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# The Convolutional Neural Network for Plant Disease Detection Using Hierarchical Mixed Pooling Technique with Smoothing to Sharpening Approach

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**Abstract:** Plant health is an important factor in agricultural production as it mostly affected by plant diseases. Due to plant diseases, the growth and crop yield gets affected which results in negative impact on agriculture in terms of economic loss to farmers. In plant disease management, early and accurate disease detection can control its spreading and avoid unnecessary loss to farmers. Traditionally, plant disease detection has been carried out through visual inspection by human experts. This method is based on subjective perception hence it has risk for error in detecting accurate disease. In recent past, researchers have proposes numerous machine learning approaches to detect the plant diseases. Due to advancement in artificial intelligence and electronic gadgets technology, there is large scope for improvement in neural network algorithms for detecting plant diseases early and accurately by extracting leaves features efficiently. To detect tomato plant diseases, the novel convolutional neural network (CNN) model has been proposed in this paper. The hierarchical mixed pooling technique for smoothing to sharpening approach has been used in proposed CNN model. The system uses tomato plant leaf images obtained from Kaggle dataset. The system has been trained with 1000 images of healthy leaf and 1000 images each for nine different diseases frequently occurs in tomato plant. The different training models has been framed and experimented to identify efficient hierarchy of pooling techniques. The CNN training model_3 exhibit smoothing to sharpening approach with "Average-Max-GlobalMax" mixed pooling hierarchy and depicts better performance with a training loss 28.88%, a validation loss 12.61%, a training accuracy 96.46%, and a validation accuracy 95.41% at 20 epochs. Also, the performance of designed system have been evaluated with different state-of-art deep learning algorithms and compared with proposed CNN model.

**Keywords:** Convolutional Neural Network, Plant Disease Detection, Pooling Technique, Agricultural System, Machine Learning System

## 1. Introduction

As world population increasing rapidly, food safety is an important concern for a globe to fulfill the food requirement in future. Plant health is very important factor in agricultural production as it mostly affected by plant diseases [1]. Due to plant diseases, the growth and crop yield gets affected which results in negative impact on agriculture in terms of economic loss to farmers or no harvest in dreadful cases [2]. In plant disease management, early and accurate disease detection can control its spreading and avoid unnecessary loss to farmers. Most of the plant diseases affect the natural appearance and ambience of plant leafs. Hence early detection of disease is possible [3] by observing and analyzing the leaf appearance.

Traditionally, plant disease detection has been carried out through visual inspection by human experts [4]. Generally, those human experts are farmer with large experience in farming. This method is based on subjective perception hence it has risk for error in detecting accurate disease [5] . For large crops, human perception based disease detection may cause heavy loss to the farmer [6]. Another method is biological examination through imaging and spectroscopic techniques but it requires proper sensors and precise instruments which results in high cost with low efficiency [7]. In recent past, researchers have proposes numerous machine learning approaches to detect the plant diseases [4]. The machine learning methods [8] extract the features from images of plant leaves by efficiently training multi-layered neural network.

Due to advancement in artificial intelligence and electronic gadgets technology, there is large scope for improvement in neural network algorithms for detecting plant diseases early and accurately by extracting leaves features efficiently [3]. Numerous researchers designed various CNN architecture for plant disease detection but it has been observed that only one type of pooling technique has been used throughout the network by most of researchers. Hence, this paper aims to design a powerful approach required for the detection of plant diseases [9] in a real-time environment. The proposed novel convolutional neural network (CNN) model with hierarchical mixed pooling techniques for the smoothing to sharpening approach has been designed to detect plant diseases. An efficient "Average-Max-GlobalMax" mixed pooling hierarchy has been implemented in the CNN model which exhibits a better smoothing-to-sharpening approach.

## 2. Related Work

In recent past, several researchers designed numerous advanced convolutional neural networks based on data enhancement and optimized approaches to enhance the system's ability to detect plant diseases.

Nie et al. proposed network for disease detection of verticillium wilt in strawberry [1]. It uses attention mechanism for feature extraction from young leaves and petioles and classify into four classes as Healthy_petiole, Healthy_leaf, Verticillium_petiole and Verticillium_leaf with 99.95% accuracy in detection of strawberry verticillium wilt. Marzougui et al. proposed system for early diagnosis of plant disease which uses ResNet architecture in convolutional neural network [2]. This system achieve better performance in classifying leaf images in two categories as diseased and disease-free. Sardogan et al. designed convolutional neural network for disease detection using Learning Vector Quantization algorithm [3]. This method able to recognize four different leaf diseases in tomato plant.

Jiang et al. proposed enhance learning approach to detect apple plant diseases [4]. The dataset of about 26,377 diseased apple leaf images were pre-processed with data augmentation and image annotation techniques and introduced GoogleNet Inception architecture and Rainbow concatenation in deep CNN [10]. The proposed model provides better solution for early detection of leaf diseases in real time scenario with faster detection speed and high accuracy. Zhou et al. addresses various issues related to real time rice diseased images like background interference, noise and blurred image edge and proposed novel method to detect rice plant diseases with Faster R-CNN and FCM-KM [5]. The complex background interference problem has been reduced by using proposed algorithm whereas noise reduction has been done by combining weighted multi-level median filter with two-dimensional filtering mask. To determine the k values of the best clustering class, the K-Means clustering algorithm was modified. This approach reduced the amount of time needed for the diagnosis of several rice diseases and achieved accuracy of between 97% and 98%.

Sunil et al. proposed disease detection method using EfficientNetV2 model and used U2–Net algorithm to remove unwanted background portion of input images of a cardamom plant [6]. This method achieved more than 98% disease detection accuracy in detecting Phyllosticta Leaf Spot and Colletotrichum Blight diseases in cardamom plants. The feature extraction based deep learning method has been proposed by Barburiceanu et al [7]. The pre-trained CNN models was used to extract texture features and then applied to machine learning classifiers. The suggested approach is effective in terms of discriminative power as well as processing times. By gathering data about environmental conditions in crop field with IoT based sensor system, the method has been proposed to predict the probability of any disease attacks [11] and uses Multiple Linear Regression (MLR) technique [12]. The effectiveness of system has been check by implementing proposed model for prediction of various diseases in Tea plant.

Another system proposed by Zeng et al. for detecting severity of citrus plant diseases using Inception_V3 model [13]. Author converted available training dataset into two fold by adopting Generative Adversarial Networks technique in deep convolutional network which improves the learning performance of proposed model. Khattak et al. develop CNN model utilizing an integrated method [14]. By combining multiple layers, the proposed CNN model captures complementing discriminative characteristics. On the Citrus and PlantVillage datasets, various cutting-edge deep learning techniques were compared to the CNN model. The novel technique was proposed for grape leaf spot identification with local spot area image data augmentation [15]. As a local spot area detector, the upgraded, quicker R-CNN was incorporated into system. For the purpose of identifying and classifying plant diseases, Lakshmanarao et al. used "Convnets" [16]. A PlantViallge dataset was obtained by the author via Kaggle. Images of 15 various plant leaf classes from the potato, pepper, and tomato are included and split the dataset into three smaller datasets and ran Convnets on each of them. Achieved accuracy of 98.3%, 98.5%, and 95% in the detection of tomato, pepper, and potato plant diseases, respectively.

The color based feature extraction technique has been used in Support Vector Machine Classifier based machine learning model [17]. The color based segmentation helps to detect grape plant diseases like Black Rot disease. In another study, Support Vector Machine and Random Forest algorithms are used to assess the detection of diseases affecting leaves [18] to help farmers with less time and expense while increasing productivity in agriculture. Early disease diagnosis is crucial in hydroponic farming because failing to do so results in significant losses in productivity, quality, and quantity. Apple fruit diseases cultivated by hydroponic farming was detected in proposed system [19]. To a greater or lesser extent (95.16 to 98.38%) than another model, the hybrid feature extraction technology [20] effectively identify and classify plant diseases. Also SVM based machine learning model has been implemented to detect various diseases of hemp plant and achieved 98% accuracy by following manual feature extraction techniques [21].

The article introduced image processing & machine learning approaches to identify and classify the plant diseases from an image [22]. Support vector & K-mean clustering methods were used to process plant disease sample processing to extract texture [23] and color data. The goal was to identify early stages of cotton illness using image processing techniques and to do so automatically rather than by visual inspection. The segmentation of images into clusters was done using the K-means clustering technique [24]. The hybrid approach for extracting texture and color features was used for feature extraction. Finally, Cercospora cotton leaves were categorized using Support Vector Machines (SVM). The accuracy was ultimately assessed using performance assessment measures for precision and recall, and 96% accuracy rate is attained.

Everyone, including farmers, is calling for new technologies that will make it simpler to detect plant diseases. As a result, Smartphones are being equipped with Deep Learning (DL) algorithms to speed up illness and image recognition. To identify plant diseases from smartphone-taken photographs, researchers are utilizing a variety of DL algorithms and training datasets. In order to understand how the accuracy was influenced with dependent variable, research was carried out using independent variable as a short training dataset [25]. Following linear regression, it was discovered that the quantity of photos in the dataset has a favourable effect on accuracy, with a large number of images requiring background reduction in order to increase accuracy. CNN accuracy does not benefit from image quality when the features are easily apparent.

CNN models encounters problems including overfitting, which happens when a model absorbs too much of the noise and detail in training data and suffers as a result when presented with new data. Reyes et al. proposed a novel pooling method known as fused random pooling which uses a random approach to activation selection to replace the deterministic pooling of CNNs in order to produce better pooled feature maps [26]. The fused random pooling was effective for accuracy improvement and reduction of error in training. The dropout function is modified with a mixed-pooling approach in the unique method, Skourt et al. developed [27]. Each element of a binary mask used to represent the dropout operation was selected randomly from a Bernoulli distribution. Max-Max pooling & Max-Average pooling are the two pooling methods that the Devi et al. proposed as part of a cascaded pooling methodology [28]. A method based on the InceptionV3 architecture of DCNN was evaluated, and superior classification results on two datasets of aerial scenes were obtained. The hybrid pooling method [29] that the Tong et al. suggests stochastically selects the particular pooling technique. The hybrid pooling has the ability to regulate the likelihood of using one of the two pooling techniques for each convolutional layer. The author demonstrates that the generalization abilities of CNNs in image classification tasks with benchmark datasets can be increased with hybrid pooling.

## 3. Proposed Methodology

The block schematic of plant disease detection system shown in figure 1. Images from the input dataset are converted into the format needed by the machine learning algorithm [30] in the image pre-processing block before being passed on to the algorithm. The output of image pre-processing block applied to convolutional neural network model for feature extraction. Then extracted features from trained model has been used to classify input image with fully connected layers which results in detection of plant diseases [7].

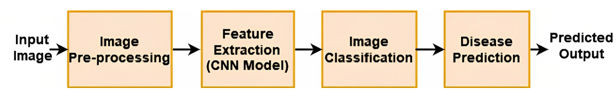


Figure 1. Block Schematic of Plant Disease Detection System

This section of paper explained the concept of different pooling techniques, proposed CNN architecture and system process flow.

### A. Pooling Techniques

Down sampling method plays an important role in dealing with sensitivity issues in output feature map while positioning the features in an input. Pooling layers in CNN models is helpful to down sample the feature map by summarizing the features in individual feature map patches [31]. Therefore, the CNN consists of several convolution and pooling layers placed one after the other. The different pooling methods is explained below.

#### 1) Average Pooling

This method takes average of elements present in particular patch in an account and presents the average of the features present in a patch as shown in figure 2.

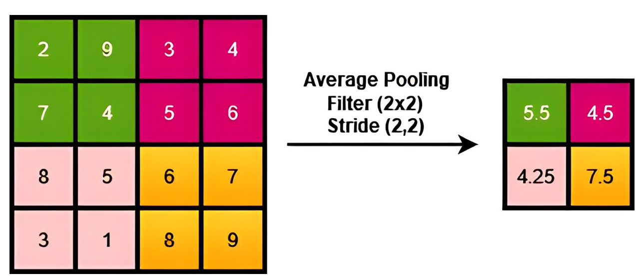


Figure 2. Average Pooling Technique

The mean of all the items in the pooling zone is determined via average pooling. The feature map's characteristics will be significantly diminished if there are a lot of zero components. The average value [26] of each pooling area with (n x n) neighborhood can be obtained by equation 1.

$$Z_{nxy} = \frac{1}{(|R_{xy}|)} \sum_{((a,b)\,\epsilon\,R_{xy})} E_{nab} \qquad (1)$$

Where, $Z_{nxy}$ is $n^{th}$ feature map pooling operator, $E_{nab}$ is the content at (a, b) within region $R_{xy}$ representing neighborhood locally around (x, y).

*2) Max Pooling*

This method takes the largest element from the feature map area covered by filter as shown in figure 3. It obtain an output feature map with most noticeable features. The other elements in the pooling zone are not taken into account by max pooling; only the maximum element is. This can possibly result in undesirable outcomes.

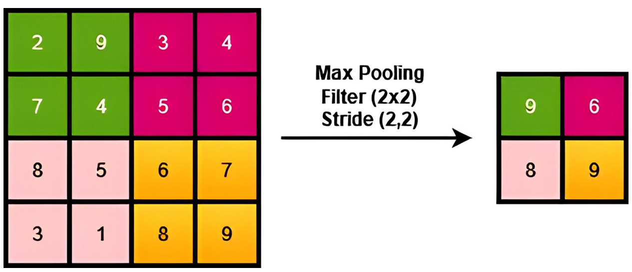


Figure 3. Max Pooling Technique

The differentiating feature disappears after maximum pooling if the majority of the components in the pooling zone are of high magnitudes. The maximum value of pooling area within n x n neighborhood can be obtain by equation 2.

$$Z_{nxy} = Max_{((a,b)\,\epsilon\,R_{xy})} E_{nab} \qquad (2)$$

*3) Global Pooling*

This method gives the single value by reducing the feature map. In global average pooling, the single value obtain by considering average of all elements values for a particular channel as shown in figure 4 whereas elements with maximum values in a channel obtain in global max pooling as shown in figure 5.

Max pooling technique effectively identifies the sharp features whereas average pooling method smoothen the image. Global pooling is more a part of the convolution framework than completely connected layers because it preserves the correlations among feature maps and categories.

*B. Convolutional Neural Network Architecture*

By taking advantages and drawbacks of different pooling techniques into account, the novel convolutional neural network architecture shown in figure 6 has been proposed with hierarchical mixed pooling techniques which follows

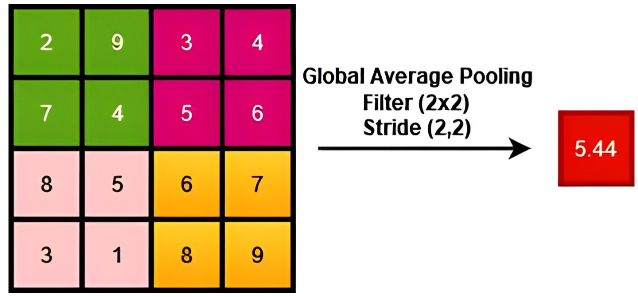


Figure 4. Global Average Pooling Technique

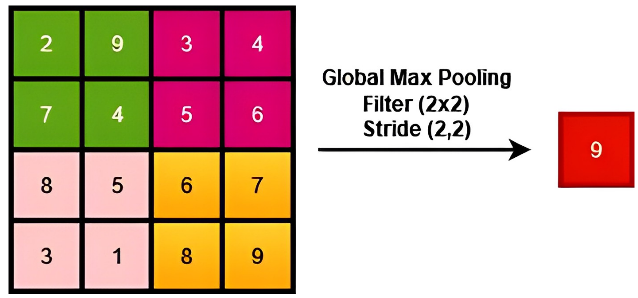


Figure 5. Global Max Pooling Technique

smoothing to sharpening approach in image processing for feature extraction.

The proposed CNN architecture consist of three convolution layers to extract the feature map of the input image with a series of mathematical operations which leads into reduction in size of input image using a filter [3]. An input image of size 224x224x3 is passed through a first convolutional layer (16, 3) for low level feature extraction followed by average pooling layer. This pooling layer takes average of elements in particular patch of feature map which leads into the smoothing of an input image. The output of average pooling layer has been passed through second convolutional layer (32, 3) which extracts high-level features. The Max pooling layer has been added after second convolutional layer which selects the largest value element while reducing the dimension of the output feature map. The Max pooling layer generates the output image with sharpen features which passed through another convolution layer (64, 3) for very high level feature extraction. The Global Max pooling layer has been used for high level sharpening of image features by considering single maximum value in complete feature map. An efficient and novel "Average-Max-GlobalMax" mixed pooling hierarchy has been implemented in the CNN model by using average pooling after the first block of the convolutional layers, max pooling technique after the second block of convolutional layers, and GlobalMax pooling after the third block of convolutional layers which exhibits a better smoothing-to-sharpening approach. The flattening procedure is applied to the feature matrix obtained from Global Max pooling layer which converts matrix into a feature vector.

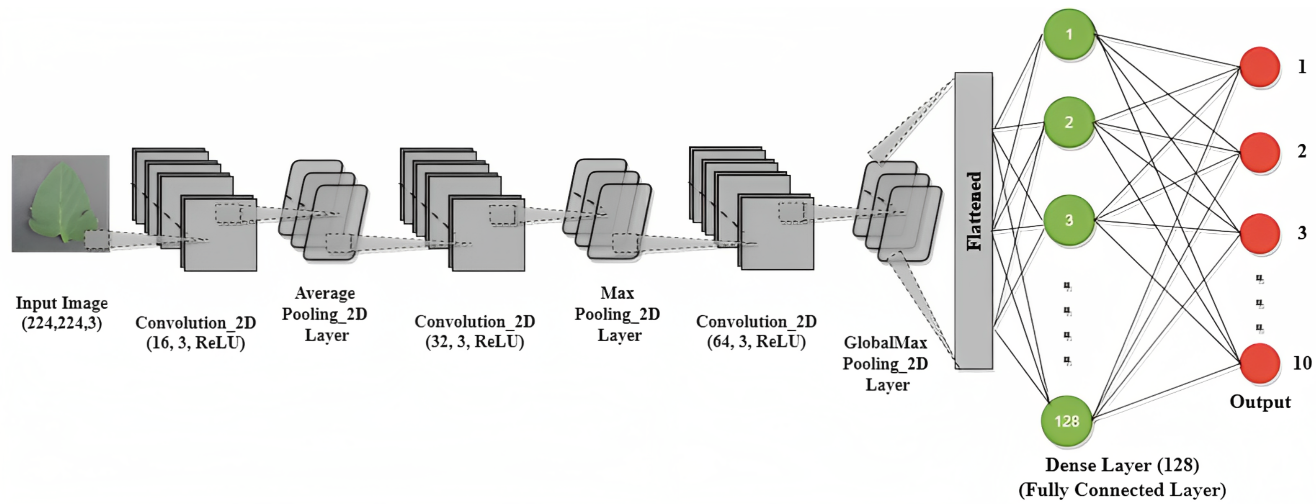


Figure 6. Proposed Convolutional Neural Network Architecture with Hierarchical Mixed Pooling Techniques Using Smoothing to Sharpening Approach

The resultant vector is fed to the 128 dense layers which are fully connected layers. This layer recognized the features and classify images into different classes. The probability of each of the 10 different tomato plant leaf diseases is determined by the use of a softmax activation function in this method. This network has been implied to detect healthy plant and nine different types of tomato plant diseases hence output contains 10 different classes.

*C. Process Flow of Plant Disease Detection System*

The process flow for proposed plant disease detection system shown in figure 7. The system flow consist of four stages as image pre-processing, feature extraction, image classification and prediction. Before image pre-processing, the system required different libraries for TensorFlow Lite Model Maker. When deploying a TensorFlow neural-network model for on-device machine learning applications, the TensorFlow Lite Model Maker module streamlines the process of converting and adapting the model to specific input data. The system uses the Model Maker library to demonstrate how a widely-used image classification [32] model may be adapted and converted to categorize plant images on a mobile device.

In this study, 10000 tomato leaf images have been obtained from Kaggle dataset [33]. The obtained dataset consist of 1000 images each for nine different tomato plant leaves diseases and 1000 images of healthy plant leaves. The dataset has been labeled before uploading it for model training. The sample images of diseased and healthy leaves of tomato plant is shown in Figure 8.

- Image Pre-processing
  The obtained dataset images have been cropped to the size 224x224 and define the batch size of 32. The resized dataset images splitted into training dataset test dataset with 80:20. The training dataset is used to train CNN model whereas test set is used in evaluation process of model once the model has been trained completely. Then the system has been implied to identify different classes of dataset and display class-wise output images.

- Feature Extraction
  The performance of the dataset has been adjusted with the aid of buffer prefetch, shuffle technique, and cache method. To ensure that the data may be read from the disc without causing I/O to become blocking, buffered prefetching have been employed. After prefetching, the dataset has been standardized by normalization technique using map function which results in rescaling of pixel values in 0 to 1 range. The proposed convolutional neural network model has been created and train with fit function. The proposed system uses “adam” optimizer during compilation of designed CNN model. The model evaluation is done with History object. A History attributes is used to keep track of training and validation metrics values at successive epochs.

- Image Classification
  The system have been loaded with evaluated model for input image classification. The input image first pre-processed and then classifier perform the classification task by comparing the probability of identified tomato leaf.

- Disease Prediction
  The disease prediction model takes input as tomato leaf image and compare its probability of matching with the help of trained model. The disease prediction model detect disease in input tomato leaf image and calculate the confidence score with Softmax function. Finally, TensorFlow lite model has been generated to

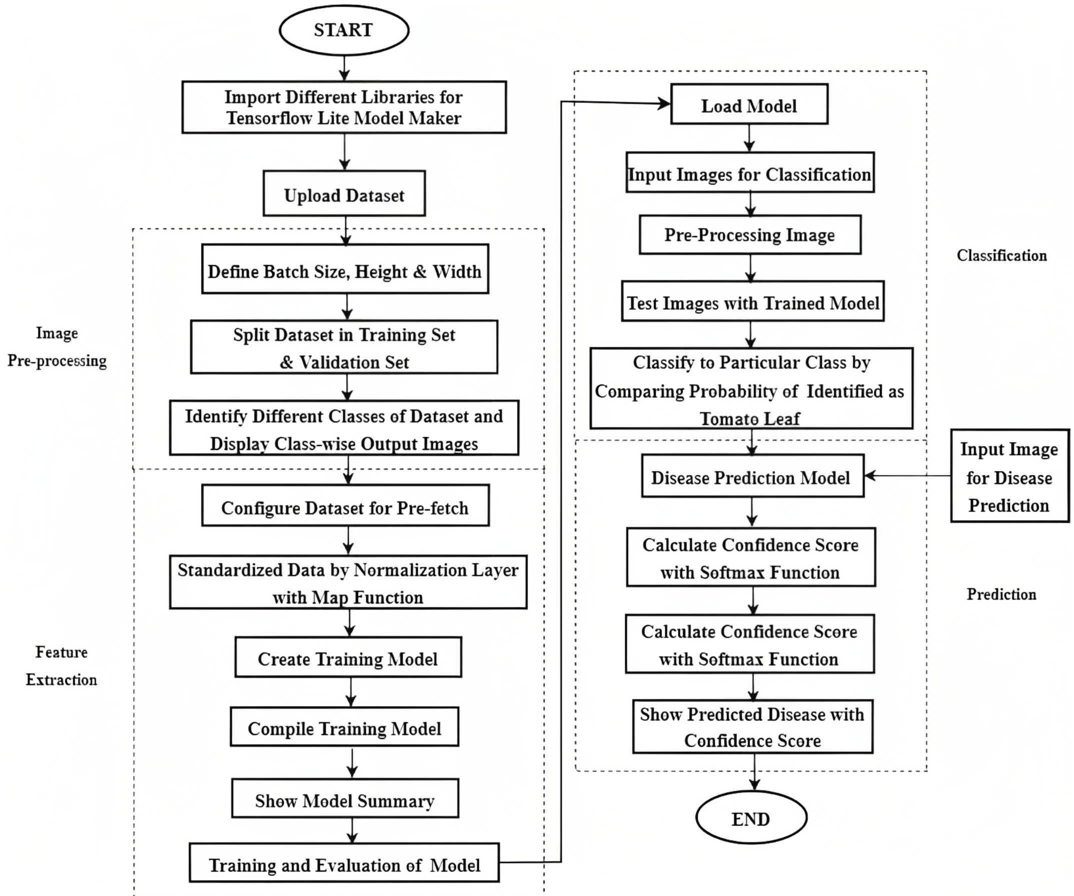


Figure 7. Process Flow of Plant Disease Detection System

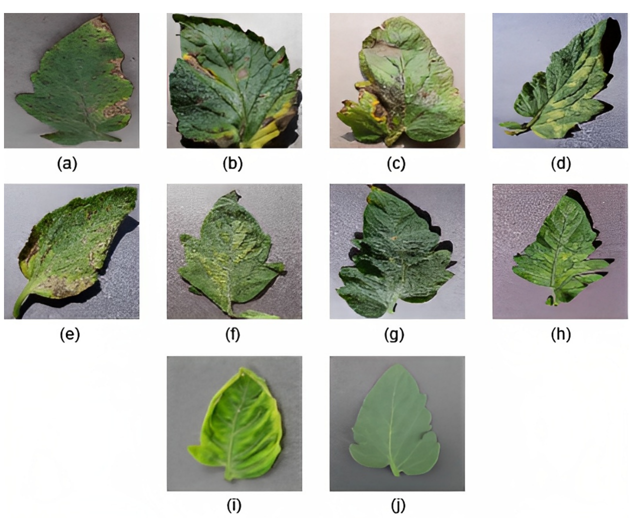


Figure 8. Sample Images of Diseased and Healthy Leaves of Tomato Plant (a) Bacterial Spot (b) Early Blight (c) Late Blight (d) Leaf Mold (e) Septoria Leaf Spot (f) Spider Mite (g) Target Spot (h) Mosaic Virus (i) Yellow Leaf Curl Virus (j) Healthy Leaf

use the trained model with on-device applications.

## 4. Experimental Work

The experiments have been carried out on healthy as well as diseased leaf images of tomato plant with different experimental setup and hyper parameters. The results has been obtained and analyzed for different models with various combination of mixed pooling approaches.

### A. *Experimental Setup Hyperparamters*

The proposed system has been implemented with following computing resources and hyperparameters as shown in Table I.

### B. *Experimental Results and Analysis*

A set of experiments have been conducted on healthy & diseased tomato leaf image datasets and the performance of the proposed method is evaluated. To identify effective mixed pooling techniques which follows smoothing to sharpening approach, the different training models have been framed based on various combination of pooling layers as shown in Table II.

The proposed CNN model consist of three convolutional layers and three pooling layers (PoolingLayer_1, Pool-

TABLE I. COMPUTING RESOURCES AND HYPERPARAMETERS USED

| Computing Resources / Hyperparameters | Specification / Values |
|---|---|
| CPU | Intel(R) Core(TM) i5-8250U CPU @ 1.60GHz |
| Language | Python 3.7 |
| Library/Packages | Tensorflow Keras |
| GPU | NVIDIA GeForce RTX2080 Ti 12GB |
| Operating System | 64-bit operating system |
| RAM | 4GB RAM |
| Disk | 22.94 GB / 78.19 GB |
| Crop Selection | Tomato Plant |
| Image Dataset Source | Kaggle Dataset |
| Number of Diseases (Classes) | 10 |
| Dataset Samples | 1000 images per disease |
| Image Dimension | 224*224*3 |
| Batch Dimension | 32 |
| Learning Rate | 0.01 |
| Normalization Range | 0 to 1 |
| Normalization Function | Map Function |
| Activation Function | ReLU |
| Prediction Function | Softmax |
| Dropout Rate | 0.2 |
| Number of Epochs | 20 |

ingLayer_2, PoolingLayer_3) arranged one after another as shown in proposed CNN architecture. The Model_1 has been frame with Max pooling technique in all three pooling layers whereas approach used in Model_2 is Average pooling technique in PoolingLayer_1 and Max pooling techniques for PoolingLayer_2 and PoolingLayer_3. The Model_3 has been designed with approach as Average pooling in PoolingLayer_1, Max Pooling in PoolingLayer_2 and Global Max Pooling in PoolingLayer_3. The Model_4 framework uses Max Pooling techniques in PoolingLayer_1 and PoolingLayer_2 and Average Pooling in PoolingLayer_3.

The proposed system performance for each model for 20 epochs has been evaluated on the basis of network performance measures. The Figure 9 shows the loss analysis and Figure 10 depicts accuracy analysis at different epochs for Different Training Model Framework Approaches. The Model_1 approach has training loss 15.43%, validation loss 73.38%, training accuracy 94.91% and validation accuracy 81.63% at 20 epochs. For Model_2 approach, a training loss, validation loss, training accuracy, validation accuracy obtain as 13.66%, 22.14%, 95.16%, and 91.8% respectively. The Model_3 approach obtained a training loss 28.88%, a validation loss 12.61%, a training accuracy 96.46%, and a validation accuracy 95.41%. The Model_4 approach has training loss 21.58%, validation loss 35.76%, training accuracy 92.43% and validation accuracy 88.27% at 20 epochs.

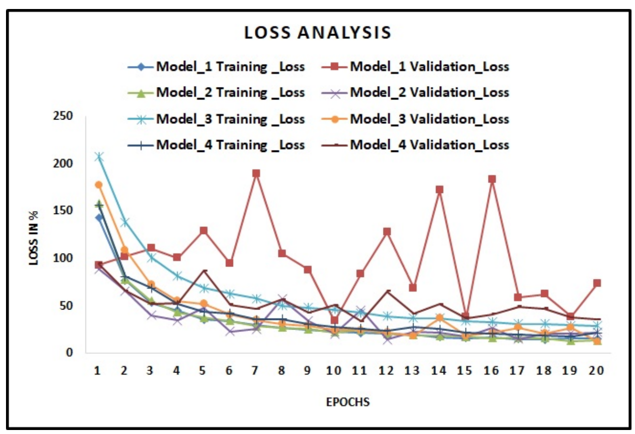


Figure 9. Loss Analysis of Training Model Framework Approaches

TABLE II. TRAINING MODEL FRAMEWORK APPROACHES

| Pooling Layer | Different Training Models | | | |
|---|---|---|---|---|
| | Model_1 | Model_2 | Model_3 | Model_4 |
| Pooling Layer_1 | Max_Pooling | Average_Pooling | Average_Pooling | Max_Pooling |
| Pooling Layer_2 | Max_Pooling | Max_Pooling | Max_Pooling | Max_Pooling |
| Pooling Layer_3 | Max_Pooling | Max_Pooling | Global_Max_Pooling | Average_Pooling |

TABLE III. LOSS AND ACCURACY PERFORMANCE FOR FRAMED TRAINING MODELS AT EPOCHS 20

| Model | Performance Measures | | | |
|---|---|---|---|---|
| | Train_Loss | Validation_Loss | Train_Accuracy | Validation_Accuracy |
| Model_1 | 15.43 | 73.38 | 94.91 | 81.63 |
| Model_2 | 13.66 | 22.14 | 95.16 | 91.84 |
| Model_3 | 28.88 | 12.61 | 96.96 | 95.41 |
| Model_4 | 21.58 | 35.76 | 92.43 | 88.27 |

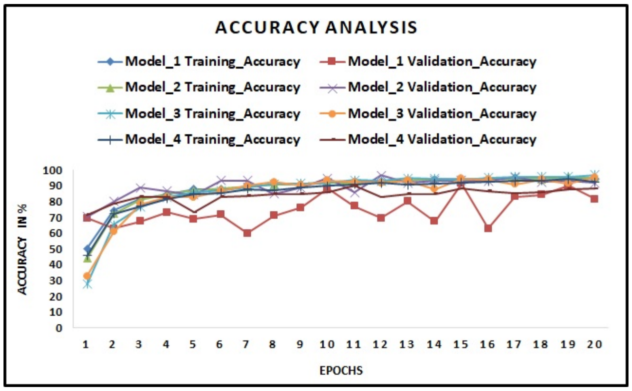


Figure 10. Accuracy Analysis of Training Model Framework Approaches

The loss and accuracy analysis at different epochs indicates that loss decreases and accuracy increases continuously with increase in epochs and stabilized around epoch 20. The Table III depicts the loss and accuracy performances for framed training models at epoch 20.

The figure 11 shows comparative performance analysis of different training model framed which indicates that Model_3 has better training and validation accuracy and also low validation loss as compare to all other models. It means that the hierarchical mixed pooling techniques used in Model_3 to follow smoothing to sharpening approach outperform.

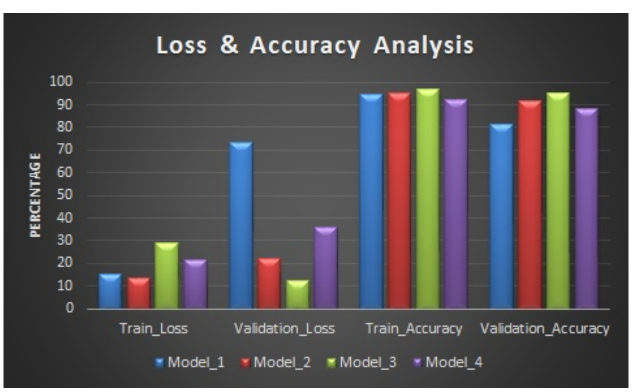


Figure 11. Comparative Performance Analysis of Different Training Models Framed

The proposed plant disease detection system has been implemented with different state-of-art deep learning models like EfficientNet-Lite, MobileNet_V2, ResNet_50 and performances was evaluated with same system specification and dataset. The performances of proposed plant disease detection system with framed Model_3 and with different state-of-art deep learning models like EfficientNet-Lite, MobileNet_V2, ResNet_50 is shown in TABLE IV.

The comparative performance analysis of different deep learning models and proposed model is shown in Figure 12. The system with proposed CNN Model_3 has lower training loss (Approximately 28.88%) and validation loss (Approximately 12.61%) than other state-of-art deep learning models. Also training accuracy (Approximately 96.96%) and validation accuracy (Approximately 95.41%) has been achieved by system with proposed CNN Model_3 which is better as compare to other deep learning models. The proposed system achieving more than 99% confidence score while detecting diseases in tomato plant.

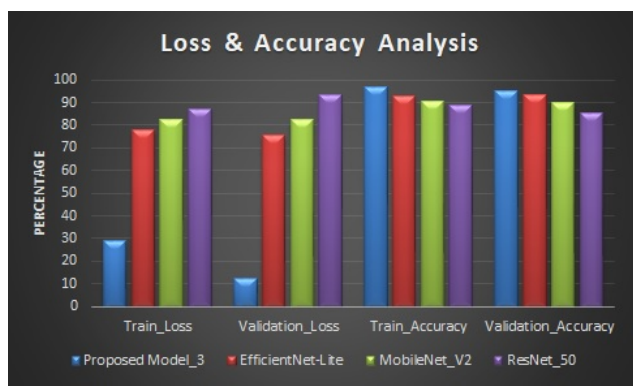


Figure 12. Performance Analysis of Different Deep Learning Models

The confusion matrix of the tomato disease classifier implemented with the designed CNN Model_3 is shown in figure 13. It indicates that the system classifies all ten tomato disease images with high accuracy. The system is getting input images other than dataset images for the prediction of diseases by using a trained model. The model achieved more than 98% average confidence score calculated by the Softmax function.

## 5. Conclusion

The novel CNN architecture has been proposed and implemented in this study to detect tomato plant diseases. The hierarchical mixed pooling technique for smoothing

TABLE IV. PERFORMANCE OF VARIOUS DEEP LEARNING MODELS

| Deep Learning Models | Performance Measures | | | |
|---|---|---|---|---|
| | Train_Loss | Validation_Loss | Train_Accuracy | Validation_Accuracy |
| Proposed Model_3 | 28.88 | 12.61 | 96.96 | 95.41 |
| EfficientNet-Lite | 77.85 | 75.39 | 93.11 | 93.6 |
| MobileNet_V2 | 82.38 | 82.42 | 90.62 | 89.9 |
| ResNet_50 | 87.3 | 93.58 | 88.73 | 85.6 |

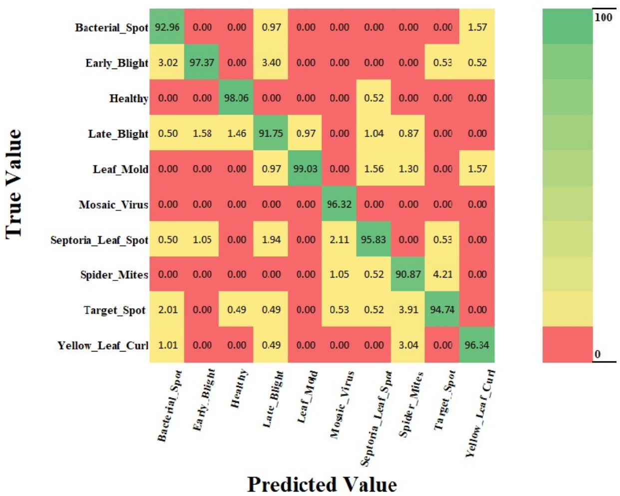


Figure 13. Confusion Matrix of Tomato Disease Classifier

to sharpening approach has been used in proposed CNN model. The hierarchy of pooling techniques has been defined as "Average-Max-GlobalMax" and its performance have been compared with different mixed pooling approaches by framing various training models. The system uses tomato plant leaf images dataset obtained from Kaggle as 1000 images of healthy leaf and 1000 images each for nine different diseases frequently occurs in tomato plant. The CNN training model_3 exhibit smoothing to sharpening approach with "Average-Max-GlobalMax" mixed pooling hierarchy and depicts better performance with a training loss 28.88%, a validation loss 12.61%, a training accuracy 96.46%, and a validation accuracy 95.41% at 20 epochs as compared to other framed approaches. Also, the performance of designed system have been evaluated for various algorithms of deep learning and compared with proposed CNN model. The experimental results shows that the plant disease detection system with proposed CNN model outperform and effectively detect healthy and nine different types of diseases in tomato plant.

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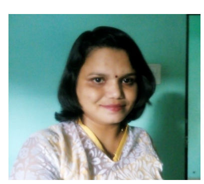

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