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Implementation of Transfer Learning Based Ensemble Model using Image Processing for Detection of Potato and Bell Pepper Leaf Diseases

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Abstract: Globally, plant diseases are responsible for significant annual yield losses estimated at 10% to 15%, equivalent to a staggering economic impact of 100-150 billion USD. This research paper undertakes the critical challenge of addressing crop diseases, which pose an imminent threat to global food security due to their potential to cause substantial reductions in agricultural yield and production.The proposed approach leverages the power of ensemble learning, specifically employing the Dirichlet distribution-based ensemble technique. By harnessing the benefits of Dirichlet ensembling, it aims to enhance the accuracy and robustness of disease detection in plants.To achieve this objective,it harnesses the potential of image processing and deep learning methodologies to enable precise and automated detection of plant diseases. This approach not only minimizes the need for manual intervention but also significantly reduces the time and expertise required for disease identification.The suggested approach introduces a deep neural network (DNN) framework, thoughtfully incorporating Residual Network (ResNet), MobileNet, and Inception models within the ensemble. This ensemble-based approach synergistically combines these models to improve disease detection accuracy and reliability.To train and validate proposed ensemble model, a comprehensive dataset comprising both healthy and diseased potato leaves is utilized. The primary aim is to effectively discriminate between two categories of infected potato leaves and the single category of healthy potato leaves. In this proposed model exhibits remarkable proficiency in identifying nuanced features, color variations, and disease types within the leaves, successfully distinguishing between potentially infected and healthy foliage. Remarkably, proposed model achieves an outstanding overall accuracy rate of 98.86%. This achievement underscores the efficacy of propsoed Dirichlet ensemble-based deep learning approach for accurate detection and classification of potato diseases, facilitated by efficient image processing techniques.This study stands as a promising milestone in the realm of automated systems dedicated to the early identification and mitigation of plant diseases. By doing so, it holds the potential to significantly enhance agricultural productivity and, in turn, bolster global food security. The incorporation of Dirichlet ensembling adds an invaluable dimension to the research, further improving the model's performance and robustness in combating crop diseases.

Keywords: Transfer Learning, ResNet, MobileNet, Inception, Potato Blight, Pepper Bell, Ensemble Model, Dirichlet ensembling, DeepStacking Approach.

1. Introduction

Leveraging the power of convolutional neural networks (CNNs) in image processing holds immense potential for revolutionizing the detection of plant diseases, ultimately leading to substantial improvements in crop yield [1, 2, 3]. In this research endeavor, This Reserach introduce an innovative approach that not only harnesses the capabilities of CNNs but also employs advanced ensemble learning techniques, specifically the Dirichlet ensembling method, to significantly enhance disease detection accuracy and robustness. In this model goes beyond the conventional stack ensemble approach, which merely combines multiple models, by incorporating the benefits of Dirichlet ensembling [4, 5]. This novel technique empowers the presented model to make more informed and calibrated predictions,

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ultimately increasing the reliability of disease classification results. To elaborate on the technical aspects of this approach, Research model employ a combination of image analysis techniques, including max pooling, convolutional layers, dropout layers, and densely connected layers. These techniques collectively enable the model to accurately classify various potato diseases with precision [6, 7].

Furthermore, in this embrace the concept of transfer learning, a pivotal component of methodology. Transfer learning involves the application of knowledge gained from solving one task to another related problem, thus allowing us to leverage expertise acquired from one domain to enhance performance in another. In this case, Research Model employ pre-trained models, namely MobileNet, Inception, and ResNet, which are renowned CNN architectures extensively used in image classification tasks [8, 9]. These models have already learned valuable features from vast datasets, and the specific problem domain, optimizing the efficiency and effectiveness of this disease detection framework. The incorporation of Dirichlet ensembling, in particular, contributes to the model's heightened accuracy and resilience in classifying potato diseases.

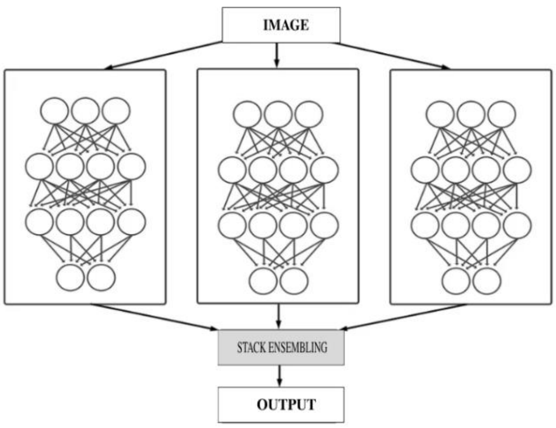

Fig 1. Representation of an Inception Module

Conventionally, the identification of diseases has been dependent on human intervention, However, these approaches are time-consuming, labor-intensive, and demand expert knowledge, posing several drawbacks. To address these limitations, artificial intelligence (AI) has emerged as a promising technology for plant disease detection. AI offers rapid and accurate diagnosis, significantly reducing human errors and biases in disease identification. The proposed study aims to tackle the existing challenges and shortcomings in AI-based plant disease detection by introducing an innovative approach. To enhance the accuracy of the potato disease classification model, The employ transfer learning and ensemble techniques. Develop a deep stack ensemble model that integrates predictions from multiple individual models, thereby elevating overall accuracy. Additionally, Construct a Dirichlet transfer learning ensemble model, harnessing pre-trained transfer learning models like MobileNet, Inception, and ResNet to generate more precise predictions. These techniques collectively contribute to optimizing the performance of potato disease classification model [10, 11]. Potato blight, caused by the fungal pathogen Alternaria solani, manifests as circular, dark spots on potato plant stems and leaves. Left untreated, this disease can significantly reduce potato yields and even lead to premature plant death, underscoring the importance of effective disease detection and mitigation for agricultural improvement.

2. Related Work

K. Moon et al.[12] proposed a deep learning-based approach for detecting bacterial spot disease in bell pepper leaves using hyperspectral images. The authors achieved promising results using a convolutional neural network with transfer learning. K. Jo et al. [13] proposed a transfer learning approach with convolutional neural networks for the detection of bell pepper diseases. The authors achieved high accuracy in the detection of four different diseases using a pre-trained network.

Y. H. Lee et al[14]. proposed a real-time detection method for powdery mildew in bell pepper using deep learning. The authors used a deep convolutional neural network with data augmentation to improve the accuracy of the model. S. Devi et al.[15] conducted a comparative study of different deep learning architectures for the detection of bell pepper diseases. The authors evaluated the performance of four different models and concluded that ResNet-50 outperformed the other models. Y. L. Wu et al.[16] proposed a machine learning approach for the identification of bell pepper diseases using color and texture features. The authors used three different classifiers and achieved high accuracy in the identification of three different diseases. Behera et al.[17] proposed a machine learning approach for the detection of diseases in bell pepper. The authors used image processing techniques to extract features and evaluated the performance of different classifiers. A. G. Vargas et al[18] proposed an automatic detection and classification method for bell pepper diseases using machine learning techniques. The authors used a combination of feature extraction and classification techniques and achieved high accuracy in the detection of three different diseases. M. H. Yeum et al[19] proposed a machine learning approach for identifying bell pepper diseases using spectral reflectance. The authors used support vector machines to classify different diseases and achieved high accuracy in the identification of four different diseases.

H. Kim et al[20] proposed a deep convolutional neural network for the detection and classification of bell pepper diseases. The authors used a pre-trained network and achieved high accuracy in the identification of four different diseases. T. D. Tran et al. [21] proposed an identification method for bell pepper diseases using machine learning and color-based image segmentation. The authors used color and texture features to classify different diseases and achieved high accuracy in the identification of three different diseases. M. A. Hussain et al[22] proposed a deep learning approach for detecting bacterial spot disease in bell pepper leaves using hyperspectral images. The authors used a deep convolutional neural network with transfer learning and achieved high accuracy in the detection of bacterial spot disease.

R. K. Thakur et al [23] proposed a machine learning approach for the detection of powdery mildew disease in bell pepper. The authors used different features and classifiers and achieved high accuracy in the detection of powdery mildew disease. Y. H. Lee et al[24] proposed an efficient approach for identifying bell pepper diseases using deep learning techniques. The authors used transfer learning and achieved high accuracy in the identification of four different diseases. A. Kumar et al [25] proposed an automatic detection method for bell pepper diseases using machine learning and computer vision. The authors used image processing techniques and different classifiers to achieve high accuracy in the detection of different diseases.

Extensive research efforts have delved into the detection and classification of diseases affecting both potato and bell pepper plants, leveraging deep learning methodologies like convolutional neural networks (CNNs) and transfer learning. These dedicated researchers have introduced a wide array of innovative frameworks and techniques, such as feature fusion, ensemble models, and hybrid approaches, all aimed at elevating the precision and accuracy of disease identification. The application of deep learning techniques has yielded highly promising results, revolutionizing the landscape of potato and bell pepper disease classification.

The need for an improved disease prediction model, leading us to conduct a comprehensive investigation and comparison of various existing machine learning algorithms. The research focused on the detection of diseases in both potato and bell pepper plants, utilizing a dataset comprising 1250 images collected from primary sources and PlantVillage. To enhance the accuracy of proposed disease detection applied various image pre-processing techniques, including augmentation, Canny edge detection, and noise reduction, for feature extraction from images of potato and bell pepper plant leaves. Evaluated and implemented three key machine learning models—MobileNet, ResNet, and Inception—assessing their performance using metrics such as accuracy, f1-Score, recall, precision, among others. Additionally, Compared these individual models with the Stacking ensemble Model and the Dirichlet ensemble Model to ascertain their effectiveness in enhancing disease prediction accuracy.

3. Proposed Model

The proposed disease detection model addresses the classification of diseases in both potato and bell pepper plants. In the proposed model, commencing with data pre-processing, which includes essential steps like data normalization to standardize input data. The suggested method employs the Canny edge detection algorithm to identify leaf edges, a key indicator of diseases. To enrich the dataset, it incorporates data augmentation techniques, such as image flipping and rotation. For image classification, it leverages pre-trained feature extraction models, namely Mobilenet_V2, Inception_V3, and ResNet V2. To enhance model performance, the proposed method employs a deep stacking approach, combining multiple models. The utilization of deep learning methodologies and ensemble learning techniques significantly elevates disease detection accuracy.

Fig 2 illustrates the learning process of the proposed model, beginning with the loading of training and testing datasets. The training dataset comprises images of healthy and diseased plant leaves, each labeled accordingly. Meanwhile, the testing dataset includes distinct images used to evaluate model performance. Subsequent to data preprocessing, which involves cleansing, outlier removal, and feature scaling, the data is refined to enhance model quality and efficacy by reducing noise and variability.Moving forward, it is trained on three distinct models—MobileNet, Inception, and ResNet—using the preprocessed data. These models are built upon various convolutional neural network architectures well-suited for image classification tasks. Finally,it employs stacking to combine the predictions of the three models, yielding the final classification results. This approach enhances the overall accuracy and reliability of disease detection in both potato and bell pepper plants.

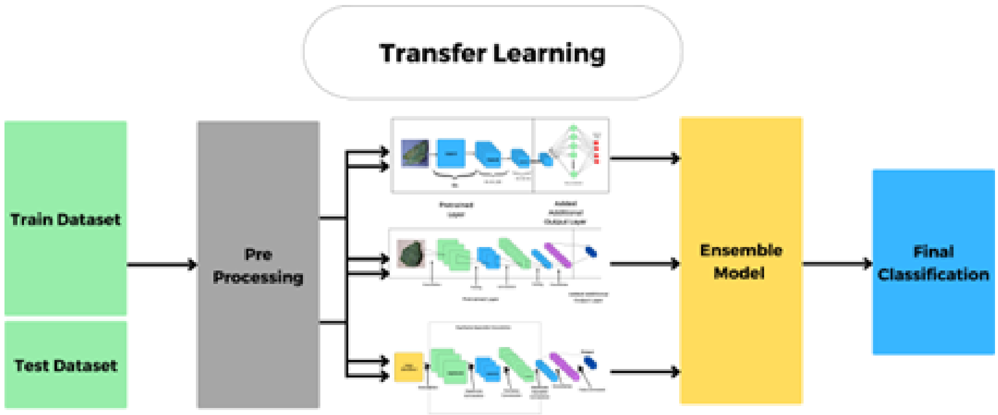

Fig 2. Block Diagram of Proposed Ensemble Model

The effectiveness of the model is demonstrated through a systematic approach encompassing multiple stages. Firstly it undertakes the critical step of data collection, gathering the necessary datasets for research. Subsequently, embarking on data pre-processing, meticulous cleaning and refining the collected data to eliminate inconsistencies and prepare it for further analysis. Following this, The model engages in development, employing suitable algorithms and the pre-processed data to create a robust framework. The collected data is then utilized for model training, facilitating iterative improvements in its performance. The pivotal phase of model evaluation follows, enabling us to meticulously assess the model's accuracy and effectiveness in achieving desired outcomes. Further employing various metrics such as accuracy, precision, recall, F1-score, and loss for a comprehensive performance analysis. Finally, the results generated by proposed model are subjected to meticulous interpretation, allowing us to draw meaningful conclusions based on the findings. This structured methodology ensures the reliability and functionality of the model throughout its development and validation process.

A. Data Collection

The proposed model for potato and Pepper Bell disease detection was primarily developed using a comprehensive dataset comprising Five distinct classes of images. This dataset was meticulously curated, drawing from both Plant Village and primary sources. In total, it consisted of 300 images depicting Early Blight, another 300 images representing Late Blight, an additional 106 images showcasing healthy potato leaves , 300 images of Bacterial spot in Pepper Bell, and 110 images of Healthy Pepper Bell leaves. For the purposes of model training and testing, proposed Model opted for an 80:20 dataset split, with 80% of the data designated for training and the remaining 20% for testing. Table II provides a concise overview of the dataset employed in theresearch.To facilitate the implementation of the proposed model, the images were uploaded to the cloud and processed using Google CoLab. For a visual representation, several sample images depicting potato and Pepper Bell leaf diseases, including Late Blight, Early Blight, Bacterial spot, and Healthy leaves are showcased in Fig 3.

(a) Late Blight (b) Early Blight (c) Healthy

(d) Pepper Bell healthy (e) Bacterial Spot

Fig. 3. Potato Leaves Images

TABLE I. DETAILS OF THE DATA SET USED FOR THE PROPOSED MODEL TRAINING AND TEST PURPOSE

Disease Name	Train Image Data set	Test Image Data set
Early Bright	300	60
Late Bright	300	60
Potato Healthy	106	31
Bacterial spot	300	60
Bell Pepper Healthy	110	38

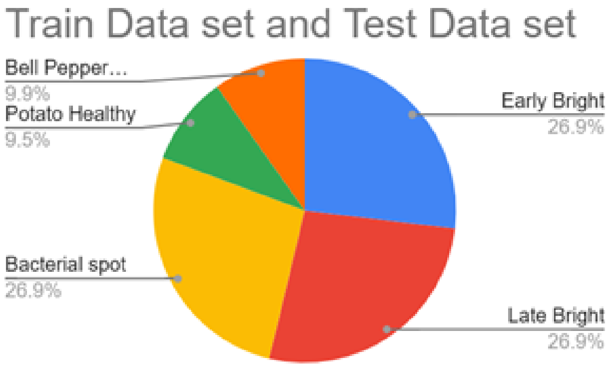

Fig. 4. Image Dataset Distribution

B. *Pre-Processing*

Data preprocessing assumes a crucial role in optimizing the efficacy of proposed plant disease detection model. A fundamental aspect of this preprocessing phase involves the implementation of data augmentation techniques, which significantly enriches the dataset by generating new images derived from the original set. This augmentation process substantially bolsters the dataset's diversity, ultimately enhancing the adaptability and performance of machine learning algorithm.Additionally,meticulous data normalization is carried out to standardize pixel values across all images to a consistent range. Furthermore, apply image processing methods to augment the visual features present in plant leaves within the images. These combined efforts serve to mitigate noise and variability within the input images, rendering them more amenable for model training. Consequently, the proposed model exhibits exceptional proficiency in acquiring high-level features from the images, yielding remarkable accuracy and robustness in the process.

Data Normalization

Data normalization assumes a pivotal role in the data preprocessing pipeline, significantly contributing to the accuracy enhancement of plant image disease detection models. This essential process involves the scaling and standardization of input data to ensure consistent and optimal model performance. Specifically, in the case of three-channel (RGB) images, the data normalization procedure encompasses the calculation of mean values for the Red, Green, and Blue (RGB) channels across the entire image dataset, utilizing list comprehension techniques. The analysis of channel distributions reveals distinct characteristics: the red channel exhibits a concentration of values toward lower intensities, accompanied by a slight positive skew. In contrast, the green channel displays a more uniform distribution, with a prominent peak around 135, indicating a predominant presence of green color in these images shown in Fig 5. Notably, the blue channel values exhibit the most uniform distribution with minimal skew, yet they exhibit substantial variability across different images in the dataset. These insights into channel distributions inform the data normalization process, ensuring that the input data is appropriately scaled and standardized for the subsequent disease detection model.

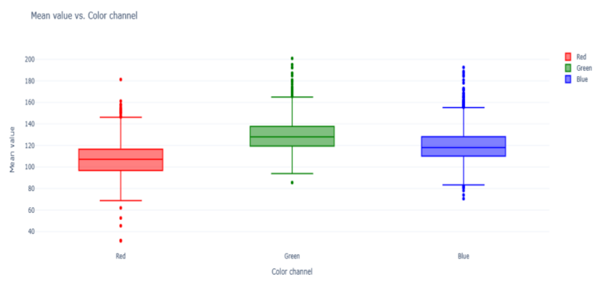

Fig. 5. channel distributions

Image Processing

The Canary edge detection algorithm serves a critical role in identifying object edges, particularly in the context of plant leaves, where it is employed to detect areas affected by diseases. This process begins with the capture of a digital image of the plant leaves, which is subsequently subjected to edge detection algorithms. The algorithm's primary function revolves around the analysis of leaf edges, focusing on alterations in texture and coloration that may signify the presence of diseases. In the context of the Canny edge detection algorithm, a fundamental step involves the calculation of the intensity gradient. This gradient represents the change in pixel intensity across the image in various directions. To achieve this, the algorithm applies a Sobel kernel to the preprocessed image in both vertical and horizontal orientations, thereby obtaining the first derivative along the vertical axis (Gy) and horizontal axis (Gx). Leveraging these two resulting images, the algorithm computes the edge gradient and direction for each pixel, facilitating precise edge detection and subsequent disease identification. Fig 6 shows the step conversion of images to identify the boundary.

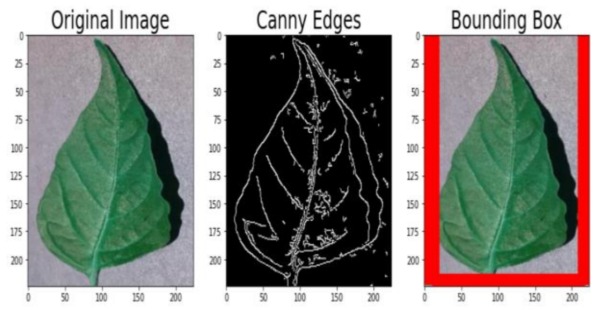

Fig. 6. Boundary Detection

The bounding box is determined by finding the most extreme edges at the four corners of the image, and the coordinates of the box are used to crop the image.

Data Augmentation

Data augmentation is a method to make a dataset bigger by changing the original pictures in different ways. As part of data augmentation process, Proposed Model apply additional transformation such as flipping the images. Flipping involves reversing the order of rows and columns, allowing us to achieve both horizontal and vertical flips. Horizontal flipping entails reversing the order of pixels within each row of the image. Vertical flipping, on the other hand, involves reversing the order of pixels within each column of the image. While flipping the images, the underlying structure and features of the objects remain the same. However, by applying this augmentation technique, reserach can create a more diverse dataset. This increased diversity can benefit model by providing it with a wider range of examples to learn from, potentially improving its performance and generalization capabilities. The above augmentations have been shown in Figure 8.

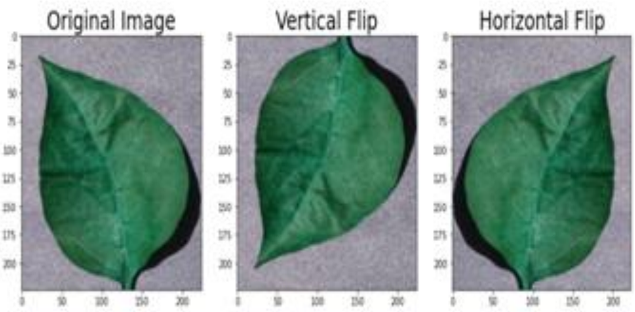

Fig. 7. Data Augmentation

Convolution is a powerful augmentation technique used in image processing. It involves applying a mathematical operation known as a kernel or window to the image. The kernel is a 2D matrix that moves across the image, performing computations at each position. This technique can be compared to a "sunshine effect" as the kernel highlights different features of the image as it moves. By convolving the image with various kernels, proposed model extract different visual patterns and enhance certain aspects of the image. Convolution plays a crucial role in building robust and accurate models. It helps in capturing local spatial relationships and extracting relevant features from the image. The convolution operation enables the model to learn and identify patterns at different scales, contributing to its ability to understand and interpret complex visual information. By applying convolution as an augmentation technique, proposed model can enhance the diversity of dataset and provide the model with a broader range of image variations to learn from. This can improve the model's performance and its ability to generalize well to unseen data.

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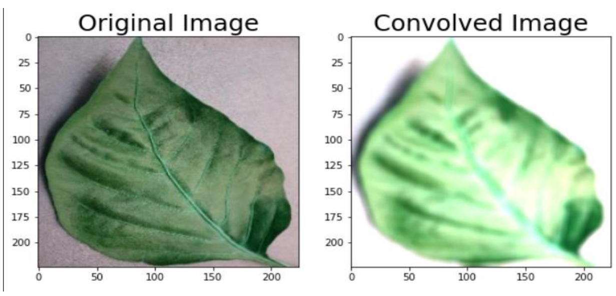

Fig. 8. Image Convolution

C. *Implementation of Proposed Ensemble Model stacking and Dirichlet ensemble*

To construct a deep ensemble model, The proposed model utilizes the Dirichlet Ensemble class from the deep stack library. Initially, importing the Keras Member class from the deep stack.base, which enables us to generate ensemble members from Keras models. Sub sequently, it generates three members for the ensemble, corresponding to each of the fine-tuned pre-trained models. By providing the respective pre-trained model and the data generators for training and validation data, The proposed create ensemble members that possess identical architecture but different initial weights, as they are trained on the same data. Once the ensemble members are established, model employ the Dirichlet Ensemble class and utilize its train() method to construct and train the ensemble model. This procedure ensures that the ensemble model is trained by combining the individual predictions from the ensemble members, resulting in a robust and accurate model. Using these modules and classes, proposed model can create a stacked ensemble model that combines the predictions of multiple base learners using a meta-learner. The base estimators can be any machine learning algorithm, such as decision trees, support vector machines, or neural networks. In the context of the deep stack, the base learners are typically deep neural networks trained on the same dataset but with different architectures or hyper parameters. The meta-learner is a machine learning algorithm that learns how to combine the predictions of the base learners to improve the overall model performance. In the deep stack framework, the meta-learner is often a simple linear model, such as logistic regression or a neural network. It takes the predictions of the base learners as input and learns the weights to assign to each prediction in order to generate the final prediction.

The ensemble model incorporates multiple pre-trained feature extraction models, each contributing its unique capabilities to enhance the ensemble's performance. These models encompass various architectures, encompassing depth, parallel convolutional layers, and skip connections, collectively providing comprehensive approach to feature extraction and image classification tasks.

D. Model Training and Evaluation

MobileNet:

Based on the insights gleaned from Fig 9, it becomes evident that the model exhibits exceptional performance even within the initial two epochs of training. The convergence between the training and validation datasets, with both showcasing nearly identical accuracy, underscores the model's prowess. Notably, the zenith of accuracy during training culminates at an impressive 98.9%, while the validation accuracy ascends to 97.2%, indicative of the model's robust generalization capabilities. Furthermore in Fig 10, the trajectory of loss values for both the training and validation datasets reveals a steep descent commencing from the second epoch onwards, ultimately reaching minimum values of 7.0% for training and 4.0% for validation. This compelling trend underscores the model's efficiency in assimilating knowledge, progressively honing its performance while steadily approaching the overarching objective of loss function minimization.

TABLE II. PARAMETERS OF MOBILENET MODEL

Mobilenet Model		
Layer type	output shape	Parameters
keras layer	none , 1001	5432713
Dense 2	none ,10	10020
Total params: 5442733		
Trainable params: 10020		
Non-trainable params: 5432713		

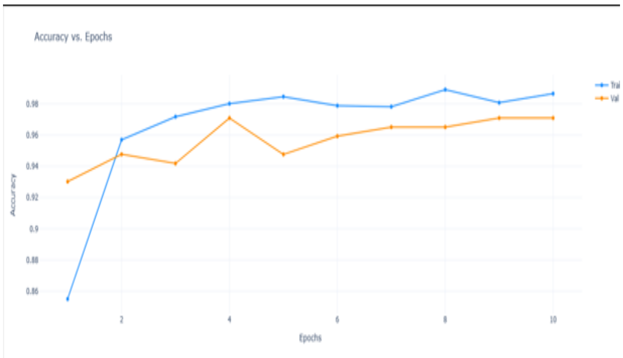

Fig. 9. Accuracy Graph of MobileNet Model

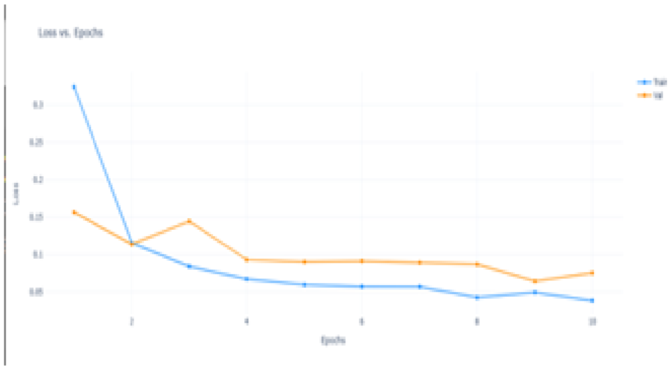

Fig.10. Loss Graph of Mobilenet

Inception:

The accuracy versus epochs graph depicted in Fig 11 illustrates notable improvements in the Inception model's performance, with significant gains observed as early as the first epoch. This model attains a pinnacle training accuracy of 96.3%, while the validation accuracy reaches a commendable 94.2%. These outcomes signify the model's adeptness in both learning from the training data and generalizing effectively to previously unseen data.

TABLE III. PARAMETERS OF INCEPTION MODEL

Inception Model		
Layer type	output shape	Parameters
keras layer 1	none , 1001	23853833
Dense 3	none,10	10020
Total params: 23863853		
Trainable params: 10020		
Non-trainable params: 023853833		

Conversely in Fig 12, the loss versus epochs graph unveils a rapid and consistent decline in losses for both the training and validation datasets. The model's training loss diminishes to a mere 9%, while the validation loss stands at a low 15%. This unequivocally highlights the Inception model's proficiency in minimizing the loss function, indicative of its capacity to extract valuable insights from the training data while maintaining robust performance on validation data.

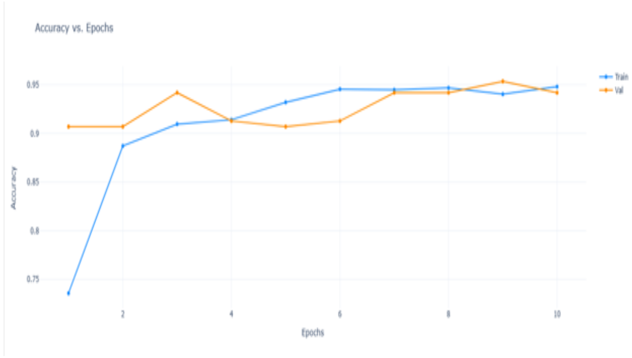

Fig.11. Accuracy Graph of Inception Model

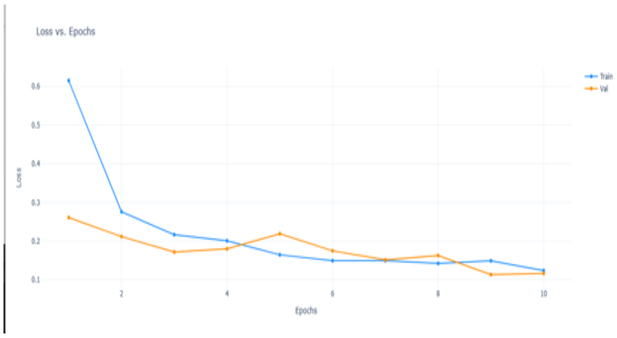

Fig .12. Loss Graph of Inception Model

ResNet:

The accuracy versus epochs plot, as illustrated in Fig 13, highlights a substantial improvement in the model's accuracy, with noteworthy advancements emerging after a mere two epochs. By the 10th epoch, the model attains a commendable accuracy of 97% during training and 92.8% for validation. These results underscore the model's capacity to acquire knowledge effectively, demonstrating strong generalization abilities to previously unseen data.

TABLE IV. PARAMETERS OF RESNET MODEL

Resnet Model		
Layer type	output shape	Parameters
keras layer 2	none , 1001	44677609
Dense 4	none ,10	10020
Total params: 44687629		
Trainable params: 10020		
Non-trainable params: 44677609		

Furthermore in fig 14, the graph depicting losses versus epochs reveals a significant and consistent reduction in both training and validation losses following the second epoch. By the 10th epoch, the model achieves impressively low training and validation losses of 9% and 18%, respectively. This compelling trend underscores the model's efficacy in the learning process, demonstrating substantial progress in minimizing the loss function while effectively harnessing the insights acquired from the training data.

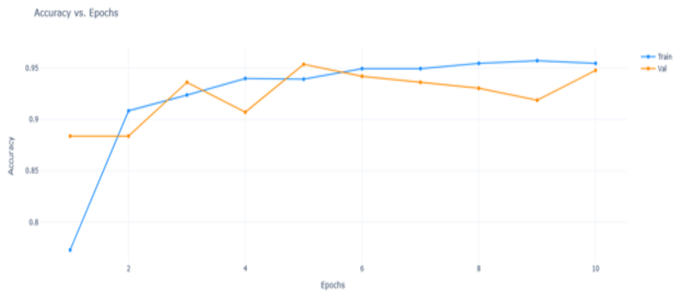

Fig.13. Accuracy Graph of the ResNet Model

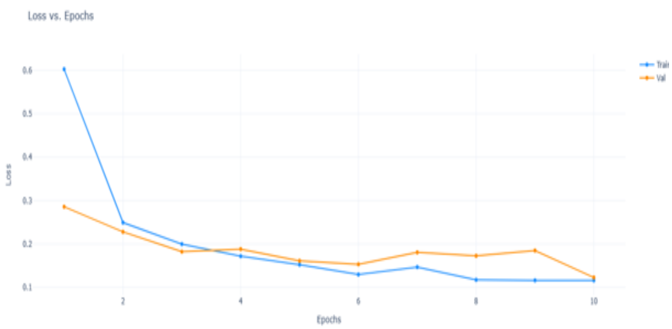

Fig. 14. Loss Graph of the ResNet Model

E. Comparative Analysis of Different Used Transfer Learning Models with Proposed Stacking Ensemble Model

Table V provides an overview of validation accuracy results obtained from various models, each utilizing 1250 images and undergoing 10 training epochs, followed by validation accuracy. Validation accuracy serves as a pivotal metric, representing the model's ability to make accurate predictions on previously unseen data. A higher validation accuracy signifies superior model performance. Notably, The proposed Ensemble model stands out as the top performer in terms of validation accuracy, achieving an impressive 98.88%. This performance surpasses that of individual models like MobileNet (97.30%), Inception (94.40%), and ResNet (93.40%). This underscores the Ensemble model's efficacy in amalgamating the strengths of diverse models while mitigating their respective weaknesses. Figure 16 provides a visual comparison of validation accuracy among these models, clearly illustrating the significant advantage held by Ensemble model.

TABLE V. OBTAINED RESULTS FROM THE DIFFERENT TECHNIQUES

Model	Images set	Classes of disease	Epoch	Accuracy
MobileNet	1250	5	10	97.30%
Inception	1250	5	10	94.40%
ResNet	1250	5	10	93.40%
Stack Ensemble	1250	5	10	97.78%
Proposed model	1250	5	10	98.88%

In summary, this section has compared the results of proposed Stack Ensemble model with three other models: MobileNet, Inception, and ResNet. In this shown that the Stack Ensemble model achieves higher validation accuracy than the other models, as well as previous works done by other researchers on plant disease detection. This validates proposed model that Stack Ensemble model can improve the quality and performance of diseased plant detection using CNN (convolutional neural networks) and data preprocessing techniques.

4. Results and Discussions

To assess the performance of the proposed disease detection model compared to existing models, an evaluation on a comprehensive dataset consisting of images of diseased plants was conducted. The experimental results clearly demonstrate that the proposed model consistently outperforms other models in terms of disease detection accuracy. In comparison to individual transfer learning models, ensemble approach combined with deep stacking techniques exhibited superior performance, achieving higher precision, recall, and F1 scores. This notable improvement in accuracy can be attributed to the synergistic effect of ensemble learning and deep stacking. By leveraging these techniques, proposed model is able to capture and utilize diverse patterns and features associated with diseases in the targeted plants. Moreover, proposed model showcased enhanced robustness, thereby reducing the risk of misclassification and false positives when compared to alternative models. The efficacy of the proposed model in early disease identification highlights its potential for real-world applications in supporting farmers and agricultural experts. By facilitating timely interventions and early-stage disease management, propsoed model has the capacity to contribute to improved crop yield, minimized losses, and enhanced food security. Fig 15 shows the final results obtained, which shows both the actual and predicted labels by the model.

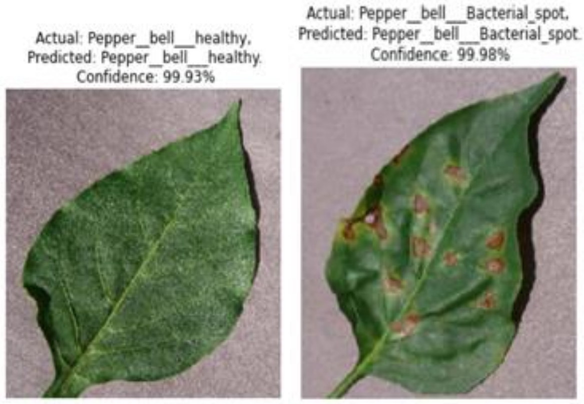

Fig. 15. Sample of output image

5. Conclusion

Efficiently detecting and diagnosing plant diseases stands as a pivotal concern impacting global food security. The conventional approach of manually identifying these diseases not only consumes valuable time but also necessitates specialized expertise, leading to challenges in achieving consistent and precise results. This is where the power of deep learning (DL) techniques comes to the forefront. This study harnesses DL to craft a robust model capable of detecting and diagnosing plant diseases, with a primary focus on Potato Late Blight, Early Blight, and Pepper Bell Bacterial spot diseases. Remarkably, the proposed model achieves an exceptional accuracy rate of 98.88%, signifying a substantial leap forward when compared to conventional methods. Leveraging a dataset comprising over 1250 images drawn from the comprehensive PlantVillage dataset on Kaggle and primary resources, The model has already demonstrated its prowess. However, there exists the potential for further enhancement by training it on more extensive datasets. By streamlining disease detection efforts and diminishing the need for extensive human expertise, this model takes significant strides towards bolstering food security and preventing yield losses, benefiting farmers in particular. Furthermore, its applicability extends beyond potatoes and Bell Pepper, offering a versatile solution for disease detection across a spectrum of crops, potentially revolutionizing the field with its efficiency, precision, and accessibility.

Furthermore, the effectiveness of the Dirichlet ensemble technique in proposed model has been pivotal in achieving these exceptional results. Nonetheless, addressing certain limitations and challenges is imperative for future work. Notably, the reliance on a single dataset for model training and testing may limit its adaptability to different datasets and scenarios. To overcome this, exploration of semi-supervised or unsupervised learning methods, such as self-training or contrastive learning, offers potential avenues to leverage unlabeled or weakly labeled data, thus augmenting proposed model's performance while mitigating the labor-intensive process of manual image labeling. This ongoing evolution holds the promise of further refining the model's capabilities and its broader applicability in agricultural and plant phenotyping contexts.

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