Plant Disease Identification using Deep Learning

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***Abstract*—The increasing incidence of leaf diseases in agricultural crops has necessitated the development of efficient and automated detection methods to safeguard crop health and maximize yield. In the field of artificial intelligence, deep learning has emerged as a major computing paradigm with immense potential for solving a broad spectrum of computer vision problems. CNN is a type of deep learning architecture that is designed to provide accurate results for tasks such as image recognition and object detection. This study utilizes state-of-the-art (CNN) models to identify and classify plant leaf diseases. We have tested and assessed the performance of VGG16, Inception V4, AlexNet, and ResNet 50. Leveraging the power of deep learning, particularly transfer learning, this study presents a strong model which has the potential to accurately classify plant leaf diseases based on high- resolution images. The proposed methodology involves dataset curation, preprocessing, and fine-tuning of the ResNet-50 architecture, demonstrating its efficacy in automating leaf disease identification. Upon examining the results, ResNet50 has demonstrated good outcomes in the identification and categorization of plant leaf diseases with an accuracy of 99.85%.**

***Index Terms*—Plants Leaf disease, · Deep Learning, · CNN, · ResNet-50**

I. Introduction

Plant diseases disrupt the regular condition and growth of plants. Plant diseases are a significant factor contributing to reduced productivity, resulting in economic losses. To achieve sustainable agriculture and maximize crop yield, it is crucial to detect plant diseases. This is because disease identification can lead to a yield gain of over 60% of the overall productivity. The Food and Agriculture Organization has estimated that pests and diseases have a significant impact on worldwide food production, affecting around 20% to 40% of the total output. This poses a substantial threat to food security (Agarwal M. et. al., 2019). The utilization of pesticides can safeguard plants against diseases or infections, hence preserving crop harvests. Nevertheless, the utilization of pesticides has detrimental effects on the environment and poses a severe impact on biodiversity, encompassing the atmosphere, water sources, avian species, insects, soil, and aquatic life. Additionally, it poses a potential hazard to human health, resulting in both immediate and long-term consequences. Knowledge of a field's phytosanitary conditions plays a crucial role in restricting the use of hazardous substances, such as pesticides. It assists farmers in implementing appropriate practices in the impacted area at the necessary time. Furthermore, it is impractical to repeatedly assess the state of the plant numerous times during a specific season on farms that cover vast geographies. Multiple methods exist for identifying plant disorders. However, most disorders manifest observable symptoms that can be largely assessed by skilled professionals. A skilled phytopathologist with strong analytical abilities can accurately detect the characteristics of illness symptoms (Agarwal M. et. al., 2020). Nevertheless, phytopathologists may encounter challenges when there is variability in the symptoms exhibited by plants affected by the disease. A computerized method capable of identifying disease-affected plants based on their fundamental symptoms and appearance simplifies the work of disease diagnosis and improves accuracy.

Figure 1. Sample of images from Plant-Village dataset

Fig. 1 shows various healthy and unhealthy leaves in our used dataset. Early detection not only safeguards farmers' livelihoods by preserving crop productivity but also contributes to the overall resilience of the agricultural sector, tackling the issues presented by changing plant diseases and climate variations.

The recent progress in technology and the affordability of inexpensive devices for capturing photos have enabled the collection of a huge number of photographs for the purpose of image-based diagnosis (Anandhakrishnan, T. et.al.). Compressed information found in digital photographs makes it difficult for computing systems to examine. To extract certain aspects such as color and shape, further procedures like pre-processing and segmentation are necessary (Ariyapadath, S. ,2021) (Ashok S. et. al.). Advancements in computer vision and artificial intelligence have created a platform that allows for more accurate identification of plant diseases. This technology also presents an opportunity to connect with precision agriculture.

Deep learning enables machines to autonomously discover the best combination of attributes for every domain without the need for human assistance.

In 1989, the emergence of Convolutional Neural Networks (CNNs) was driven by the demanding nature of machine vision tasks (Bhowmik S. et. al., 2020). CNN has proven to be the most effective learning algorithms, particularly for tasks involving picture comprehension. The effectiveness of this approach has been demonstrated in a range of visualization tasks, including segmentation, detection, and classification. The utilization of CNNs for the analysis of plant diseases has been carried out from its beginning (Siddharth, S. C. et. al.). The availability of powerful processing hardware and advancements in learning methods have made it possible to train large-scale deep CNN in the 2010s. AlexNet is widely recognized as a significant advancement in the field of deep learning. Due to the increased availability of powerful processing systems, CNN architectures have become more complex and deeper.

The plant disease dataset differs from other picture datasets in terms of its size and the variation of features that need to be extracted for classification. Providing precise classification results for disease classification problems using machine learning algorithms is challenging when employing manually designed features. CNN obviates the necessity for manually designed features, hence enhancing the resilience of plant disease classification models in comparison to conventional ML models. Furthermore, it is feasible to visually represent the disease characteristics that have been extracted at each layer. This enhances the visual appeal of the model and assists agricultural professionals in comprehending the stages of disease classification.

II. RELATED WORK

Several studies employed CNN models to address intricate tasks. (Sibiya M. et al) employed CNN to classify illnesses in maize plants. The model influence was demonstrated using histogram approaches. Their overall model accuracy reached 92.85%. (Zhang K. et al) utilized CNN architectures, specifically AlexNet, ResNet, and GoogleNet, to detect tomato leaf diseases. ResNet achieved superior performance compared to other networks, with the maximum accuracy of 92.28%. The study conducted by (Amara J. et al) utilized the LeNet architecture to identify and diagnose illnesses affecting banana leaves. In this study, the authors utilized the CA and F1-score metrics to assess the performance of the model using both grayscale and color images. (Konstantinos P. Ferentinos) conducted a comparative analysis of the accuracy of classifying leaf diseases using the AlexNet, GoogleNet, and VGG CNN architectures. The VGG network achieved superior performance compared to all other networks, with a plant disease classification accuracy of 99.53%. (Tu¨rkoglu M. et al) categorized 8 distinct plant diseases using several classifiers. The researchers evaluated the performance of KNN, SVM, and ELM algorithms when used in conjunction with the features extracted from cutting-edge deep learning models. The researchers evaluated multiple CNN models, including ResNet-50, ResNet-101, Inception- ResNetv2, Inception-v3, and other models. The ResNet-50 model combined with SVM yielded the most optimal outcome when assessed using several performance measures. (Amanda Ramcharan et. al) employed the Inception-V3 model to identify cassava disease, with an average accuracy of almost 95% across six disease categories. (Fujita E) employed two distinct variants of CNN and attained an accuracy of 82.3% in classifying cucumber plant illnesses. (Yamamoto K et al) conducted a study on tomato disease classification using CNN. They utilized various degrees of image resolution techniques to assess the accuracy of super- resolution compared to other approaches. The results presented in the research demonstrated that the super-resolution method significantly surpassed conventional methods in terms of accuracy. (Rangarajan A.K et al) conducted a classification study on tomato leaf diseases using the deep learning architectures AlexNet and VGG-16. Among them, AlexNet achieved the highest accuracy of 96.38% with a minibatch size of 32 and a learning rate of 40. In their study, (Brahimi et al.) introduced a saliency map to visualize the symptoms of plant disease. The planned architecture attained an accuracy of 99.76%. (Sladojevic S. et al) utilized the CaffeNet CNN model to classify 13 diseases and achieved a classification accuracy of 96.30%. (Sharada P. Mohanty et al.) conducted a comparative analysis of the performance of two convolutional neural network designs, namely AlexNet and GoogleNet, using the Plant-Village dataset, which consists of leaf illnesses. The researchers conducted experiments on three different scenarios, namely color, grayscale, and segmented images, to evaluate the performance of CNN models. According to the performed review, it has been discovered that deep neural networks have been successfully implemented in various fields for end-to- end learning. It facilitates the correlation between an image depicting a sick leaf (input) and a combination of crop and disease (output). The primary obstacle in developing a deep neural network lies in accurately mapping the nodes and edge weights from the input to the output, which is crucial for determining the network's structure. The deep neural network training involves fine-tuning the network parameters through a procedure that establishes a mapping between the I / O layers. To create a highly accurate plant disease detection model using deep neural networks, it is necessary to have a substantial and verified collection of photos depicting both healthy and ill plants. Nachtigall et al. [18] made use of CNNs to detect and classify nutritional deficiencies and damage on apple trees. AlexNet was used as CNN architecture, so they made a comparison between Multilayer Perceptron (MLP) and the CNN, which was compared with seven volunteer experts. The results showed an accuracy of 97.3% obtained by CNN, while the human experts had 96%, and the MLP obtained the lowest accuracy at 77.3%.

III. METHODOLOGY

A. Data Collection

We utilize the Plant Village dataset, an openly accessible dataset accessible via Kaggle, for our study **(Mohanty et al. 2016)**. With approximately 70,000 images encompassing both healthy and unhealthy crops, the dataset features 38 pre-identified categories. Table 1 shows all the categories of images in our dataset. Due to an imbalance in the number of fit and infected plant leaves, a strategy is employed to make the number of samples equal per category and mitigate potential bias in the network. The strategy involves considering the start healthy, middle healthy, and end healthy categories. Employing an 80-20 training-test split, about 80% of input images are utilized for training and transformation, while 20% are reserved for validation and testing.

Table 1. Sample of images from Plant-Village dataset

Serial Number	Plant / Diseases	Images per each class of plant disease
1	Tomato__Late_blight	1851
2	Tomato__healthy	1926
3	Grape__healthy	1692
4	Orange__Haunglongbing_(Citrus_greening)	2010
5	Soyabean__healthy	2022
6	Squash__Powdery_mildew	1736
7	Potato__healthy	1824
8	Corn_(maize)__Northern_Leaf_Blight	1908
9	Tomato__Early_blight	1920
10	Tomato__Septoria_leaf_spot	1745
11	Corn_(maize)__Cercospora_leaf_spot Gray_leaf_spot	1642
12	Strawberry__Leaf_scorch	1774
13	Peach__healthy	1728
14	Apple__Apple_scab	2016
15	Tomato__Tomato_Yellow_Leaf_Curl_Virus	1961
16	Tomato_Bacterial_spot	1702
17	Apple__Black_rot	1987
18	Blueberry__healthy	1816
19	Cherry_(including_sour)__Powdery_mildew	1683
20	Peach__Bacterial_spot	1838
21	Apple__Cedar_apple_rust	1760
22	Tomato__Target_Spot	1827
23	Pepper_bell__healthy	1988
24	Grape__Leaf_blight_(Isariopsis_Leaf_Spot)	1722
25	Potato__Late_blight	1939
26	Tomato__Tomato_mosaic_virus	1790
27	Strawberry__healthy	1824
28	Apple__healthy	2008
29	Grape_Black_rot	1888
30	Potato__Early_blight	1939
31	Cherry_(including_sour)__healthy	1826
32	Corn(maize)__Common_rust	1907
33	Frape_Esca_(Black_Measles)	1920
34	Raspberry__healthy	1781
35	Tomato__Leaf_Mold	1882
36	Tomato__Spider_mites Two-spotted_spider_mite	1741
37	Pepper_bell__Bacterial_spot	1913
38	Corn_(maize)__healthy	1859

B. Data Preprocessing:

A very important part of building machine learning models is pre-processing, which makes sure that the raw data is good enough to be analyzed. ResNet-50 uses a data pre-processing approach to optimize its performance on an image dataset. This process involves loading and inspecting images for consistency, resizing them to a suitable size, employing data augmentation techniques, and normalizing pixel values, to improve model generalization. These pre-processing steps contribute to optimizing the training process and enhancing ResNet-50's performance on the given image dataset.

C. Convolutional Neural Network (CNN):

CNN is a deep learning architecture that efficiently processes structured grid data like images, utilizing convolutional layers to autonomously acquire hierarchical characteristics from input data. Convolutional Neural Networks (CNNs) have transformed computer vision and image processing by allowing precise item categorization, object detection, face recognition, and autonomous vehicle capabilities. They learn hierarchical representations for object classification, identify multiple objects in images, and aid in disease diagnosis in medical imaging by analyzing radiological images. CNNs, despite their success, face challenges such as overfitting,

imaging by analyzing radiological images. CNNs, despite their success, face challenges such as overfitting, computational costs, interpretability issues, security concerns from adversarial attacks, and handling variations in scale, orientation, and occlusion. Transfer learning is a strategic method used to overcome difficulties in object recognition and classification tasks, especially in CNN models.

D. Transfer Learning Approach:

Transfer learning is a technique which involves the usage of pre- trained networks to effectively apply parameters based on a specific intended set of data to solve problems, especially in image recognition and classification tasks. CNN training is time-consuming, but trans- fer learning achieved 63% accuracy in half the epochs, compared to 25% after 200 epochs, depending on the pre-trained model and dataset's characteristics.

E. ResNet-50:

A deep learning model, ResNet-50, identifies and labels objects in images with remarkable precision. The network is specifically engineered to discover residuals, which represent the discrepancy between the desired and current outputs. This is regarded as a more manageable task than learning the desired output per se. ResNet-50 employs skip connections, which bypass layers to append input to the subsequent layer's output. The ResNet-50 architecture introduces skip connections, allowing the model to effectively learn and retain information even in the presence of very deep networks. Fig 2. shows Accuracy V/s No. of epochs graph of ResNet-50.

The ResNet50 architecture consists primarily of four com- ponents: (1) fully connected layers; (2) activation layers; (3) pooling layers; and (4) convolutional layers. Table-3 shows the architecture of ResNet-50. Convolutional layers are employed to extract features from unprocessed data, such as textures and margins, whereas activation layers utilize non-linear functions to discover intricate patterns. In pooling layers, the data is down sampled, keeping the major particulars. Finally, fully connected layers sort the data into groups based on the convolutional and pooling layers' findings. This deep neural network excels in classifying images, finding objects, and semantic segmentation due to skip links and residual learning.

Implementing a ResNet-50 CNN for leaf disease identification involves several steps, including data preparation, model creation, training, and evaluation. The Plant Village dataset, containing over 70,000 images of healthy and diseased crops, is utilized, divided into training and validation sets. The model architecture consists of 50 layers and introduces residual blocks, including skip connections, to ease the vanishing gradient problem. The final layer of the pre-trained ResNet-50 is modified that matches the number of output classes with the matching plant disease classes. Cross-entropy loss is commonly used for multi-class classification problems, while Stochastic Gradient Descent (SGD) is employed as the optimizer. Learning rate scheduling is applied to adjust the learning rate during training for better convergence. The training process includes iteration of training dataset in mini-batches, forward-passing the input through

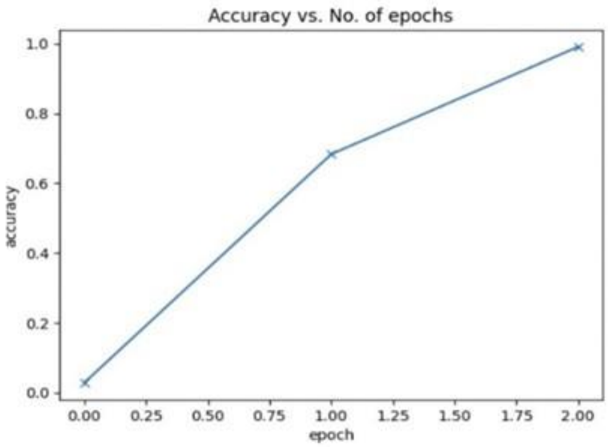

Fig. 2. Accuracy vs. Number of Epochs

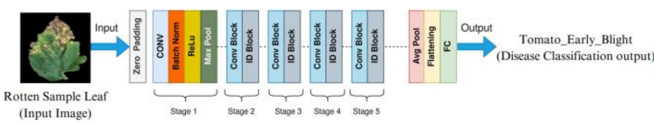

Fig. 3. ResNet-50 Architecture

the network, calculating the loss, and updating the model's weights through backpropagation. Learning rate scheduling helps prevent overfitting and aids convergence. After training, the performance of the model is evaluated over the validation set, providing insights into its generalization capability. Further considerations include data augmentation techniques, GPU acceleration, fine-tuning, and future improvements such as exploring advanced architectures, incorporating more sophisticated data augmentation techniques, and ensemble learning for improved accuracy.

IV. Results and Discussion

The results of using the ResNet-50 architecture for leaf disease detection can be evaluated based on various performance metrics. The study's evaluation criteria, such as Recall-value, Support-value, Precision-value and F1 score, are based on research objectives and focal points. To assess the performance of the model, recall-value, support-value, precision-value and F1 score accuracy were computed using designated evaluation matrices. Table 2, Table 3 and Table 4 show the comparison between the 4 models on the basis of their performance by calculating their Recall Value, F-1 Score, Precision value respectively. These performance metrics of deep learning algorithms serve as benchmarks for evaluating their effectiveness. These results offer significant insights on their capacity to precisely detect positive instances, capture pertinent instances, and maintain a balance between Precision and Recall. By identifying true positives, false negatives, false positives, and false positives, the Confusion Matrix provides an exhaustive analysis of the model's approximations.

Table 2 Recall Comparison Table

Plant/Diseases	InceptionV4	VGG16	AlexNet	ResNet50
Tomato_Early_Blight	0.95	0.97	0.98	0.98
Tomato__Septoria_leaf_spot	0.99	0.96	0.99	1.00
Corn(maize)__Cercospora_leaf_spot Gray_leaf_spot	0.97	0.99	1.00	1.00
Strawberry__leaf_scorch	1.00	1.00	0.96	0.97
Peach__healthy	0.94	0.98	0.97	0.99
Apple__Apple_scab	0.98	0.99	0.98	1.00
Tomato__Tomato_Yellow_Leaf_Curl_Virus	1.00	0.96	1.00	1.00
Tomato_Bacterial_Spot	1.00	0.99	1.00	1.00
Apple__Blackouts	0.96	0.97	0.99	0.98
Blueberry__Healthy	0.98	0.96	0.96	0.98
Cherry__(including_sour)__Powdery_mildew	0.97	0.99	0.98	0.97
Peach__Bacterial_spot	1.00	0.96	0.99	0.99
Apple__Cedar_apple_rust	0.95	1.00	0.99	0.99
Tomato__Target_spot	0.99	1.00	1.00	0.99
Pepper_bell_healthy	0.97	0.98	0.97	1.00
Grape__Leaf_blight_(Isariopsis_Leaf_Spot)	0.96	0.99	0.96	1.00
Potato__Late_blight	1.00	0.96	0.99	1.00
Tomato__Tomato_mosaic_virus	1.00	0.97	0.97	1.00
Strawberry__healthy	1.00	1.00	1.00	0.99
Apple_Healthy	0.99	1.00	1.00	0.97
Grape_Black_rot	0.96	0.99	1.00	0.98
Potato__Early_blight	0.97	0.96	1.00	1.00
Cherry_(including_sour)__healthy	0.96	0.98	0.99	0.99
Corn(maize)__Common_rust	0.97	0.95	0.98	1.00
AVERAGE	0.97	0.98	0.98	0.99

Table 3. F-1 Score Comparison Table

Dataset	Inception V4	VGG 16	AlexNet	ResNet 50
Tomato_Early_Blight	1.00	0.99	0.98	0.99
Tomato_Septoria_leaf_spot	0.99	1.00	0.98	1.00
Corn_(maize)_Cercospora_leaf_spot gray_leaf_spot	1.00	1.00	0.99	1.00
Strawberry_Leaf_scorch	0.96	0.97	0.98	1.00
Peach_healthy	0.96	0.98	1.00	1.00
Apple_Apple_scab	0.98	0.98	0.98	1.00
Tomato_Tomato_Yellow_Leaf_Curl_Virus	0.99	0.97	1.00	1.00
Tomato_Bacterial_spot	0.99	0.97	0.98	1.00
Apple_Black_rot	0.99	0.96	1.00	1.00
Blueberry_healthy	0.97	1.00	0.99	0.99
Cherry_(including_sour)__Powdery_mildew	1.00	0.99	1.00	1.00
Peach_Bacterial_spot	0.98	0.98	0.98	1.00
Apple_Ceadr_apple_rust	1.00	0.98	0.97	1.00
Tomato_Target_spot	1.00	1.00	0.99	1.00
Pepper_bell_healthy	0.96	1.00	0.98	1.00
Grape_Leaf_blight_(Isariopsis_Leaf_Spot)	0.98	0.96	0.98	1.00
Potato_Late_blight	0.97	0.96	0.99	0.99
Tomato_Tomato_mosaic_virus	0.99	0.96	0.99	0.99
Strawberry_healthy	1.00	0.99	0.97	1.00
Apple_healthy	1.00	1.00	1.00	1.00
Grape_Black_rot	0.96	1.00	0.98	1.00
Potato_Early_Blight	0.97	0.98	1.00	0.99
Cherry_(Including_sour)_healthy	0.99	0.97	0.98	0.99
Corn(maize)_Common_rust	1.00	1.00	1.00	1.00
Average	0.97	0.98	0.98	0.99

Figures 4 and 5 show the graphical insights of the performance of various models based on their precision, F-1 and recall values respectively. Understanding the performance of a model during training requires monitoring the loss and accuracy for both training and validation. Accuracy, a fundamental measure, reflects the overall correctness of the model's predictions by calculating the ratio of correctly classified samples to the total number of samples. The loss function graph in leaf disease detection represents how the model's loss, a measure of the difference between predicted and actual values, changes over the course of training. Typically, the loss decreases as the model learns from the training data. Figure 7 showcases the accuracy and loss of our model throughout the training and validation process. Diverse architectures have been contrasted to determine the optimal model. Performance was enhanced through the implementation of diverse optimization techniques,

Table 4. Precision Comparison Table

Dataset	Inception V4	VGG 16	AlexNet	ResNet 50
Tomato_Early_Blight	1.00	0.99	0.96	1.00
Tomato_Septoria_leaf_spot	0.99	1.00	0.98	1.00
Corn_(maize)_Cercospora_leaf_spot gray_leaf_spot	0.99	1.00	0.98	1.00
Strawberry_Leaf_scorch	0.99	0.98	0.99	0.99
Peach_healthy	1.00	0.98	1.00	1.00
Apple_Apple_scab	0.98	0.98	0.97	0.98
Tomato_Tomato_Yellow_Leaf_Curl_Virus	0.99	0.97	1.00	1.00
Tomato_Bacterial_spot	0.99	0.97	0.96	0.99
Apple_Black_rot	0.99	0.96	0.96	0.99
Blueberry_healthy	0.97	1.00	0.97	1.00
Cherry_(including_sour)__Powdery_mildew	1.00	0.99	1.00	1.00
Peach_Bacterial_spot	0.98	0.97	0.96	0.98
Apple_Ceadr_apple_rust	1.00	0.97	0.99	1.00
Tomato_Target_spot	1.00	1.00	0.99	1.00
Pepper_bell_healthy	0.98	1.00	0.99	1.00
Grape_Leaf_blight_(Isariopsis_Leaf_Spot)	0.98	0.95	0.96	0.98
Potato_Late_blight	0.97	0.95	0.96	0.99
Tomato_Tomato_mosaic_virus	0.97	0.96	0.97	0.98
Strawberry_healthy	0.96	0.99	1.00	1.00
Apple_healthy	1.00	1.00	1.00	1.00
Grape_Black_rot	1.00	1.00	0.99	1.00
Potato_Early_Blight	0.97	0.98	0.97	0.98
Cherry_(Including_sour)_healthy	0.99	0.97	0.97	0.99
Corn(maize)_Common_rust	1.00	0.98	0.97	1.00
Average	0.98	0.98	0.97	0.99

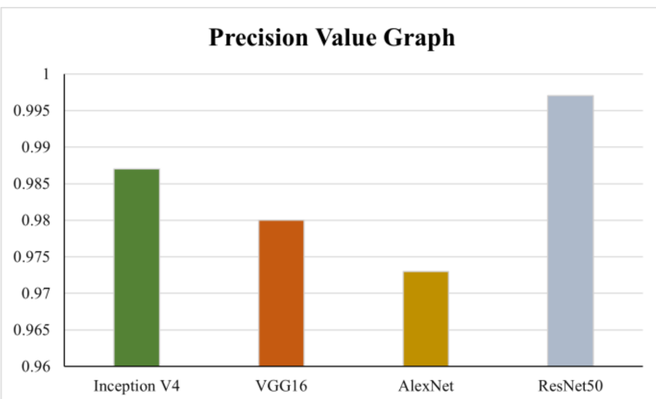

Fig. 4. Precision Value Graph

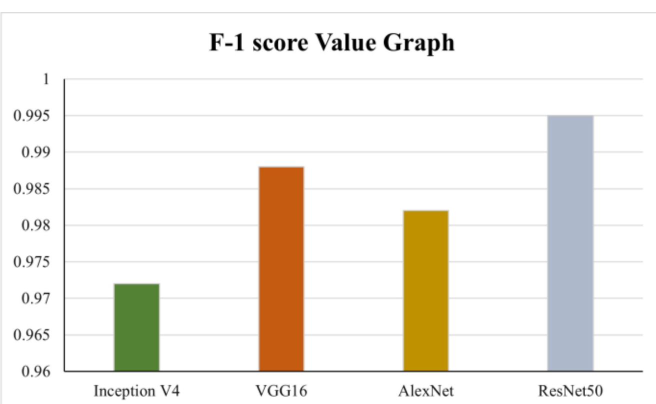

Fig. 5. F-1 Score Value Graph

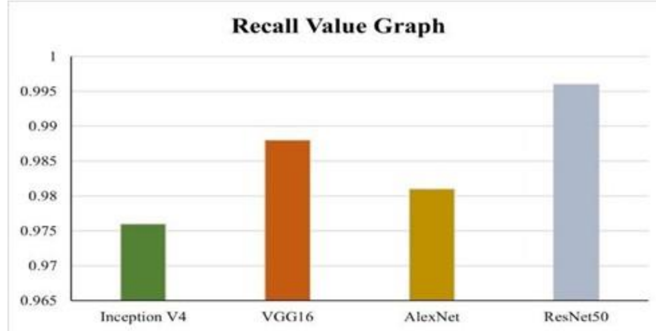

Fig. 6. Recall Value Graph

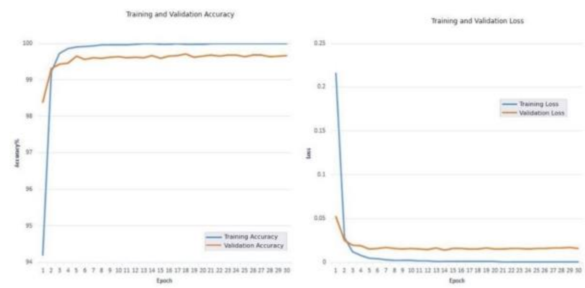

Fig. 7. Training and Validation Accuracy and Loss of ResNet-50 model.

as determined by precision and loss metrics derived from both training and validation tests. We performed a thorough evaluation of the VGG16, Inception V4, AlexNet and ResNet 50 models, optimizing the pre-trained models for peak performance.

Table 5. Comparison Table of Inception V4, VGG16, ResNet50, AlexNet

Model	Params	Accuracy (Training) (%)	Accuracy (Validation) (%)	Accuracy (Testing) (%)	Loss (Training)	Loss (Validation)	Loss (Testing)
Inception V4	41.2 M	**98.36**	98.30	98.36	0.0160	0.0643	0.674
VGG 16	119.6 M	83.43	82.30	81.63	0.6089	0.6978	0.7021
ResNet 50	23.6 M	99.85	99.76	99.70	6.436e-04	0.0210	0.0317
AlexNet	28.11 M	94.34	95.38	95.10	0.0954	0.0960	0.0951

Table 5 represents the results of the assessment revealed that ResNet-50 exhibited outstanding test accuracy at 99.85%, surpassing Inception V4 at 98.36%, VGG16 at 83.43% and AlexNet at 94.34%. These results highlight the promising capabilities of ResNet 50 in accurately identifying various plant leaf diseases.

V. Conclusion

This research provides a significant contribution to the field of plant pathogenesis by using the capabilities of ResNet50 to detect leaf diseases on plants. By conducting an extensive investigation of the dataset in conjunction with the advanced architecture of ResNet50, a failsafe model was developed that demonstrated a remark- able 99.7% accuracy rate in identifying a broad spectrum of diseases affecting various plant species. A variety of models were contrasted in the study, including VGG 16, Inception V4, AlexNet, and ResNet-50. With a 99.70% accuracy rate, ResNet-50 outperforms alternative architectures when it comes to classifying plant leaf maladies after a specified number of epochs. With its efficiency in using fewer parameters and requiring less time, image-based detection and classification of plant leaf diseases is the recommended method. By utilizing automated systems to detect maladies in a timely manner, producers can effectively implement targeted interventions, reduce pesticide usage, and optimize resource utilization. As a result, this leads to implemented sustainable agricultural methods and a diminished ecological footprint.

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