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Plant IVRNet- A deep transfer Learning Model with stacked pre-trained models for plant leaf disease detection

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Abstract — Detection of plant leaf disease detection always remains a critical area of research in agricultural science, as prompt and precise identification of diseases can significantly enhance the crop management and yield. Current advancements in deep learning (DL) demonstrate that deep transfer learning models can enhance classification performance across various tasks. In this work, we introduce a deep transfer learning-based model for plant leaf disease classification. The proposed Plant IVR Net architecture integrates convolutional neural networks (CNNs) with VGG-16 and ResNet-50 models to leverage the strengths of these pre-trained networks. The model applies a loss function to minimize overall system loss and improve classification accuracy. The key components of the proposed Plant IVR Net include combination of convolution layer for feature extraction, pooling layers to address the spatial size issues and fully connected layer to obtain the final classification. To address class imbalance, data augmentation procedures such as rotation and noise addition, flipping and cropping are employed. Fine-tuning the pre-trained models further enhances performance. This approach effectively classifies plant leaf diseases, providing a robust tool for precision agriculture and plant health monitoring. The performance of Plant IVR Net approach is measured on publically available Plant village dataset where the Plant IVR Net approach has obtained the overall accuracy as 99.98% which shows significant improvement when compared with the existing transfer learning and deep learning models.

Keywords: *Plant disease, CNN, VGG-16, IVR, Machine Learning, Deep Learning, ResNet-50, VGGNet.*

1. INTRODUCTION

Agricultural production is vital to the global economy and essential for economic development. The Food and Agriculture Organization of the UN projects that the world inhabitants will reach 9.1 billion by 2050 [1]. Consequently, to meet the nutritional demands of this growing population, food production must increase by 70% by 2050 [2]. However, various challenges hinder this growth, such as limited availability of land for cultivation and scarcity of clean water. Additionally, crop diseases considerably decrease both the capacity and quality of agricultural production, which has severe economic impacts, including lower farmer incomes and higher food prices for consumers [3]. These issues can lead to serious food shortages and widespread hunger, especially in developing countries where preventive measures are less accessible. India, being an agrarian country, relies heavily on its agricultural sector for economic stability. Agriculture contributes 16% to the Indian Gross Domestic Product (GDP) and 10% to its total exports. Several studies have reported that the around 75% of Indian population depends agriculture directly or indirectly for their livelihood [4]. Therefore, ensuring the production of high-quality, disease-free crops is crucial for the nation's economic growth [5]. The manual inspection of plant leaf diseases has been widely used however this approach is complete rely on observer’s skill, moreover, it becomes time and resource consuming process and accuracy of this system remains below the desired standards. Therefore, authors have suggested to develop automated approach. The current advancements in computer vision technology has been adopted in various tasks such as autonomous driving [6], visual surveillance system, object detection and tracking [7]. The computer vision-based applications have provided solutions to various problems by automating the applications process. Several researchers have used this approach in this context of plant leaf detection, classification. Similarly, these methods have been used for plant leaf related disease detection and classification. Traditionally, ML based methods have been used in various classification tasks. In this context of plant leaf disease classification, several machine learning-based methods have been adopted to classify disease in plant leaves. For example, Panigrahi et al. [8] presented ML based approach for plant disease detection and developed automated process. This model uses Naïve Bayes, Decision Tree, K-Nearest Neighbour, SVM and Random Forest to perform the classification of maize plant disease detection. Shrivastava et al. [9] presented ML based model for identifying the rice plant disease. This model uses color-based feature extraction model where 14 different color features are extracted and later color spaces are extracted leading to form a feature vector with 172 features. These features are then fed to 7 different classifiers where SVM has outperformed by achieving highest classification accuracy as 94.65%. The current advancement in this domain of computer vision-based applications has adopted the DL-based techniques for plant leaf disease classification. The advanced DL based systems include CNN, deep belief network, Recurrent Neural Network etc. which are widely used in various real-time applications of image segmentation, and classification. Several researches have been carried out in this domain of plant leaf disease detection using DL based approaches. For example, Haridasan et al. [10] introduced DL based approach for to improve the performance for paddy plant leaf disease detection and classification for paddy. Chowdhury et al. [11] presented used DL based EfficientNet architecture to classify the disease of tomato leaves. The segmentation task is performed by using UNet and Modified UNet models and the segmented region is used for training by using EfficientNetB7 for binary classification task. In [13] authors emphasized on optimizing the DL performance and introduced optimized deep learning model where Ant Colony Optimization process is combined with the CNN. The feature extraction process includes colour, and texture information which are used to train the proposed optimized CNN model. Currently, transfer learning-based models are also adopted in various computer vision tasks discussed before. In [14] authors introduced a transfer learning model by using VGGNet as pre-trained module on ImageNet and Inception module. This model doesn’t perform training process rather it uses weights of pre-trained model. Similarly, Paymode et al. [15] used VGG based pre-trained deep learning model multi-crop disease classification.

2. LITERATURE REVEIW

In this section, we discuss about existing methods of plant disease detection, prediction and classification. as discussed before, the machine and deep learning methods are widely adopted in this field to automate the complete process.

This segment describes the brief summary of current deep transfer learning-based approaches which are based on the concepts of machine and DL based methods. The current advancements show that the deep learning-based methods have been adopted widely in various agricultural related activities where plant leaf disease detection is also studied widely. This section presents the brief overview about existing methods, highlights their contributions and drawbacks in this field.

Ashwin kumar et al. [16] discussed the importance of deep learning methods for plant leaf disease detection and presented an optimal mobile network-based (OMN-CNN). This approach is carried out in several stages such as data pre-process where bilateral filtering and Kapur's thresholding is implemented to generate the segmented image. The next stage includes feature extraction where existing MobileNet model is used to extract the features and feature extraction process is optimized by applying emperor penguin optimizer mechanism. Finally, extreme learning classifier model is implemented to assign the class labels.

Tiwari et al. [17] presented a DL model for plant leaf disease detection and classification. The traditional models have not considered the variations in image resolutions therefore this work performed the classification task on varied resolution of images. This work considers large plant leaves dataset from different countries with inter-class and intra-class dissimilarities along with the complex circumstances. The CNN model uses 5-fold cross validation model and tested on unseen data.

Yadhav et al. [18] presented CNN based model for plant leaf disease detection and prevent the damage to plants from pathogenic viruses. In CNN, activation function plays important role by incorporating non-linearity functionality. Several methods have adopted ReLU activation function but it has a drawback where its derivative of function is zero for the negative values which leads to disrupt the functionality of model. To address this issue, a new activation function is presented to enhance the classification performance. Finally, the K-means clustering is incorporated to enhance the overall performance.

Chen et al. [19] deliberated the implication of automated plant leaf disease detection and introduced image processing-based application where pre-processing steps were performed which includes gray transformation, and image denoising tasks. The filtering model includes gradient inverse weighted algorithm. In next phase, image segmentation task is performed. The segmented image is then used in feature extraction phase where texture and colour features are extracted. Later, PCA method is employed to reduce the feature dimensionality. Finally, Group Method of Data Handling is model is applied for classification.

Ahmad et al. [20] discussed the importance of CNN based models in computer vision related classification tasks. However, their resource constrained nature needs to be optimized for resource-constrained portable devices. Therefore, authors introduced DL based approach to detect the plant leaf disease using CNN. Moreover, this model introduces a transfer learning-based approach to address the data imbalance problem.

Hernández et al. [21] discussed that several methods have been introduced in this domain of plant leaf disease detection where deep learning has gained huge attention in this context of image classification. however, the performance of these models is affected when the classification task is performed on unseen images. To overcome this issue, authors have developed probabilistic programming approach where Bayesian DL approach.

Pandian et al. [22] proposed a 14-layered deep CNN architecture to detect plant leaf disease. This model incorporates several data augmentation mechanisms such as image manipulation, adversarial learning-based image generation etc. The deep learning-based model require efficient hyperparameters to improve the training performance. This model has outperformed the existing transfer learning approaches.

Vallabhajosyula et al. [23] reported that early detection of plant leaf diseases is a challenging task for agrarians due to complexity in distinguishing color, shape and texture of the plant leaves. To simplify the detection process, authors have proposed a deep learning model where pre-trained models are fine-tuned with the help of transfer learning approach. The pre-trained models include ResNet 50, Inception V3, DenseNet 121, DenseNet 201, ResNet 101, and MobileNet.

Bedi et al. [24] discussed that state-of-art methods have developed DL and ML based methods however these methods rely on millions of training parameters and suffer from computational complexities and low accuracies. In order to overcome this issue, authors have introduced a novel hybrid model where convolutional autoencoder and CNN models have been combined for plant disease detection. This model requires comparatively a smaller number of parameters resulting in reduced computational overhead and improved hyperparameters helps to enhance the classification accuracy.

Syed-Ab-Rahman et al. [25] focused on citrus disease classification and presented deep learning based model for disease classification. The proposed approach is carried out into two main stages where first stage performs the extraction of affected region with the help of region proposal network, and in next stage, a classifier module is constructed convolution and fully connected layers. The obtained features from feature extraction module are shared between RPN and classifier to minimize the training overhead. Moreover, a new loss function is also introduced to average the loss of RPN and classifier.

Li et al. [26] introduced deep learning-based model where DenseNet121 architecture was used as main network to extract the features for maize disease detection. Later, multi-dilated DenseNet model is developed along with the attention mechanism. Further, this model uses adversarial learning model with transfer learning to enhance the diversity in the dataset.

Pal et al. [27] presented AgriDet, a framework for agriculture detection by using deep learning-based Inception and Kohonen-based deep learning. Along with classification, this model also presents a severity grading model. The occlusion scenarios were handled by the multi-variate grabcut approach to enhance the outcome of segmentation. The overfitting issue was solved by incorporating drop out layer.

Garg et al. [28] discussed that the traditional methods require huge dataset to achieve the desired performance therefore authors introduced a lightweight transfer learning approach which uses few samples to generate the classification results. This model uses aggregated loss function where triplet loss and cross-entropy loss function are combined with MobileNet V2 classifier. Alaeddine et al. [29] developed wide residual network to accomplish the task of leaf disease detection. This model uses transfer learning model where shallow network architecture which requires less time to train the network. Chug et al. [30] introduced a hybrid DL model where efficient models were used as feature extractor and other ML models were used as classifier.

While these approaches offer significant advancements in plant leaf disease detection, they often face challenges such as high computational requirements, complexity in model design and optimization, and potential overfitting. Additionally, the dependency on extensive datasets and resource-intensive processes can limit their practical applications, particularly in resource-constrained environments.

3. PRAPOSED METHODOLOGY

The previous two sections have described the importance of plant leaf disease detection and current studies related to deep learning-based approaches. The current advancement in deep learning schemes shows that the deep transfer learning-based models have reported improved classification performance for several tasks. In this work, we adopt deep transfer learning mechanism for plant leaf disease classification.

3.1. OVERVIEW OF PROPOSED PLANT IVR NET SCHEME

The overview of proposed model is discussed in this section where transfer learning based protocol is used for detection of disease in plants by analysing plant leaves. The Plant IVR Net model uses a amalgamation of convolutional network, VGGNet-16, and ResNet-50 to construct the transfer learning model. Further, a loss function is employed to minimize the overall loss of the system and to improve the accuracy. Horizontal and Vertical Flipping: Flip the image horizontally or vertically. This can help make the model invariant to left-right or top-bottom orientation.

3.2. Convolutional Neural Network (CNN).

The DNN models are based are constructed by performing mathematical operations known as convolution. The CNN model is an architecture which contains several hidden layers, pooling layers, and FC layers as output layer. These hidden layers are constructed with the help of a sequence of convolutional layer with different filters which are used to perform the image classification. The pooling layer has decisive role by minimize the spatial size of the leaf image data. Moreover, it also helps to reduce the computational complexity. Thus, the overfitting issue in CNNs is resolved. The CNN model consists the ReLU activation function is presented as followed:

$$f(y) = \max(0, y) \tag{1}$$

The ReLU activation function improves the training speed and minimizes the computational complexity of the neural network. the input image is resized into 256x256 to overcome the overfitting issue. The input plant leaf image is passed through the various layers of network where feature extraction and dimensionality reduction tasks are performed. In order to obtain the output, the FC layer is used with the corresponding classes and performs nonlinear transformation on the considered feature set. The obtained attributes are then processed through the FC layer and softmax layer for classification. The general architecture of CNN is depicted in below given figure.

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \tag{2}$$

Where z represents the softmax function input vector which contains n number of attributes for the considered target samples.

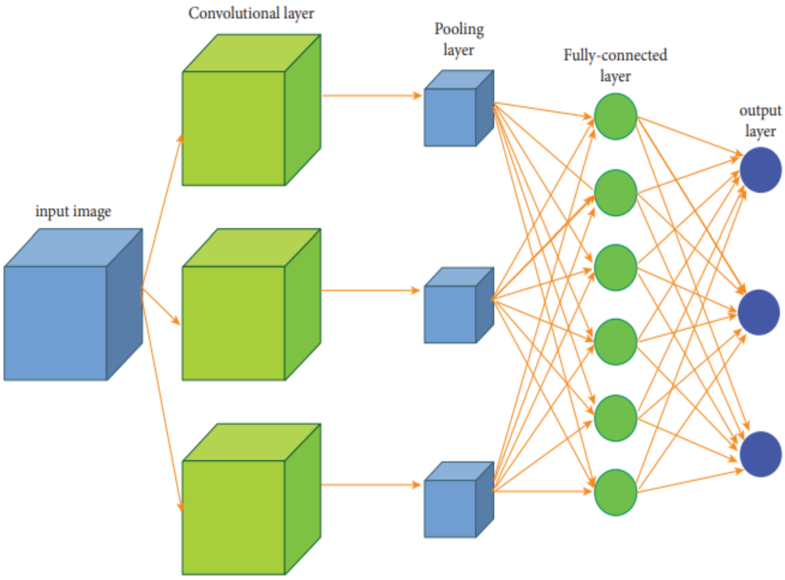

Fig.1. CNN architecture [2].

3.3. Architectures used for Transfer learning

In this work, we have focused on improving the performance of CNN model by incorporating transfer learning-based approach. The transfer learning is a concept of artificial intelligence which is based on the working principal of machine learning. In transfer learning models. The DL model is training for specified tasks and later it is reused to train and analyses another DL based model. Thus, the pre-trained model becomes the starting point for the second task. These models use the knowledge gained from another model. These systems have been adopted in various applications and reported efficient classification performance. however, the state-of-art models require huge amount of resource and increases time complexity to train the model by utilizing the knowledge of previously learned task. In this work, we have used three pre-trained architectures such as VGG-16, Inception-v3, and ResNet50 to classify the plant leaf diseases.

❖ VGG16 MODEL.

This section presents an overview of VGG-16 Model which is based on the CNN model. This model consists of 16 convolutional layers. This model accepts the plant leaf image with a dimension of 224x224x3. This model includes convolutional layers with fixed 3 × 3 filters and five max-pooling layers of 2 × 2 size. The VGG model uses combination of ReLU activation, two FC layer and a softmax layer as output layer. The complete VGG network consist of total 138 million hyper-parameters. This model is constructed by stacking multiple convolution layers and the obtained network structure is capable in learning the complex and non-handcrafted attributes. The performance of VGG network also relies on the hyperparameters because these parameters are crucial in regulating the behaviour of deep learning model and achieving improved classification performance to minimize the pre-defined loss function. The important hyperparameters includes neurons, epochs, activation function, learning rate and number of convolutional layers. Moreover, increased depth of ConvNets improves the network’s capacity to learn the hidden features efficiently. Below given figure depicts the general architecture of considered VGG-16.

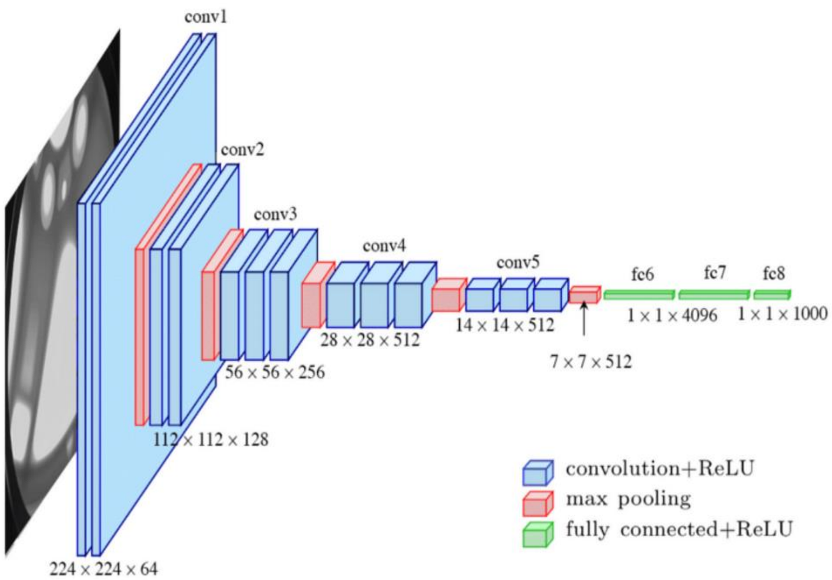

Fig.2. VGG-16 Architecture.

❖ INCEPTION V3 MODEL.

The initial incept model was introduced by the Google Brain team. This network consists of 22 layers and includes 5 million parameters, using filters with dimensions of 1 × 1, 3 × 3, and 5 × 5, along with max-pooling layers. It helps to capture the feature information at varied scales. The 1 × 1 filters help reduce computation time while maintaining the overall performance of the network. In 2015, Google introduced the advanced version of Inception and named it as Inception-V3. This updated version is comprised of 48-layer deep neural network which can be used to perform classification on any multiclass or binary class image classification problem. In this work, we have used this model to classify the plant leaf disease images because this model is also capable in overcoming the overfitting related issues. Inception-v3 can extract and analyze various handcrafted features for plant leaf image classification. This model considers input image data of size 299x299 pixels. This data later processed through various phases such as batch normalization, RMSprop and different convolution operations to enhance the outcome of the model for computer vision related tasks. Below given figure 3 shows the overall architecture of considered Inception V3 model.

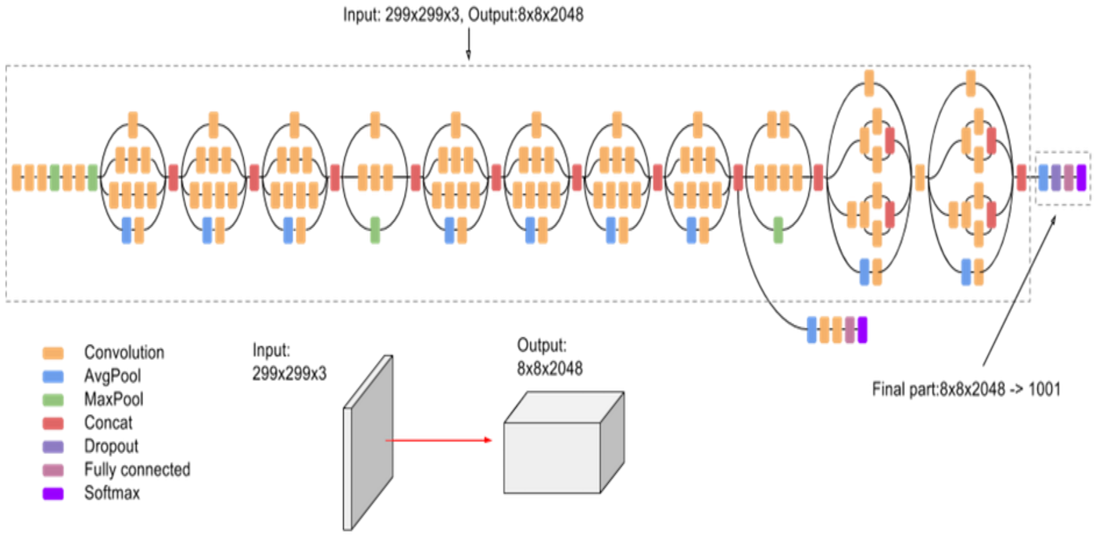

Fig. 3. Architecture representation of of Inception V3.

❖ RESNET50 MODEL

ResNet-50, i.e. Residual Network a type of deep CNN which comprised of 50 layers. This model is introduced based on the concept of residual learning. It was developed by researchers at Microsoft and won the ILSVRC in 2015. ResNet-50 addresses the problem of training very deep networks by using residual blocks. These blocks help to learn the identity mappings of the given dataset. The complete working process of the network is divided into five main stages where each stage has multiple residual blocks. The principal layer organization is as follows: initial convolution layer, 7x7 convolution operation with 64 filters, and a max pooling layer. Later, stage 1 consists of 3 residual blocks with 3x3 and 1x1 convolution, in next three stages 4,6 and 3 residual blocks are used and finally, a fully connected layer is applied after global average pooling layer. The core idea behind ResNet-50 is the residual block, which comprises of two or three conv layers and a short connection is layer is used to bypass these layers. This short connection connects the input of the block to the corresponding output. Thus, it helps to learn the residual characteristics. This alleviates the issue of vanishing gradients and makes training deep networks more effective. Further, ReLU activation functions are applied which helps to induce non-linearity characteristics in the training model. This helps to improve the network's ability to learn the complex patterns. Figure 4 shows the general architecture of ResNet 50.

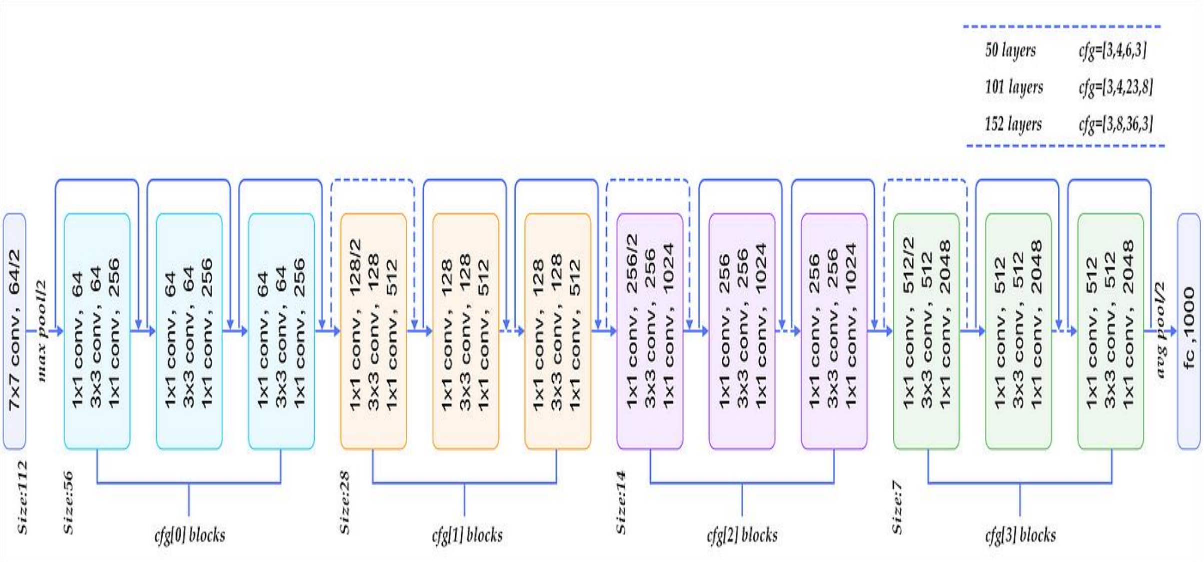

Fig .4. ResNet 50 Architecture

3.4. TRANSFER LEARNING MODULE.

This section presents the proposed solution for transfer learning-based classification model by using aforementioned deep learning architectures for plant leaf disease classification. below given figure depicts the overall architecture of Plant IVR Net transfer learning scheme for classifying the plant leaf diseases.

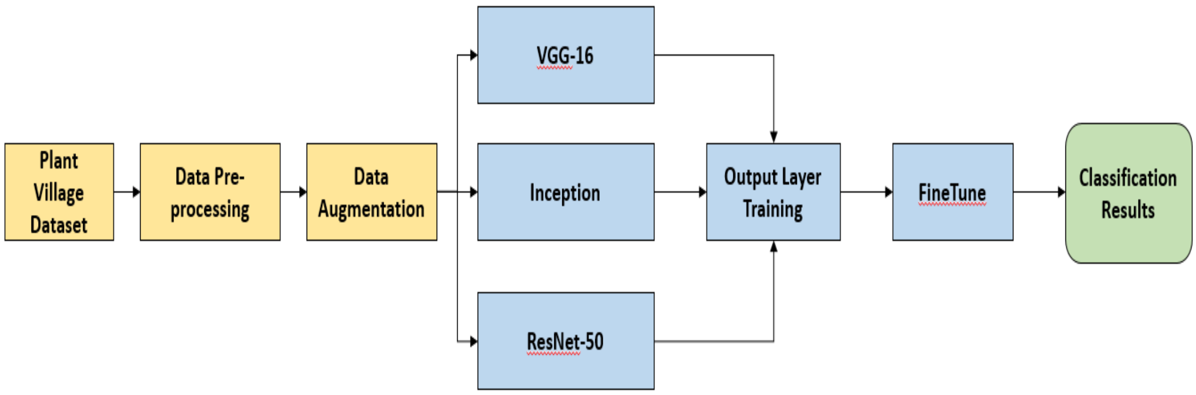

Fig.5. Proposed Deep Transfer Learning Model [6].

According to this approach, the raw images are considered as input to the model for training. In order to handle the class imbalance problem, we perform data augmentation process where rotation, adding noise, image cropping tasks are performed. In next step, the base deep learning models VGG-16, Inception V3 and ResNet 50. Further, the dense layer is used to train the model. However, these pre-trained model require fine-tuning therefore, we introduced a fine-tuning approach for these models to minimize the loss function. Let us consider that the complete is denoted as X and its corresponding labels are denoted as Y. The loss of Plant IVR Net network can be minimized which can be expressed as:

$$(W) = -\frac{1}{n}\sum_{x_i=1}^{n}\sum_{k=1}^{K}\left[y_{ik}\log P(x_i = k) + (1 - y_{ik})\log\left(1 - P(x_i = k)\right)\right] \quad (3)$$

4. RESULTS AND DISCUSSION

In this section, we present the outcome of proposed model and compare the obtained performance with state-of-art plant leaf and disease classification models. The first subsection presents the brief details about the dataset used in this work, next subsection describes the parameters used to measure the classification performance, finally, the comparative analysis is presented to show the robustness of proposed model.

4.1. DATA DETAILS

This segment describes the experimental analysis of Plant IVR Net model and compares the obtained performance with the existing methods. The proposed experiment is carried out using Python 3.8 installed on windows 11 platform. The operating system has 8 GP of NVIDIA GPU and 1TB of hard drive. The first subsection presents the brief overview of dataset use in this work. Next subsection describes the data augmentation steps. Finally, comparative analysis is presented.

4.2. DATASET DETAILS AND AUGMENTATION

The Plant IVR Net transfer learning approach is evaluated by using Plant village dataset which contains a huge collection of various plant species such as apple, cherry, corn, potato, and grape etc. Along with the disease samples. Below given table 1 shows the different species and their image count in this dataset.

Table I. Dataset details: Plant Village

Species	Category	Image Count	Species	Category	Image Count
Apple	Scab	630	Grape	Black rot	1180
Apple	Black rot	621	Grape	Black measles	1383
Apple	Cedar apple rust	275	Grape	Isariopsis leaf spot	1076
Apple	Healthy	1645	Grape	Healthy	423
Cherry	Healthy	854	Orange	Citrus greening	5507
Cherry	Powdery Mildew	1052	Peach	Healthy	360
Corn	Gray Leaf Spot	513	Peach	Bacterial spot	2297
Corn	Common Rust	1192	Pepper	Bacterial spot	997
Corn	Healthy	1162	Pepper	Healthy	1478
Corn	Northern leaf blight	985	Pepper	Early blight	100
Potato	Healthy	152	Raspberry	Healthy	371
Potato	Early Blight	1000	Strawberry	Healthy	456
Potato	Late blight	1000	Strawberry	Leaf scorch	1109
Tomato	Bacterial spot	2127	Tomato	Yellow leaf curl virus	5357
Tomato	Early blight	1000	Tomato	Mosaic virus	373
Tomato	Healthy	1591	Tomato	Target spot	1404
Tomato	Late blight	1909	Tomato	Two spot spider mite	1676
Tomato	Leaf mold	952	Tomato	Blueberry	1502

This dataset contains total 54,306 images in 38 classes and covers total 24 types of disease and 14 types of crops. This dataset includes plant diseases such as bacterial, mold, viral and mite disease.

Further, we apply several steps of data augmentation such as flipping, rotation, scaling, blur, cropping, normalization and adding the noise. Below given figure 6 shows the augmented samples of the plant village dataset.

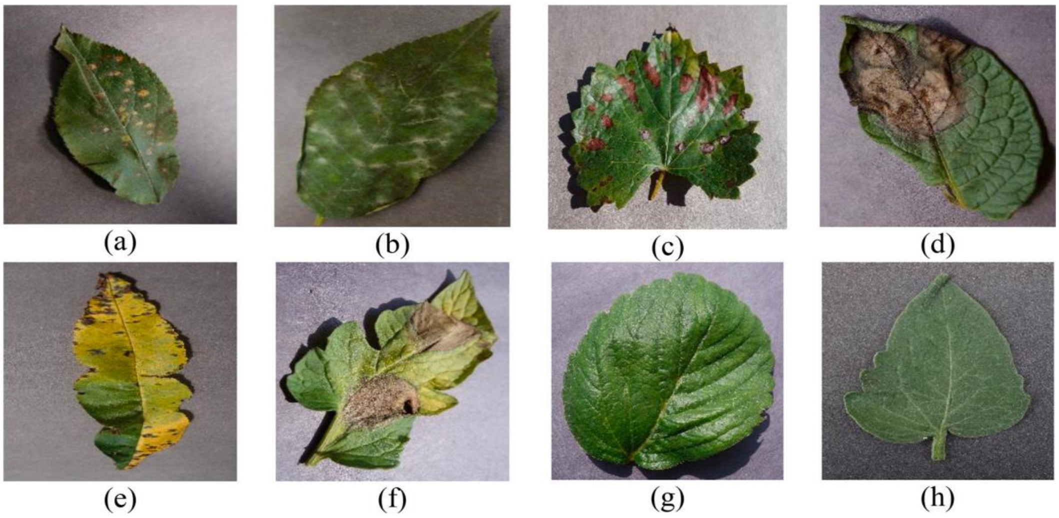

Fig. 7 Data augmentation [7]

4.3.Performance Measurement Parameters

The performance of Plant IVR Net classification model is evaluated in terms of accuracy, sensitivity, specificity and F-measure. These parameters are computed based on the confusion matrix which is obtained based on the outcome of classification. the classification outcome shows the total count of true positive, false positive, true negative and false negative. Below given table 2 shows the general representation of confusion matrix where all samples are categorized based on their corresponding labels.

Table.II. Confusion matrix representation

	Positive	Negative	Total
Positive	T_p	F_p	$T_p + F_p$
Negative	F_N	T_N	$F_N + T_N$
Total	$T_p + F_N$	$T_p + T_N$	

Based on this matrix, the aforementioned performance measurement parameters can be computed. Below given table 3 shows the performance matrix, its computation formula.

Performance Matrix	Formula
Accuracy	$\frac{T_p + T_N}{T_p + T_N + F_p + F_N}$
Sensitivity	$\frac{T_p}{T_p + F_N}$
Specificity	$\frac{T_N}{T_N + F_p}$
$F - measure$	$\frac{2 \times T_p}{2 \times T_p + F_N + F_p}$

4.3.Comparative Analysis

Based on aforementioned experimental setup and performance analysis setup, we estimate the outcome of proposed model and compare its outcome with existing models. This section presents the complete comparative analysis for varied epochs. Below given table 3 shows the outcome of proposed model for training set for 20 epochs and compares the performance with existing models.

Table 3. Accuracy analysis for 20 epochs

Models	Training Accuracy %	Validation Accuracy %
VGGNet-19	94.15	92.55
Inception V3	99.83	98.00
ResNet -50	99.52	97.60
DenseNet-121	99.95	98.91
InceptionResNetV2	99.68	97.98
MobileNet V2	97.09	97.00
Mobile DANet	97.35	97.41
SE-MobileNet	97.62	97.43
Es-MbNet	97.12	98.96
Proposed Plant IVR Net Model	99.50	99.30

According to this experiment, we have simulated the proposed model for 20 epochs for training set where the proposed model has reported the overall accuracy as 99.50 and 99.30 for training and validation set. In next experiment, the epoch count is increased to 100 and obtained performance for 100 epochs is presented in table 4.

Table IV. Accuracy analysis for 100 epochs

Models	Training Accuracy %	Validation Accuracy %
VGGNet-19	95.53	91.74
Inception V3	99.96	98.69
ResNet -50	99.99	98.21
DenseNet-121	100.00	99.13
InceptionResNetV2	99.98	98.26
MobileNet V2	99.80	98.48
Mobile DANet	97.84	98.69
SE-MobileNet	97.72	98.57
Es-MbNet	97.37	98.96
Proposed Plant IVR Net Model	99.98	99.50

According to this experiment, as the number of epochs are increased the proposed model has reported the increased validation accuracy as 99.50% whereas the existing DenseNet has reported the validation accuracy as 99.13%. The desnenet model requires high storage space which require excessive time to train the model whereas proposed model is based on the concept of transfer learning where it directly uses the weights of pre-trained model which increases the speed and accuracy of the system. further, we compared the performance of proposed Plant IVRNet Model in terms of accuracy, recall and F1-score for 10 class scenario as given in table 5.

Table 5. comparative analysis for 10 class scenario

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Plant Types	Accuracy		Recall		F1-score	
	Existing Model Es-MbNet	Proposed Plant IVR Net Model	Existing Model Es-MbNet	Proposed Plant IVR Net Model	Existing Model Es-MbNet	Proposed Plant IVR Net Model
Apple Healthy	99.80	99.85	99.84	99.90	99.22	99.30
Apple Scab	99.80	99.90	100.00	100.00	99.21	99.30
Maize Healthy	99.23	99.85	100.00	100.00	94.59	97.80
Maize cercospora	99.23	99.80	80.00	95.10	88.88	97.60
Grape Health	99.61	99.75	100.00	100.00	98.24	99.10
Grape Blak Rot	99.71	99.75	98.72	99.10	99.36	99.40
Tomato Healthy	99.42	99.45	99.15	99.35	97.50	97.65
Tomato blight	99.61	99.70	97.32	98.50	98.19	99.20
Potato healthy	99.71	99.80	90.00	97.80	94.73	97.80
Potato blight	99.90	99.90	100.00	100.00	99.50	99.55
Average	99.61	99.75	98.08	98.97	98.08	98.67

CONLUSION

In this work, we developed a deep transfer learning-based model for the classification of plant leaf diseases, integrating advanced architectures such as VGG-16, Inception V3, and ResNet-50. The proposed approach leverages the pre-trained capabilities of these models, augmenting their performance through fine-tuning and data augmentation techniques to handle class imbalances. The proposed model demonstrates significant improvements in classification accuracy, benefiting from the strengths of CNN for feature extraction and dimensionality reduction and classification is computer vision-based applications. The utilization of transfer learning permits the model to efficiently learn and adapt to new datasets with limited training data, making it highly effective for real-world agricultural applications. The incorporation of data augmentation techniques ensures robustness and generalization across diverse plant leaf images, addressing potential overfitting issues. The performance of Plant IVR Net model is evaluated on publically available plant village dataset where the Plant IVR Net model has reported the overall performance as 99.75%, 98.97, and 98.67 in terms of Accuracy, Recall, andF1-score, respectively.

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