# AN IMAGE-BASED TOMATO EARLY BLIGHT DISEASE PREDICTION USING OPTIMIZED TRANSFER LEARNING MODELS

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Nikita Sareen[1] Anuradha Chug[2] Amit Prakash Singh[3]
nikisareen29@gmail.com,[1] anuradha@ipu.ac.in,[2] amit@ipu.ac.in[3]
*USIC&T, Guru Gobind Singh Indraprastha UniversitySector — 16C, Dwarka, New Delhi-110078, INDIA*

**Abstract**

*From many years, the area of plants has evolved, they have been playing a vital role in every field from agriculture to health care. However, plants also suffer from diseases and early detection of diseases is very important in order to prevent production from being affected. The Optimized Transfer Learning approach provides an optimal solution to this problem, i.e., choosing the best model for prediction and detection of diseases. This is possible by selecting the right hyperparameters to get the best model. The VGG16 and ResNet50 models have been used for plant disease prediction. The Hyperparameter Tuning is also used for getting efficient results. The current study uses an image-based Tomato Early Blight Disease dataset. Different image pre-processing techniques such as Background Removal, Image Augmentation, Resizing, Noise Removal, and Segmentation were applied to refine the dataset. Further, Hyperparameter Optimization was done using the Random Search technique to optimize the parameters and obtain the best model with the best accuracy. The performance of proposed VGG16 and ResNet50 models have been calculated using various metrics, namely, Precision, Recall and F1-Score. The accuracy achieved in the VGG16 model was 99%, and in the ResNet50 model, the accuracy achieved was 96%. This model can be used by farmers for early detection and prediction of disease in tomato plants and using the best model for prediction of diseases will reduce the workload of farmers.*

***KEYWORDS:*** *Tomato, Plant Disease, Early Blight, Transfer Learning, Image pre-processing, Segmentation, VGG16, ResNet50*

## 1. INTRODUCTION

The plant disease recognition, classification, and detection are one of the challenging tasks in the field of agriculture [1]. Although it can be done using traditional methods, but with advancements in technology, image processing is used for the monitoring of plants. The monitoring of crops from remote places leads to successful cultivation. Amongst these, choosing the best model for disease detection is a crucial task. The Transfer Learningmodels are used for prediction and detection of diseases in plants as they make the training process easier by having pre-trained architectures. The best prediction model can be selected by optimizing the parameters. However, every learning system, be it machine learning system, deep learning, and transfer learning has two typesof parameters, namely, Internal or training parameters which are learned during training phase and Hyperparameters which are specified before the learning phase initiates. Hyperparameters are basically the parameters that are used for configuration of a model or

algorithm. The optimization of these parameters is the task of finding the optimum parameters to achieve the best model with the best accuracy. It is done on Deep Learning and Transfer learning [2] models to optimize the models and their performance. The brute force search can be done for optimization, but it's a time- consuming and tedious process. On the contrary, Random Search [3] Strategy selects the random combination of hyperparameters. For each hyperparameter, a distribution is specified for random search. However, still the selection of hyperparameters and their proper optimization remainsa challenging task. The main objective of this paper is to find the impact of hyperparameter [4] optimization on transfer learning models using random search for prediction of disease in tomato plants and analysing using performance metrics.

So, in this paper, Tomato Early Blight Disease Dataset has been used for the prediction of diseases in the tomato [5] plants by using an optimal transfer learning model. Various techniques have been applied to obtain the refineddataset, thus, making it suitable for training. Background Removal was done by applying different masks (yellow, green, brown). Further, pre-processing techniques were applied, which include- Resizing to obtain an image of the desired region. Denoising of images was done using a Median filter. Segmentation [6] was applied using *k*- means clustering for further processing of an image. Hyperparameter Optimization using random search [7] was done on Transfer Learning Models- VGG16 and ResNet50 to optimize the parameters and thus achieving the best model with optimized parameters. Finally, for evaluation of the model, different performance metrics were calculated and analysed- Precision, Recall, and F1-Score.

To conduct this study, following Research Questions (RQ) have been framed:

RQ1: Which transfer learning model between VGG16 and ResNet50 give better performance for prediction ofdisease in tomato plants based on accuracy metric?

RQ2: Which transfer learning model between VGG16 and ResNet50 give better performance for prediction ofdisease in tomato plants based on precision, recall and f1-score metrics?

RQ3: What is the role of hyperparameter optimization in prediction of diseases in plants?

The rest of the paper is organized into the following sections- Section 2 describes the literature review. Section 3presents the materials and methods of this paper. Section 4 shows the research methodology which is used in thispaper. Section 5 presents the results after optimization of hyperparameters. Section 6 provides the conclusion andfuture directions of the paper.

## 2. LITERATURE REVIEW

Several researchers have applied and proposed various prediction models for disease detection so that predictionand early detection of diseases can be done appropriately. Few of the researchers' work has been described in thissection. In 2019, Kumari et al. implemented an algorithm for the detection of leaf diseases. Segmentation and classification were done using *k*-means clustering and ANN, respectively. The average classification accuracy achieved was 92.5% [1]. In the same year, Hasan et al. implemented the Inceptionv3 model for the detection of tomato plant diseases. The model was used for classification and applied to various inputs and filters, thus achieving an accuracy of 99% [2]. Subsequently, in 2019, Feurer and Hutter discussed about carious black-box optimization methods for solving the problem of HPO (hyperparameter optimization) and various multi- fidelity methods of black-box functions [3]. In the next year 2020, Verma et al. implemented two CNN architectures – AlexNet and ResNet via transfer learning. AlexNet and ResNet achieved best accuracies with a batch size of 32 and 24, respectively [4]. Subsequently, in the same year 2020, Ouhami et al. implemented three transfer learning architectures- DensNet121, DensNet161, and VGG16, wherein pretrained weights were used from VGG16 and applied to the first convolutional layer. DensNet161 achieved the best accuracy of 95.65% [5]. Again, in the year

2020, Ramesh and Vydeki implemented an optimized deep neural network using Jaya Optimization Algorithm for recognition and classification of paddy leaf diseases and compared the results amongst ANN, DAE, and DNN. The best accuracy achieved was 98.9% for blast affected [6]. In the same year 2020, Andonie and Florea compared the weighted random search method with several hyperparameter optimization methods using CNN- Particle swarm optimization, Bayesian optimization, Random Search, Nelder Mead, Sobol Sequences, and Tree parzen estimator. Amongst these architectures, the weighted random search method achieved the best accuracy of 85% [7]. Again, in the year 2020, Yu and Zhu reviewed different optimization algorithms for deep learning networks- Grid Search, Random Search, Multi bandit algorithms and made the comparisons between them. They also discussed about the problems when applying hyperparameter optimization using deep learning [8]. Subsequently, Saleem et al. performed localization and classification of 26 types of diseases wherein meta architectures- Single-Shot Multibox Detector, Faster Region-Based Convolutional neural Network, and Region-based Fully Convolutional Networks were applied. The single-shot multibox detector achieved the highest mean precision value of 73.07% [9]. Again in the same year, Bhatia et al. developed Extreme Learning Machine Models for Tomato powdery mildew balanced datasets obtained by applying resampling techniques and inbalanced datasets. The best accuracy achieved was 89.19% using Importance Sampling technique. [10] In the same year 2020, Bhatiaet al. developed Logistic Regression and Support Vector Machine classifier hybrid for prediction of powdery mildew disease in tomato plant. The model achieved an accuracy of 92.37% [11]. Subsequently, Verma et al. compared implementation and results using Transfer Learning for classification of diseases in potato plants, of original network capsule with pretrained architectures of CNN with networks capsule having accuracy 91.83%. [12]. In same year, 2020, Bhatia et al. proposed a methodology for enhancing the performance of decision tree algorithms, C4.5, Classification and Regression Tree (CART), Bagging CART (Bag-CART), Partial decision Tree (PART-DT), and Boosted C5.0 (B-C5.0). Also, feature selection techniques were used for dimensionality reduction- Consistency (Cons), Correlation-Based feature selection (CFS), and Random Forest Importance (RFI). The best accuracy achieved was 98.10 % along with area under curve of 97.79% using RFI and C4.5 method [13]. In the same year, Bhatia et al. discovered a classifier amongst other classifiers using machine learning algorithms and also used Friedman Test for ranking of multiple classifiers and did Nemenyi Test for post hoc analysis. The best classifier found was Gaussian Support Vector machine having accuracy 94.74% [14]. Later, in 2021, Miranda et al.conducted a study and implemented Bayesian optimization convolutional neural networks based knowledgetransfer for the selection of hyperparameters. The model achieved an accuracy of 98% on test data [15].

Although several transfer learning models and algorithms have been implemented, but none of the researchers have applied prediction models on real-time dataset of tomato plants. The selection of the right number of hyperparameters using transfer learning models is an important task. So, two transfer learning models - VGG16 and ResNet50 were optimized using Random Search, and different performance metrics were also applied to analyse the performance of models.

## 3. MATERIALS AND METHODS

This section describes the materials and methods used in this study. The current work was implemented in Python language using Jupyter Notebook IDE and Google Colaboratory. Jupyter Notebook IDE was used for performing various image pre-processing techniques- Background Removal, Resizing, Denoising, Augmentation and Segmentation. Google Colaboratory was used for performing Hyperparameter Optimization because of its GPU configuration asit helps in training the models faster.

Disk Space- 68.35
GBRAM- 12.69 GB

### 3.1 Overview of Dataset

The Tomato Early Blight diseased dataset, which is used in this research, was collected from IARI (Indian Agricultural Research Institute). 300 images of tomato early blight disease and 300 images of tomato healthy plantwere captured using DSLR under heterogeneous backgrounds and different light intensities. Background removalwas applied on images using the different masks to make homogeneous background for processing the images easier. The augmentation [8] technique was applied to increase the size of the dataset by applying various operations- shear, flip, rotation, etc. and specifying their Boolean values and frequencies. After augmentation, dataset size increased to 1000 images in total for both diseased as well as healthy image dataset.

### 3.2 Image pre-processing techniques

Image pre-processing is a very essential and crucial step for processing as well as enhancement of images to extract Region of Interest, denoising the images and thus improving the infected area of the images. It includes various processes such as background removal, resizing, and noise removal filters [8] (Bilateral, median, mode). The current study uses techniques such as coloured masking for background removal, cropping for resizing, and median filter for denoising, which is discussed in detail in the following sub-sections:

### 3.3 Coloured Masking

Background removal is done to remove unwanted regions [9]. In this study, the coloured masking technique has been used to remove the heterogeneous background of images. So, images are converted from BGR (blue, green,red) to RGB (red, green, blue) and finally from RGB (red, green, value) to HSV (hue, saturation, value). In the final modified image, different colors present on the leaf (brown, green, yellow), wherein masking is done by adjusting the pixels values according to the color intensity of the image.

#### 3.3.1 Cropping

For resizing of images, the cropping method is applied. It is a method to resize the image by removing undesiredregions. Parameters [10] for cropping were – top, bottom, height, left, right, which were adjusted as per the size of the image

#### 3.3.2 Median Filter

The median filter is applied to the images to denoise the images. Firstly, it picks the value of the median pixel ofthe desired size. It considers each pixel of the image and checks whether neighboring pixels are part of its surroundings, and replaces the values of pixels with the median of values [10]. From the neighboring pixels, to calculate the median, all the pixels are sorted orderly, and the chosen pixel is replaced with the middle value of the pixel.

### 3.4 Segmentation using k-means clustering

Segmentation is done wherein images are divided into various segments. These segments are areas, [11] the portion of the image which are used for processing the image. Segmentation using *k*-means clustering algorithm is implemented for further processing [11] of the images where k represents the number of clusters. The k- meansalgorithm is applied in the image of the 2D array, which was converted from a 3D array. The mathematical function for the k-means clustering algorithm is the squared error

function:

$$J = \sum_{i=1}^{k} \sum_{j=1}^{n} (\|x_i - v_j\|)^2 = 1 \quad (1)$$

Where $||x_i - v_j||$ is Euclidean distance between point $x_i$ and centroid $v_j$, iterated over all $k$ points in the $i^{th}$ cluster, for all $n$ clusters.

### 3.5 Transfer Learning Models

The models used in this study are Transfer Learning Models. Transfer learning is a technique in which a model already trained for a problem can be used for another problem. The weights in re-used layers can be used for training the model, or new layers can be added from scratch. We can either freeze all the layers except the last layer and train the model or unfreeze all the layers and customize the model accordingly. Various architectures can be used in transfer learning which are described in the following sub-sections:

#### 3.5.1 VGG16

VGG16 [12] is one of the most used pre-trained model used for image classification. It consists of 13 convolutionallayers, 5 pooling layers, and 3 dense layers. This model can be directly used for image classification and feature extraction. Another way is- Freezing some of the layers and unfreezing the rest layers and building the unfreezedlayers, and training the model. VGG16 architecture is depicted in Figure 1.

#### 3.5.2 ResNet50

It is also one of the predominantly used pre-trained model. ResNet [12] also has different versions- ResNet18, ResNet101 etc. ResNet50 stands for residual network. This model consists of 50 layers of deep network. For eachresidual function, 3 layers are stacked one over the other. The 1x1 convolutional layers reduce and restore the dimensions. The 3x3 layer serves as a bottleneck for smaller input/output dimensions. This model can be directly used for image classification and feature extraction. Another way is- Training the model from scratch by user- defined model. Figure 2 represents the ResNet50 architecture.

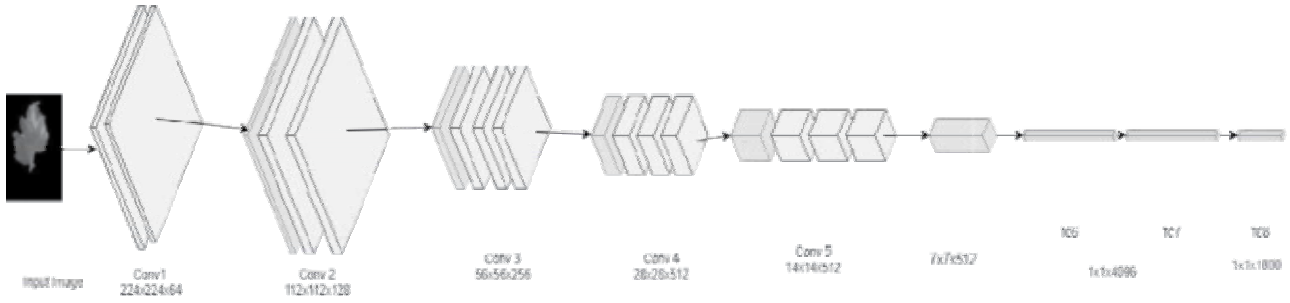



Figure 1: VGG16 Architecture

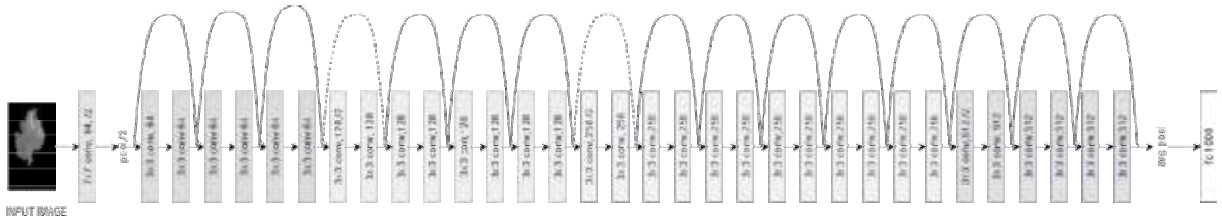


Figure 2: ResNet50 Architecture

### 3.6 Performance Metrics

The performance metrics [13] are used in transfer learning models for the performance evaluation of the models.In this study, the different performance metrics used are – Precision, Recall, and F1-score. These performance metrics were calculated and analysed after hyperparameter optimization of transfer learning models.

#### 3.6.1 Precision

The precision [14] is defined as the ratio of the correctly predicted positive samples to total predicted positive samples. The formula for precision is presented as follows:

$$Precision = \frac{True\ Positive}{True\ Positive + False\ positive} \quad (2)$$

#### 3.6.2 Recall

The recall [14] is defined as the ratio of correctly predicted positive samples to the summation of samples that were predicted correctly and number of samples that were predicted incorrectly. The formula for the recall is defined as follows:

$$Recall = \frac{True\ Positive}{True\ Positive + False\ positive} \quad (3)$$

#### 3.6.3 F1-Score

The F1-score [14] is defined as the harmonic mean of precision and recall. The F1-score formula is defined asfollows:

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (4)$$

### 3.6.4 Classification Accuracy

Classification Accuracy [14] is defined as the ratio between the number of predictions that were accurately made by the classification model and the total number of predictions. The formula for classification accuracy is definedas follows:

$$Classification\ Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions\ made} \quad (5)$$

## 3.6 Hyperparameter Optimization

Hyperparameter Optimization [15] is defined as the automatic optimization of hyperparameters by using a combination of values to find the optimal parameters which will give the best model achieving the best accuracy.The optimization can be done using different methods, namely, Grid Search, Random Search, Bayesian Optimization, etc.

In the current study, the Random Search technique [3] has been used wherein it selects the random combinationof hyperparameters based on the distribution specified. The search space is sampled randomly. The number of trials needs to be specified. If two parameters are correlated, it precisely finds the optima of each parameter. Thehyperparameters used for optimization were - learning rate, number of units, and dense activation.

## 4. RESEARCH METHODOLOGY

The current study introduces an efficient approach for early detection of tomato plant diseases by choosing the best model using hyperparameter optimization. Figure 3 represents the research methodology diagram for hyperparameter optimization and detection of diseases in tomato plants.

### 4.1 Dataset Selection

In the beginning of this study, the Tomato Early Blight Diseased dataset was collected from IARI. The dataset contains images of both diseased (early blight) and healthy tomato fruit collected under heterogeneous backgrounds and different light intensities. The detailed description of the dataset is described in Section 3.1

### 4.2 Pre-processing and segmentation of TEBD dataset

Pre-processing was applied to the TEBD dataset for enhancement of images and improving the infected area of the image. The background removal technique was applied to make the backgrounds of the images identical, thusremoving the undesired regions. For this, the images were converted to HSV. The images were masked with different colors (yellow, green, brown) according to color intensities. After obtaining the images with identical background, the size of the dataset was increased by applying the augmentation technique which includes variousoperations like Shear, Horizontal Flip, Vertical Flip, Rotation Range, Zoom, Brightness, along with the boolean value and frequency range was specified. The cropping method was applied for resizing the image and adjusting the parameters accordingly as per the size of the image. Denoising of the image was done using median filter (size=2) in which filter picked median pixel value. After denoising, *k*-means clustering was applied for segmentation in which *k*,

represents the number of clusters and value of k=24 was specified, and thus, after converting the image into a 2D array, clustering was applied on the modified image.

### 4.3 Hyperparameter Optimization

For hyperparameter optimization using transfer learning models- VGG16 and ResNet50, by random search technique, firstly, all the layers of both the models were freezed except the last layer. Optimization was done on the last layer by choosing hyperparameters which needs to be optimized, and their range was also specified. Someparameters which were taken into consideration while training have been represented in Table1. The hyperparameters chosen were- Learning Rate, Number of units, and Dense Activation. Their range values have been shown in Table 2. Also, After training each model for the specified number of epochs, the best model accuracy was obtained.

### 4.4 Performance Evaluation of the Model.

The different performance metrics- Precision, Recall, and F1-Score were taken into consideration to evaluate theperformance of the model, and the same were presented in Table 3. The confusion matrix was recorded representing the true positive, true negative, false positive, and false negative images of the dataset. Also, precision, recall, f1-score were calculated for each optimized model.

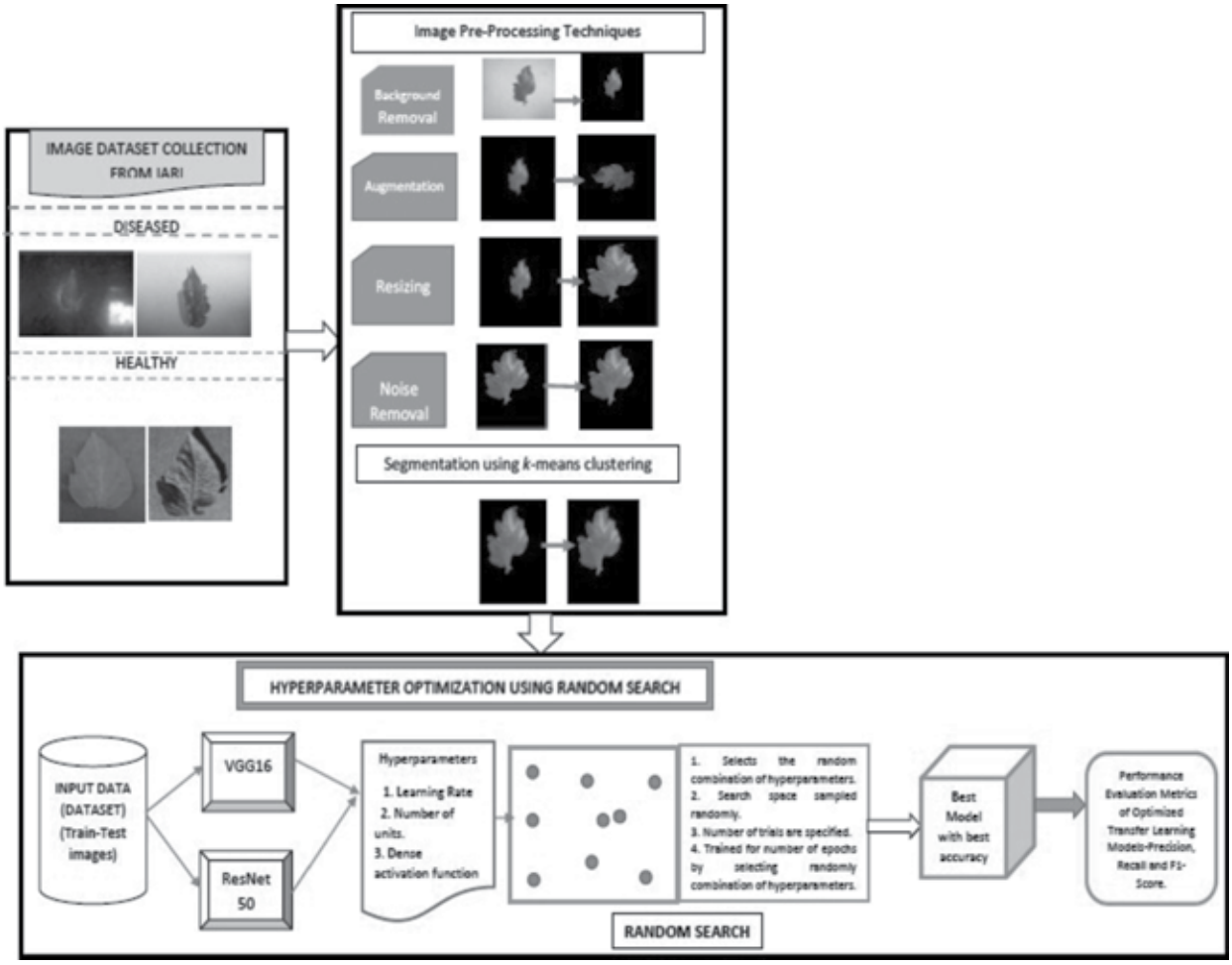



Figure 3: Research Methodology diagram for Hyperparameter Optimization

## 5. RESULTS AND DISCUSSIONS

In the current study, data collection of TEBD dataset was done and pre-processing techniques were applied to refine the dataset. Further, segmentation using *k*-means clustering was performed. Afterwards, hyperparameter optimization was done on transfer learning models (VGG16 and ResNet50) using random search by specifying the range of values for hyperparameters which were optimized, namely, number of activation units, dense activation function and learning rate to achieve best accuracy and performance of models was analysed using performance metrics such as, Precision, Recall and F1-Score.

This section represents the performance results of detection of disease in tomato plants after hyperparameter optimization of transfer learning models and evaluation of the models performance. The optimized parameters selected for transfer learning models are represented in Table 2. The analysis of performance metrics calculated are represented in Table 3.

The hyperparameter optimization was performed using Random Search for Transfer learning models to optimizehyperparameters such as, activation unit, learning rate, and dense activation functions. For VGG16 model, the possible values for activation units were between 32-1024, dense activation function were Sigmoid and ReLU andlearning rate range was between $1e^{-4}$ to $1e^{-2}$. Similarly, for ResNet50 model, the range of activation units was 32-1024, dense activation function were Sigmoid and ReLU and possible values of learning rate were between $1e^{-4}$ to $1e^{-2}$.

After optimization, VGG16 achieved an accuracy of 99%. Optimized learning rate was- 0.0049, activation units-128 and dense activation was ReLU. Similarly, ResNet 50 achieved an accuracy of 96%, the learning rate observedwas 0.0001, activation unit- 768, and dense activation function was ReLU.

Table 1: Hyperparameters used for Random Search (not optimized)

| HYPERPARAMETERS | |
|---|---|
| MAX_EPOCHS | 5 |
| MAX_TRIALS | 5 |
| EXECUTION_PER_TRIAL | 2 |
| N_EPOCH_SEARCH | 4 |

This section answers the RQ's that were framed in Introduction Section.

RQ1: Which transfer learning model between VGG16 and ResNet50 give better performance for prediction of disease in tomato plants based on accuracy metric?

This RQ has been answered by optimizing the hyparameters in given range for both ResNet50 and VGG16 model,namely, activation units, dense activation function and learning rate.After training the Resnet50 model, it achievedan accuracy of 96% having activation unit of 768, dense activation function as ReLU and learning rate of 0.0001.On the other hand, VGG 16 model after training achieved an accuracy of 99% with activation units of 128, denseactivation function as ReLU and learning rate of 0.0049. The VGG16 model gave best accuracy and optimized parameters for prediction of disease in tomato plants because ReLU is computationally more efficient than Sigmoid because only few number of neurons are activated. It shows better convergence than sigmoid. Learningrate of 0.0049 signifies obtaining the optimal weights faster, i.e., less training time. Less learning rate will take time to obtain optimal weights.

The optimized parameters and accuracies for both transfer learning models have been represented in Table 2. Graphical representation of accuracies of models have been represented in Figure 4.

Table 2: Results after Hyperparameter Optimization of Transfer Learning Models.

| Model | HYPERPARAMETERS OPTIMIZATION | | | Accuracy |
|---|---|---|---|---|
| | Hyperparameters | Possible Values | Optimized Values | |
| ResNet50 | Activation units | 32-1024 | 768 | 96% |
| | Dense activation | Sigmoid, ReLU | ReLU | |
| | Learning Rate | $1e^{-4}$ to $1e^{-2}$ | 0.0001 | |
| VGG16 | Activation units | 32-1024 | 128 | 99% |
| | Dense activation | Sigmoid, ReLU | ReLU | |
| | Learning Rate | $1e^{-4}$ to $1e^{-2}$ | 0.0049 | |

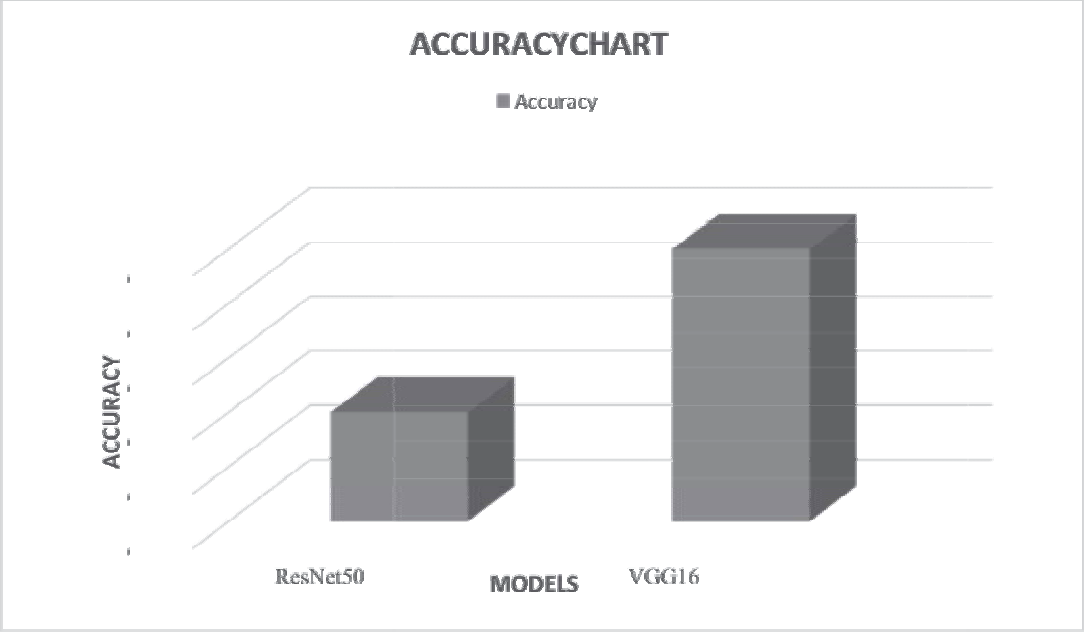



Figure 4: Accuracy Comparison Chart for Transfer Learning Models.

RQ2: Which transfer learning model between VGG16 and ResNet50 give better performance for prediction of disease in tomato plants based on precision, recall and f1-score metrics?

For answering this RQ, performance metrics, namely, Precision, Recall and F1-Score of prediction models were calculated and analysed as discussed in Section 3.6. The analysis of metrics are represented in Table 3 and graphical representation for the same have been illustrated in Figure 5. From the graph, it can be seen that, since VGG16 model performed better with better accuracy (as shown in Figure 4), so it's Precision, Recall and F1- Score values are also better than Resnet50 model. On the contrary, Resnet50 model have very less precision valuethan VGG16 model, recall value is little lower

than VGG16 and f1-score is also lower than VGG16 model. The graphical representation of performance metrics is illustrated in Figure 5.

Table 3: Results after Performance evaluation using performance metrics.

| Model | Precision | Recall | F1-Score |
|---|---|---|---|
| ResNet50 | 0.9270 | 0.9780 | 0.9518 |
| VGG16 | 0.9895 | 0.9895 | 0.9895 |

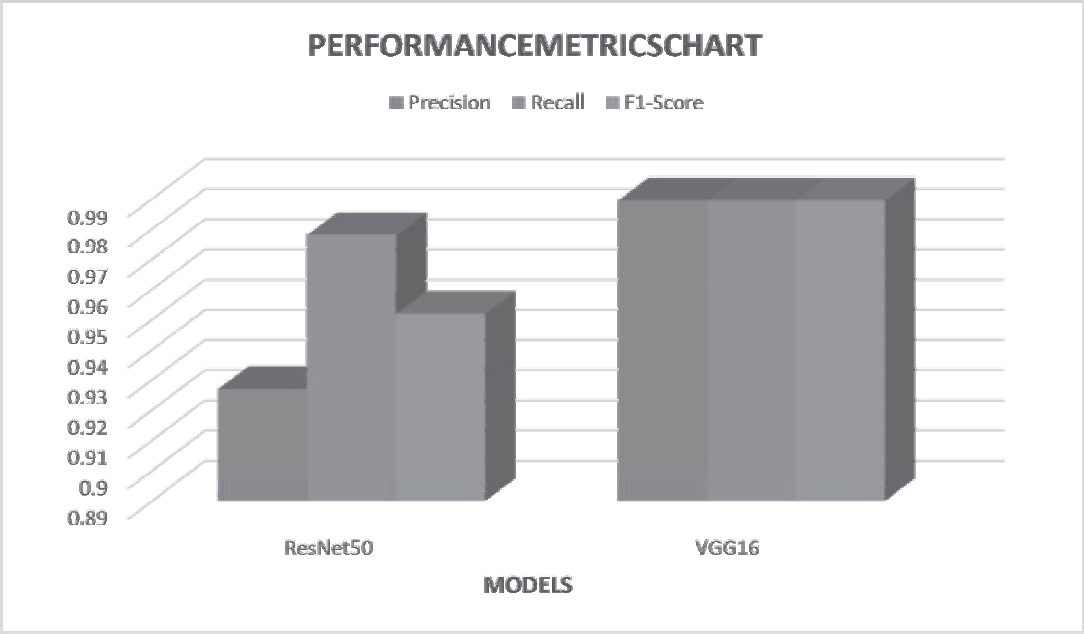



Figure 5: Performance metrics for Transfer Learning models

RQ3: What is the role of hyperparameter optimization in prediction of diseases in plants?

In Hyperparameter Optimization, hyperparameters are an essential part of the process which controls the behaviour of the model. Hyperparameter Optimization is a process of finding the suitable combination of hyperparameters to achieve the best model in less time with best parameters. It helps in optimizing the parameters by defining a certain range, thus, improving the accuracy as well as performance of the model. In this, it works by defining a range of parameters and running the model for multiple trials and adjustments are made based on previous trial for subsequent trial and hence, optimized hyperparameters are obtained or more aptly, Hyperparameters are tuned. Thus, for prediction of diseases in tomato plants, hyperparameter optimization is necessary to obtain the best model.

## 6. CONCLUSION AND FUTURE SCOPE

In this study, Transfer Learning Models were used for hyperparameter optimization of the model. The Tomato Early Blight Diseased dataset (Collected from IARI) was used for conducting the current

study. Different image pre-processing techniques were used and applied on the dataset to fine-tune the original dataset. After pre- processing, segmentation of images was also done using the k-means clustering technique. Further, the optimization of hyperparameters was done using random search taking into consideration learning rate, the number of units, and dense activation function for optimization. The performance of the prediction model was checked by various metrics such as precision, recall, and F1-Score. The best accuracy was achieved by VGG16 model with accuracy of 99%.

However, the proposed model was implemented successfully for the prediction of early blight disease in tomato plants, but still, there are some limitations of the current study. The proposed study cannot be used for images wherein there is a bunch of leaves. So, the object detection technique, as well as boundary box, can be applied to segregate the leaves from the bunch and applying classification on each leaf separately. The genetic algorithm can be used for optimizing transfer learning models. Different optimization techniques can be applied using both transfer learning, and deep learning, and comparison can be made between both approaches.

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