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Transfer Learning for Multi-Crop Leaf Disease Image Classification using Convolutional Neural Network VGG

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ABSTRACT

In recent times, the use of artificial intelligence (AI) in agriculture has become the most important. The technology adoption in agriculture if creatively approached. Controlling on the diseased leaves during the growing stages of crops is a crucial step. The disease detection, classification, and analysis of diseased leaves at an early stage, as well as possible solutions, are always helpful in agricultural progress. The disease detection and classification of different crops, especially tomatoes and grapes, is a major emphasis of our proposed research. The important objective is to forecast the sort of illness that would affect grapes and tomato leaves at an early stage. The Convolutional Neural Network (CNN) methods are used for detecting Multi-Crops Leaf Disease (MCLD). The features extraction of images using a deep learning-based model classified the sick and healthy leaves. The CNN based Visual Geometry Group (VGG) model is used for improved performance measures. The crops leaves images dataset is considered for training and testing the model. The performance measure parameters, i.e., accuracy, sensitivity, specificity precision, recall and F1-score were calculated and monitored. The main objective of research with the proposed model is to make on-going improvements in the performance. The designed model classifies disease-affected leaves with greater accuracy. In the experiment proposed research has achieved an accuracy of 98.40% of grapes and 95.71% of tomatoes. The proposed research directly supports increasing food production in agriculture.

1. Introduction

To contribute to the development of nations, knowledge of agriculture sectors is crucial. Agriculture is a one-of-a-kind source of wealth that develops farmers. For a strong country, the development of farming is a necessity and a need in the global market. The world's population is growing at an exponential rate, necessitating massive food production in the next 50 years. Information about different types of crops and diseases occurring at each level and its analysis at an early stage play a key and dynamic role in the agriculture sector. A farmer's main problem is the occurrence of various diseases on their crops. The disease classification and analysis of illnesses is a crucial concern for agriculture's optimum food yield. Food safety is a huge issue due to a lack of infrastructure and technology, so crop disease classification and identification are important to be considered in the coming days. This is necessary for yield estimation, food security, and disease management. Detection and recognition of crops illnesses is an important study topic because it could be capable of monitoring huge fields of crops and detecting disease symptoms as soon as they occur on plant leaves. As a result, finding a quick, efficient, least inexpensive, and effective approach to determine crops diseases instances is quite important (C. J. Chen et al., 2021).

Artificial intelligence (AI) provides considerable assistance to agriculture, which enhances a nation's gross domestic product (GDP) mostly through this sector. Climate change, labour scarcity, rainy season uncertainty, natural disasters, and various diseases on plant leaves are all major issues in agriculture. The plant leaves recognition and detection studies with edge intelligence applied to agriculture. There is a new advancement with different deep learning models that overcomes the challenge. The YOLOv3 neural network model is based on deep learning and is built on an embedded system and the NVIDIA Jetson TX2. The system is implemented on a drone, and photographs of plants are taken, pest positions are identified, and pesticides are applied as needed; this is a novel approach based on deep learning (Al Hiary et al., 2011).

Hyper spectral and multispectral knowledge acquisition techniques and applications have exhibited their utility in improving agricultural production and practises by providing farmers and agricultural management with crucial data on the elements impacting crop condition and growth. This technology has been widely employed in a variety of agricultural applications, including sustainable agriculture (Ang, 2021).

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Weed detection in vegetable plantations is more difficult than in crop plantations due to uneven plant spacing. Deep Learning technology is a novel method that blends with image processing. This approach concentrates solely on recognising plants, avoiding the handling of numerous plant species. Furthermore, by reducing the amount of training image collection and even the complexity of weed detection, this technique can improve plant diagnosis accuracy and performance (Jin et al., 2021).

The massive crop loss occurred because of the failure to predict disease at an early stage, which always results in lower crop production. As a result, identifying and analysing crop diseases is a critical step in ensuring crop quality (Wu, 2020). As high computing speed and power have recently improved, the availability of massive datasets improves the system's efficiency.

In this section, there are various techniques for detecting and classifying crop leaf disease. We present the related survey as a system that employs a variety of classifier techniques. There are two types of combinations: serial and hybrid, with the combination of serial and parallel achieving the significant performance parameter within 600 images (Massi et al., 2020). The hybrid combination has a recognition rate of 91.11%, which is higher than the serial, parallel, and deep learning approaches. For identifying and analyzing leaf illness, a deep learning convolutional neural network (CNN) model was used to classify healthy and sick images. The model train contained 25 different plants, 58 classes' sets, including healthy and diseased plants, and had 87,848 images. Using several (Ferentinos, 2018) model architectures, the best performance success rate was 97.53%. The Multi-Context Fusion Network (MCFN), a deep learning-based method, is built and prepared for crop disease detection. The MCFN aids in the extraction of visual information from 50,000 crop photos. The MCFN produced 77 common crops infected using a deep fusion model, with a 97.50% identification accuracy (Jin et al., 2021).

The identification of weeds in crops using the CovNet algorithm is also a potent and cutting-edge approach. In recent research, bounding boxes were drawn across cropped images and the model was trained. Colour-based segmentations are applied to images and colour information, and visual categorization is calculated for weed images. The colour index was examined with a genetic algorithm and Bayesian categorization (Jin et al., 2021). The deep residual network and the deep dense network are combined in the hybrid deep learning model. The hybrid deep learning model reduces training parameters while increasing accuracy by up to 95.00 % (Zhou et al., 2021).

Deep transfer learning is an amazing performance methodology for identifying plant diseases. For pre-trained datasets, Inception and ImageNet modules were utilized (Chen et al., 2020). The performance of pepper, vegetable, potato, and tomato leaf images in the plantvillage database was studied and enhanced using support vector machine (SVM) and multi-layer perceptron. After training the model the system achieves a higher performance accuracy of 94.35 % (Kurmi et al., 2020).

To detect and recognize corn dietary sickness, a Deep Convolutional Neural Network was deployed., The recognition of corn leaf diseased accuracy was 88.46 %, and the usage of hardware, such as a raspberry pi3 with an Intel Movidius Neural Compute Stick and a system GPU that pre-trained the CNN Model, resulted in superior metric accuracy performance (Sun et al., 2020).

With the rapid growth of artificial intelligence and deep learning technology, computer vision (CV) made a breakthrough. The CV-based approaches are commonly utilized for diagnosing grape leaf diseases. The principle component analysis (PCA) and back propagation methods aid in the diagnosis of grape diseases such as downy mildew and powdery mildew, with a research accuracy of 94.29 % (Xie et al., 2020), using VGGNet. The weights are initialized using ImageNet pre-trained datasets, and over through the real - world dataset, such approaches had a validation accuracy of 91.83 %.

2. Material & methods

2.1. Datasets

To support our research in the area of collection of images available from Pennsylvania state university named plantvillage dataset. The dataset plant-village included 152 crop solutions, 38 crop classes, and 19 crop categories, for 54,303 crop leaves images. In the datasets, high quality JPEG image format with 5471width and 3648 height pixels are available. In the pre-processing, de-nosing, segmentation and after images are 256 X 256 pixels (Gandhi et al., 2018). The plantvillage is a well-known dataset for crop disease, with a large number of public datasets available. A plantvillage dataset images were captured in the lab, thus they are used as training datasets. Our model tested on real field captured images, As a result, we must concentrate on developing our own field database. The test images were captured with a separate Megapixel camera and stored in a database. The datasets prepared in the field are available and be used in the proposed research. The agrodeep mobile application was used to capture some on-field crops images.

The field photographs were taken with the redmi Note 5 Pro MIUI Global 11.0.5.0(PRIMEXM), Android Version PKQ1.180904.001, and a camera frame 4:3 high picture quality on 16 MP+5MP with f/2.2 aperture pixel, in a variety of natural environments. The disease-affected and healthy photos are the most common image categories collected for research purposes. Healthy spot contaminated, mosaic virus, yellow leaf curl virus, septoria leaf spot bacterial spot, early blight, late blight, leaf mould, septoria leaf spot, and spider mites are examples of tomato imagery.

2.2. Proposed research

The schematic in Fig 1 depicts a potential view for multi-crop leaf disease classification and analysis. Initially, plant leaf disease images are collected and classified into several categories. Picture filtering, grey transformation, picture sharpening, and scaling are some of the image-processing techniques. By using data augmentation methods, new sample photos are created from available photos to enhance and prepare the dataset. Augmentation procedures like turning, translation, and randomized transformation are employed to enhance the size of the dataset. The photos are then used as input to the suggested approach for training the model in the following stage. The newly trained architectural model is used to anticipate previously unseen images. Eventually, the findings of plant disease detection and identification are achieved. Finally, complete details of these steps are depicted in later parts (Table 1).

2.3. Sample images category

The sample images of crops shown in Fig. 2 depict the category of field's tomato leaf images of various disease and healthy classes. The images are one-of-a-kind for each type of disease symptom, pattern, spot, and colour mark. Specific tomato plant leaf diseases such as bacterial wilt, leaf mold, and grey spots are identified and detected as disease impacted recognition traits (Paymode et al., 2020).

Fig. 3 depicts field images of grape vine leaves obtained in the Nashik district of Maharashtra, India. A grape category, Healthy 423, Black Rot 1180, Black Measles 1383 and Leaf Blight 1076 images were recorded, recognized, and captured. The datasets for grape plant leaves were generated by adjusting the brightness and hue of images from the A to D category (See Figs. 4-5).

The second crop of tomatoes sampled Early blight 1000, Mosaic virus 373, Bacterial spot 2127, Late blight 1909, Leaf mould 952, Septoria leaf spot 1771, 1404 spot, spider mites 1676 and Yellow leaf curl 3209. The deep learning based methods are state-of-the-art in computer vision, which is used in image recognition and classification. In general, dataset collecting, data pre-processing, image segmentation, feature extraction, and classification are the four stages of Artificial Intelligence (AI) in agriculture

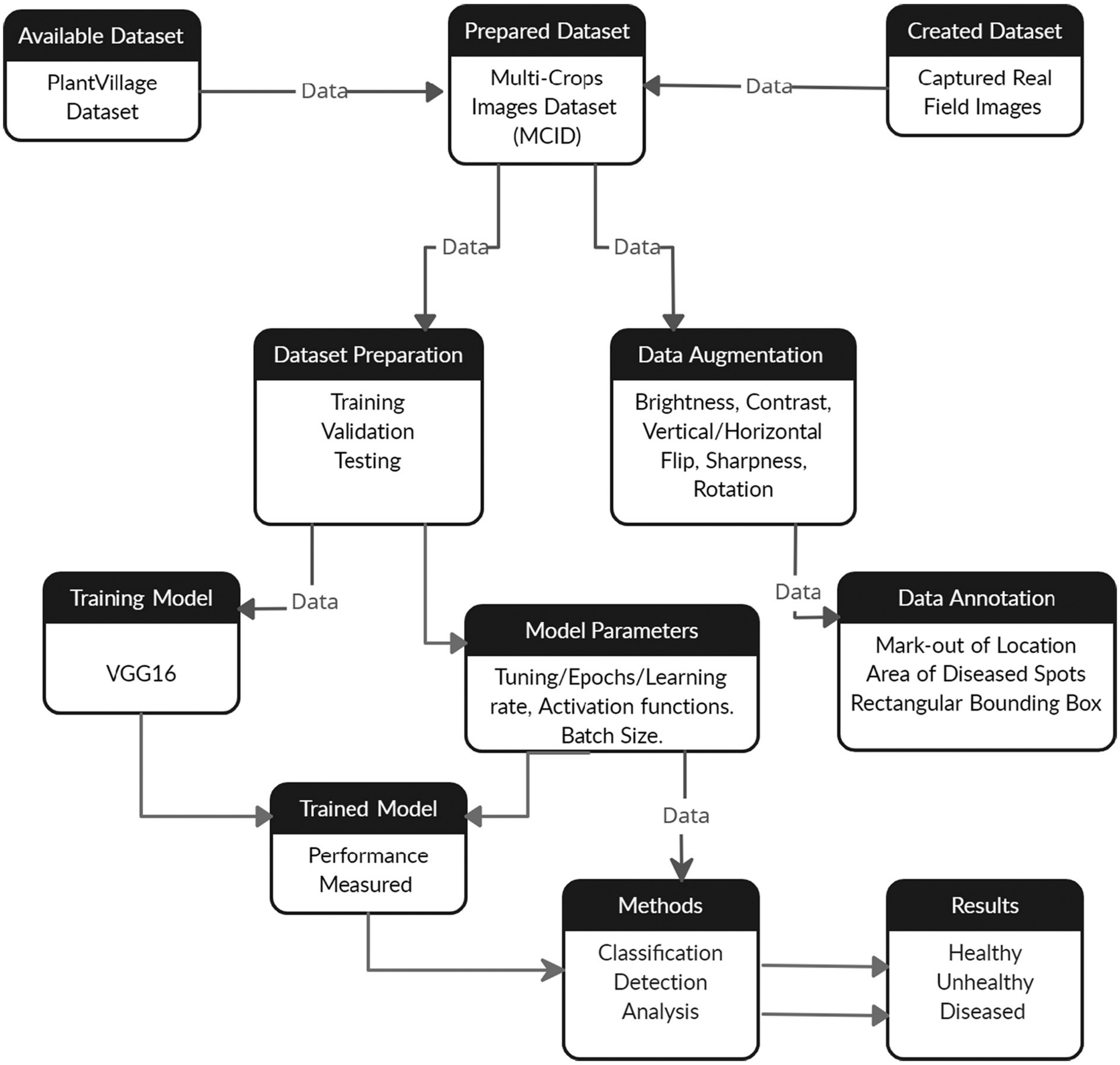


Fig 1. Proposed research system flow diagram.

approaches for crop leaf disease detection and classification utilising Convolutional Neural Network (CNN). A Google Colaboratory platform was used to pre-process the image, extraction of features, and classify it.

2.4. Image augmentation

The large number of datasets improves the learning algorithms' performance and prevents overfitting. Obtaining a real-time dataset for use as input to a training model is a complex and time-consuming operation. As a result, data augmentation broadens the range of training data available to deep learning models. Deep learning-based augmentation approaches include image flipping, cropping, rotation, colour transformation, PCA colour augmentation, noise rejection, Generative Adversarial Networks (GANs), and Neural Style Transfer (NST) (Arun Pandian et al., 2019). The Faster DR-IACNN approach for detecting grape leaf diseases is based on deep learning. The automatic extraction of spots on leaves has a high detection speed and accuracy. There are 4449 original photographs and 62,286 photos developed using data augmentation techniques.

Table 1
A study of deep learning techniques with classification and recognition rate (See Fig. 12).

Approach	Classification	Model	Recognition rate (%)
Hybrid Combination (Massi et al., 2020)	Three SVM	SVM	91.11
Deep Learning (Ferentinos, 2018)	CNN	VGG	97.53
Multi-Context Fusion Network (MCFN) (Wu, 2020)	CNN	AlexNet &VGG16	97.50
Deep Transfer Learning (DTL) (Chen et al., 2020)	CNN	VGG	91.83
Machine Learning (Kurmi et al., 2020)	SVM	MLP	94.35
Deep Learning (Sun et al., 2020)	DCNN	DCNN	88.46
Deep Learning (Xie et al., 2020)	Faster DR-IACNN	Inception-v1 ResNet-v2	81.11

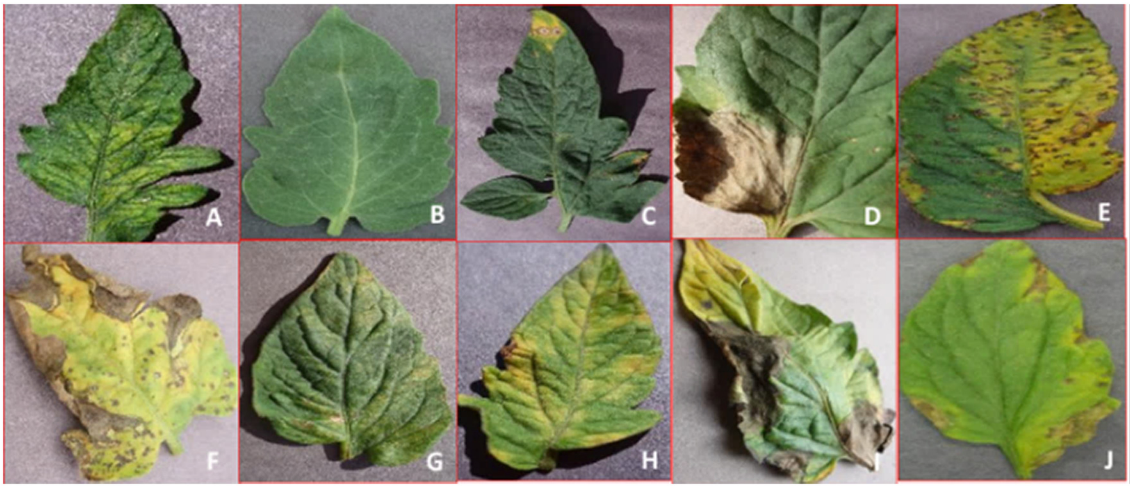


Fig 2. Sample tomato leaf images (A: Mosaic Virus, B: Healthy, C: Target Spot, D: Late Blight, E: Bacterial Spot, F: Septoria Spot, G: Spider Mite, H: Leaf Mold, I: Early Blight, J: Yellow Leaf.

The images are converted into a vector of fixed features through feature extraction in segmentation. The color, texture, and shape are the system-adopted features. A means, confidence intervals, and sleekness have been employed as colored methods, with HSV and RGB color spaces being retrieved. The gray-level co-occurrence matrix is preferred when extracting texture features from a colour image. This approach is used to identify plant diseases.

2.5. Transfer learning

The model's optimization and training is a tough and time-consuming operation. A powerful graphical processing unit (GPU) is required for the training, as well as millions of training examples. However, transfer learning, which is employed in deep learning, solves all of the problems. The pre-trained Convolutional Neural Network (CNN) used in transfer learning is optimized for one task and transfers knowledge to different modes (Nevavuori et al., 2019). The multi-crop image dataset model comprises a size of 224 X 224. The residual network (ResNet) needed to be tweaked. In all ResNet models, the final layer before the softmax is a 7 X 7 average-pooling layer. A smaller image can fit into the network when the pooling size decreases. The basic picture preparation is necessary for the transfer learning considerations with the multi-cropped image dataset.

3. Results & discussion

3.1. Convolutional neural network

The convolutional layers, pooling layers, fully-connected layers, and dense layers constitute the architecture of the Convolutional Neural Network (CNN) (See Fig. 6). The layers' description is shown below.

3.1.1. Convolutional layer

Convolutional layers' fundamental function is to extract unique features from images. The implementation of convolutional layers on a normal basis facilitates the extraction of input features (Chen et al., 2020), The features extraction (Hi) among several layers in CNN is computed using the formula below.

$$\mathrm{H}_i = \varphi\,(\mathrm{H}_{i-1}\,\mathrm{W}_i + \mathrm{b}_i) \tag{1}$$

Where, Hi - Feature map, Wi –Weight, bi is offset and φ – Rectified Linear Unit (RELU)

3.1.2. Pooling layers

The pooling layers are a crucial component of a Convolutional Neural Network (CNN). It shrinks the size of convolved features in dimension while simultaneously minimizing the computational resources necessary for image processing. Pooling arise categorized into two types: max pooling and average pooling. Max pooling returns the maximum value of images, whereas an average pooling returns the average value of the image section.

3.1.3. Drop-out layers

The dropout layers improve the capability of a trained model. It provides regularization and prevents the model from over-fitting by decreasing the correlation between the neurons. The drop out process is used in all the activation functions but it is scaled by factor (Liu, 2020).

3.1.4. Flatten layers

It collapses the spatial dimensions of the mapped pooled features while retaining the channel dimensions. The flattened layer adds extra dimensions and after it is transformed into a vector. The vectored feed

Fig 3. Sample grapes plant leaf images. (A: Grape Black Rot, B: Grape Esca (Black Measles), C: Healthy, D Grape Leaf blight (Isariopsis Leaf Spot).

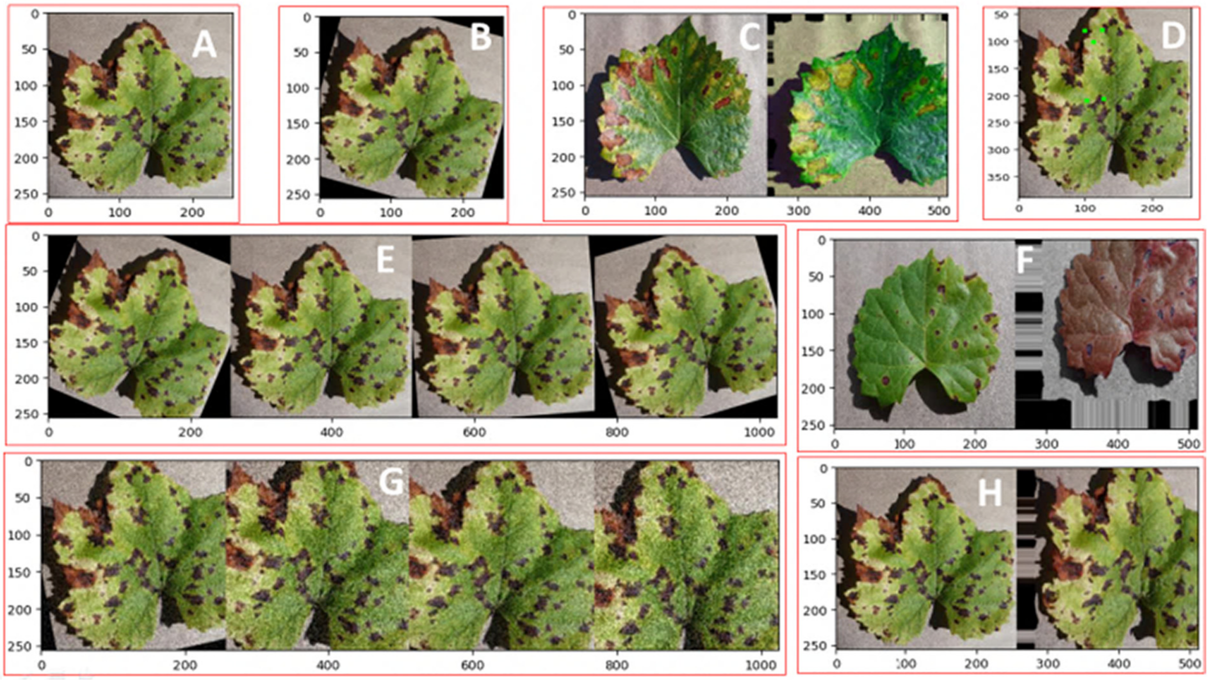


Fig 4. Multi-crops image augmentation (a) (A: Original B: Rotate, C: Color, D: Image Point, E: Hstack, F: Size G: Gaussian Noise, H: Shape).

to fully connected layers also known as the dense layer or fully connected layers.

3.1.5. Fully-connected layers

Fully connected layers are needed for extracted images classification features because of their special purpose. The softmax function predicts earlier extracted image attributes from preceding layers. Softmax is a multiclass classification activation function in the output layers. The neural network layer uses a multilayer perceptron model (MLP) as a classifier for two-class classification. The model with nonlinearity, which is introduced in the full vectors using rectified linear unit (RELU) activation. The versatility of class separation is greater when employing a support vector machine (SVM). The essentials of SVM are as described in the following:

$$Minimize\ \tfrac{1}{2} \sum_{j=1}^{n} W_1^2 + C \sum_{j=1}^{N} \xi j \tag{2}$$

Where C is the tuning measure, subject to the constraint $y_j\,(\overline{W}{\cdot}\overline{X} + b) \geq 1 - \zeta, j = 1, 2, 3\ldots$ N. The softmax parameter $\gamma = 1$ and $C = 1$ are used throughout training and test sets of the classification algorithm.

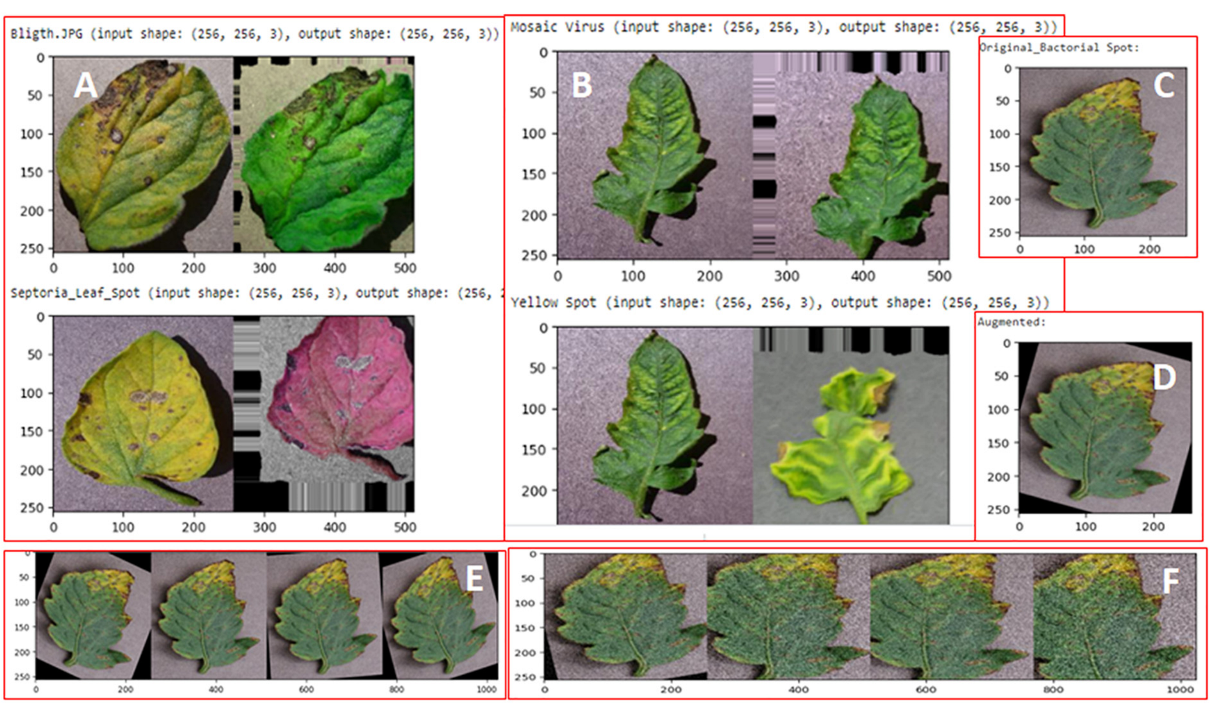


Fig 5. A B: H Stack, C: Original, D: Augmentation, E: Batch H stack, F: Adaptive Gaussians Noise.

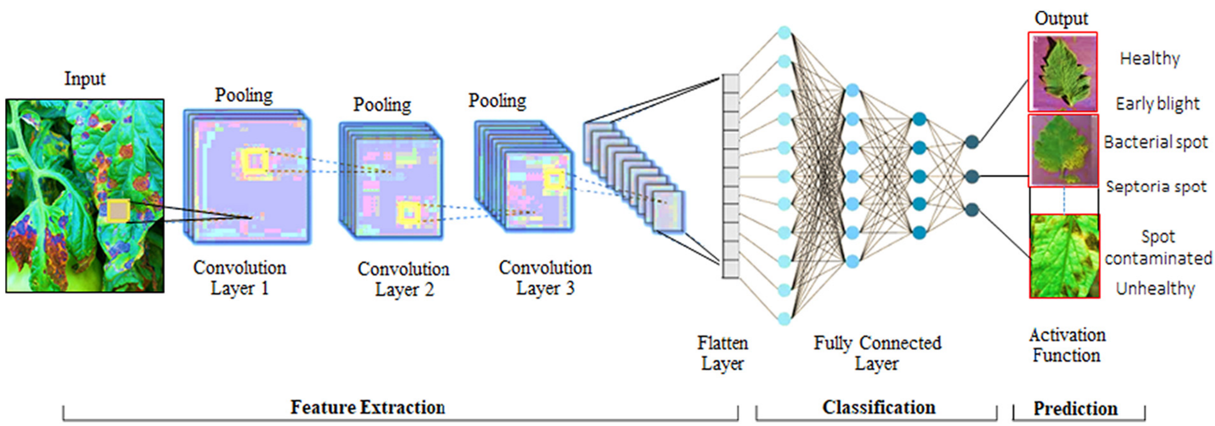


Fig 6. Proposed convolutional neural network CNN architecture.

The ConvNet architecture design's main component is its depth. By defining additional design parameters and growing the network depth continuously, by adding more convolutional layers that are doable by using extremely small (3 x 3) convolution filters in all layers. As a result, they've developed substantially more accurate ConvNet architectures that not only reach state-of-the-art accuracy on fixed dataset classification and localisation tasks, but are also applicable to other image recognition datasets, where they perform admirably even when utilised as part of relatively simple pipelines(Simonyan and Zisserman, 2015).Our ConvNets are fed a fixed-size 224 x 224 RGB picture during training. The only pre-processing we perform is removing each pixel from the mean RGB value determined on the training set. We apply filters with a very small receptive field 3 x 3 to send the image through a stack of convolutional layers. We also use 1 x 1 convolution filters in one of the configurations, which are a linear change of the input channels (followed by non-linearity). The convolution stride is set to 1 pixel, and the spatial padding of the convolutional layer input is set to 1 pixel for 3 conv. layers so that the spatial resolution is kept after convolutional. Five max-pooling layers, which follow part of the convolutional layers, do spatial pooling (not all the convolutional layers are followed by max pooling) Max-pooling is done with stride 2 over a 2 x 2 pixel window.

3.2. VGG16

The Convolutional Neural Network based VGG16 pre-trained models are used to improve the performance and classify the crop images as healthy and disease images. For quality detection and analysis of crop leaf images, the initial model transfers information from pre-trained VGG16 models. The Convolutional Neural Network (CNN) model retained new images of the field and learned to perform a model for disease detection and classification (Alencastre-Miranda et al., 2021).

The VGG model improved with large kernel-sized filters, with 11 and 5 convolutional layers with a 3 x 3-kernel filter size. The input image size is fixed at 224 x 224. Following image pre-processing, images were passed through a convolutional layer with a filter size of (3 x 3).For linear transformation of the input channel, the filter size is set to (1 x 1). The stride size is fixed to 1 and max pooling is performed with 2 x 2 sizes and stride set to 2. In the next steps, fully connected layers have the same configuration with 4096 channels in each layer. The final layer is the softmax activation layers, followed by the RELU activation functions (See Fig. 7).

3.3. Performance measure

The F1 score, accuracy matrix, and Receiver operating characteristic (ROC), as well as the area under the curve (AUC), are being used to evaluate segmentation performance (AUC). The performance of the classifier is measured using evaluation metrics.

3.3.1. Accuracy metrics

The model performance for all classes is accurately measured. The accuracy is calculated by adding the total number of correct predictions to the total number of predictions. The performance parameter calculation of precision and recall and F1-Score are measured. The accuracy is expressed in terms as follows.

$$AC = \frac{(TP + TN)}{(TP + FP + FN + TN)} \tag{3}$$

Where, TP is True Positive, TN True Negative, FN False Negative and FP False Positive Samples. The classifier performance measure using evaluation metrics are gives as;

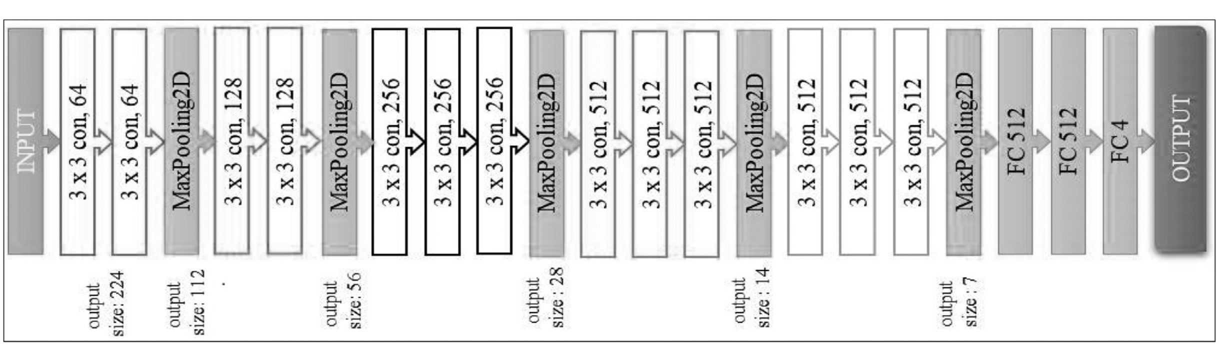


Fig 7. Proposed convolutional neural network (CNN) VGG16 architecture.

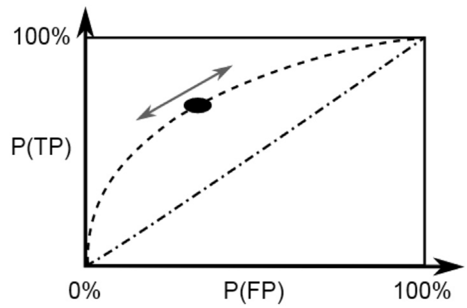


Fig 8. Receiver operating characteristics FP versus TP

Table 2
Parameter setting for trained the model

Hyperparameter	Value Setting
Crops	Grapes & Tomatoes
Convolutional Layers	13
Max Pooling Layer	5
Dropout Rate	015/0.25/0.50
Activation Function	Relu, Softmax
Epochs	20/25/30/40/45
Learning Rate	0.00001/0.0001
Image Size	224 x 224 x 3

$$TPR = (Sensitivity) = \frac{TP}{(TP+FN)}, TNR = (Specificity)\ \frac{TN}{(TN+FP)} \tag{4}$$

$$FPR = \frac{FP}{(FP+TN)} \tag{5}$$

Where, TPR is True Positive Rate, TNR True Negative Rate, and FPR False Positive Rate.

$$Precision = \frac{TP}{(TP+FP)}, Recall = \frac{TP}{(TN+FN)} \tag{6}$$

$$G{-}Mean = \left(\prod_{K=1}^{m} Recall_K\right)\frac{1}{m} \tag{7}$$

Here m represents the number of categories and G denotes the TNR and FPR accuracy ratio.

Mean average precision (mAP), which consists of Precision, Recall, and Mean, is the algorithm assessment standard employed. Image processing and detection rely heavily on the mAP. From the entire results, the accuracy has classified correctly. From the complete findings, the recall is correctly classified.

The F1 score is another important metric for evaluating the algorithm. It's precision and recall fundamental that's presented as follows:

$$F1\ Score = \frac{2 \times Precision \times Recall}{(Precision + Recall)} \tag{8}$$

3.3.2. Receiver operating characteristic

The receiver operating characteristic (ROC) curve is used to understand deterministic indications of categorization sorting as well as computational modeling challenges. The curve is a graph that shows the ratio of false positives to true positives under different standard limits (See Fig. 8).

A prototype also with largest true negative rate values was used to correctly categorize defectives, and the model with the highest true positive rate values was used to correctly classify healthily. To boost productivity by reducing processing time for training and testing, the MCC (Matthews Correlation Coefficient) is employed for the total computation. MCC is a criterion for categorizing complex data into distinct categories. MCC is a superior method to accuracy which only has significant importance if the true positives, true negatives, false negatives, and false positives outcomes are all positive. The MCC ranges from 1 (poorest judgment) to 1 (perfect predictions), with an MCC of 0 suggesting a random guess.

The model is tuned by the number of epochs, hidden layers, hidden nodes, activation functions, dropout, learning rates, and batch size. The model performance is affected by hyper parameter tuning. The term "hyper parameter tuning" refers to the process of repeatedly adjusting hidden layers, epochs, activation function, or learning rate. The model is fine-tuned to achieve the best accuracy while minimising the average loss.

The experimental analysis was carried out on Google research products on Google Colaboratory. The Colaboratory platform supports python programming, and nearly all of the Python libraries are uploaded and installed for research purposes. The Python 3 Google Compute Engine backend (GPU) with RAM of 12.72 GB and disc space of 68.40 GB is available while experimenting. The dataset is uploaded with the drive mounted, and the model is trained on the Google platform with high configurations. A Python convert to image function is used for converting all the images to an array and fetching images from the directory.

The processed images come from a directory, and all label images are transformed using the label binarized sklearn python package. The total number of images is divided into train and test using train-test-split python functions. The model parameters were set as shown in Table 2, and the model was trained to calculate all trainable and non-trainable parameters. The Adam optimization algorithm is used to train the deep learning convolutional neural network model. The algorithm optimized the sparse gradient noise issue.

The input network uses 224 X 224 images, and the batch size is 30 for grapes and 25 for tomatoes, respectively, and the same test is performed for different epochs with batch size and learning rate. In every polling layer with a 2 x 2-pool size and the RELU function utilized in the network, the model performs a max-pooling operation. The output of the last layer is a oftmax-activation multi-crop-developed prediction. During the network's training phase, hyper parameters such as learning rate and epoch size were adjusted. The average accuracy achieved was 98.40% for grapes and 95.71% for tomatoes, respectively. The learning rate is tested at different values to optimize targeted performance measured. The validation process is based on a total number of images from the multi-crop dataset. With the setting of different epochs and batch size, the accuracy improved and grew.

The crops-leaf images datasets are used to train the model and identification of class and category of disease with transfer learning techniques including VGG16. The original datasets are divided into training data 80%, validation data 10% and testing data 10%.

Table 3
Experimental results of the grape model for setting different parameters.

No. of epochs	Learning rate	Dropout rate	No. of images	Training loss	Training accuracy	Validation loss	Validation accuracy
40	0.00001	0.25	450	0.0897	0.9840	0.0486	0.9889
30	0.0001	0.50	450	0.1136	0.9585	0.0686	0.9867
45	0.00001	0.25	400	0.0995	0.9796	0.0529	0.9858
45	0.0001	0.25	750	0.0875	0.9696	0.0521	0.9853
30	0.0001	0.50	450	0.1326	0.957	0.0686	0.9843
40	0.001	0.30	600	0.1139	0.9606	0.0529	0.9831

Table 4
Experimental results of the tomatoes model for setting different parameters.

No. of epochs	Learning rate	Dropout rate	No. of images	Training loss	Training accuracy	Validation loss	Validation accuracy
25	0.0001	0.25	200	0.1643	0.9571	0.2627	0.9432
35	0.00001	0.20	180	0.2203	0.9281	0.3143	0.9013
30	0.00001	0.15	200	0.2624	0.9097	0.3345	0.8926
30	0.00001	0.25	200	0.3042	0.8983	0.3736	0.8849
30	0.00001	0.25	180	0.4871	0.8354	0.4149	0.8671
30	0.00001	0.50	200	0.5226	0.8255	0.4508	0.8538

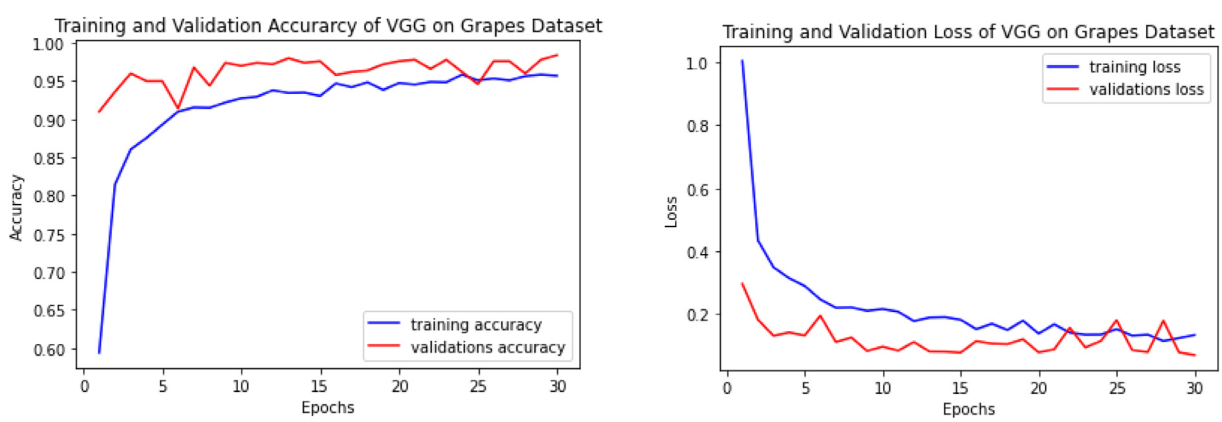
3.4. Training and validation accuracy

Training and validation accuracy is measured by setting different values while training the model. The experiments were carried out at Google Colaboratory on the available RAM of 12.50 GB. While performing the experiment, different values are set for the following: the number of epochs, learning rate, dropout rate, and the number of images noted as training loss, training accuracy, validation loss, and validation accuracy. A model's performance is measured and verified on the grape and tomato crops' leaves. Table 3 and Table 4 show the details of the results of experiments carried on grapes and tomatoes, respectively.

3.5. Figures and graphs

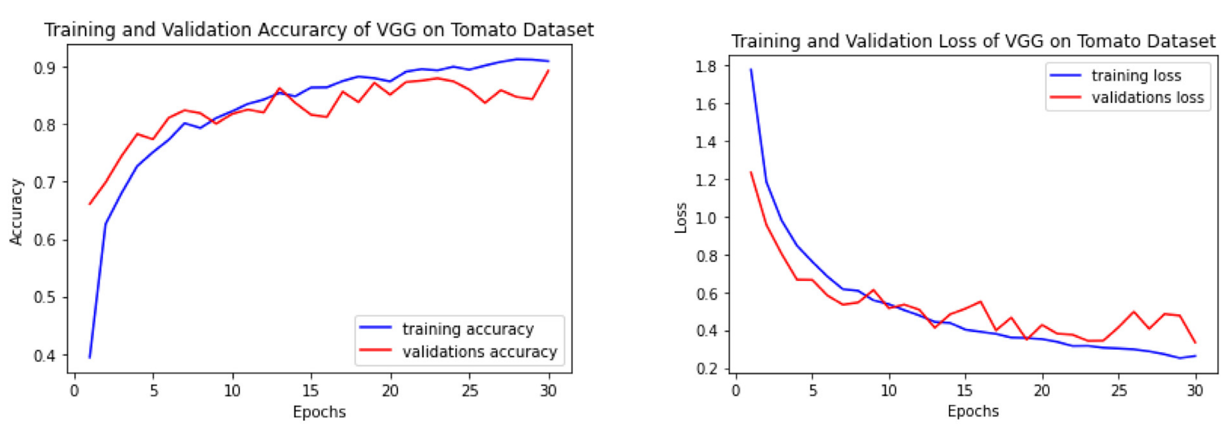
A model's performance is measured and verified with training, testing, and validation methods for grapes and tomatoes leaves. Fig 9 and Fig. 10 show the training and validation accuracy and loss of the grape leaves and tomatoes, respectively.

The confusion matrix has been used to measure the performance parameter for grapes and tomatoes leaves, as shown in Fig. 11. Experiment with the facts collected. The suggested approach is tested using our grapes and tomatoes image datasets, which were taken in a real-field with various backdrop and light intensities, similar to the tests done in Section 4.4.



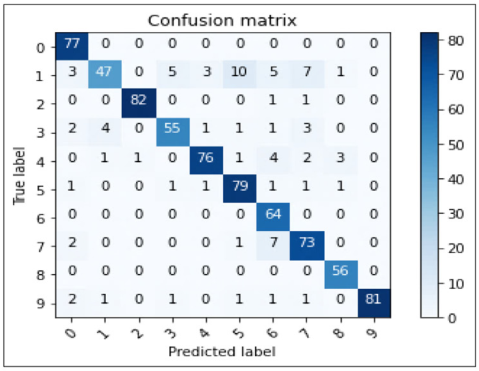
(a) **(b)**

Fig 9. Training and validation. (a) Accuracy and (b) loss of VGG16 grapes.

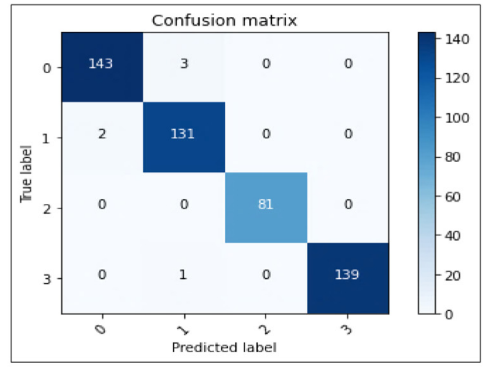


(a) **(b)**

Fig 10. Training and validation. (a) Accuracy and (b) Loss of VGG16 tomatoes.



(a)



(b)

Fig 11. Confusion matrix. (a) Tomatoes and (b) grapes.

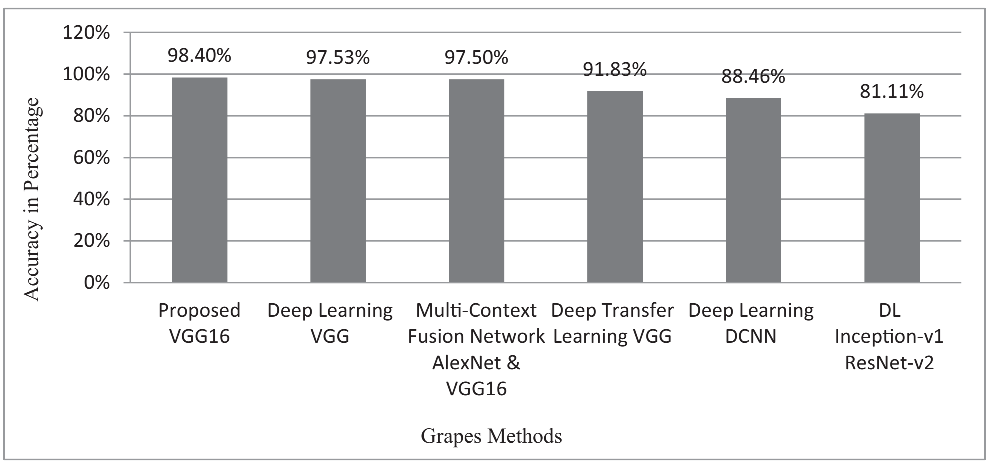


Fig 12. Comparison between different model vs accuracy in percentage(%) with proposed VGG16 grapes.

To assure the diversity of sample images and avoid the over fitting problem, data augmentation techniques such as random rotation, flipping, and scale transform, as well as associated pre-processing activities, are used to extend the training samples. The processes are described in more detail below.

1. Image resize: The total images scaled into size of 224 x 224 pixels, for the model fit and minimum 200 images taken from each healthy and unhealthy category are augmented with data augmentation methods.
2. Image pre-processing: Image pre-processing is used to darken the different lengths of the image data, going to bring them into ratio

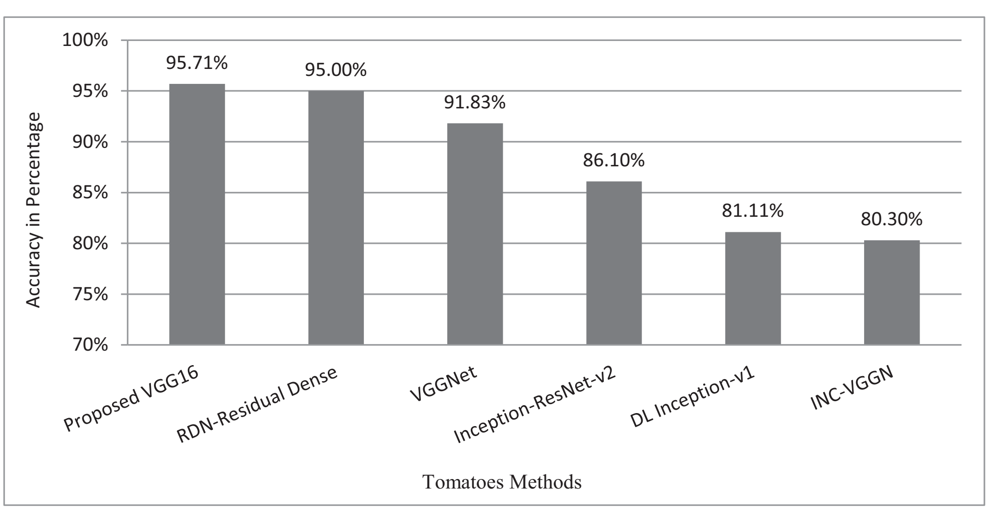


Fig 13. Comparison between different model vs accuracy in percentage (%) with proposed VGG16 tomatoes.

and retaining the initial images' knowledge formation while attempting to prevent image deformation.
3. The dataset partition and training. In this section a selection of random sample images for proposed experiments and calculated with carried out the result as per Section 4.4.
4. Validation and testing. The testing is done on the images that were used to evaluate the model, and new images from outside modeling are used to check the model effectiveness. The output results are compared to the real categories, the effectiveness of the control that goes with them is computed.

The residual block collection and DesnseNet used in task of tomato leaf disease identification with RDN restructured model. After input image normalizing and adding the convolutional layer residual modules dense layer classify the tomato disease images with 95% accuracy disease dataset (Zhou et al., 2021). The public data set of the AI Challenger Competition in 2018 used the Inception-ResNet-v2 model using the RELU activation function, with an accuracy of 86.1%. (Ai et al., 2020), under complex background conditions, the accuracy of VGG Net is 91.83 %. One more approach to INC-VGGN rice disease detection with an average accuracy of 80.38% for both "Phaeo- sphaeria Spot" and "Maize Eyespot" diseases (J. Chen et al., 2020) (See Fig. 13).

4. Conclusion

In this paper, there are two types of crop disease leaves were collected and prepared as a dataset with available data. The techniques of data augmentation, dataset pre-processing, training, and testing are applied to the convolutional neural network-based VGG16 model. The proposed model is built and tested to improve the performance measured and compared. The evaluation metrics parameters are higher and increased as compared to other available datasets and methods. Therefore, our proposed research work increased accuracy for grapes by 98.40% and for tomatoes by 95.71%. Always improving the performance of on-field crops, leaf images and diseases classification and analysis is a critical step, but with our model achieved the highest performance, which supported agricultural development. The major focus of research is to provide advancement in the agriculture sector and an increase in food production. The collection and preparation of genuine datasets and applying to the deep learning models with multiple crops leaves images is a future target. In the future, the use of Inception V3 and ResNet-based CNN models for much deeper analysis of crop images is anticipated. Our work encourages and stimulates farmers, which ultimately raises farm income and helps to build up powerful countries.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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