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# ENHANCING TOMATO LEAF DISEASE DETECTION: A DEEP DIVE INTO HYPERPARAMETER OPTIMIZATION IN DEEP LEARNING ARCHITECTURES

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**Abstract**:
The majority of people in India, a nation with a sizable agricultural sector, rely on farming to support their lifestyle. Farmers face a wide range of cultivation issues as a result of bio environmental changes, and they need assistance to get beyond these issues with vegetation and farming. Crop growth could be enhanced and losses could be avoided with early disease diagnosis. The identification of plant diseases, soil testing, crop recommendations, and other aspects of agriculture are all altered by technological advancements. Image processing with deep learning algorithms, produces astounding results by swiftly locating and extracting the properties of damaged leaves. This research experiment explores Hyperparameter Optimization(HPO) within deep learning architectures to enhance the timely detection of tomato leaf diseases, ultimately preventing losses for farmers.The results confirm that the EfficientNet deep learning architecture attains a higher accuracy of 99.98% compared to CNN, ResNet-50, U-Net, and XceptionNet .
**Keywords :** Tomato Leaf Disease, Hyperparameter Optimization, CNN, ResNet-50, U-Net, and XceptionNet, EfficientNet

## 1. Introduction

Consumers of tomatoes are numerous and inescapable on a global scale. A staple vegetable for human consumption, tomatoes are currently the focus of tomato vegetation because of rising demand. Tomatoes come from South America, but they have different characteristics depending on where you are. External factors, including bacteria and fungal illnesses, posed minimal hindrance to the growth and productivity of the plant. Because of this virus infection, which impairs tomato growth, manual inspection takes longer, costs more to hire people, and causes farmers to lose money and time.To prevent a reduction in tomato yield, this research takes these leaf diseases into account. Thus, feature extraction was done using the images from k-means clustering technique, and hyper parameter tuning was tested using CNN, ResNet-50, U-Net, XceptionNet and EfficientNet classification. The accuracy, f1 score, sensitivity, and specificity of the findings were assessed. The organization of this paper starts with the related work and methodology, concluding with results, discussion, and conclusion.

Existing problem:

The majority of experiments utilized CNN, with only a limited number focusing on the analysis of hyperparameters for disease detection.

Table 1 Illustrates the existing research in this context.

| **Author & year** | **Dataset** | **Algorithm** | **Accuracy** |
| --- | --- | --- | --- |
| Kapucuoglu et al.(2021) | Plantvillage dataset | CNN with Hyperparameter Optimization | 92% to 98% |
| Alkaff et al. (2022) | Tomato Leaf Disease Detection dataset | CNN with Hyperparameter Optimization | Training 95.690%. Testing 88.50% |
| Khan et al. (2023) | Plantvillage dataset | Hyper Parameter Optimization Artificial Rabbits Algorithm | 99.7% |

Proposed experiment:

This paper aims to identify the positive aspects of hyperparameter optimization in the detection of tomato leaf diseases through deep learning methods. This experiment attempts to train CNN, ResNet-50, U-Net, XceptionNet and EfficientNet with hyperparameter optimization and analyze specific parameters to determine their supporting capability for prediction. It offers guidance to farmers to protect tomato leaves from diseases, thereby increasing overall yield.

## 2. Related Work

*Prajwala* et al.(2018), proposed the study to provide a result with limited time and power. For that CNN used with small variation which is named LeNet and experimented with 18,160 images which achieves an accuracy of around 95%. *Ananda* et al.(2021), developed AgroDeep mobile application to capture various leaf images of tomato, soybean, sugarcane, onion, grapes, and cotton. The Convolutional Neural Network (CNN) classification, aimed at identifying leaf diseases, yielded an accuracy rate of 97%. *Ashok* et al.,(2020), planned to develop a authenticate, secure matching system for leaf disease with tomato plant which accomplished by segmentation and clustering with fuzzy logic and CNN.

Chaitanya et al. (2023) employed transfer learning for classifying nine diseased leaves against healthy leaves, achieved accuracy rate of 91.2% .

*Reesali* et al.(2022), proposed the implementation of machine learning methods, including support vector machine, logistic regression, and random forest algorithms, for the detection of tomato leaf diseases. Histogram oriented Gradient method is utilized to extract image features, and the model's performance is assessed through recall, precision, and f1 score during classification. Hareem et al.,(2021) employed Convolutional Neural Network (CNN)-based models, namely GoogleNet and VGG16, for the identification of tomato leaf diseases. Utilizing a dataset consisting of 1073 leaf images from Plant Village, VGG16 demonstrated an accuracy of 98%, while GoogleNet excelled with an accuracy of 99.23%. *Priyanka et al.(2022,*diagnosed the tomato leave diseases by CNN model with four convolutional layers and four max pooling layers in proposed CNN which achieved an accuracy of 96.26% . *Shruti* et al. (2023), developed CNN, KNN, and VGG-19 models for the examination of plant diseases on tomato leaves . The findings indicated that the KNN model surpassed all other models across all evaluation criteria.

*Haridas* et al. (2020), Explored various classification algorithms and features like color, texture, and shape for automated tomato plant disease detection and assessment to evaluate the system's performance. *Khalid* et al. (2022), Identified various tomato plant illnesses using a dynamic intelligent model with the histogram-based k-means clustering algorithm and backpropagation neural network. Utilized Convolutional Neural Networks for disease detection.

*Manpree* et *al. (2020),* Used a pre-trained deep learning model to recognize and categorize ailments on tomato leaves, evaluating it based on improved F-score, specificity, accuracy, and precision. The model is recommended for disease identification.

*Sagar* et al. (2023), Introduced convolutional and depth-wise convolutional layers in a deep learning-based technique for distinguishing tomato leaf diseases. The proposed model, comprising only 17,209 trainable parameters, achieved a 92.10% accuracy in predicting tomato crops using a publicly available Plant Village dataset.

*Ayesha Batool et.al* (2020),Implemented an advanced classification model for identifying and categorizing tomato leaf diseases. Utilizing 450 images for feature extraction, the KNN algorithm was employed to classify the data. The AlexNet model achieved a high accuracy rate of 76.1%.

*Pallavi Shetty et.al(*2023), Utilized an extensive array of machine learning algorithms, including Linear Discriminant Analysis (LDA), Logistic Regression (LR), Support Vector Machine (SVM), K Nearest Neighbor (KNN), Decision Tree Classifier (CART), Random Forest Classifier (RF), and

Gaussian Naive Bayes (NB), for the prediction of health and different diseases in tomato leaves. The diseases encompassed leaf mould, bacterial spot, late blight, and early blight.
*Harsh Baheti* et.al (2022) suggested a classification model to evaluate 10 distinct plant illnesses from leaves. Several machine learning techniques were used, and the Random Forest algorithm produced the best results (98% accuracy).
*Paarth Bir et al.(* 2020), utilised the features extrapolated by the VGG 19, EfficientNetB0, and MobileNetV2 models in order to create mobile devices with the lowest possible cost. The 15,000 photos used in this investigation included both healthy and diseased images. *Nithish* et al.(2020), explored transfer learning using ResNet-50 to solve the categorization challenge. This model has a 97% accuracy rate and makes use of data augmentation to boost the dataset size. *Mamta Gehlot* et.al (2021), experimented VGG-16, AlexNet, DenseNet-121, GoogleNet, and ResNet-IOI to conduct experiments on the PlantVillage dataset with the aim of developing a classification model for the detection of tomato leaf diseases. The accuracy, precision, F1-score, and recall of all models were found to be essentially similar. Notably, DenseNet-121, with a size of only 89.6MB, is significantly smaller compared to ResNet-IOI and other models.
*Hasibul* et al., (2021), proposed Deep Learning architecture for CNN to quickly and effectively identify tomato plant leaf diseases. *Iftikhar* et al.,(2020), employed ResNet, Inception V3, VGG-16, and VGG-19 ,CNN architectures to analyse damaged leaf regions. good precision is achieved. *Mosin* Et al.,(2019), employed CNN with transfer learning and an inception model to detect tomato leaf illnesses. 2100 photos from the data set and 500 photographs of local farms were used in the experiment. A high accuracy of 99% was reached. *Nagamani* et al.,(2022), Explored machine learning tools for tomato plant leaf disease detection, including Region-based Convolutional Neural Networks, Fuzzy Support Vector Machines , and CNN.
*Hesham et al.,(2022),* analysed, MobileNetV3 Small and MobileNetV3 Large to find illnesses in tomato leaf photos. MobileNetV3 Large had a 99.81% accuracy rate compared to MobileNetV3 Small's 98.99%. The models were additionally evaluated for their performance on a Raspberry Pi 4 to construct an Internet of Things (IoT) device for tomato leaf disease detection.
*Antonio et al.,(2023),* presented a CNN for classifying tomato leaf diseases that uses generative adversarial networks to prevent overfitting and achieves good accuracy. *Ashwani et al.,(2022),* recommended a deep learning system that classifies the leaves into three categories—disease-free, bacterial-spotted, and seportia-spotted—while haphazardly extracting features for neural network-based categorization. *Alvaro* et al., (2021), employed an expanded dataset with 14 classes, of which 5 are target classes for tomato plant diseases. The effectiveness and capacity of the proposed approach were demonstrated through experiments. The detector has a 93.37% mean average precision appreciation rate for target classes on the inference dataset. *Shengyi* et al.,(2021), Suggested a model proficient in accurately discerning complex features of various diseases. According to comprehensive collation testing findings, the proposed model attains an average detection accuracy of 96.81% on the tomato leaf disease dataset. *Mehdhar* et al.,(2022), suggested a technique for diagnosing illnesses of tomato leaves using transfer learning and feature concatenation. The authors collected features using weighted pre-trained kernels from NASNet Mobile and MobileNetV2. Using kernel principal component analysis, they then merged and decreased the dimensionality of these features.
*Saleh et al.,(2022),* employed a transfer learning model to identify disease on tomato plant leaves and got an average accuracy of 99.98%. *Gnanavel* et al.,(2022), applied in favour of a technique for identifying and classifying diseases based on convolutional neural networks. The model uses two pooling layer configurations. InceptionV3, ResNet152, and VGG19, which were pre-trained models, were outperformed by the recommended model, according to the research' findings. The CNN model achieved an accuracy of 98% during training and 88.17% during testing. *Alvaro et al.,(2017),* recommended and advisable to employ a deep-learning approach for the detection and identification

of ailments and pests affecting tomato plants. Selecting the most suitable deep-learning model for our specific task is the most equitable and effective course of action.

*Siti* et al.,(2020), tested a reliable deep learning model to accurately identify pests and sick tomato leaves. *Naresh et al.,(2021)*, assigned to classify tomato diseases using a convolutional neural network (CNN). Three thousand photos in all were tested for the ability to identify a healthy leaf and nine distinct diseases. *Anandhakrishnan T et al.,(2020)*, Utilized a dataset sourced from the Plant Village dataset, the model was designed to assess images of both unhealthy and healthy plants. *Showmick* et al.,(2023), created a straightforward basic convolutional neural network (CNN) model and organised tomato leaf illnesses using the TL-based models VGG-16 and VGG-19. *Maha et al.,(2022)*, Suggested a CNN model that, used to test images of tomato leaves, achieves a very promising accuracy of 97.2%.

## 3. Materials and Methods

Using an unsupervised learning strategy in digital image processing, the suggested method was created to detect tomato leaf disease. It starts with image acquisition, followed by processing, segmentation, feature extraction, classification, and finally, outcome evaluation. The overall process is shown in the following diagram.

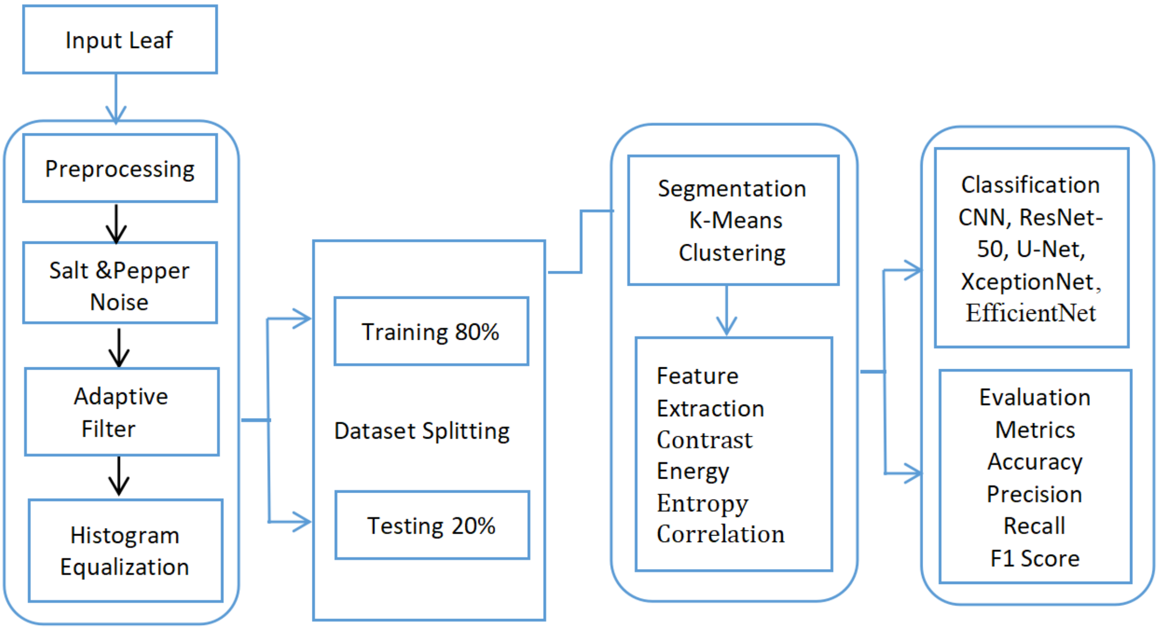


***Figure.1.*** *Methodology*

### 3.1 Image Acquisition and Preprocessing

The image under test was obtained from Kaggle, which has about 1000 examples of both healthy and unhealthy images [10]. Images have a 256 × 256 resolution. To improve the image, preprocessing is used. Images have noise, lighting, and various contrasts because varied capturing circumstances provide diverse results. In this experiment, the image was improved using histogram equalization, with an emphasis on the contrast and light effect of the image. By preventing visual blur and producing an enhanced version of the image, an adaptive filter is utilized to remove the salt and pepper noise. The preprocessing of the tomato-dead leaf image is displayed in the following figure.

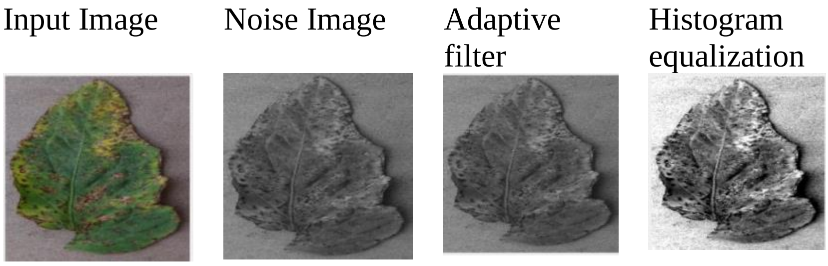


***Figure.2.*** *Preprocessing*

**3.2 Clustering**

Segmentation describes the process of locating flaws in an object. The division of the image into groups is known as segmentation. Finding the location of an object in a image can be done using this simple technique. The same type of pixels typically belong to the same label when it locates labels to pixels.Disease detection is a crucial step for farmers to avoid losses.. In this study, segmentation was accomplished using K-means clustering, one of many strategies for moving forward with image localization.

Homogeneous subgroups are the foundation of clustering. It is an unsupervised learning technique that places a strong emphasis on the data's structure by gathering it in several subgroups. Clustering-based segmentation heavily relies on K-means clustering. It forms a cluster by adhering to the following rule.

1. Specify the K-value for the clusters.
2. The centroids are initialized by splitting the dataset into K data points.
3. Up until no more centroid data points change, iteration continues.

**Algorithm for K-MC**

*Input the diseased Tomato leaf image.*
*Salt & Pepper Noise employs an adaptive filter for preprocessing.*
*Create cluster points*
*Set up the centroid points.*
*To achieve a similar pixel value cluster, this process is continued until all of the image's pixels have undergone it.*
*The cluster component that had been correctly segmented had finally arrived.*

Clustered images were used to extract GLCM features for this study. The images of a tomato leaf used in the following illustration to detect disease.

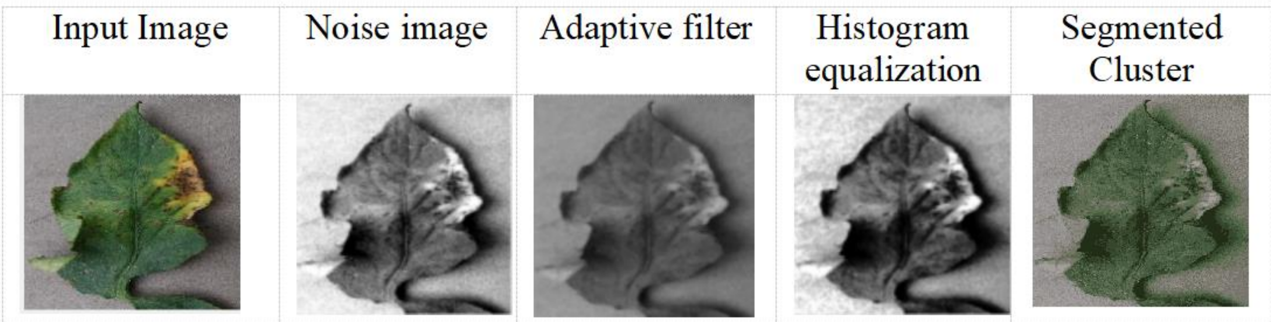


***Figure.3.*** *Tomato leaf disease detection by Clustering*

## 4. Feature Extraction

One of the popular approaches to take into account before categorization is feature extraction. It is also a dimensionality reduction technique that can eliminate information while reducing a significant number of features. It aids in extracting useful features from the image and aids in creating the classification model. Images of tomato leaves are segmented to yield four Haralick characteristics. Energy, contrast, entropy, correlation, and I and J are image pixels, thus these features were acquired in this way and used for categorization. The features were represented as follows,

**Table 2.** GLCM Features

| Contrast | Energy | Entropy | Correlation |
|---|---|---|---|
| $\sum_{i,j=0}^{N-1} P_{ij}(i-j)^2$ | $\sum_{I,J=0}^{N-1} (P_{ij})^2$ | $\sum_{Ii,j=0}^{N-1} -\ln(P_{ij})P_{ij}$ | $\sum_{i,j=0}^{N-1} P_{ij}\frac{(i-\mu)(j-\mu)}{\sigma^2}$ |

## 5. Classification

The process of classifying a thing involves placing it into several groups. Classification plays a crucial function in image processing because it aids in determining the right kind of image class. Identification of benign and malignant tumors is a prerequisite for classification in medical image processing, which also supports classifying the various classes of images and demonstrates the relationships between classes. CNN, ResNet-50, U-Net, Xception Net, and Efficient Net with Hyperparameter Optimization (HPO) carried out deep learning classification. In this study, classification was tested both before and after deep learning classifiers were applied with HPO.

**Hyperparameter Optimization (HPO) :**

This study focused on the optimization of those parameters to enhance the performance of unsupervised learning algorithms, which have remarkable performance for hyperparameters. In order to provide effective categorization, different learning rates, batch sizes, and optimizers were tested for deep learning architectures such CNN, ResNet-50, U-Net, Xception Net, and Efficient Net.

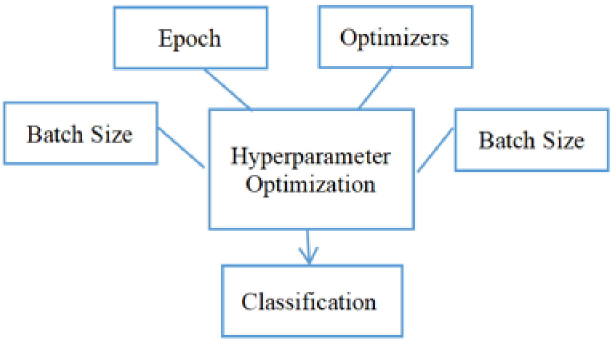


***Figure. 4.*** Hyperparameter Optimization(HPO)

**Optimizer:** In order to increase accuracy and decrease loss, it concentrates all parameter values, including learning rate and weight, in the neural network.

**Epoch:** The number of times the algorithm runs on a test dataset.

Batch Size: sample sizes used to change the model's parameters.

**Loss / Cost function:** The difference between the actual and anticipated values was computed using it.

**Learning Rate:** In the neural network, it focuses on the most recent model weights.

**Weight/ Bias:** The signal between two neurons in the model is communicated by these learnable parameters.

Several optimizers, including RMSProp, AdaDelta, and Adam, with learning rates of 0.01, 0.001, and 0.0001, and loss function binary cross entropy, were used in this experiment.

**RMSProp Optimizer :** It lessens the aggressiveness of the learning rate, which precisely determines the gradient value.

**AdaDelta Optimizer :** AdaDelta was able to resolve the problem of manual allocation of the starting learning rate in Adagrad and RMSProp.

**Adam Optimizer :** This technique is an expansion of stochastic gradient descent (SGD). This is meant to update a neural network's weights while it is being trained. Compared to other optimizers, it is more trustworthy.

### *5.1* Convolution Neural Network (CNN)

All other deep learning architectures are built on the foundation of CNN. An operation of convolution results in a feature map. It typically consists of sigmoid function, fully connected layer, Adam optimizer, Max pooling, ReLu activation function, binary cross entropy, and Adam optimizer. In this CNN model, the following terms are used:

***Max pooling :*** Denoise the image.

***ReLu Activation*** : it delivered he solution for vanishing gradient problem.

***Batch Normalization:*** It reduce the dropout and encourage self learning of layers.

***Binary cross entropy :*** It identified the wrong labeling of data.

***Adam optimizer:*** Update the neuron weights.

***Sigmoid function:*** Activation function for fully connected layer.

***Fully connected layer:*** High-level features are captured for output layer.

### 5.2 U-Net:

The ideal architecture for segmenting images is the U-Net. The U form is produced by combining convolutional layers with encoders and decoders. The encoder network, also known as the contracting network, is composed of four encoder blocks, two 3×3 convolutional layers, valid padding, Max pooling, and the ReLu activation function. For the given input image, the decoder network samples the feature map. It has a 2× 2 transpose layer and four decoder blocks. The decoder block and encoder block are linked together by the skip connection.

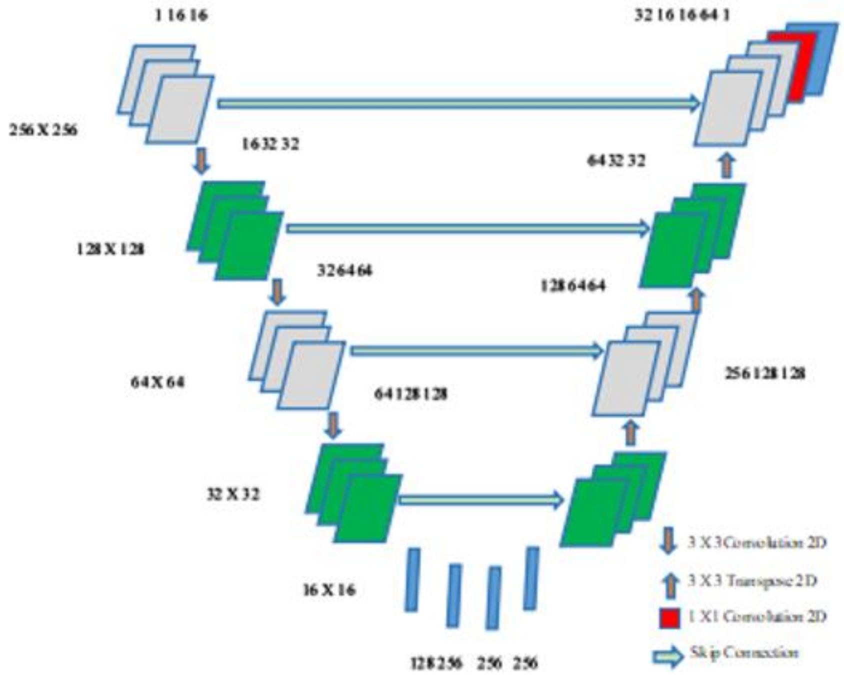


*Figure. 4. U-Net Architecture*

### *5.3* ResNet-50*:*

Residual networks are referred to by the acronym ResNet. It is made up of 50 neural networks that have many different variations on the skip connection principle. It comprises three bottleneck blocks with three convolution layers in each block. The 5 stages with 23 million trainable parameters were created by the convolution and identity blocks, and they are simply presented as follows:

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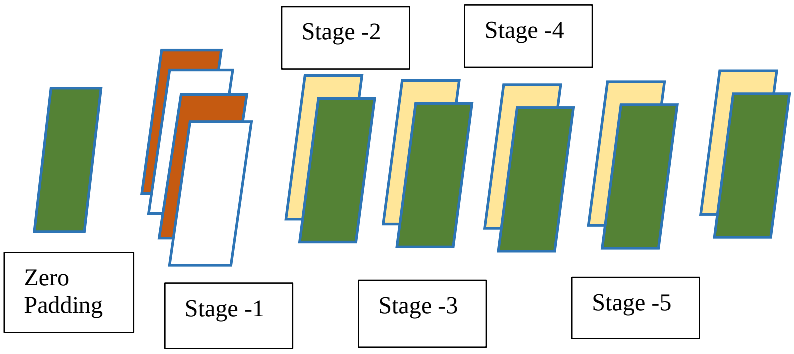


***Figure.5.*** *ResNet -50 Architecture*

Stage 1 : Zero padding: add (3,3) to the input.

Stage 2 : Conv + Batch Normalization + ReLu + Maxpool .

- Convolution layer secure the dominant features of image.
- Performance each layer can improved by Batch Normalization.
- Hidden layers worked in hidden layers
- Maxpooling layer hold the important features of previous feature map.

Stage 3 to 5 : Conv + ID Block

Final layer : Avg pooling + Flatten layer + Fully connected layer.

Skip connections minimize the problem of vanishing and exploding gradient.

**5.4 XceptionNet *:***

Convolution, SeparableConvolution layer, input flow, middle flow, and exit flow are all components of the Depthwise Separable Convolution technique employed by XceptionNet. 8 times are processed during the middle flow. It is an additional application of the inception model that eliminates non-linearity and lessens the bottleneck issue in in-depth observation.

**5.5 EfficientNet:**

It is made up of neural architecture search (NAS) and model scaling. It used the concept of the compound coefficient, which is based on the scaling of width, depth, and resolution, which optimizes the network's width, depth, and resolution. NAS automatically selects the suitable network for the given task.

To create its architecture, it employed MBConv (Mobile Inverted Residual Bottleneck Convolution). Therefore, model scaling efficiently increases the network's width, depth, and resolution. Compound scaling keeps network dimensionality uniform, and the overall working methodology speeds up and lowers the cost of the model. Similar to MobileNet V2, EfficientNet is based on the AutoML MNAS framework and has been fine-tuned.

**Evaluation metrics**

The model performance of segmentation and classification can be easily evident by following metrics

***Accuracy*** : It is determined as the following ratio between actual and anticipated pixels:

$$Accuracy = \frac{TruePositive+TrueNegative}{TruePositive+TrueNegativ+FalsePositive+FalseNegative}$$

***Precision*** : It predict the number of correct positive predictions. It is calculated as follows

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Recall : Recall also termed as Sensitivity . It is calculated as follows

$$\text{Recall} = \frac{True\ Positive}{True\ Positive + False\ Positive} *100$$

***F1 Score :*** It combines precision and recall and prioritizes class performance over overall performance.

.

$$\text{F1 Score} = 2 * \frac{Precision * Recall}{Precision + Recall}$$

## 6. Result & Discussion

Following table demonstrate the segmentation performance evaluation for K-Means clustering. For all charts X axis - Algorithm, Y axis - Experimental values used

Table.3 : performance of K-MC

| **Sementation Algorithm** | **Accuracy**(%) | **Precision** (%) | **Recall** (%) | **F1 Score** (%) |
|---|---|---|---|---|
| **K-MC** | 95.88 | 94.22 | 89.56 | 93.89 |

Following graphical representation shows the performance of Density based K-Means clustering.

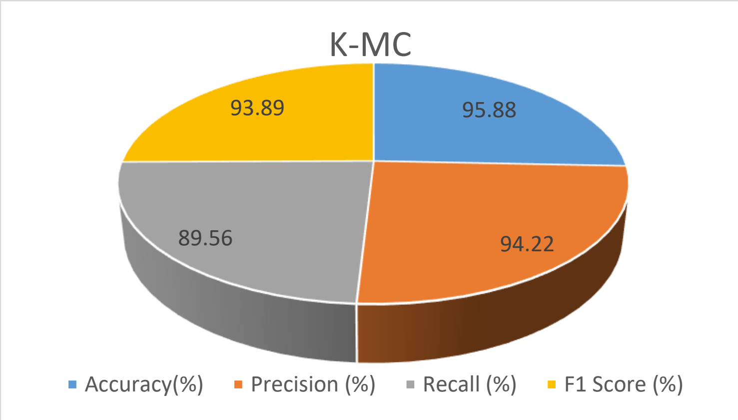


***Figure 6.*** *performance of K-MC.*

Following table display the evaluated result before applying HPO which presented in (%) value

Table.3 : Evaluated result before applying HPO

| **Classifiers** | **Accuracy** | **Precision** | **Recall** | **F1 Score** |
|---|---|---|---|---|
| **CNN** | 87.78 | 91.22 | 86.56 | 90.89 |
| **ResNet-50** | 87.97 | 92.30 | 86.77 | 89.63 |
| **U-Net** | 88.47 | 90.20 | 85.06 | 90.08 |
| **XceptionNet** | 99.13 | 92.10 | 96.24 | 93.51 |
| **EfficientNet** | 99.53 | 96.01 | 97.23 | 95.66 |

Following table presents the evaluation metric values after applying HPO which presented in (%) value, The best leaning rate, optimizer only presented.

Adam optimizer, learning rate = 0.0001

Table.4 : Evaluated result after applying HPO

| **Classifiers** | **Accuracy** | **Precision** | **Recall** | **F1 Score** |
|---|---|---|---|---|
| **CNN** | 88.18 | 91.32 | 87.00 | 91.00 |
| **ResNet-50** | 88.07 | 92.41 | 86.97 | 89.84 |
| **U-Net** | 88.87 | 90.30 | 85.56 | 90.66 |
| **XceptionNet** | 99.83 | 92.77 | 96.64 | 93.91 |
| **EfficientNet** | 99.98 | 96.81 | 97.53 | 96.76 |

Following pictorial representation of before and after applying HPO in deep learning architectures

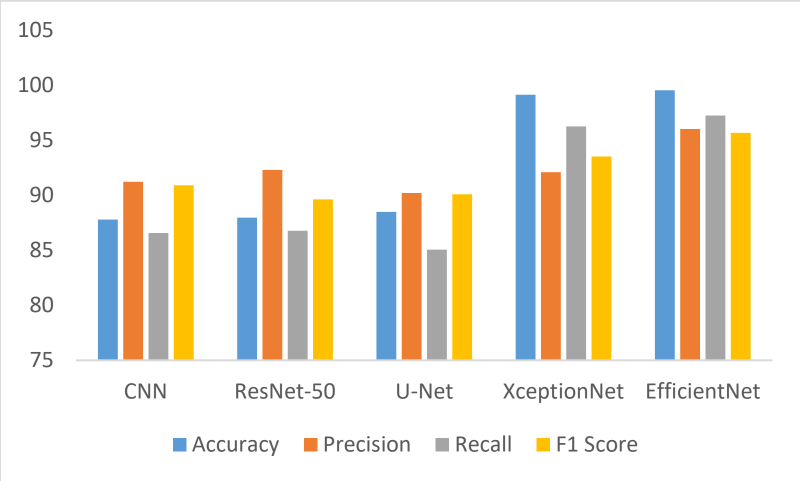


*Figure.7. Before applying HPO in DL architectures*

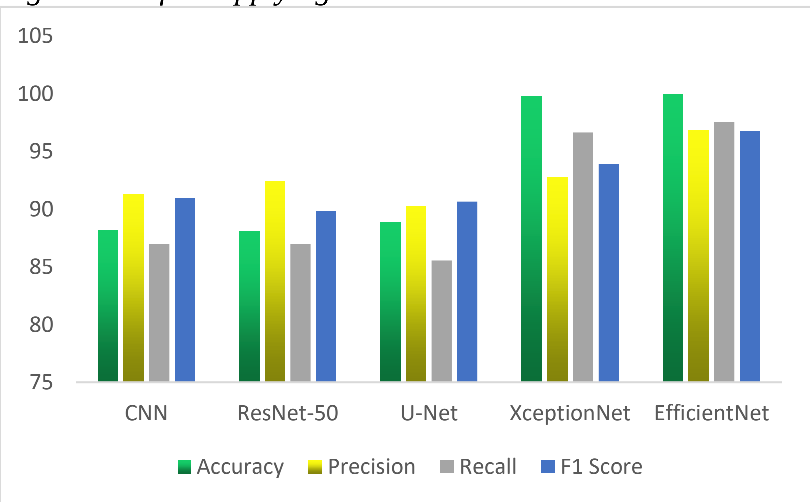


*Figure.8.After applying HPO in DL architectures*

Following table exhibits the accuracy of DL architectures before and after applying HPO

Table.5 : Accuracy before & after applying HPO

| Classifiers | Accuracy before HPO | Accuracy after HPO |
|---|---|---|
| **CNN** | 87.78 | 88.18 |
| **ResNet-50** | 87.97 | 88.07 |
| **U-Net** | 88.47 | 88.87 |
| **XceptionNet** | 99.13 | 99.83 |
| **EfficientNet** | 99.53 | 99.98 |

Following graphical representation shows off the accuracy deep learning architectures before and after applying HPO

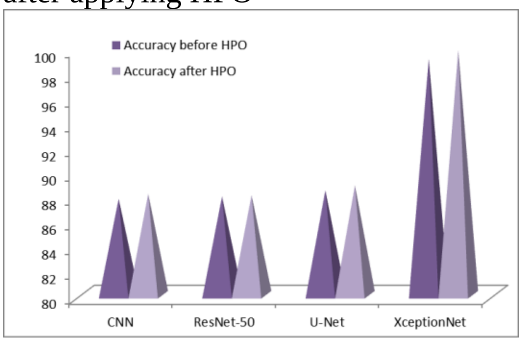


*Figure.9. Accuracy before & after applying HPO*

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Following figure discovered the model performance of DL architectures for Adadelta optimizer.

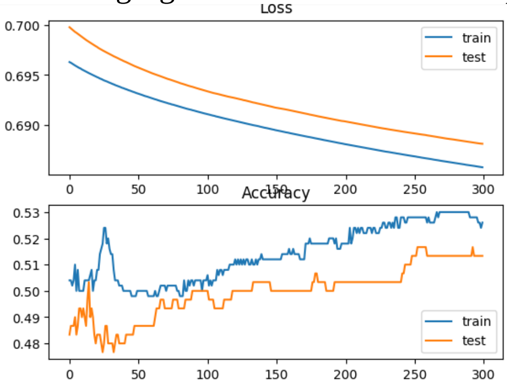


*Figure.10. Performance of model CNN*

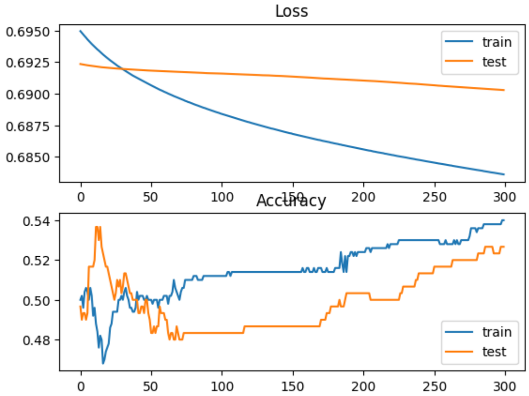


*Figure.11. Performance of model ResNet-50*

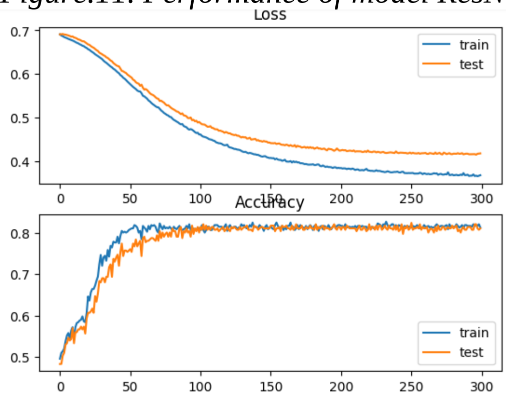


*Figure.12. Performance of model U-Net model*

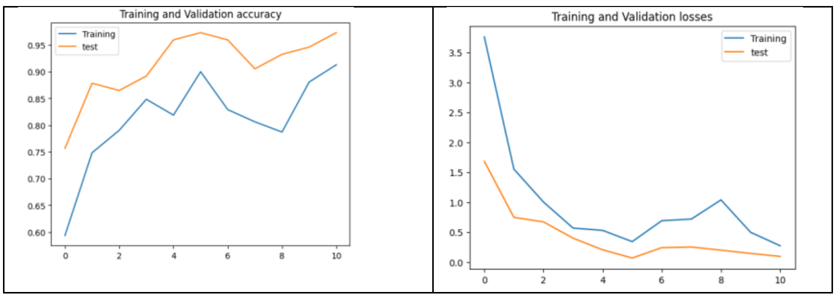


*Figure.13. Performance of model XceptionNet*

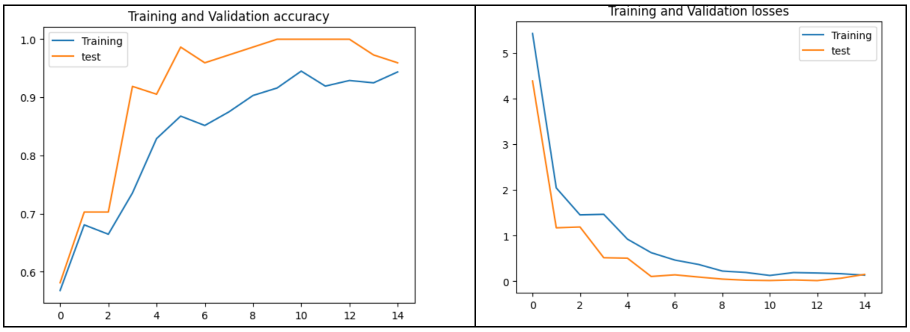

*Figure.14.EfficientNet model performance*

*Findings:*

- ➢ HPO produced improved result for Tomato leaf disease detection.
- ➢ This experiment recommend learning rate 0.0001, AdaDelta optimizer with EfficientNet for Tomato leaf disease classification.
- ➢ EfficientNet perform well than other state of art methods.

## 7. Conclusion

To segment and categorize tomato leaf diseases, researchers must put forth a lot of time and effort. This experiment's main goal is to develop a low-cost, quick-to-use segmentation and classification model for tomato leaf disease detection. In this study, a segmentation method with a 95.88% accuracy rate is proposed: K-means clustering. With the major adjustments in hyperparameter optimization, the accuracy for CNN, ResNet-50, U-Net, XceptionNet, and EfficientNet's was 88.18%, 88.07%, 88.87%, 99.83%, and 99.98%, respectively. This improved method of HPO using deep learning architectures shown that HPO had a considerable impact on image classification over earlier approaches.

## 8. References

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