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PLANT DISEASE DETECTION USING DEEP LEARNING MODEL

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Abstract

Farming is the primary avenue of employment, direct or indirect, and serves as the chief source of nutrition to humanity. Crop diseases are a significant risk to food safety and can hurt a country's economy. Timely detection of crop disease and suggestion of a possible cure can significantly improve the yield. Traditional methods to achieve the same are entirely manual and time-consuming, expensive and error prone. This paper describes an automated solution using Convolutional Neural Networks to analyse plant leaf images to detect and classify several disease patterns and the absence of any disease with an accuracy rate greater than 98%. After detecting the disease pattern, this solution also suggests a cure.

Keywords: *Convolutional Neural Networks.*

I. Introduction

Plant disease can be defined as a situation where the plant cannot live to its full potential. Plant diseases are sometimes infrequent to detect and sometimes very contagious, contaminating the whole crop or the neighboring plants. In a broad sense, plant disease can be categorized into two types, namely:

- Abiotic Plant Disease
- Biotic Plant Disease

Abiotic Plant Disease

These diseases are non-contagious but are highly common. Living organisms do not cause these, but the primary source is the environment surrounding them. Of the many causes of abiotic diseases, soil compaction is the leading cause.

Biotic Plant Disease

As opposed to abiotic, biotic plant disease, is caused by living agents. These living agents are called pathogens when they infect plants. They can infect any plant and cause damage to parts of the plant, including leaves, roots etc.

Diseases in Tomato Plant

The most widespread plant and one of the most consumed veggies in our nation are tomatoes. India eats almost 20,000,000 tonnes of tomatoes yearly, according to a report. Tomatoes are a crop that is grown in more than nine Indian states and are a strong source of vitamins A and C. Therefore, it follows that every sickness that affects a plant or vegetable also affects us. The primary emphasis of this initiative is tomato plants and the diseases that impede their development. However, with additional training, the application can also aid other plants with their difficulties. Deep learning enables us to identify illnesses at a much earlier stage, saving the plant from additional harm. A variety of illnesses attack tomato plants, and each one produces a unique set of symptoms that are visible on the leaves and can be used to identify the disease.

1.Early Blight: The fungus Alternaria solani is responsible for the disease Early Blight. The leaves exhibit the symptoms. The leaves start to discolour and develop brown spots. Later on, the leaves curl up and eventually drop off the plant. Phytophthora infestans is the culprit behind late blight. In ideal circumstances, it flourishes. The edges of the leaves begin to grey and turn brown. Brown patches appear on the tomatoes from these affected plants as well.

2.The fungus Passalora fulva is the culprit behind leaf mould. The disease's signs include the leaves developing a bright green shade. In early stages, the tomato is not significantly impacted, but later, the produce suffers significant damage.

3.Septoria Leaf Spot is brought on by Septoria lycopersici. Wet environments are more favorable for the pathogen's proliferation, as found in other disorders. On the leaves of the infected plants, there are numerous brown patches to be seen.

4.Target Spot: The fungus Corneyspora cassiicola is the culprit behind this sickness. Black borders surround brown dots on the leaves. Only the upper half of the leaves have the markings visible.

5.Mosaic Virus: The virus causes wrinkles to appear on plant leaves. The size of the leaves progressively shrinks. Crop output is impacted by this illness.

6.Tomato Curl Virus: The plant's leaves curl and fold because of the Beet Curly Top Virus. The leaf's underside turns purple.

II. Literature Survey

1. Shi-Feng Yang et al. suggested a method for a plant to generate an ultrasonic sound resource signal while under disease stress. The two-dimensional FFT transform will be used to redesign its three-dimensional sound field model, which describes the relationship between helpful resource signals, disease forecast, disease species, pathological changes position, disease degree, transpiration quantity, soil moisture, atmospheric saturation degree, air temperature, illumination, and so on.
2. According to Lakshmana Rao et al., agriculture is critical to a nation's ability to innovate. Agriculture, which produces food and raw resources, is the foundation of all nations. Agriculture is a major source of food for humans. As a result, early diagnosis of plant diseases has become a primary concern. There are proven methods for detecting plant sickness. Plant pathologists or agricultural professionals, on the other hand, have traditionally utilised empty eye examination to detect leaf disease. This approach of detecting plant leaf disease typically requires a big team of specialists with considerable understanding of plant diseases and can be subjective, costly, and time-consuming. Plant leaf diseases can also be detected using a software approach that is being tested.
3. According to Fatma Marzougui et al., all professionals should identify the plants visually; in severe circumstances, a biological investigation is a backup alternative. They are typically both expensive and time-consuming. This prompted several computer systems to spot plant blights in leaf pictures. They use a computer methodology based on Deep Learning systems based on artificial neural networks, this branch of which also allows for the early detection of plant diseases by applying convolutional neural networks (CNNs) familiar with some of the famous architectures, particularly the "ResNet" architecture, with acceptable accuracy rate, using an augmented dataset containing images of healthy and diseased leaves (each leaf is manually cut and placed on a uniform background).
4. According to Sammy V. Militante et al., recent advances in computer vision enabled by deep learning have cleared the way for a technique for detecting and diagnosing plant ailments that uses a camera to record pictures as the foundation for recognizing various plant diseases. This research provides a useful way for promptly recognizing numerous plant diseases. The technology was meant to detect and identify plant species such as apple, corn, grapes, potatoes, sugarcane and tomatoes. The technology can also detect a variety of plant diseases.

Abbreviations and Acronyms

CNN: Convolution Neural NetworkFFT: Fast Fourier Transform ReLU:
Rectified Linear Unit
VGG 16: Visual Geometry Group 16

A. *Tools used:*

- Python IDE (VS Code) for model development.

- Kaggle for collecting datasets.
- OS (windows eight or above or Unix)
- flask, Numpy, TensorFlow, sci-kit libraries
- HTML
- CSS
- JavaScript

III. Methodology

This solution is based on a deep learning algorithm that takes a collection of images and finds patterns in those images using multiple layers consisting of nodes with their weights and thresholds. The regular database is usually chosen, but sometimes we need access to one. Therefore, we can gather the photographs and create our new database in such circumstances. The data presented here has yet to be labelled. The database must be labelled and cleaned as the first step of image processing. Due to the extensive databasesize, the images chosen to have an excellent resolution and better angle. After choosing the images, we should be well-versed in the various leaf types and diseases plants suffer.

The repository of the Plantsville organization is used for extensive study. Various plant image kinds are researched and matched. After careful analysis, the images are labelled according to various diseases.

- **CNN**

Convolution Neural Network is a deep learning algorithm useful in scenarios where we must accept images as input. CNN contains multiple hidden layers, which help to decode the image. The convolution layer, the pooling layer, the ReLU layer, and the last one, the fully connected layer, are the four most essential hidden layers. When a node's output exceeds a threshold, it is active, and the result is sent to the next layer, and so on until the last layer, which is the output layer. The following layers aid CNN in picture recognition:

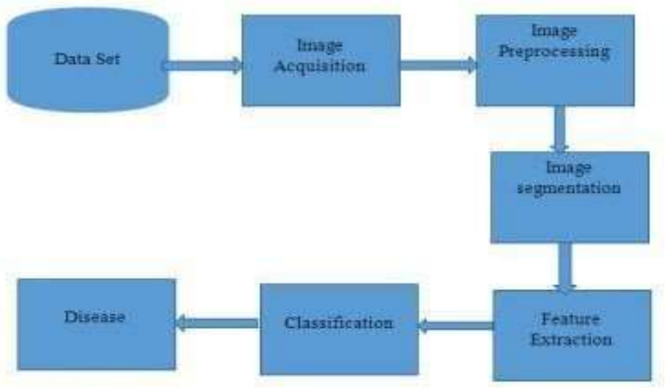

Fig 1. Flow Diagram

Convolution Layer: This is the first layer on CNN. In this layer, the image is broken down into a matrix of pixels. The matrix is numbered in Boolean digits, 1's and 0's. The image is contained in the image matrix, and another matrix named filter is maintained. Convolved matrix is obtained by the dot product of these two matrices.

ReLU Layer: Rectified linear unit, also known as ReLU Layer, takes feature maps as input. This layer converts the non-positive pixels to zero. The convolution and ReLU layers are continuously applied to the image to get a feature map.

Pooling Layer: After going through many convolutions and ReLU layers, the map is reduced to a more convenient dimension in the pooling layer. The output from a pooling layer is the pooled feature map.

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Flattening: After the pooling, the map is flattenedto a single-dimension vector. This is the end stage in which the image is converted to a vector and sentto the fully connected layer for image recognition.

Deep Learning Optimisers

During the first stage of the proposed model, the Stochastic Gradient Descent was utilised to train all the DL models. Following the achievement of the best DL architecture, an improvement in plant disease categorization was also carried out. In this regard, we trained the DL models that achieved the best validation accuracy and F1 score in the first stage of the study using multiple cutting-edge deep learning optimisers. These optimisers have the following characteristics:

1.SGD: This is the most basic deep learning optimizer. It features a quick convergence ability and a set learning rate for all parameters that needs the duration of the entire training.

2.Adagrad: For each parameter in the specified model, this optimiser employs a distinct learning rate. It adjusts the learning rates based on the frequency with which each parameter is updated.

3.RMSProp: The RMSProp optimisation functions were developed to minimise the training time seen in Adagrad, and its learning rate decays exponentially.

4.Adadelta: This is a more advanced version of the Adagrad optimiser that collects past gradients over a set time frame, guaranteeing that learning continues even after multiple repetitions. Adadelta employed Hessian approximation to remove the learning rate from the update rule and guarantee the update direction was negative.

5.Adam: The adaptive moment estimation technique (Adam) computes adaptive learning rates from the first and second moments of gradients. It combines the benefits of two enhanced variants of the SGD method: Adagrad and RMS-Prop. Unlike the RMS-Prop, this estimates the average of the second moment gradient and uses past gradients to accelerate learning.

6.Adamax: A variant of Adam based on the infinite norm was also described, which might be useful for sparse parameter updates such as word embeddings.

IV. Implementation

The plan leaves dataset is sourced from Kaggle and is stored locally for processing. The dataset contains sets of images that are divided into specific sections that each represent sets of diseases which are:

Bacterial spot
Early Blight
Healthy
Late Blight
Leaf Mold
Septoria leaf spot
Target spot
Yellow leaf curl virus
Mosaic virus
Two-spotted spider mite

Bacterial Spot **Early Blight**

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Healthy Late Blight

The dataset contains the images separated into training,testing and validation. The user interface uses HTML, CSS, JavaScript, and Flask.The process flow is depicted in the following diagram:

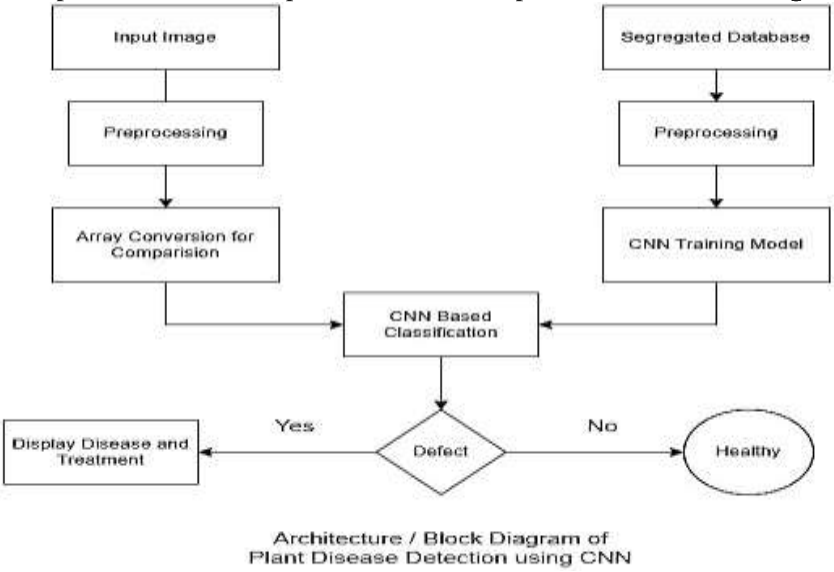

Fig 2. Block Diagram of Plant Disease Detection using CNN.

The initial step of this model includes preprocessing and training of CNN. The preprocessed database is transformed into an array form, such as resizing and reshaping images. Because there is a database containing numerous plant species, any image may be used as a test image for the software.

First, the input image is broken down into pixels and fed into different neural network layers. It is analogous to an RGB coloring scheme where every color is described in a number format and is defined as a combination of red, blue, and green. The image that the user uploads to check which kind of disease has affected the plant is taken as testing, which helps improve the model's accuracy. Finally, the model categorizes the images into two various categories. Disease-affected and disease free. If the result falls under the disease-affected category, then the model tries to identify which category of the above disease the plant is associated with. There are various steps involved in the identification of the disease.

- **Image Input**: The Image taken as input is first resized,then colored to a specific color and then fit into the model.
- **Digital Image Processing:** This step involved training the model with all the collected images from the dataset. The algorithm used images to determine the specific factors required to discover the plant's disease.
- **Data Preprocessing:** Data preprocessing cleans thedata and ensures that no unnecessary data is sent to the model for training and testing. It involves resizing all the images to a particular size so the machine can identify them. It also involves reducing the number of pixels in the image. The final step is removing any unwanted information in the image, known as noise.
- **Feature Extraction:** This is the most crucial step in the process. This step involves extracting all the necessary features required for discovering the disease. Extracting features is very important to prevent the overfitting of the data, which can lead to poor accuracy.

- **Classification:** Following the extraction of features, the model must determine which categories it was trained in and which characteristics to match. If the model is adequately trained, it can readily determine which illness the input picture corresponds to, such as early Blight, late Blight, healthy, and so on.
- Following the extraction of all features, a Convolutional Neural network was built. This model included four stages, which were as follows:
  - convolution
  - Pooling
  - flattening
  - full connection

The first was creating a convolution layer using 32 filters, with kernel size as 3x3 and ReLU as the activation function. The input shape was changed to (128, 128, 3).

The second step was 2D Maxpooling to normalize the batchto a size of (2,2). This was done after each layer so that the previous layer output was normalized, thus allowing each of the other layers to improve its learning.

The third step was to add another convolutional layer using the same 32 filters and ReLU as the activation function, but the input shape needed to be specified for this layer.

Finally, flattening was done. Flattening converts the multidimensional array into a single-dimensional array. After the flattening, a complete connection was established using the classifier by creating 128 units of neural networks with accurate activation functions and ten units of neural networks using sigmoid as the activation function. The sigmoid activation function transforms the values between 0 and 1 inclusive. The formula for sigmoid is.

F(x)=1/(1+e^-x)

It forms an S-shaped value on the graph and is a non-linearfunction.

ReLU function was used because it does not allow all the neurons to be activated simultaneously. It is a linear function. If the transformed value is negative, ReLU converts it to zero,thus preventing it from being activated. The formula for ReLU is.

R(x)=max(0,x)

If x<0, then R(x)=0 If x>=0, then R(x)=x

Adam is the optimiser used in this model, with the loss function being categorical cross-entropy. The metrics parameter was set to accuracy, determining the difference between predicted and actual values. All the images that fit into the model were resized so that all the images used to train, test and validate the model can be the same, and the model is transparent.

The model (CNN) is trained using the training database to recognize the training sample image and the disease it suffers from. CNN consists of the following layers: Max pooling 2d, Convolution 2D, Dense, Activation, Dropout and Flatten. If the crop species have been added to the database after the model has been trained successfully, the algorithm can identify the disease. After preprocessing and practical training, the trained model and the input image are compared to identify the disease.

The parameters used in the convolutional neural network are as follows:

- **Epochs**: It determines how many iterations the model trains with the training data. The number of epochs used in this model is 50.
- **Batch size:** This refers to the amount of training data used during each epoch. The batch size was 6 for the training and 3 for the validation sets.
- **Optimiser:** Optimisers are generally used to reduce the loss, which can lead to less difference between the predicted output and the actual output. The optimizer used here is Adam. It is primarily an efficient optimiserandis very helpful if the data is significant.
- **Loss:** A loss function compares the difference betweenthe predicted values and the actual values. It is used to minimize this difference. Categorical cross-entropy is one such loss

function that is used in this model.

The learning rate affects accuracy. A low learning rate was chosen for this problem of image classification. Lower learning rates generally result in higher accuracy even though the training time is often a lot, and it is good because it helps improve the model's overall accuracy. Also, the batch size is inversely proportional to the robustness of the noise. In this model, a larger batch size was chosen to lower the robustness of the noise in the dataset. All of these were done to create a reasonably accurate model for predicting the disease. After creating themodel, it was stored in a hierarchical data format. A hierarchical data format stores a large amount of scientific data. The model is then converted into a JSON file and is converted into the hierarchical data format. After storingthe model, it is loaded into a model. The input image is converted into a Numpy array and is normalized. The dimension of the image was also changed from 3-dimensional to 4-dimensional. The prediction function was then used to check whether the plant had a disease. Theresult of this function was an integer between 0 and 9 inclusive.

Each integer was mapped to a category of the condition of the plant, such as early Blight, late Blight, bacteria spot disease, healthy and fresh etc. Then flask API connected the model to the application's user interface. The user can inputone image at a time into the application. The image is stored in a central location. The model then takes the file from where the image was stored and predicts whether the plant is affected by a disease. Once the prediction is made, the result is displayed to the user. The result specifies what kind of disease the plant is affected with or if is disease free. If the plant is affected by a disease, the application specifies what kind of disease the plant is affected by and what can be a possible cure.

Method Comparison:

We compared several research articles after researching and analyzing them. Their precision, the approach they used, and the benefits and downsides. The resulting table is as follows:

Models

VGG16: VGG-16 is a 16-layer deep convolutional neural network. We can load a pre-trained version of the network that has been trained on millions of photos. The pre-trained network can categorise photos into thousands of object categories, including keyboards, pencils, mice, and a variety of animals.

Inception Resnet V2: ResNet-v2 is an Inception-ResNet-trained convolutional neural network trained on over a million photos from the ImageNet collection. The network has 164 layers and can identify photos into thousands of item categories such as keyboard, pencil, mouse, and a variety of animals.

MLCCN is an abbreviation for multilayer convolutional neural network.

Inception-v4 is a convolutional neural network architecture that builds on prior generations of the Inception family by simplifying the topology and employing more inception modules. It has 22 layers (27 if you count the pooling levels). At the end of the previous inception module, it employs global average pooling.

Xception: Xception is a 71-layer convolutional neural network. We can use ImageNet to load a pre-trained version of the network that has been trained on millions of photos. The pre-trained network can categorise photos into thousands of object categories, including keyboards, pencils, mice, and a variety of animals.

Metrics

The comparison of Deep Learning architectures to pick the best model yields results for enhancing the performance of the best-suited models utilizing various DL optimization methods. All of the findings were assessed in terms of training, validation accuracy/loss, and F1-score. The F1 score is regarded as an essential performance parameter, particularly when the distribution of classes is unequal; hence, the model/optimiser with the greatest F1 score was regarded as the best design for identifying plant disease. Line graphs depict the performance of all DL architectures, and it was empirically discovered that it took 60 epochs for training/validation accuracy and loss to converge.

Article	Method	Accuracy	Advantages	Disadvantages
A DeepCNN Approach for PlantDisease Detection.	Deep Learning	96%	Cost-effective andless time-consuming	It is challengingto implement the algorithm.
Plant disease detection and diagnosis based on the theory of acoustic holography.	Acoustical Holography	91%	The mechanism gives a detailed report of the plant and soil conditions.	A lengthy process that can be done by professionals.
Detection of an unhealthy plant leaf region using image processing and genetic algorithm.	Genetic algorithm	89%	It requires lesser information.	It is too slow compared to other algorithms.

Tables

MODELS	EPOCHS	TRAINING TIME (in hours)
VGG16	59	38.13
INCEPTION RESNET V2	58	32.83
RESNET-50	55	26.33
MLCNN	57	67.33
INCEPTION V4	59	52.92
XCEPTION	34	56.28

Table:1

MODELS	TRAINING ACCURACY	VALIDATION ACCURACY	TRAINING LOSS	VALIDATION LOSS
VGG16	0.8339	0.8189	0.5328	0.5651
INCEPTION RESNET V2	0.9551	0.9091	0.153	0.3047
RESNET-50	0.9873	0.9423	0.0468	0.1923
MLCNN	0.9583	0.9402	0.1335	0.182
INCEPTION V4	0.9586	0.9489	0.141	0.1828
XCEPTION	0.999	0.9798	0.014	0.0621

Table:2

MODELS	PRECISION	RECALL	F1-SCORE
VGG16	0.8182	0.8194	0.8188
INCEPTION RESNET V2	0.9075	0.9105	0.9089
RESNET-50	0.9351	0.9358	0.9354
MLCNN	0.9386	0.9411	0.9398
INCEPTION V4	0.941	0.9466	0.9438
XCEPTION	0.9764	0.9767	0.9765

Table:3

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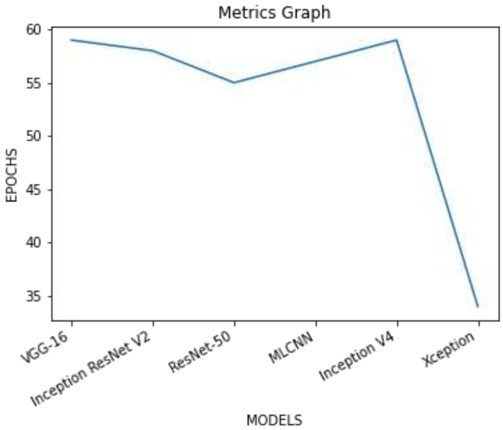
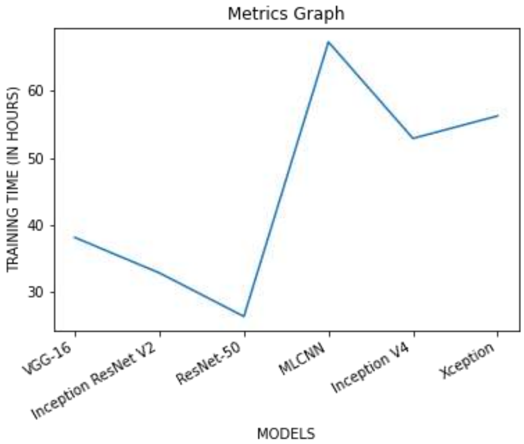
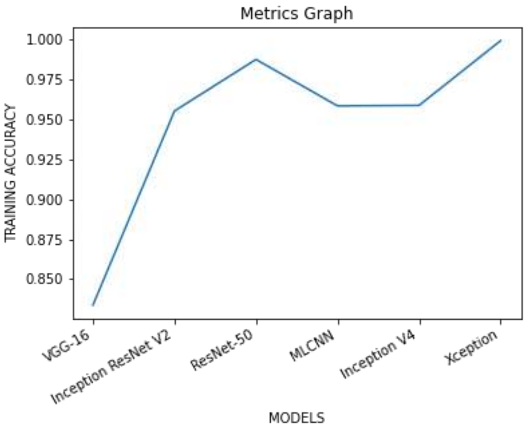
Graphs



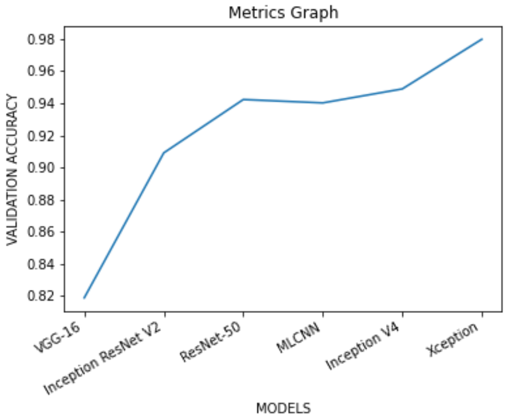
Epochs



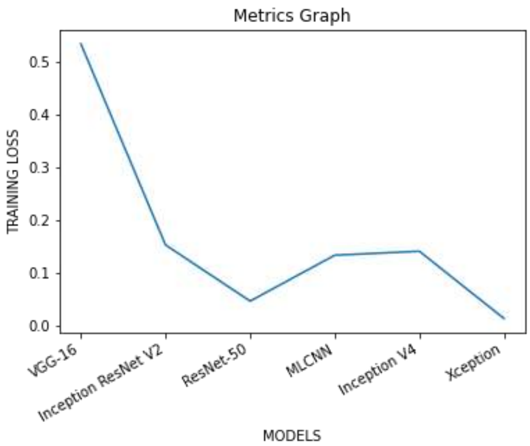
Training Time (in hours)



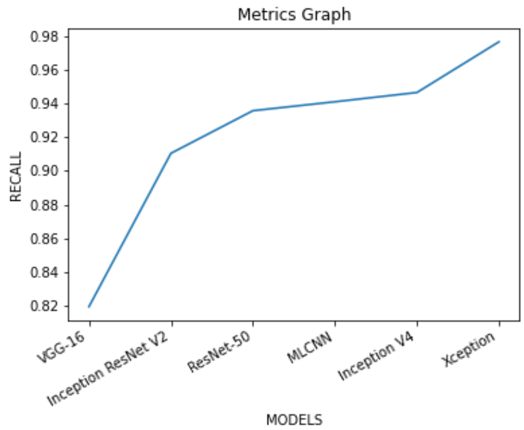
Training Accuracy



Validation Accuracy



Training Loss



Recall

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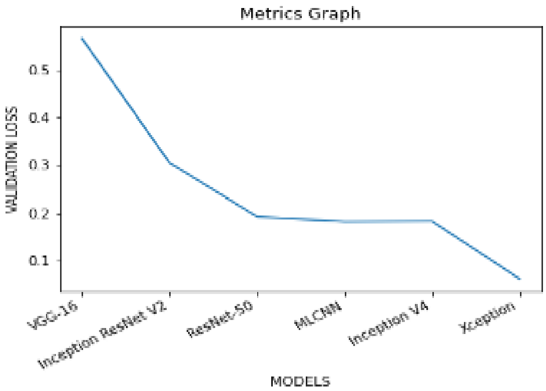
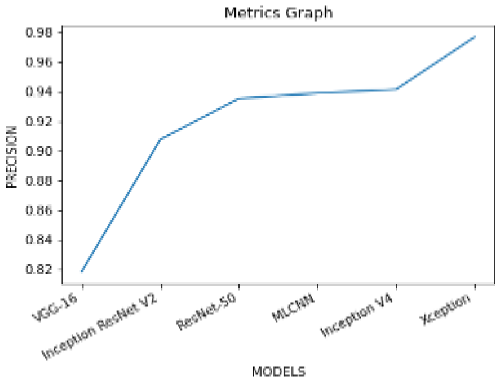
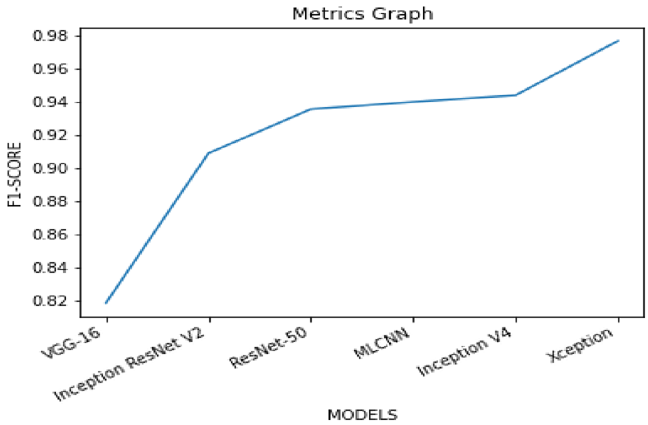


Validation Loss



Precision



F1 - Score

V. Results Discussion

Among all well-known CNN models, the Xception model had the greatest F1-score, validation accuracy, and validation loss. As a result, this model is without a doubt the best CNN architecture for classifying plant illnesses on the dataset. It claims that under the Xception model, the notion of a modified form of depth-wise separable convolution aids in obtaining a superior classification result. Furthermore, when compared to the other DL designs, this DL model converges to its end value at the 34th epoch. Completing one epoch, on the other hand, took a large amount of time (about 3400 sec). As a result, future research should develop another version of the DL architecture that can attain Xception-level accuracy while requiring less training time per epoch. Inception V4 ranked second in terms of F1-score/validation accuracy. As a result, the architecture's increased number of activation maps and lower filter size enhanced its performance. The MLCNN architecture had a high F1 score because it included a dropout layer after each max pooling layer. It also lowered the amount of filters in the architecture's early convolution layers. Due to the additional parameters, our updated DL architecture needed much longer training time each epoch.

The ResNet-50 architecture thus received an outstanding F1 score as well. The Resnet 50 is a better model since it has fewer parameters and hence takes less time to compute. The pointwise and depthwise convolutional layers aided in the classification process. As a result, a future CNN model based on the ResNe-50 architecture may be presented. Furthermore, when compared to other models, this model required fewer epochs to obtain its ultimate accuracy and loss.

It was also shown that DL models, such as VGG-16, needed 58-59 epochs to converge training/validation plots, greatly increasing training time. The VGG-16 model proved inadequate for plant disease classification since it performed worse in terms of validation accuracy/F1 score and validation loss than the other well-known DL architecture. The VGG model's performance has suffered because of its decreased filter size.

VI. Conclusion

A thorough comparison of several deep learning architectures has been carried out. Furthermore, the performance of the best-obtained model was enhanced by employing multiple deep-learning optimisation techniques. The Xception model was determined to have the best validation accuracy and F1 score. The Xception model trained by the Adam optimiser earned the greatest F1-score of 0.9978, indicating that this model-optimisation algorithm combination is the best for identifying plant illness. Deep learning optimisers like Adam and Adadelta can also help with research on various agricultural applications including crop discrimination, plant recognition, weed classification, and so on. The classification performance of additional plant disease datasets can be enhanced by using the approaches provided in the study. Although the Xception model produced the best results based on the study, it took a long time to finish each epoch. As a result, an attempt should be made to obtain Xception level precision in a short amount of time.

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