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Plant Disease Detection Using Visual Geometry Group Technique Based Deep Learning Approach

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Abstract: Disease detection and prevention is a prevalent factor affecting crop yield and productivity. Deep learning and image processing techniques have become prominent smart farming tools. Therefore, identifying plant diseases from leaf images has been an existing issue in most farming problems. This research focuses on detecting these diseases effectively using deep learning models such as transfer learning based on VGG19 approaches. The proposed VGG19 transfer model has been trained using 42000 images and tested against 43000 unseen samples. This model could classify the disease images and could identify the disease type for the unhealthy specific images. VGG19 with transfer learning has been applied for training the image classification and disease detection based on large datasets of around 60 million images of different kinds of leaves. VGG19 is one of the CNNCNN-based architectures deep-learning neural network Image classification based on VGG model is performed using ReLu and Tanh activation functions. The image dataset consists of unhealthy leaf images of the following leaves apples, corn, potatoes, and grape. The transfer learning neural network model is applied to identify and detect diseases at the early stages of their growth and was proposed. This proposed system utilizes leaf images as the key factor in training the model and later tested with unseen samples for the prediction of diseases to facilitate plant disease detection through image classification techniques. The proposed Leaf Specific VGG model provides a solution for monitoring symptoms of plant leaf disease. The learning rate, activation functions, epochs, batch size, and dropout layers are the set of significant hyperparameters of this model. The proposed VGG model attained the optimal prediction accuracy of 99.76% for the datasets containing 85000 images than other existing methods like SVM, CNN, ImageNet, image processing methods, and VGG16.

Index Terms: Transfer Learning, Visual Geometry Group, Transformer neural network, Image recognition techniques, Pathogens, Hyper Parameters, Epoch, Batch Size, Activation Functions.

1. Introduction

Plant diseases deteriorate the overall yield and growth of the plan. [1,2]. It destroys most of the functions in the plants from their original purpose. Plant diseases are a prevailing factor in the agriculture sector, affecting crop production and economic profit [3]. It is efficient that Plant diseases can be identified in the earlier stage to avoid losses to the agricultural economy. Plant diseases are of wide range, in this work they have used different types of plants to identify the diseases that target the plant's leaf at an alarming rate [4]. The common plant diseases identified are Black spots, leaf spots, Blight, and canker. Leaf spots can be caused by the fungal pathogen. The leaf spot may occur in the 1.25-diameter veins on the leaves. The lesions are surrounded by veins and the shape of the veins is angular in general [5]. Blight is the most common disease occurring in weak plants. It may fall suddenly yellowing on the parts of the plants. Blight cannot be controlled. Instead, it can be treated by burning all the plants affected by this disease [6]. Rice plants and grasses are the most common plant affected by early blight and late blight respectively [7]. Cankers can enter into plants through stomata, and light, and leaves big wounds on the leaves [8]. There is no way to cure this citrus canker disease.

Plant disease detection is the process of identifying the pathogens causing the plant to reduce the work of monitoring big land plants [9]. Detection of plant diseases is of high concern in the agricultural field to ensure food safety and security, robust growth of harvesting, the plant's good health status, improve plant nutrition, and increase intensity. Weather conditions can be controlled through the process of plant disease detection. Early-stage protection is the easiest way of achieving the goal to protect our environment [10]. An immediate understanding of plant disease detection can provide the appropriate monitoring of plant growth [11]. The plants are trained and tested using preprocessing methods with the help of laboratory images and open-source images. Those trained sampled images are classified using feature extraction and classification layer .

Section2 represents the literature review for the plant disease detection. **Section 3** represents the materials and methods with the dataset, preparation of data, plant disease detection using the method VGG19 of CNN extraction and the structure of VGG19. **Section 3** represents the Algorithm of VGG19, Feature extraction of model with data augmentation, Feature extraction of model without data augmentation and Finetuning the model. **Section 4** represents the data acquisition and preprocessing, Evaluation metrics and Accuracy and Comparison of VGG19 model with existing algorithms. **Section 5** represents the results of both disease detection and disease classification. **Section 6** represents the Discussion of plant disease classification and future work.

2. Literature Review

In this section, the review of two types of plant disease detection will be introduced and discussed. The first type is direct methods use serological methods and molecular methods. Collecting the leaves may vary depending on their process [12]. The leaf images can be collected through the in-built data and processing data like capturing the images. Microscopic evaluation is the most common direct method of identifying plant diseases.The diseases can be identified through the visible eye contact of changes in size, color, shape, and characteristics of plants These identifiers are widely used for the depiction of individual identification [13-16].

The second type is indirect methods, which are the over-controlling preprocessing of diseases using advanced methods. Some of the indirect methods of plant disease detection are imaging techniques, spectroscopic techniques, and gaseous metabolite profiling [17]. Statistical parameters can be maintained by feature extraction [18-19].

Nowadays, the real-time environment faces many challenges in the detection of plant diseases. The huge number of datasets consists of a huge number of convolutional architectures with collaborated techniques. Pre-processing methods need better convergence methods for the classification of pre-trained weights [20]. Increasing the productivity of crops, improving the technologies, and maintaining the crop with the help of the force of sustainable methods may improve and control the problem in the agricultural field [21-23].

Plant disease detection methods were proposed in the way of digital and analog methods [24]. The traditional methods have lower sensitivity of finding the diseases in the plant and require the expertise to control the problem in the connectivity of time and labor intensive [25]. In the part of overcoming these problems, deep neural networks are applied.

Image processing analyses are used to determine the influenced or affected region of the plant. Image acquisition, image preprocessing, image segmentation, image thresholding, and image augmentation methods are supported for the performance of detection [26]. The determination of the yield and quality of plants is carried out with the help of image processing methods and is increasingly presented using image-based identification of plant diseases [27,28]. Clipping of images may segment the diseases from the classified images and smoothing can be done by the image smoothening method. And improve the contrast of the image with the help of image enhancement [29]. This approach mainly focused on traditional plant diseases and pest approaches [30].

The deep learning model promises a lot of problems to improve the higher accuracy in their determination of research works [31]. Greater transparency for the plant disease detection problem can be obtained to eliminate the research gaps before the symptoms appeared on the plant. Agriculture in India manifests most of the plants, pulses, and grains in the sector [32]. Deep learning approaches mainly focused on fine-tuning the hyperparameters like batch size, epoch, learning rate, activation function, loss function, and computational time. Deep learning algorithms exploit the automatic functionalities of neurons. Several deep learning models compare the different numbers of kernels, filters, and pooling and compare them in the form of developed models. Deep learning approaches mainly focused on identifying the diseases of the stem, root, and leaf, and detecting the sick area of the plants. Deep learning architecture uses different learning rates and optimizers for the early detection of disease to eliminate crucial agriculture [33].

3. Materials and Methods

A. Dataset

It consists of datasets acquired from different kinds of plant-like apples, corn, potato, and grapes of a total of 85000 image samples with 38 classes transmitted over 14 crop species and 26 kind of disease about both healthy and non-healthy plants. This dataset is supplemented for the testing, validation, and training with different classes of the plant's diseased and non-diseased leaves [34]. Concerning the consistency and reliability of the dataset, the model achieves better accuracy. **Table1** represents the different kind of plants with their symptoms of diseases and number of images used in the dataset. The plants present in the dataset are Apple, Potato Corn and Grape. The total number of dataset taken from the PlantVillage datasets are approximately 15000. The common diseases of plants are Black rot, Leaf blight, Grey spot. The dataset from the Plant Village repository has been utilized for model training and testing. Images of both healthy and diseased plant leaves make up the widely used PlantVillage dataset, which is used to detect plant diseases. For the purpose of developing and testing machine learning models for the identification of plant diseases, it can be a useful tool.

Data Preprocessing: To enhance model generalization, preprocess the photos by shrinking them to a consistent size, standardizing pixel values, and, if needed, expanding the dataset.

Model Selection: Convolutional neural networks (CNNs), which excel at image classification tasks, are a good choice for machine learning models for plant disease diagnosis.

Training: Using the previously processed photos from the PlantVillage dataset, train the chosen model. To evaluate the model's performance, use part of the dataset for training and put aside another piece for validation.

Evaluation: Utilizing the validation set, analyze the trained model's effectiveness in identifying plant diseases by computing measures including accuracy, precision, recall, and F1-score.

Fine-tuning: To further enhance the model's performance, adjust its hyperparameters in light of the validation outcomes.
Testing: To determine whether the finished model can generalize to new, untested data, test it on a different test set from the PlantVillage dataset.

Table. 1. Different diseases of plants in the plant village dataset with their symptoms and the number of images in the dataset

Different types of the plant	**Grape plant**	**Apple plant**	**Corn plant**	**Potato plant**
Diseases name	Pierce disease of grape Black rot ESCA	Cedar disease Rust Black rot	Cercospora leaf spot Northern leaf blight Gray leaf spot	Early blight Late blight
Disease symptoms	Yellow around the leaf margins, pale yellow lesions, Downward rolling of leaves	Twigs covered with a powdery mass Small patches of white or gray powder	Grayish tan lesions The darker border on the lower leaf	Necrotic ring spots roughened rings of darker brown skins
Number of images in the dataset	4062	3102	3852	2152

B. Data Preparation

The provided training data can be ordered by the classification and localization error with the combination of multiple convolutional networks. Plant disease detection can be analyzed by the data-centric annotation for the performance of strategy and consistency [35,36]. The clear color variation between the normal and abnormal leaves is sustained with the boundary separable method. **Fig.1** represents the elements of model VGG19, Inception and ResNet modules. Both input layer and output layer are introduced in the convolutional and max pooling layers in the form of Conv2D and MaxPooling2D. Color lesions must be allocated to the normal area which is similar to the end of the leaf. The abnormal method destroys the inexplicable coverage and cannot explain the given model's vested authority [37].

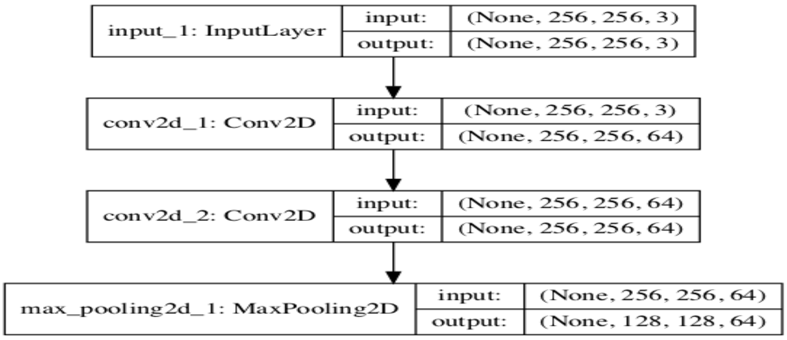


Fig. 1. Elements of VGG model, Inception, and ResNet modules

C. Plant disease detection using VGG19

VGG19 network is mainly applied for image classification in numerous fields with the help of large datasets with around 60 million parameters and 650,000 neurons. VGG works for multi-class classification, achieving or identifying more than 2 plant diseases. The VGG model mainly dissolves feature extraction of the input images and classifies the diseases present in the leaf images according to those features [38]. Several studies show that the VGG model from convolutional neural networks helps to overcome the problem with greater accuracy, specificity, and sensitivity. Without any further delay, the farmers can take action on the foundations of treatment and consider the clear direction of the deep learning models. The training procedure of the VGG model prepares the images initially to acquire the image classification where the data can be classified to propose the best models [39].
The mathematical function TanH (Hyperbolic Tangent) squashes its input to a range between -1 and 1.TanH captures both positive and negative correlations in the data, which aids the neural network in learning complex patterns for plant disease detection. Rectified Linear Unit, or ReLU, is an additional activation function with a lower computational complexity. It applies zero to all of the input's negative values. ReLU is frequently utilized in deep learning because it can avoid the vanishing gradient problem and speeds up network learning.To enhance the model's capacity to recognize and identify patterns in the image data, TanH and ReLU activation functions in neural networks for plant disease detection can be used. Accurately detecting plant diseases can be improved by experimenting with different configurations of these functions.

D. Structure of the VGG model

The VGG network system has five convolutional layers and fully connected layers with unique characteristics in nature. Comparing the models of CNN with 1 convolutional layer, 2 convolutional layers, N convolutional layers, and VGG-19 pre-trained models to obtain the best accuracy results [40]. The first layer is a standard layer that can connect to the infrastructure of the second layer. The second layer is the max pooling layer with which the maximum value can be connected to the feature map and achieves the pooled layer of the first layer to the feature map. The Third layer is the layer that can be directly connected to the 4th layer called the last convolutional layer and the output layer is the activation function called the softmax layer that can predict the multinomial probability distribution. VGG is the subset of deep learning neural networks with 16 convolutional layers and 3 fully connected layers [41]. Figure 1.1 shows the Architecture of VGG convolutional neural network for the classification method.

A plot of the model architecture is created providing a different perspective on the same linear progressive of layers.

Figure 1.1: Architecture of VGG convolutional neural network for the classification method

ConvNet Configuration					
A	**A-LRN**	**B**	**C**	**D**	**E**
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
Input(224*224 RGB image)					
Conv3-64	Conv3-64 LRN	Conv3-64 Conv3-64	Conv3-64 Conv3-64	Conv3-64 Conv3-64	Conv3-64 Conv3-64
Maxpool					
Conv3-128	Conv3-128	Conv3-128 Conv3-128	Conv3-128 Conv3-128	Conv3-128 Conv3-128	Conv3-128
Maxpool					
Conv3-256 Conv3-256	Conv3-256 Conv3-256	Conv3-256 Conv3-256	Conv3-256 Conv3-256 Conv3-256	Conv3-256 Conv3-256 Conv3-256	Conv3-256 Conv3-256 Conv3-256 Conv3-256
Maxpool					
Conv3-512 Conv3-512	Conv3-512 Conv3-512	Conv3-512 Conv3-512	Conv3-512 Conv3-512 Conv1-512	Conv3-512 Conv3-512 Conv3-512	Conv3-512 Conv3-512 Conv3-512 Conv3-512
Maxpool					
Conv3-512	Conv3-512 Conv3-512	Conv3-512 Conv3-512	Conv3-512 Conv3-512 Conv1-512	Conv3-512 Conv3-512 Conv3-512	Conv3-512 Conv3-512 Conv3-512 Conv3-512
Maxpool					
FC-4096					
FC-4096					
FC-1000					
SoftMax					

3. Algorithm of VGG model

A. Algorithm of VGG model

In feature extraction, the image dataset cannot be differentiated into testing and training processes. Instead of that, it can be classified into training and validation sets [42]. Feature extraction uses the tensor flow as a backend to import all the images into the layers, models, and optimizers

[43]. The 2 ways of using the feature extraction methods are feature extraction without data augmentation and feature extraction method with data augmentation. **Table.2** represents the step by process of plant disease detection using VGG19. Consider all plant leaf images as input.

B. *Feature extraction without data augmentation*

The pre-trained network runs all the images with the 3d convolutional base to get 2D arrays. Data augmentation does not take place in this method to not change any features in the images [44,45]. This function is extracting the features on returns (features and labels). Varied collection of plant photos from actual agricultural environments are gathered. In order to guarantee the model's resilience and capacity for generalization, the dataset ought to comprise pictures of diverse crops, illnesses, and environmental circumstances. To guarantee uniformity in image size, format, and quality, the real-world dataset are pre-processed. Plant disease detection model's performance using common assessment metrics, like accuracy, precision, recall, and F1-score, on the real-world dataset are assessed. To determine how well the model generalizes, comparing the metrics to found on the original dataset. Utilize cross-validation on the real-world dataset to evaluate the consistency and dependability of the model on various data subsets.

C. *Feature extraction with data augmentation*

Adding dense layers to the 3D convolutional base, the pre-trained model is used in this method [46]. This process makes to allow data augmentation. Using data augmentation, the feature extraction method becomes slower. Image data generator always multiplies the training catagen and validation datagen in the feature extraction [47]. In train data generator, batch size, target size, and class mode look into possible regulations in dealing with the allegation formation [48].

D. *Fine-tuning of VGG19*

Fine-tuning the VGG19 model with data augmentation improves the accuracy of the transfer model variable. Importing the VGG model passes the necessary arguments [49]. Fine-tuning the model committed to high learning rates The weights of the pre-trained networks cannot update the training datasets in the form of fine-tuning [50]. After training the model, the performance of the model can be evaluated and predicted on new data using the test set. This technique is usually performed or recommended using large parameters similar to the original and training datasets. If VGG can be used as a backbone network, it can also use the pre-trained weights to initialize the same network architecture. It also pre-trained the autoencoder but was a bit lost in the tasks. Some terminologies prepare the segmentation tasks for the necessary weights [51].

Table. 2. Algorithm : VGG19 model

Algorithm : VGG19 model Step1: Input: Plant Village Dataset of Apple plant, corn plant, Grape plant, Potato plant, and disease control samples. Step2: Define the size(s), color©, sharpness(S), and leaf length(l) of the plant and create a leaf color chart(L). Step3: Output: Disease Identification of Healthy Leaves and Non-healthy leaves of Plants and accuracy of disease classification. Step4: Collect the dataset and do the Data Preparation For each dataset If VGGNet >ImageNet >80%

```
top-1 accuracy
Else
83% faster than ResNet-50
Higher accuracy
Else
100% faster than ResNet -101
Higher accuracy
   Plant village dataset = 54620 leaf images
               Fix 224*224*224 RGB image
                        Stride fix to pixel
               Do RGB value - each pixel
Stride fixed to 1 pixel
    While Padding is 1 pixel = 3*3*3
Window size = 2*2*2
1st layer = 4096(ReLU)
2nd layer = 4096(ReLU)
3rd layer = 1000(Softmax)
            1st layer= 2 max – 512
Train Batch size = 256(M = 0.9, L2 = 0.0005, D = 0.5)
Learning rate = 0.01 – 10
Train Image size {
S= 256,
Differ S(Smin, Smax) = (256, 512)
}
                        Validate Image size {
                                                            s= 384, then 224*224*224
}
Healthy leaves= 32,460
Non-healthy leaves = 22,160
No.of.Epochs =500
Total Weight = 19 layers
End
```

4. Experimental Setup

A. *Data Acquisition and Preprocessing*

The six augmentation techniques for increasing the data size are image flipping, Gamma correction, noise injection, PCA color augmentation, rotation, and Scaling. The ability of our models to provide a way to predict the correct crop-disease pair, given 38 possible classes, is how we evaluate their performance. The best-performing model achieves a 99.87 percent overall accuracy, demonstrating the technical feasibility of our approach. The findings are the first step toward developing a VGG plant leaf disease detection system. **Figure 2** represents the proposed workflow model of plant disease detection. The dataset has been loaded and trained on the image processing data. The plant images are extracted in the form of feature extraction map. The preprocessing methods are trained the classifier to obtain the classification problem. Activation function and Loss function are applied to the model to generate the images. The images are tested and the model has been trained with the pretrained weights of images after applying the functions. To obtain an understanding of the model's performance and pinpoint any possible weaknesses or areas for enhancement, the predictions made by the model on the real-world dataset are visualized.

VGG is a super simple ConvNet architecture achieving more than 80% of accuracy on image-net with a stack of 3 stages conv and ReLU. Figure1 describes the proposed workflow diagram for the plant disease classification.

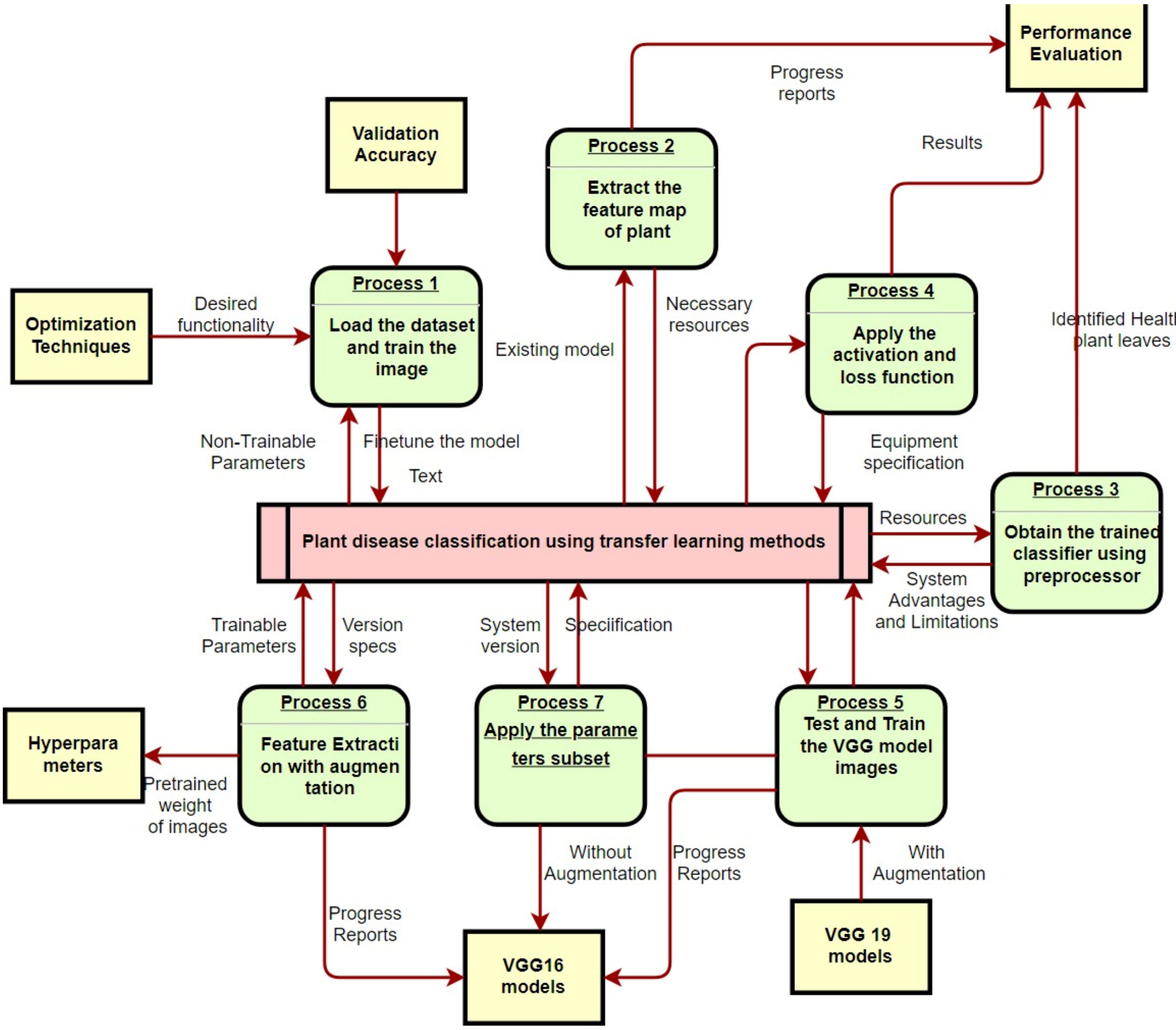


Fig. 2. Proposed workflow diagram for the plant disease classification.

B. *Evaluation Metrics and Accuracy*

Evaluation metrics will be varying depends on their study in a particular study. The strength of our metrics are as follows:

High Accuracy: Draw attention to the model's ability to correctly identify photos as healthy or unhealthy if it achieves a high overall accuracy.
Specificity and Sensitivity: To demonstrate the model's efficacy in class distinction, talk about its specificity—the capacity to accurately identify healthy plants—and sensitivity—the capacity to correctly identify ill plants.
resilience: Stress the model's resilience and generalizability if it regularly performs well across many datasets or settings.
Efficiency: Mention the model's computational efficiency as a strength since it can help the model work better in practical situations.The common evaluation metrics can be calculated using accuracy, precision, recall, mean average precision, and F1 score based on precision and recall.
The limitations of our metrics are as follows:
Overfitting: Take steps to prevent the model from doing well on training data but failing to generalize to new, untested data due to overfitting. This can be a very big drawback, particularly for complicated models.
Unbalanced Data: Talk about how the model's performance and the accuracy of its metrics may be impacted if the dataset is unbalanced, meaning that there are more samples from one class than the other.
Interpretability: If the model is of the "black-box" variety (deep learning models, for example), discuss how difficult it may be to understand its conclusions, which may restrict its use in specific situations.
Table 3 represents the Accuracy of potato plant with the application of different deep learning models for the different levels of epochs.
Accuracy

Accuracy is the most commonly used evaluation metric for image classification problems due to its simplicity.

For binary classification, the concept is the same, but it consists of the following items:

•True Positive (TP): This is the number of positive class problems predicted correctly.
•True Negative (TN): This is the number of negative class problems predicted correctly.
•False Positive (FP): This is the number of positive class problems predicted incorrectly. In the probability of expression, it’s known as a Type-I error.
•False Negative (FN): This is the number of negative class samples our model predicted incorrectly. In the probability of expression, it’s known as a Type-II error.
Accuracy = (TP+TN) / (TP+FP+TN+FN)
Precision = TP / (TP+FP)
Recall=TP / (TP+FN)
F1−score = 2 ∗ (precision ∗ recall) / (precision + recall)

Table 3: Accuracy of various models of the potato plant

DL models	**First 20 Epochs**	**First 30 Epochs**	**First 40 epochs**	**Average training time**
CNN	0.95	0.92	0.97	2
GoogleNet	0.62	0.83	0.95	4
ResNet50	0.94	0.98	0.98	13
VGG16	0.33	0.33	0.33	17
VGG19	0.97	0.98	0.99	20

C. *Performance comparison of existing algorithms*

The algorithms like transfer learning, machine learning, VGG, and CNN models are applied and compared with the diseases of the corn plant of their results. Figure3 explains the comparison chart of our model VGG19 of corn plant with existing models.The existing models includes the transfer learning, SVM, VGG16 and CNN.The corn plant are verified majority to expose the results of our particular models. Figure 4 shows Diseases of different apples along with the models like EfficientNetB7, DenseNet, VGG19, and ResNet50. The major diseases identified through our model presented in the apple plant are apple scab, black rot canker, Alternaria leaf blot.

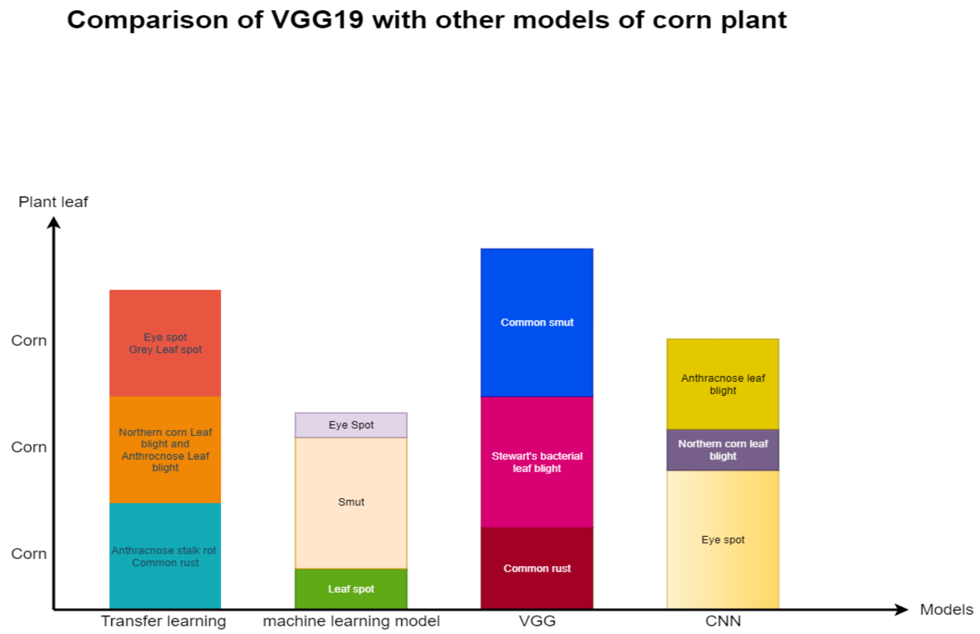


Fig. 3. *Comparison of VGG19 with other models of the corn plant*

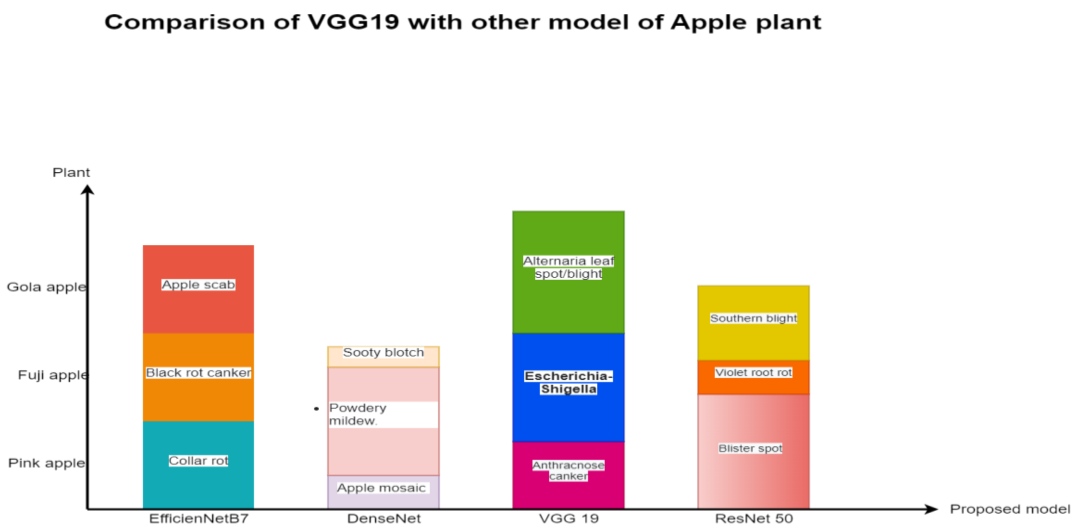
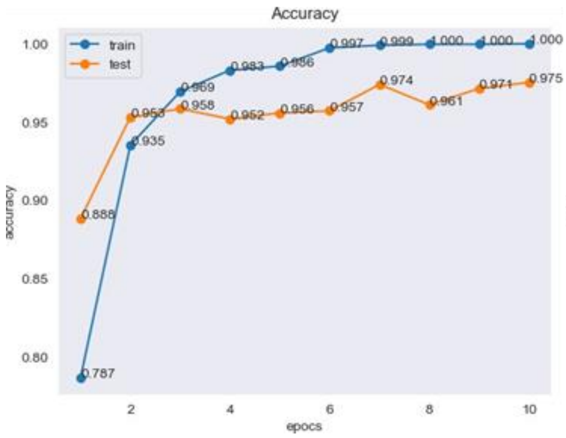


FIG.4. *Diseases of different apples along with the models like EfficientNetB7, DenseNet, VGG19, and ResNet50.*

5. Results

A. *Disease Detection*

Deep learning widely numerous methods for detecting and classifying plant diseases, namely convolutional Neural Networks, Recurrent Neural Networks, and deep convolutional are some of the stable approaches acquired by most researchers. Figure 5 shows the accuracy comparison between the training and testing accuracy to the epochs of sorn plant. The corn plant has the 100% of training accuracy and 97.5% of testing accuracy. Training the model has increasing accuracy than the testing accuracy. Figure 6 represents the loss values of apple plant with its epochs for the both training and testing process. The loss values of training process is 0.0 and loss values of testing process is 0.39in their perspective results. The VGG model is represented to suit both healthy and unhealthy leaves and the images are used to train and test the algorithm for both kinds of leaves together and the output is determined by the input leaf.



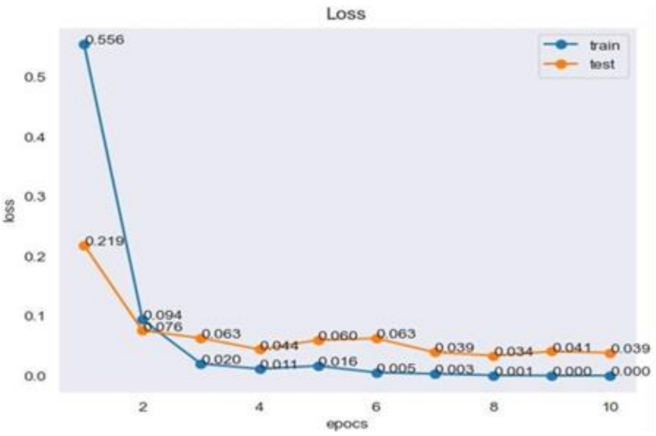


Fig. 5. Result: Corn – Accuracy with its epochs Fig. 6. Result: Apple – Loss with its epochs

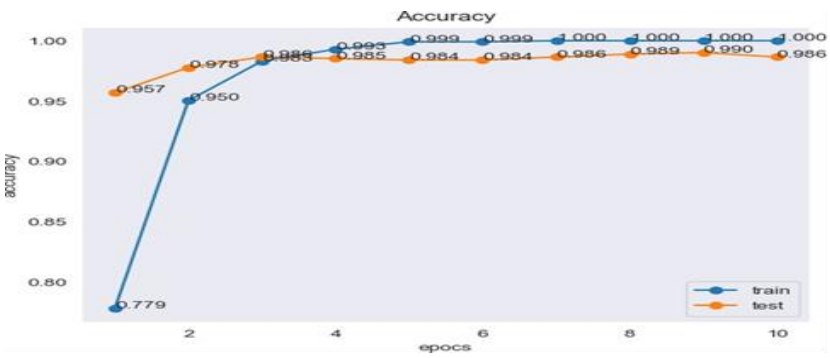


Fig. 7. Result: Apple – Accuracy with its epochs

B.Disease classification

The improvement of network design and lower learning rate may make the testing accuracy and training accuracy for the epoch stop consecutively. Image classification, speech recognition, natural language processing, object detection, and recommender systems are some of the broad applications of deep CNNs. Figure 8 represents the diseases of grape with its accuracy and their epochs. The diseases of grape include Black rot, Black measles and Leaf spot. Figure 9 shows the disease classification of corn with its accuracy and their epochs. The diseases include Cercospora leaf spot gray, Common rust and Northen leaf blight. Figure 10 demonstrates the classification of potato disease with its accuracy and epochs. The diseases of potato plant include early blight and late blight. Figure 11 represents the diseases of apple with its accuracy and epochs. The diseases of apple include Apple scab, Black rot and cedar apple rust. Deep learning enables to transfer of information from a pre-trained model into a new one. Sentiment classification, activity recognition, plant classification, and software defect prediction are used in various applications for deep learning.

Fig. 8. Result: Grape – Accuracy with its epochs

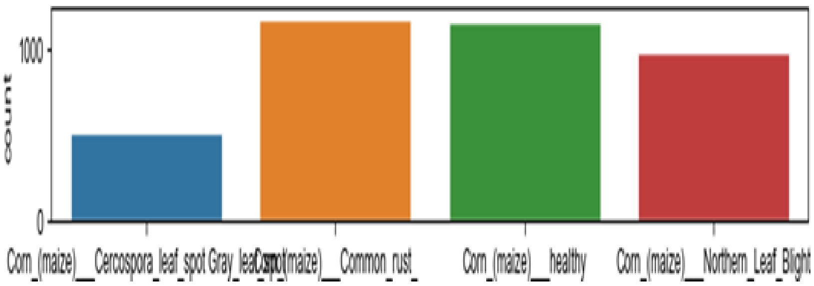


Fig. 9. Result: Corn(Maize) – Accuracy with its epochs

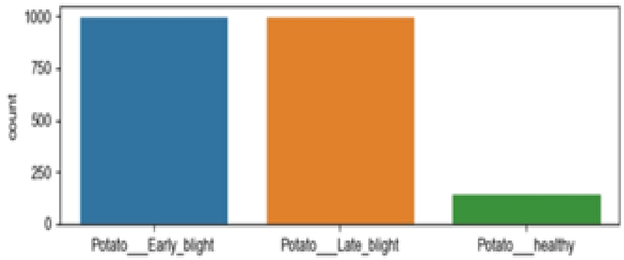


Fig. 10. Result: Potato – Accuracy with its epochs

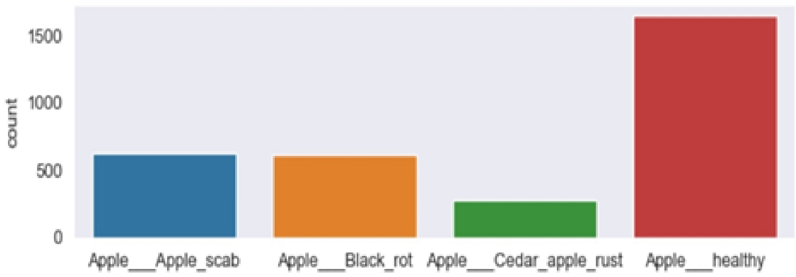


Fig. 11. Result: Apple – Accuracy with its epochs

Table. 4: Different metrics in the validation loss

Category	Val_loss	Val_mse	Val_mae	Val_mape
Apple	0.2465	0.2465	0.2465	123228376
Corn	0.0211	0.0211	0.0253	12651115
Grape	0.0043	0.0043	0.0067	3330437.5000
Potato	0.0129	0.0129	0.0198	9884743.0000

4.3. Activation function

The model training used different activation functions namely the Dense layer, Flatten layer, RELU function, and mainly softmax layer. The SoftMax activation function is used for the output layers. This activation function is a kind of logistic regression and is capable of manipulating the inputted vector into the output layers [Flatten(), Dense(4, activation function='Softmax')] as a new vector with a probabilistic distribution to the value of 1. This function is mainly calculated as the weighted sum of inputs along the threshold value to the output of the transfer function. When we closely look at Table 4, the different category of plants with their appropriate validation loss to manifest with the other validation progress report in the particular time were demonstrated. Table 5 shows the Learning rate reduction of different kinds of plant in the validation metrics.

4.4. Loss function

VGG loss is the kind of loss function that mainly depends on the RELU activation function. This VGG loss is mainly concentrated in real images and generated images. The specifically used algorithm in the loss function is logistic regression for the image classification problem L1 and L2 are the two common loss functions in neural networks to minimize errors. Binary cross entropy loss and log loss are the common loss function used in the VGG model. L1 loss is better than L2 loss for the shrinkage coefficients to zero value and L2 loss leads to the shrinkage value of evenly distributed. L1 is more robust due to the absolute values of weights and L2 loss proceeds from the square values of weights. Figure 12 represents the loss function of apple plant with its epochs between the training and testing process. Figure 13 represents the loss function of corn plant with its epochs between the training and testing process.

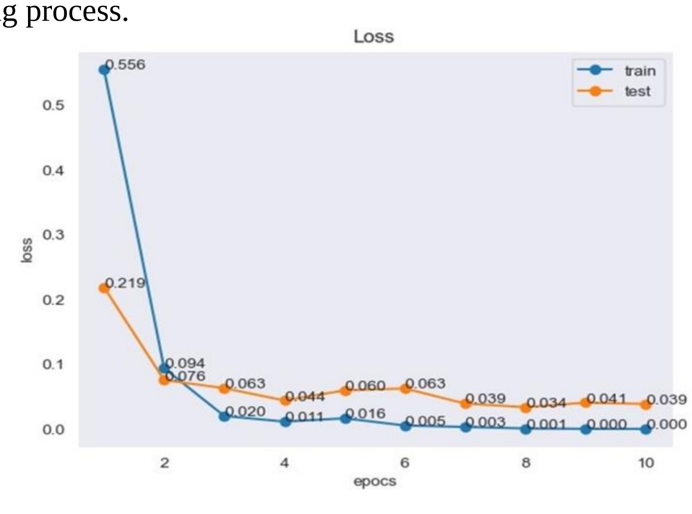


FIG. 12. Apple plant – Loss function

Table 5: Learning rate reduction of different kinds of plant in the validation metrics

Category	Loss	Accuracy	Val_loss	Val_accuracy
Apple	1.5427	1.000	0.0386	0.9843
Corn	9.1426	1.000	0.1087	0.9754
Grape	3.7971	1.0000	0.0459	0.9865
Potato	5.8980	1.0000	0.0721	0.9791

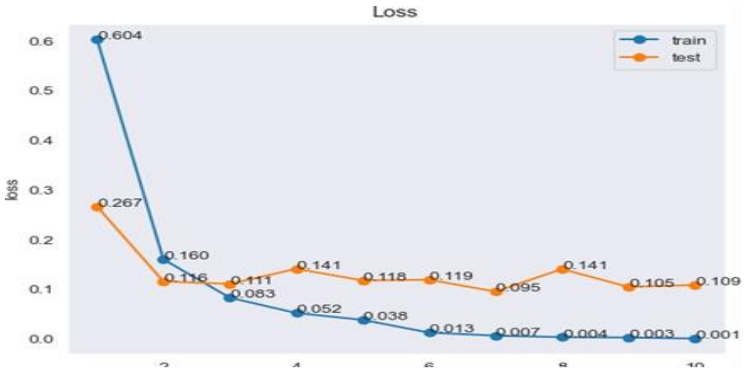


Fig 13. Corn Plant – Loss function

The ratio of accurately predicted positive observations to the total number of predicted positives is known as precision. The ratio of accurately predicted positive observations to all actual positive observations is known as recall. The harmonic mean of recall and precision is known as the F1-score. Another crucial statistic for assessing how well a classification model performs, particularly when it comes to the identification of plant diseases, is recall, which is sometimes referred to as sensitivity or true positive rate. The recall metric quantifies the percentage of real positive cases, or sick plants, that the model accurately detects.

Computational Resource Requirements:

Model Complexity: Deep learning models, such convolutional neural networks (CNNs), can be computationally demanding, needing GPUs for both training and inference. CNNs are frequently employed for image-based disease identification.

Size of Dataset: Training larger datasets, particularly for deep learning models, may necessitate the use of greater computing power.

Real-Time Processing: The system must be able to process images rapidly in order to detect diseases in real time. This may need the use of sophisticated hardware.

Algorithm Efficiency: Without sacrificing performance, efficient algorithms and model structures can aid in lowering the need for computational resources.

Environmental Impact: Energy Consumption: Using computational resources, particularly GPUs, can have a large energy consumption impact. This can lead to carbon emissions and other environmental problems.

manufacture and Disposal of Hardware: Electronic waste and environmental degradation may result from the manufacture and disposal of computing hardware.
Impact on Data Centers: Take into account the energy usage and environmental effects of the data centers that house cloud services if processing is done through them.

8. Discussions and Future Work

A. *Discussions*

In this research, Plant Disease Detection Using Visual Geometry Group Technique Based Deep Learning Approach has been proposed. Kaggle notebook with the GPU support was used for all the experiments. The transfer learning approaches has been performed better with the VGG19 architecture of CNN model than the other existing approaches used in this research. In fact theTraining samples and computing distance are very high in progress leading to sensitive and irrelevant inputs. Deep learning datasets are often achieved on a large number of datasets. The most critical facing challenge in plant disease detection small dataset size problem. Some of the collected training data resulted in low coincidence and high cost of the diseased image. Early identification leads to small-size lesions. Fuzziness and background disturbance are the main sorts of fine-grained identification problems in the deep learning model. Overcoming these types of problems ensures and stimulates the algorithms to learn features and extract the features using the breakage of datasets into small datasets with which both Plant Village and Plant disease datasets to proceed further approaches in this field. This issue can be circumvented using several augmentation techniques with the help of increasing a greater number of datasets. The current study enabled the 97.5 % of accuracy with the help of all existing models, but our new proposed model has been achieved with improved results of 100% of accuracy with only 20 number of epochs.

B.Future Work

In future, the focus of the strategy will be applied on large amount of data with the different set of plants of real field data image capture using drone system. Recommendations of good chemicals and futuristic models to control the ratio of further spread of diseases after the identification of diseases. The VGG model is not only identifying the diseases but also classifies the nutrient deficiency of prospective plant leaves. Future work can also be predicted the automatic severity of the respective methods of diseases. Effective crop management and regulatory programs are the cause of the determination of epidemiology and distribution of diseases. The main focus of deep learning applications to face the obstacles are new tasks such as filter size, learning rate, step size, and number with strong internal dependence. The disruptions and the uncertainty caused due to the global financial crisis. India responded to the crisis by increasing domestic investment, a large part of which came from its public sector.

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