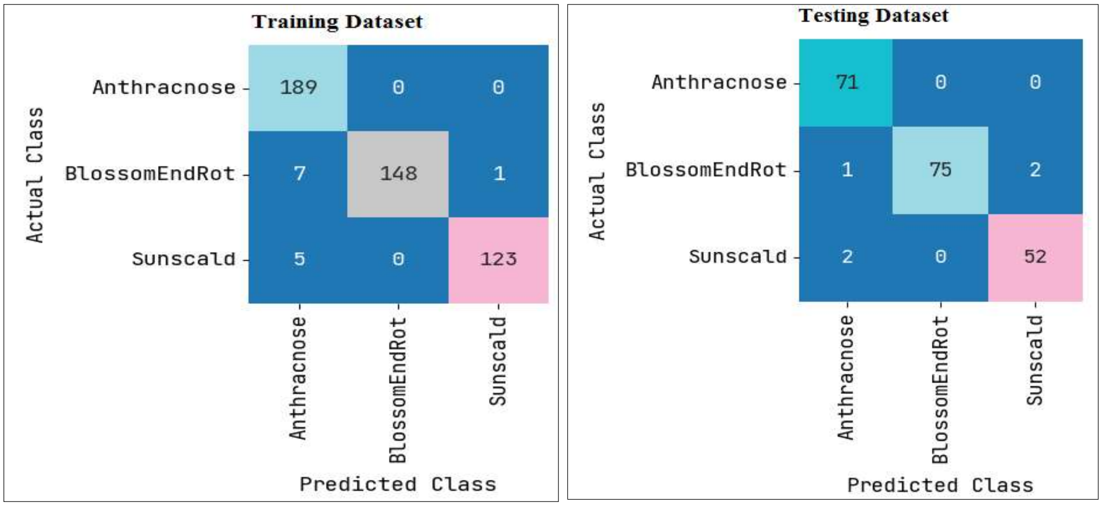

Figure 12. Tomato Fruit Disease Confusion Matrix

4.6. Performance Evaluation

Precision, accuracy, recall, F1 score are usual metrics of performance evaluation which analyze the classification operation of the proposed classifier. MCC is a different statistical measure that indicates the overall execution. Table 3 shows the performance metrics of tomato leaf and fruit disease classification in both the training and testing datasets.

Table 3. Classification Performance of proposed system

S.No.	Metrics	Tomato Leaf		Tomato Fruit	
		Training Values	**Testing Values**	**Training Values**	**Testing Values**
1.	Accuracy	0.9885	0.989	0.9774	0.9814
2.	Precision	0.9805	0.9802	0.9774	0.9741
3.	Recall	0.9977	0.9978	0.9849	0.9879
4.	F1-Score	0.9796	0.98	0.973	0.9742
5.	MCC	0.9775	0.9779	0.9596	0.9623

Figure 13 displays the performance values achieved by the proposed ensemble classifier during testing phase.

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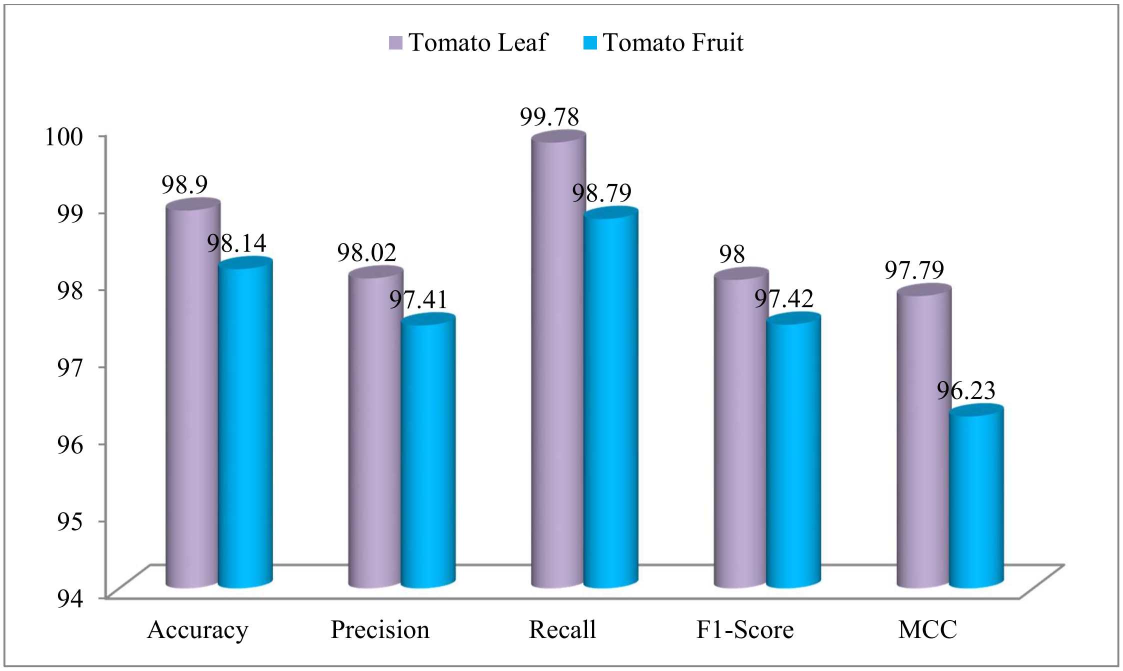

Figure 13. Tomato leaf and fruit disease classification performance

4.7 Performance curves

Performance curves give us an easy pictorial representation of the performance achieved by the proposed ensemble classifier. Figure 14 illustrates the curve of training and validation accuracy attained when classifying tomato leaf and fruit diseases.

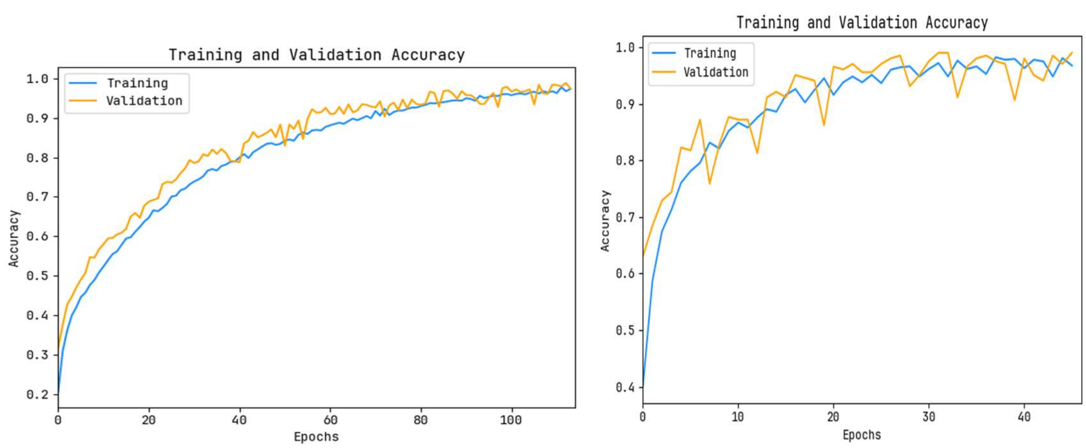

Figure 14. Training and validation accuracy curves

Similarly figure 15 depicts the curves related to training and validation loss.

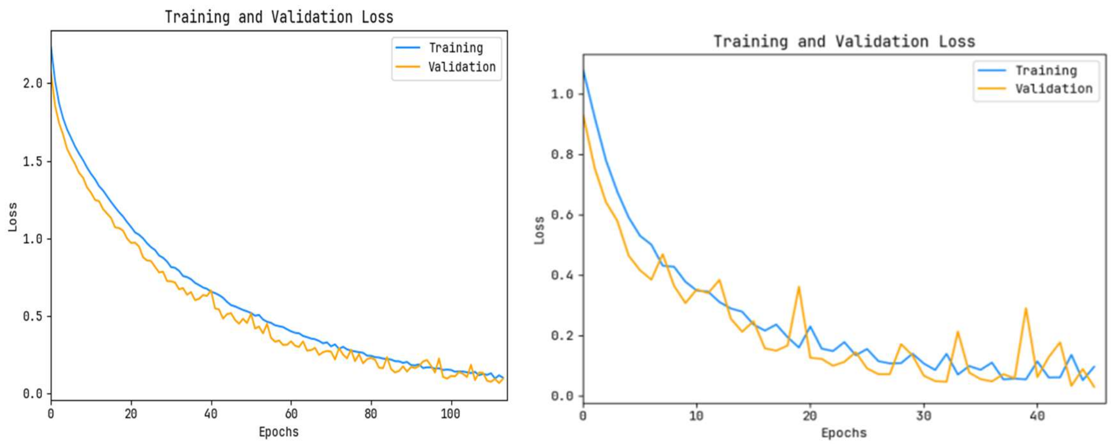

Figure 15. Training and validation loss curves

Figure 16 shows the precision recall curve analyses of tomato leaf and fruit disease classifications. It can be seen from the curve that for all the diseases of tomato fruit and leaves, the value is higher than 0.9 which indicates excellent classification performance displayed by the ensemble classifier.

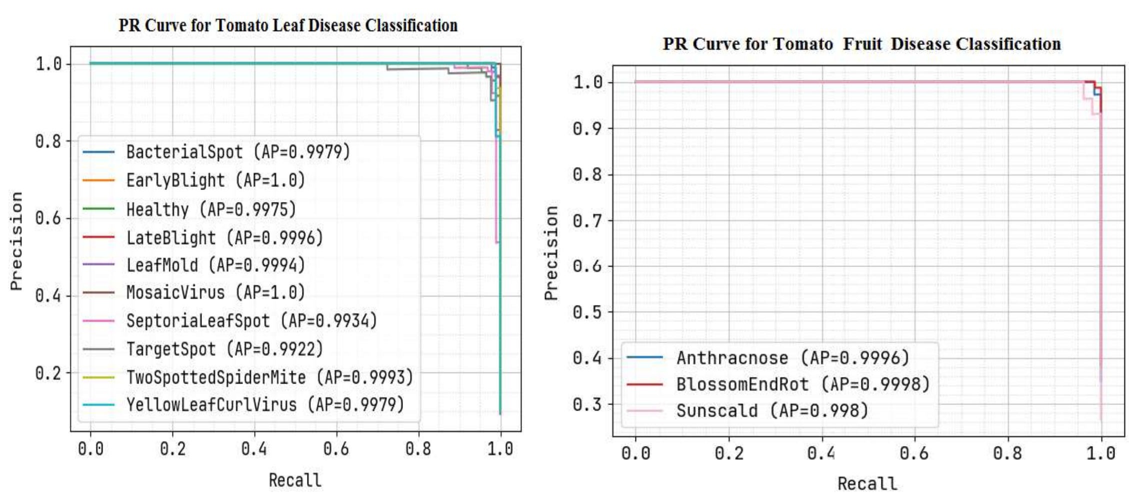

Figure 16. Precision – Recall curve analyses

Figure 17 portrays the ROC curve analyses of tomato leaf and fruit disease classification in testing phase. The AUC values are higher than 0.99 for all the diseases thus indicating the superior performance of the proposed ensemble classifier with shuffled shepherd optimization.

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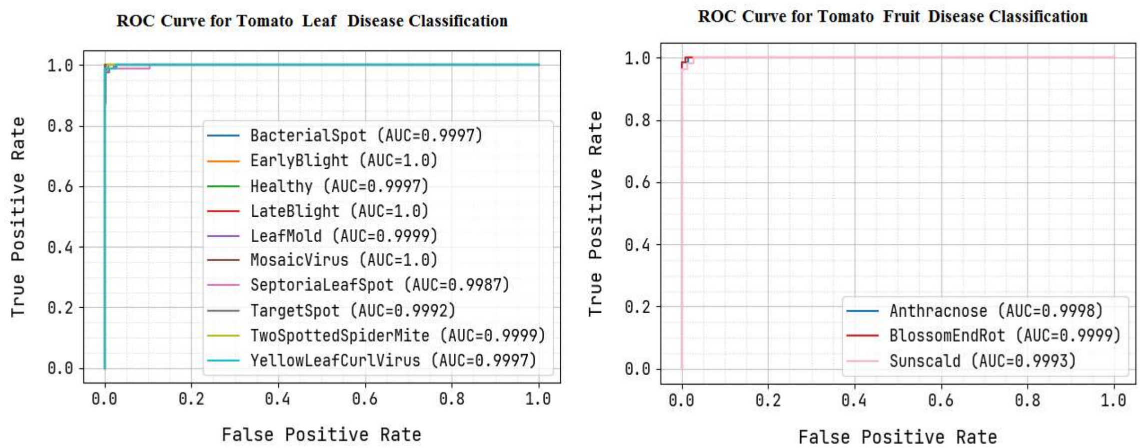

Figure 17. ROC curve analyses

4.8. Comparison of Existing methods

The performance of the proposed ensemble system has been compared to that of existing methods such as InceptionV3, MobileNet, VGG166, CNN, Kernel Extreme Learning Machine (KELM), Convolutional Gated Recurrent Unit (CGRU). Table 4 lists the classification accuracy achieved by all of these algorithms.

Table 4. Performance Comparison

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.	CGRU	96.90
7.	Proposed Ensemble classifier	98.90

InceptionV3 reached an accuracy of 63.4%, MobileNet scored only 63.75%, VGG16 generated an accuracy of 77.2%, CNN yielded 91.2% accuracy, Kernel Extreme Learning Machine (KELM) achieved a good accuracy score of 94.42 and convolutional gated recurrent unit attained an accuracy of 96.90%. Our proposed model has touched a phenomenal accuracy of 98.90%. Hence it can be concluded that our proposed work is better and efficient than the other previously existing techniques. Figure 18 below shows the comparative performance of the above said methods in a graphical format.

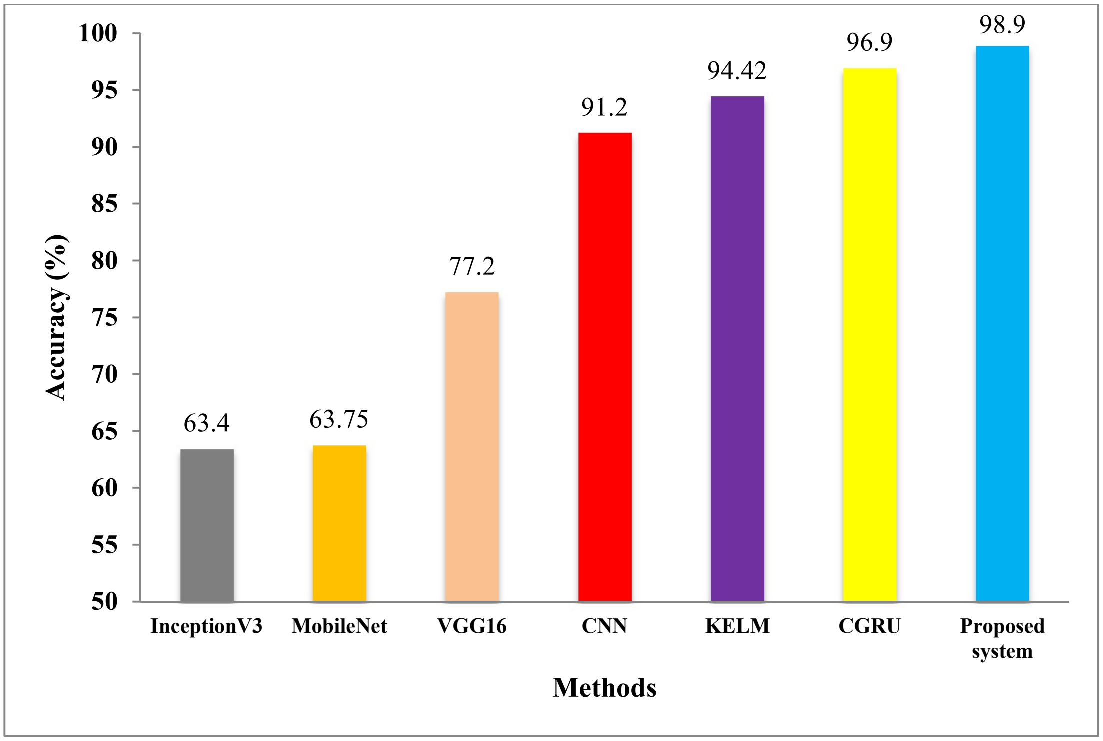

Figure 18. Comparative analysis of algorithms

5. CONCLUSION

Though there are several models available for plant disease detection and identification systems, there has always been a constant demand for new, efficient and even more intelligent systems which is the driving force behind this project. The proposed ensemble based classifier outperforms all the previous models as it a combination of three high performing classifiers. Much importance is given to the phase of preprocessing like background removal using U2Net, noise removal with the help of median filter and contrast enhancement is accomplished through dynamic histogram equalization. SegNet and NasNetLarge techniques are used for segmentation and feature extraction stages. Finally, in order to heighten the classification results secured by the classifier, the proposed system uses shuffled shepherd optimization algorithm which has resulted in an accuracy of 98.9%, precision of 98%, recall value of 99.78%, F1-Scoreof 98% and MCC score of 97.79% that seems to be advanced than InceptionV3, MobileNet, VGG166, CNN, Kernel Extreme Learning Machine(KELM), Convolutional Gated Recurrent Unit(CGRU) classifiers.

REFERENCES

[1] VA. Natarajan, MM. Babitha, and MS. Kumar, "Detection of disease in tomato plant using Deep Learning Techniques", *International Journal of Modern Agriculture*, Vol.9, No.4, 2020, pp. 525-540.

[2] D. Das, SK. Biswas, and S. Bandyopadhyay "Detection of Diabetic Retinopathy using Convolutional Neural Networks for Feature Extraction and Classification (DRFEC)", *Multimed Tools Appl*, vol.82, 2023, pp. 29943–30001

[3] MA. Ganaie, M. Hu, AK. Malik, M. Tanveer and PN. Suganthan , "Ensemble deep learning: A review", *Engineering Applications of Artificial Intelligence*, vol.115,no.105151.

[4] Liu, Li, Zhengkun Li, Yufei Lan, Yinggang Shi, and Yongjie Cui. (2019). Design of a tomato classifier based on machine vision. *PloS one*. Vol. 14, no. 7, 2022, pp. e0219803.

[5] M. Astani, M. Hasheminejad, and M. Vaghefi, "A diverse ensemble classifier for tomato disease recognition. *Computers and Electronics in Agriculture*, vol. 198, no. 1, 2022, 107054.

[6] P. Kaur, S. Harnal, V. Gautam, MP. Singh, and SP. Singh, "Performance analysis of segmentation models to detect leaf diseases in tomato plant", *Multimedia Tools and Applications*, pp.1-25, 2023.

[7] S. Saravanan, and R. Karthigaivel , "A fuzzy and spline based dynamic histogram equalization for contrast enhancement of brain images", *International Journal of Imaging Systems and Technology*, vol.31, no.2, 2021, pp.802-827.

[8] K. Radhika, K. Devika, T. Aswathi, P. Sreevidya, V. Sowmya, and KP. Soman, Performance analysis of NASNet on unconstrained ear recognition", *Nature inspired computing for data science*, 2020, pp. 57-82.

[9] AM. Abdel-Zaher, and AM. Eldeib, "Breast cancer classification using deep belief networks", *Expert Systems with Applications,* vol.46, 2016, pp. 139-144.

[10] CK. Sunil, CD. Jaidhar, and N. Patil, "Cardamom plant disease detection approach using EfficientNetV2", *IEEE Access*, vol.10, 2021, pp.789-804.

[11] H. Ulutaş, and V. Aslantaş, "Design of Efficient Methods for the Detection of Tomato Leaf Disease Utilizing Proposed Ensemble CNN Model", *Electronics*, vol.12, no.4, 2023, pp. 827.

[12] A. Kaveh, and A. Zaerreza, "Shuffled shepherd optimization method: a new Meta-heuristic algorithm", *Engineering Computations*, vol.37, no.7, 2020, pp.2357–2389.

[13] R. Bandi, S. Swamy, and CS. Arvind, "Leaf disease severity classification with explainable artificial intelligence using transformer networks", *International Journal of Advanced Technology and Engineering Exploration*, vol. 10, no.100, 2023, pp. 278.

[14] A. Pavithra, G. Kalpana and T. Vigneswaran, "Deep learning-based automated disease detection and classification model for precision agriculture", *Soft Computing*. 2023, pp.1-12

[15] Y. Kumar, R. Singh, MR. Moudgil, and A .Kamini, "Systematic Review of Different Categories of Plant Disease Detection Using Deep Learning-Based Approaches", *Archives of Computational Methods in Engineering*. 2023 pp.1-23.

[16] P. Maheswari, P. Raja, and VT. Hoang, "Intelligent yield estimation for tomato crop using SegNet with VGG19 architecture", *Scientific Reports*, vol.12, no.1, 2022, pp.13601.

[17] S. Khatoon, MM. Hasan, A. Asif, M. Alshmari, and YK. Yap, "Image-based automatic diagnostic system for tomato plants using deep learning. *Computers, Materials and Continua*. Vol. 67. No. 1, 2021, pp. 595-612.

[18] X. Qin, Z. Zhang, C. Huang, M. Dehghan, OR. Zaiane, and M. Jagersand , "U2-Net: Going deeper with nested U-structure for salient object detection*", Pattern recognition*, vol.106, no.1, 2020, 107404.

[19] A. Hemalatha, and J. Vijayakumar, "Automatic tomato leaf diseases classification and recognition using transfer learning model with image processing techniques", Smart Technologies, *Communication and Robotics*, 2021, pp. 1-5.

[20] S. Lin, Z. Lin, T. Guo, and B. Tang, "Contrast enhancement by intensity preservation-based dynamic histogram equalization for electrowetting display", *IEEJ Transactions on Electrical and Electronic Engineering,* vol.15, no.1, 2020, pp.121-127.

[21] BS. Rao, " Dynamic Histogram Equalization for contrast enhancement for digital images", *Applied Soft Computing*, Vol. 106114, 2020.

[22] S. Kolhar and J. Jagtap, "Convolutional neural network based encoder-decoder architectures for semantic segmentation of plants", *Ecological Informatics*, vol.64, no.101373, 2021.

[23] AO. Adedoja, PA. Owolawi, T. Mapayi, and C. Tu , "Intelligent mobile plant disease diagnostic system using NASNet-mobile deep learning", *IAENG International Journal of Computer Science*, vol.49, no.1, 2022, pp. 216-231.

[24] J. Xiong, D. Yu, S. Liu, L.Shu, X. Wang and Z. Liu, "A review of plant phenotypic image recognition technology based on deep learning", *Electronics*, vol.10, no.1, 2021, pp. 81.

[25] T. Daniya and V. Srinivasan, "Shuffled shepherd social optimization based deep learning for rice leaf disease classification and severity percentage prediction", Concurrency and Computation: *Practice and Experience*, vol.35, no.4, 2023, pp.e7523.