International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

Enhanced Disease Detection for Potato Crop Using CNN with Transfer Learning

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Abstract—As the fourth most popular basic food in the world,potatoes are widely available. In addition, the worldwidemarket is causing the demand to rise daily. Diseases likeearly and late blight have a significant impact on the quantity and quality of potatoes. Determining which potato leaves are afflicted with a certain illness becomes more challenging when interpreting these diseasesmanually. Thankfully, it is possible to identify potato leafdiseases by examining the leaf conditions. This proposedstudy presents a technique that employs deep learning toidentify the two types of diseases and generates an accurate classifier using heavy designs for convolutionalneural networks, such as GoogleNet, Resnet15, VGG16,and Xception. We achieved 97% accuracy in the first 40 CNN epochs, demonstrating the practicality of the deep neural network approach.

1. Introduction

Though there are many other kind of occupations as well, agriculture is the most prevalent. This is also seen in the highly agriculturalized Indian economy. Potatoes are the most adaptable crop in India, accounting for around 28.9%of total agricultural production. Potatoes rank as the world's fourth-largest crop, after rice, wheat, and maize. India is the world's second-largest producer of potatoes, with an annual production of 48.5 million tonnes [1]. The Agricultural and Processed Food Products Export Development Authority (APEDA) states that more than 30.33 percent of India's potato output comes from Uttar Pradesh. Potato starch (farina) is used in the textile industry to worsted and scale cotton.

Potatoes are an excellent source of potassium, fiber, and vitamins, particularly C and B6. By lowering total blood cholesterol, it helps treat conditions including cancer, heart disease, and high blood pressure. Plants and agricultural regions are impacted by diseases. Microorganisms, genetic abnormalities, and infectious substances such as bacteria, fungi, and viruses cause these ailments.

Potato leaf diseases are mostly caused by bacteria and fungi. While late and early blight are fungal diseases, soft rot and common scab are caused by bacteria [2]. Therefore, by recognizing and diagnosing these illnesses on such vital plants, an automated approach was established in this suggested literature that may increase farmer profit, enhance agricultural yield, and considerably benefit the country's economy. Several specialists in computer visionand image processing had previously recommended using traditional image processing techniques like K-means clustering [3] and LBP [4] to find these leaf diseases. Deeplearning models are more successful at mapping tasks, which leads to the generation of better features. This work developed a deep learning model that uses many classifiersto identify potato leaf diseases. The primary objectives of the proposed study methodology are the classification and identification of healthy and ill leaf states through the application of a Deep Learning algorithm. The architecture used in this work is VGG16, a Convolutional NeuralNetwork architectural model with a VGG Network Group.This study also makes use of other CNN architectures, such as ResNet50 and GoogleNet. Techniques for ensemble learning and transfer learning from the traditional approach were also used and contrasted.

2. Literature survey:

According to L. Li et al. [5], there are three main areas forcrop leaf disease detection studies. utilizing a well-known, traditional deep learning architecture is the first option; utilizing an architecture that has been pre-trained on big datasets is the second; and using new or modified DL architectures is the third.

2.1.Classic well-known deep learning architecture:

Barbedo [6] and Lee et al. [7] examined the usage of individual lesions and spots rather than considering theentire leaf since each disease site has unique properties.Benefits of this technology include the ability to identifymany illnesses on the same leaf and the potential toimprove the data by segmenting the leaf picture intodifferent sub-images.

Publication [8] used the GoogLeNet model in an experimental and varied field situation to identify 79 diseases in 14 different plant species. Isolated lesions and spots exhibited a greater overall accuracy of 94% compared to the complete picture's 82%. Lee et al.'s tests[7] shown that training models with common illnesses wasmore universal, independent of culture, and did not requirethe use of fresh data or cultures, particularly from diverse domains. In order to identify diseases, this novel strategy to detection placed more weight on the disease's common name than its crop-target category.

To detect rice blasts, Liang et al. [9] gathered a set of 2906 positive samples and 2902 negative samples. The results of the trial also showed that senior features generated by CNN outperformed manual approaches such as the wavelet transform (Haar-WT) and local binary pattern histogram (LBPH) in terms of identification and efficacy.To detect areas afflicted by wheat disease, Qiu et al. [10] used Mask-RCNN, whose feature extraction network is either ResNet50 or ResNet101. The accuracy of the test data set was 92.01% on average.

According to Li et al., the accuracy was 92.19% for the field dataset and 98.44% for the lab dataset. [11] used it toascertain the different ginkgo biloba levels. The InceptionV3 model's accuracy was 92.3% and 93.2%, respectively.

2.2.Transfer Learning:

Four distinct pretraining convolution neural networks—VGG19, VGG16, ResNet, and Inception V3—were employed by Ahmad et al. [12]. The models were trained by varying parameters. According to the experimental findings, Inception V3 outperformed the other two datasets (the field dataset and the laboratory dataset). Furthermore, on the laboratory dataset, the average performance was 10% to 15% higher than on the field dataset.

In complex outdoor backgrounds with few data, Xu et al. [13] proposed a convolutional neural network model (VGG16) based on transfer learning to achieve maize leaf disease photo recognition (healthy, leaf blight, and rust). When the weight parameters of the VGG16 model were introduced to the model after it had been trained on ImageNet, the average recognition accuracy was 95.33%. The Plant Pathology 2020 Challenge dataset contained four different apple leaf diseases that were analyzed using the ResNet50 network, which had previously been trained on ImageNet. The model's overall test accuracy was 97%. Nevertheless, the recognition accuracy was only 51% when the group of complex disease patterns was excluded [14]. (the concoction of many illness symptoms). Long et al. [15] employed two distinct training approaches using AlexNet to detect disease on camellia leaves. training from the beginning while utilizing the knowledge of ImageNet (4 illnesses and health). According to the results,transfer learning may significantly improve the model's capacity for classification and convergence rate, with a 96.53% classification accuracy.

2.3. Improved Deep Learning Architecture:

Several CNN classifiers were employed by Dechant et al.

[16] to examine high-resolution images of crop disease. The experimental results showed that the accuracy rate was 90.8% with a single CNN classifier, 95.9% with two first-level classifiers, and 97.8% with three first-level classifiers.

Picon et al. [17] replaced the initial 7 x 7 convolutional layer of the ResNet50 network with two 3 x 3 convolutions and utilized the sigmoid activation function in place of the softmax layer in order to extract the particular of the symptoms of the wheat illness. It utilized the upgraded ResNet50 network to detect the first three wheat diseases—rust, tan spot, and septoria—with 96% accuracy on the balanced dataset.

In order to create a mixed-cost function, Fan et al. [18] added a batch standardization layer to the Faster R-CNN model's convolutional layer. They also employed a stochastic gradient descent technique to improve the training model. For their study, they focused on nine different types of complicated field-history maize leaf diseases. The improved method beat the SSD approach with an average accuracy gain of 4.25% and a single photo detection time reduction of 0.018 s under the same testing conditions. Additionally, the enhanced method increased accuracy by 8.86% on average.

In order to create a multi-receptive field recognition model based on AlexNet known as Multi-Scale AlexNet, Guo et al.

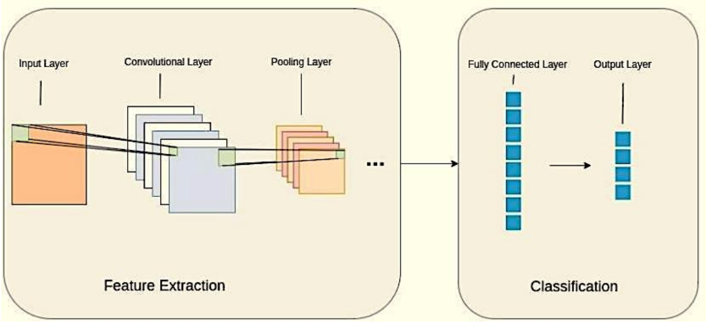
[19] modified the fully connected layers of the AlexNet network, eliminated the local response normalization layer, and set a multi-scale convolution kernel as the feature extraction mechanism. The study objectives are the PlantVillage dataset and the self-collected dataset of seven distinct types of leaf damage caused by tomatoes. The model increased the average identification accuracy of tomato leaf diseases and each disease in its early, middle, and late phases to up to 92.7% while decreasing the memory requirements of the original AlexNet by 95.4%. Chen et al. [20] introduced an improved VGG model (INC- VGGN) based on the VGG model framework by adding two Inception modules, a pooling layer, and altering the activation function. Furthermore, an average of 92% of leaf diseases in maize plants could be correctly recognized.Additionally, 92% of corn plant leaf diseases could be accurately identified on average.

Table 1: Summary of recent research works about the application of DL framework directly and improvement of DL in plant disease detection

Reference	Object	DL frame	Dataset	Sample Size	Data Enhancement	Metric

[7], 2020	Plant	VGG16,Inception V3, GoogleNet	PlantVillage, IPM,Bing	54305	Random Cropping and Mirroring	Top-1
[12], 2020	Tomato	VGG-16, VGG- 19, ResNet, Inception V3	Self-acquired in field and LAB	2681-15216	-	Average Accuracy
[9], 2019	Rice	CNN	Self-acquired in field and LAB	5808	None	Accuracy,ROC, and AUC
[10],2019	Wheat	Mask RCNN	Self-acquired in field and LAB	20-2809	Chunking + traditional enhancement	Average Accuracy
[11],2020	Ginkgobiloba	VGG, Inception V3	Self-acquired in field and LAB	3730-15670	Rotate, Flip	Average Accuracy
[8], 2020	Apple	ResNet152, inceptionV3, MobileNet	Self-acquired in field	334-2004	Random Rotation forcutting and grayscale	Average Accuracy, Processing time of each image
[13],2020	Corn	VGG-16	Self-acquired in field	600-5400	Rotate, Flip	Average Accuracy
[18], 2020	Corn	Faster R - CNN with Batch Standardization layer	China Science Data Network, Digipathos Network and self- acquired in field	1150 - 1150*8	Flip, Brightness Adjustment, Saturation Adjustment, and addGausian Noise	Average Accuracy, Average Recall, F1- score, Overall average accuracy
[19], 2019	Tomato	Alexnet	PlantVillage + Self- acquired in field	5766–8349	Random Cropping, Flip, Rotation, Color dithering, Add noise	Average Accuracy
[20], 2020	Rice, Corn	Improved VGG model (INC-VGGN)	Self-acquired in field	966-4000	Rotate, Flip,Scale transformations	Accuracy, Sensitivity, Specificity

3. Conceptual Work



An overview of some of the key ideas and techniques used in the proposed model is provided in this section.

3.1 *Convolutional Neural Network:*

Among the deep learning systems that assess visual input is CNN [21]. Convolution is employed to get diverseattributes from the images. Next, the image is reduced in size to enable faster processing without sacrificing many of its original characteristics. The initial layers of a CNN learn low-level spatial

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qualities, which are frequently associated with edges, boundaries, or the basic characteristics of the objects. Simultaneously, deeper layers acquire more intricate and complicated feA. Featureextraction and classification, which are the two main partsof CNN, are shown in Fig. 1. These include things like intricate shapes and item orientations.

Fig 1: The convolutional neural network structure. It consists of two main building blocks: feature extraction and classification.

3.2 Classification Process:

The retrieved feature maps are utilized in this phase to establish a mapping between the features and the targeted yield classes, which usually consist of completely connected layers. In totally related layers, every contribution from one layer is connected to every enactment unit of the following layer. They function as a classifier in the tail of the organization, where a layer comprising different neurons is employed to synchronize the quantity of yield classifications. In multi-class orderingissues, the SoftMax starting work is used to standardize the yield into decimal quality for the contribution's chance of belonging to a certain class. The SoftMax activation function for a classification issue with K classes may be expressed mathematically as in (1).

where (Z)i is the likelihood that the input belongs to the ith class, xi is the I th dimension output, and I is a class number from 1 to K.

3.3 Transfer Learning

With the aid of the powerful strategy known as transfer learning, a model that was developed and trained for one task may be utilized again for another [22]. This can reducethe training time required for such models and save days or even weeks on modern hardware. There are two approaches of using transfer learning: The first two phases are to create a new model approach and retrain an existing model approach. The procedures in constructing a model approach include selecting a job that is similar to the activity at hand, generating a source model, and using a large amount of data. If the model matches the data and performs adequately, it might be used as a starting point for the second task. Selecting an existing pre-trained model is the pre-trained model strategy. For example, pre-trained weights from the ImageNet dataset [23] are often employed in image-related tasks and serve as a basis for training a model on an additional dataset that already exists. Transfer learning functions by eliminating the top fully connected layer, which was responsible for classifying the dataset it was trained on, and using the model's pre-learned weights as a feature extractor. Next, a classification layer is added to the model to teach it how to transfer the feature extractor's output classes to the new dataset's output classes. In this study, pre-trained CNNs Resnet50, VGG16, and Xception were used.

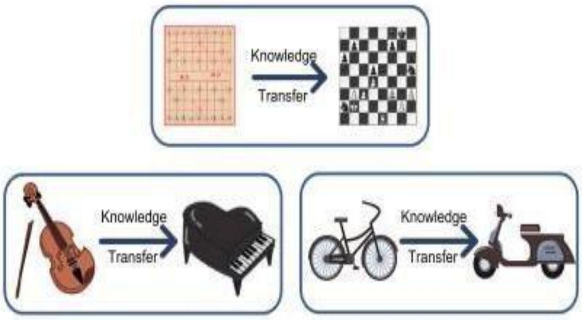

Fig 2: Intuitive examples about transfer learning.

3.4 Ensemble Learning:

An ensemble in the context of machine learning is a system composed of several distinct models running simultaneously, the output of which is combined using decision fusion techniques to provide a single solution to a particular problem. have a wide definition [26].

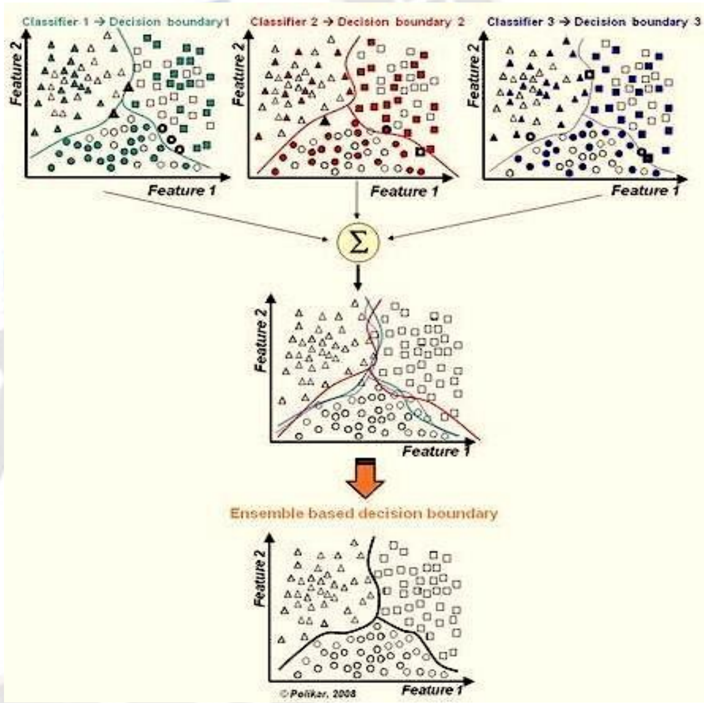

Fig 3: Combining an ensemble of classifiers for reducing classification error and/or model selection.

4.Proposed Work

4.1 Dataset:

In the proposed study, 900 photographs are utilized to trainthe model, and 300 photos are used for validation. The dataset may be refered at:

https://www.kaggle.com/abdallahalidev/plantvillagedataset

it was collected using the Kaggle platform. The datasetcontains images from categories such as Healthy, LateBlight, and Early Blight.

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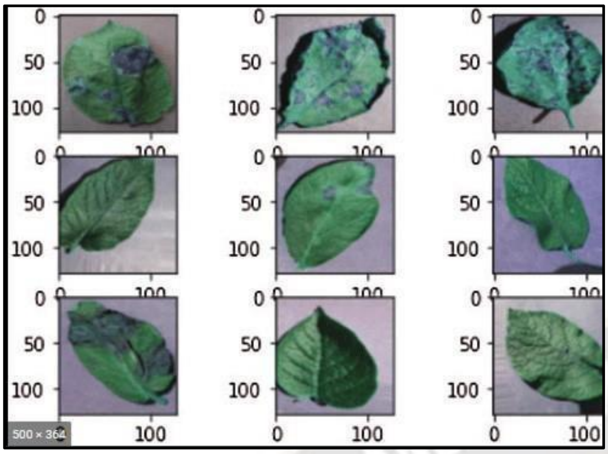

Fig 4: Dataset

4.1 Data Preprocessing

Addition of new data is the essence of data augmentation. Data augmentation is the process of producing many believable copies of each training sample in order to artificially increase the size of the training data set. As such, overfitting is reduced. During data augmentation, each picture in the training set is subtly rotated, moved, and scaled by different percentages. All of the resulting photos are then added to the training set. Consequently, the model can better account for changes in the size, orientation, and placement of visual items. You may adjust the contrast and lighting in your photos. It is possible to rotate the images both horizontally and vertically [31].

4.2 Workflow

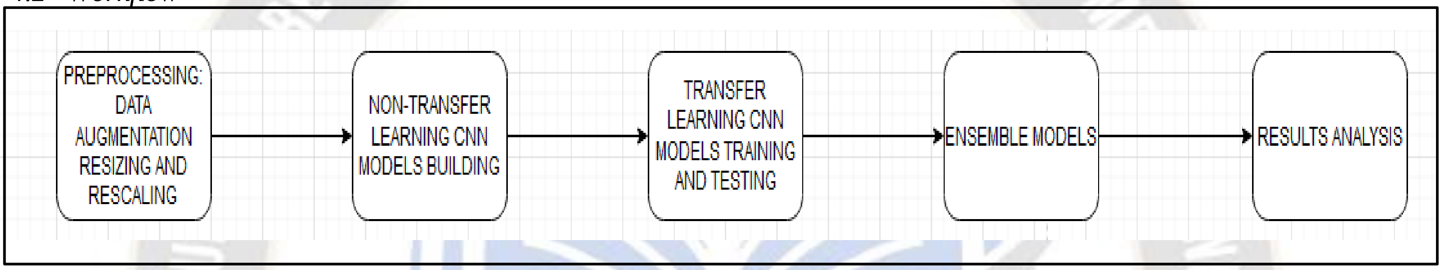

Fig 5: Workflow

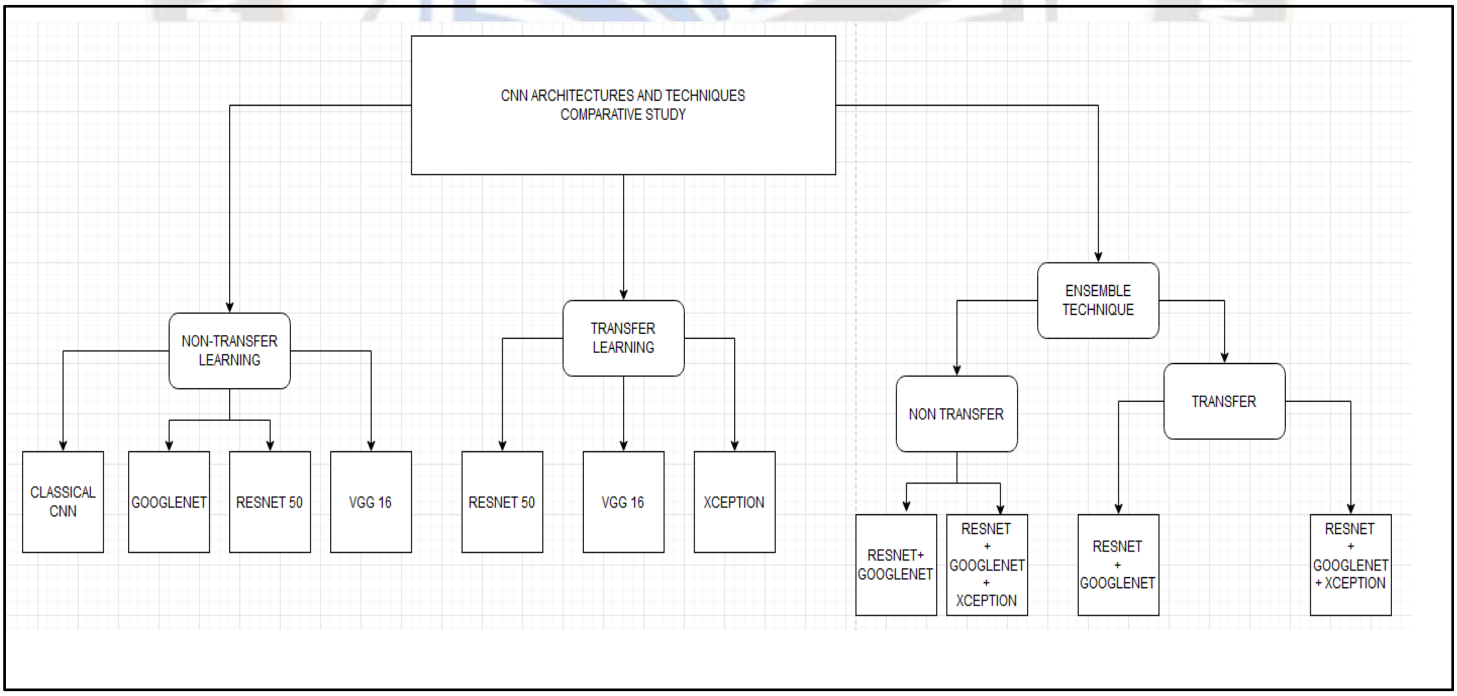

Fig 6: Architecture

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4.5 Model Building

1. *Non-Transfer Learning: CNN, Googlenet, Resnet, vgg16*

A. *Classical CNN*

CNN neural networks are constructed using max pooling and convolution layers. While the hidden layers utilize the non-linear Relu activation function, the output layer uses the softmax activation function [31].

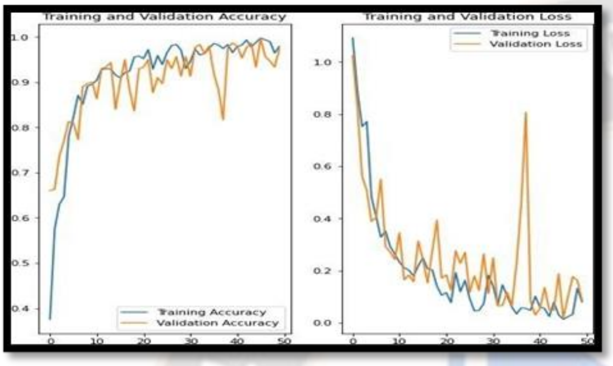

Fig 7: CNN architecture result on proposed dataset

Googlenet

One of the main features of this system is improved network computing resource utilisation. We were able to increase the depth and breadth of our network while keeping the same processing budget thanks to a well-thought-out design. The multi-scale processing intuition and the Hebbian principle served as the cornerstones for the architectural decisions taken in order to maximize quality [25]. The deep convolutional neural network Inception Network developed by Google researchers was modified into GoogLeNet, a 22-layer network. At the ImageNet Large-Scale Visual Recognition Challenge 2014 (ILSVRC14), the GooLeNet architecture was proved to perform computer vision tasks like as object identification and picture classification. In this study, Googlenet is trained using the recommended dataset rather than the pre-trained model [31].

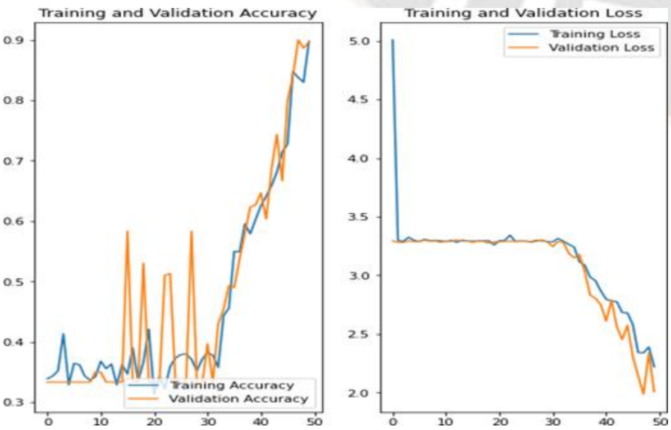

Fig 9: Googlenet result on proposed dataset

B. *Resnet50*:

It gets harder to train more complicated neural networks. We provide a residual learning method that simplifies the training of networks that are much deeper than those that have been used in the past [24]. A residual block was first proposed in this design as a solution to the gradient vanishing/exploding issue. In this network, a technique known as skip connections is utilized. By omitting layers in between, a jump connection joins the activations of one layer to another. Thus, a leftover block is produced. To build resnets, these leftover blocks are piled. Resnet is trained on the proposed dataset in this study, as opposed to using a pre-trained model that has been trained on Imagenet data [31].

D.VGG 16:

There are 16 layers in the 16-layer deep convolutional neural network VGG-16. A pretrained version of a network that has been trained on over a million images may be loaded from the ImageNet database. A pre-trained network can classify images into 1000 distinct object categories, such as keyboards, mice, pencils, and various animals. In this study, VGG is trained on the proposed dataset rather than using a pre-trained model that has been trained on Imagenet data [31].

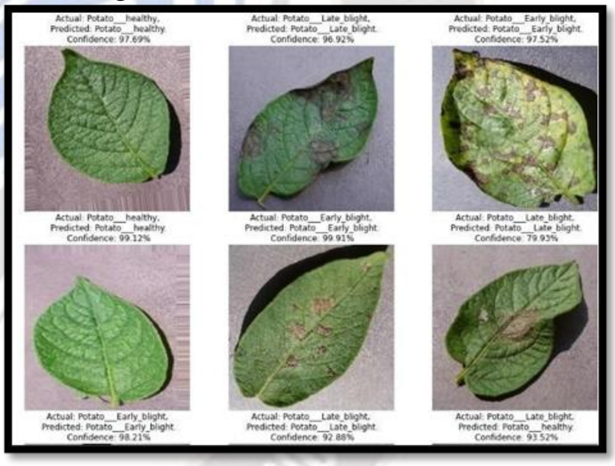

Fig 10: Visualization of Googlenet result on proposed dataset

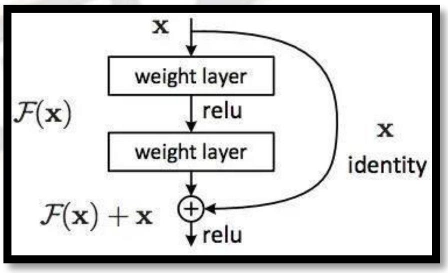

Fig 11: Residual learning: a building block. [24]

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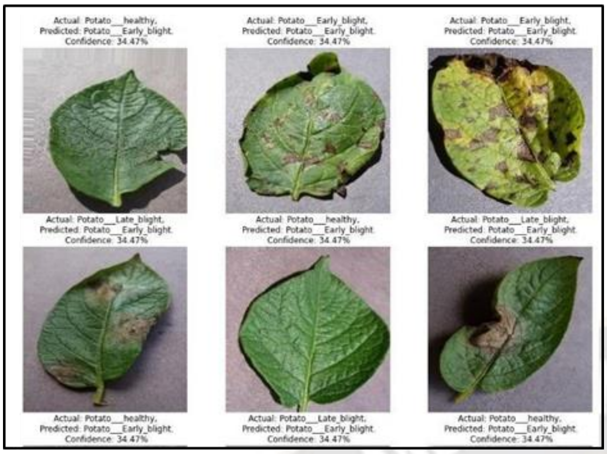

Fig 12: Resnet50 result on proposed dataset

Fig 13: Visualization of Resnet50 result on proposed dataset

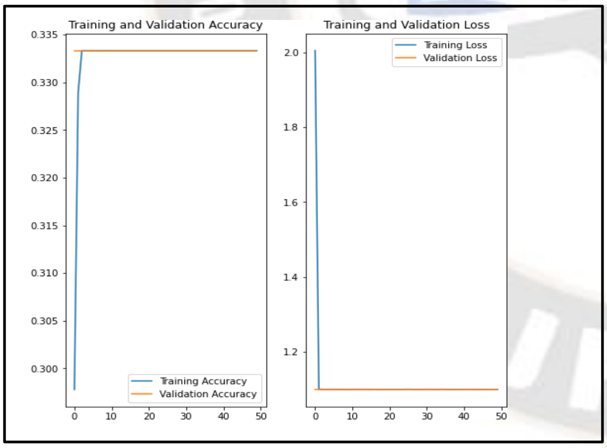

Fig 14: VGG16 result on proposed dataset

2. *Transfer Learning- Resnet, VGG16, Xception:*

Pre-trained CNN architectures are employed in this case, meaning that the suggested dataset is used just as is, without any training [31].

3. *Ensemble technique:*

Ensembling is a quite popular practice that involves aggregating multiple CNN models into one. Here, two variations have been studied and analyzed.

A. *Non-Transfer Learning:*

Instead of being pre- trained, each member model in this case is trained on the suggested dataset before working together. Here, two ensemble models are developed in the suggested literature [31].

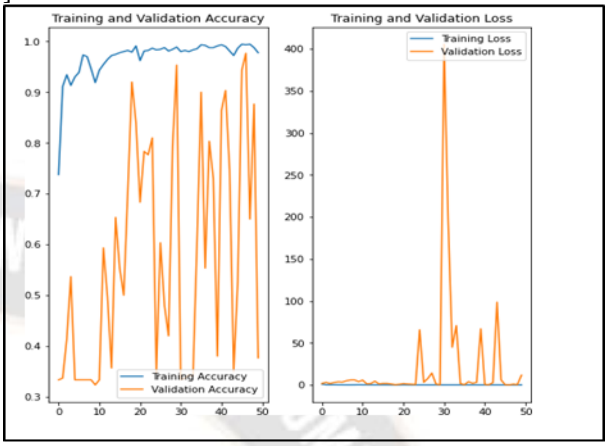

Fig 15: Visualization of VGG16 result on proposed dataset

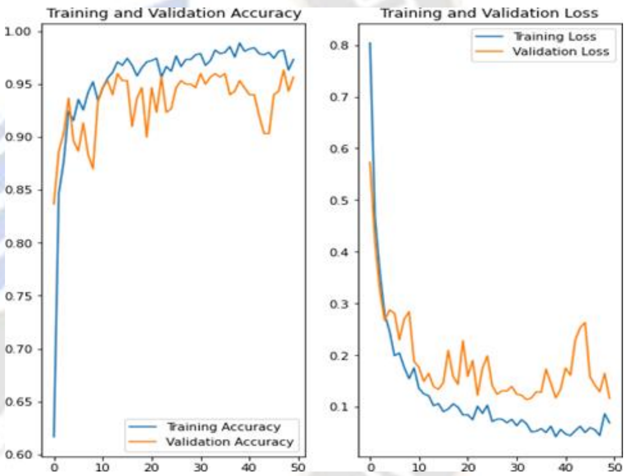

Fig 16: Resnet Performance Analysis (pre-trained model)

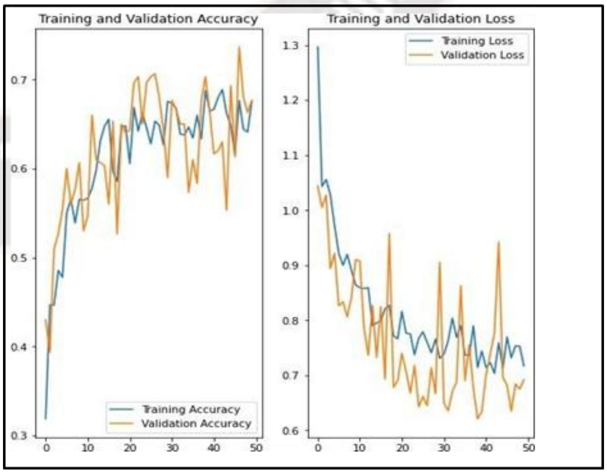

Fig 17: VGG-16 Performance Analysis (pre-trained model)

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B. Transfer Learning:

Here, some or all member models are pre-trained. In the proposed work two ensemble models are created:

1. Resnet + Googlenet: Here, only Resnet is pre-trained.
2. Xception + Googlenet + Resnet: Here, only Xception and Resnet are pre-trained [31].

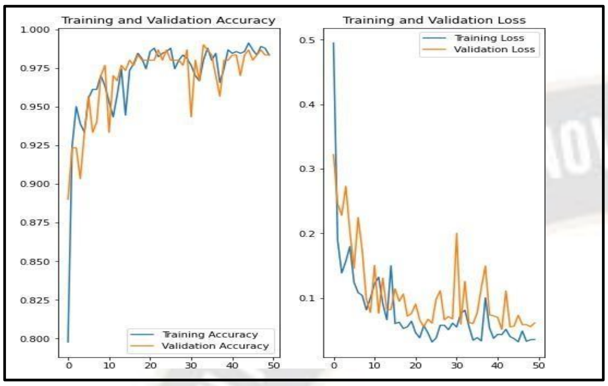

Fig 18: Xception Performance Analysis (pre-trained model)

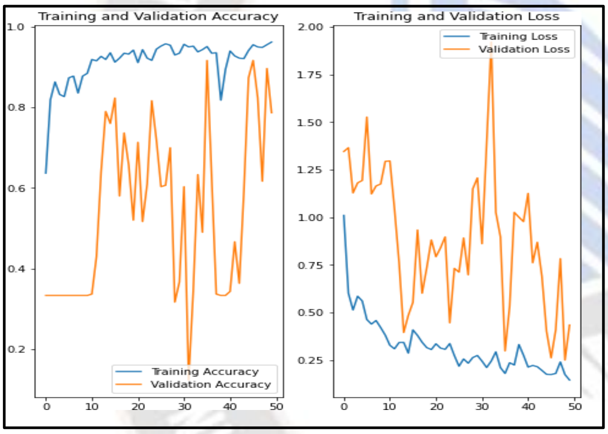

Fig 19: Resnet+GoogleNet

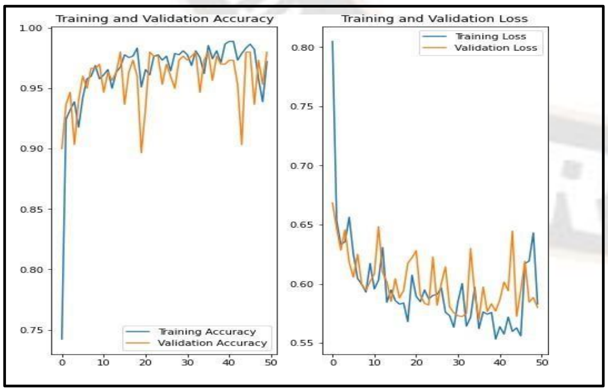

Fig 20: Resnet+Googlenet+Xception

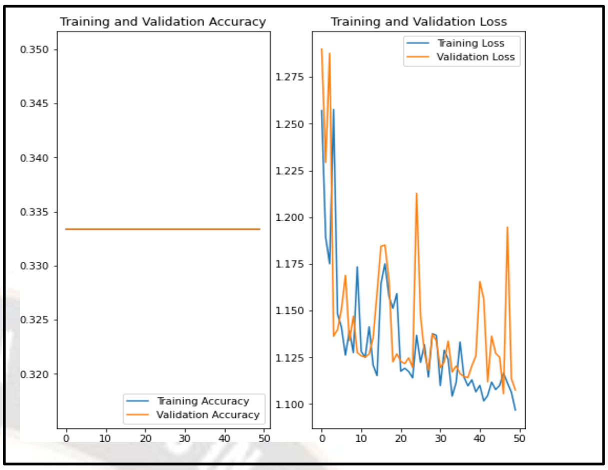

Fig 21: Resnet + Googlenet

5.Result & Discussion

1. *Classic CNN Architectures:*

Table 2: Classic CNN Architectures

DL model	Validation Accuracy				
	CNN	Google Net	Resnet50	VGG16	Xception
Non-Transfer Learning	98.67	88.33	37.67	33.33	-
Transfer Learning	-	-	72.00	96.67	96.00

Evaluation of Models trained on training data:

- The CNN architecture proposed in this work performed the best having around 99% accuracy on the testing data also GoogleNet performed better having an accuracy of more than 88%.
- Deep Convolutional Neural Networks like Resnet15 and VGG16 underperformed with only37.67% and 33% of accuracy respectively [31].

Evaluation of Models pre-trained on ImageNet dataset:

- This study employed three pre-trained models: ResNet15, VGG16, and Xception.Resnet's accuracy was just 72% but comparing it with the one not pre-trained, it is double.
- VGG16 has an accuracy of 96.67% and it is near to triple that of not pre-trained.
- The Xception model also had an accuracy greater than 95%.

2. Ensemble Technique

Table 3: Ensemble Technique

DL model	Validation Accuracy	
	Resnet + GoogleNet	Resnet + GoogleNet + Xception
Non-Transfer Learning	80.00	88.33
Transfer Learning	33.00	97.00

Evaluation of Models trained on training data:

- The first model is a combination of Resnet and GoogleNet model and it gives an accuracy of 80%.
- This second model, which is a composite of three models, is improved by the addition of the Xception model and has an accuracy of 88.33%.Evaluation of Models pre-trained on ImageNet dataset [31].
- The first model is the combination of ResNet and GoogleNet where the ResNet model was pre- trained on Imagnet dataset. The accuracy of this ensemble model was the worst i.e.just 33%.
- However, adding a pre-trained Xception model made it the best with 97% accuracy on the testing data.

6.Conclusion

The results of this work enable us to conclude that the accuracy of potato plant disease classification is increased when the transfer-learning approach is used to algorithms with several convolutional layers on tiny picture datasets. We can conclude from the comparative analysis that the methodology based on the transfer-learning technique for ensemble learning performs better than the accuracy scores reported in the non-transfer learning technique for ensemble learning. The methodology based on the transfer-learning technique for ensemble learning produced a classification accuracy score of 97.00%. Additionally, a significant increase in classification accuracy was seen when transfer learning was used on traditional CNN architectures like VGG16 and Resnet50.

7.Future Scope

Subsequent research may employ a same technique to identify more plant- and potato-related ailments using digital images. Additionally, a variety of CNN combinations and augmentation techniques may be assessed for feature extraction. Furthermore, the results of this study may be examined in many contexts by utilizing a variety of feature extractors and fusion approaches with any dataset [31].

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