

A Robust And Novel Multilayer Convolutional Neural Network For Classification And Validation Of Plant Leaf Disease

Vinay Singh¹, Jyoti Sharma², Aditya Tandon³, Sanjiv Sharma⁴

¹Department of Computer Science Engineering, ABES Engineering College, Ghaziabad, UP, India, vinaysingh@abes.ac.in

²Department of Computer Science Engineering, ABES Engineering College, Ghaziabad, UP, India, jyotisharma@abes.ac.in

³Department of Computer Science Engineering, ABES Engineering College, Ghaziabad, UP, India, aditya.tandon@abes.ac.in

⁴Department of Computer Science and Engineering, Galgotias University, Greater Noida, India, martin.mmmec@gmail.com

Abstract

The core of the Indian economy is agriculture, yet the persistent problem of plant disease detection jeopardizes its productivity. Plant diseases can significantly lower the quality and quantity of agricultural goods, which has a severe effect on food production safety. Plant diseases can potentially completely prevent grain harvests in extreme circumstances. In the realm of agricultural informatics, the automatic identification and diagnosis of plant diseases is therefore widely desired. Numerous approaches have been put out to tackle this task, with deep learning emerging as the go-to approach because of its remarkable results.

As a result, a Multilayer Convolutional Neural Network (MCNN) is suggested for this work in order to classify the disease-affected plant leaves. This work has been verified using a real-time dataset that was Offline augmentation . This dataset, which is divided into 38 classes, includes over 87K rgb photos of both healthy and damaged crop leaves. The entire dataset is split up into training and validation sets in an 80/20 ratio while maintaining the directory structure. For prediction purposes, a new directory with 38 test photos is later established. Findings indicate that, in comparison to other cutting-edge methods, the suggested MCNN model has a better classification accuracy.

Keywords: Plant disease identification, Deep learning ,Convolution neural networks, Image classification.

I. INTRODUCTION

Cultivating land and rearing animals are among the first known human endeavors. Over the ages, humans have significantly improved agricultural farming's productivity and efficiency by developing a variety of cutting-edge new technologies. However, there is a shortage of farmland due to population growth, necessitating creative solutions that increase output while utilizing the least amount of space. Leaf infections are a common cause of crop problems for farmers worldwide [1]. The most common illnesses are caused by fungi (leaf spots, discolouration), bacteria (grayish mildew), and viruses (leaf curl). As a result, the end product's quality and quantity both decline. Continuous monitoring helps farmers produce more since it allows for the early identification of problems and the application of appropriate solutions[2]. Leaf infections can be diagnosed using a variety of methods [3][4].

The plant pathologists and farmers are involved in the traditional methods of managing diseases. It is increasingly common to diagnose and apply pesticides in fields. This is a laborious, difficult process that frequently leads to an inaccurate diagnosis and inappropriate use of pesticides [4]. Advancements in Computer Vision (CV), Machine Learning (ML), and Artificial Intelligence (AI) have led to the development of automated models that facilitate the precise and timely identification of plant leaf diseases. Artificial intelligence (AI) and machine learning (ML) have garnered enormous interest. It has been acknowledged in recent years that deep learning (DL) has been primarily applied in the field of agriculture [5]. The adoption of new technology, algorithms, and equipment in agriculture is at the foundation of smart farming approach [5, 6].

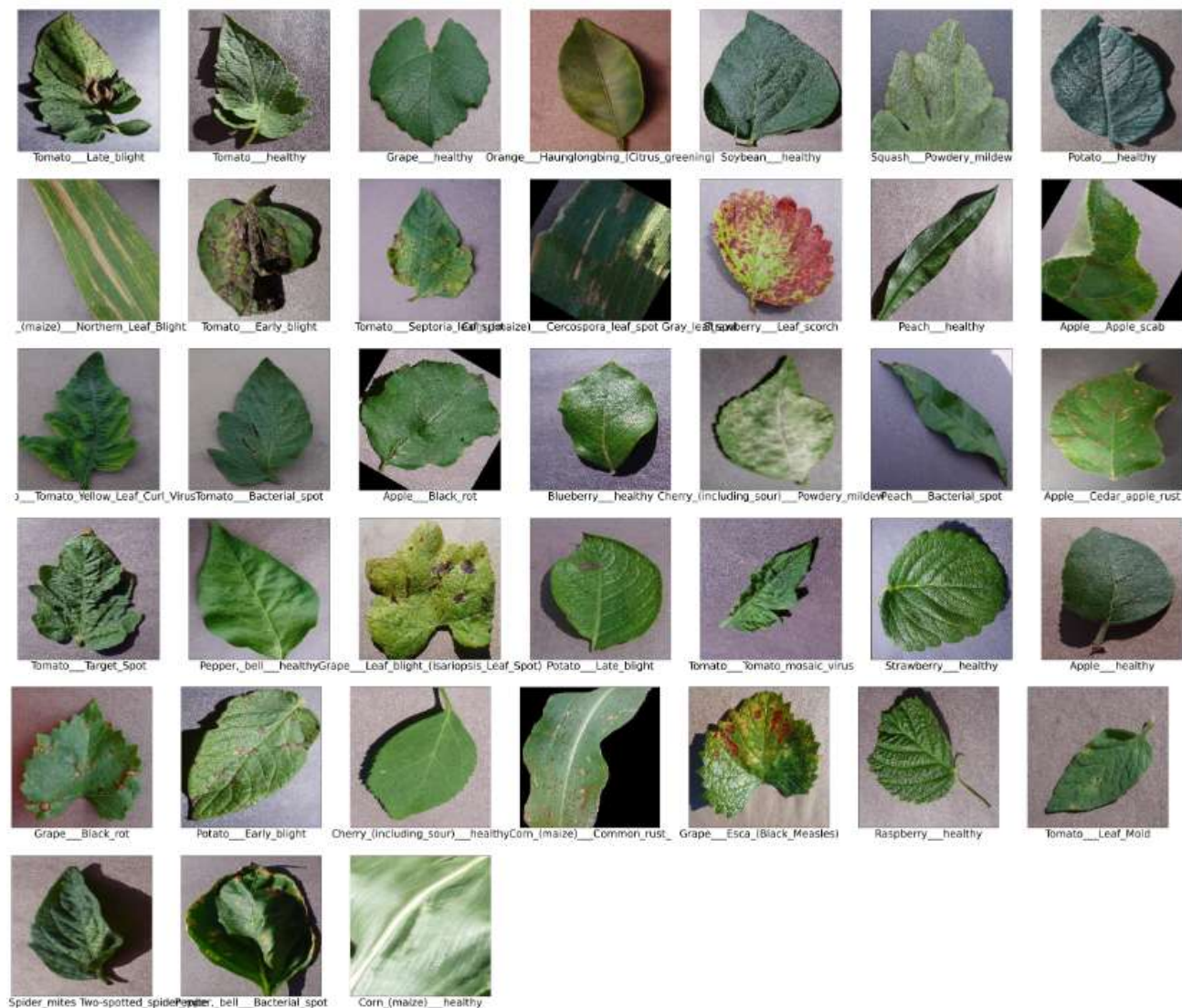


Fig. 1. Listed images of plant leaves.

The plant's ability to function depends on both patterns. Veins carry nutrients and water throughout the plant, and how they are arranged affects how these resources are distributed [7,8]. The ability of the plant to carry out photosynthesis and control transpiration can also be impacted by the venation pattern. Consequently, any harm done to the venation patterns may have a major effect on the plant's health and yield. Damage to the leaf veins can result in a number of illnesses that compromise the health and yield of plants. Table 1[6] lists some of the main leaf diseases that are thought to be caused by damaged leaf venation in both reticulate and parallel patterns and are taken into consideration when examining the effectiveness of the suggested model.

Table 1. Major Associated Leaf Venation Damages Affected due to Disease Infection

Disease	Description	Sample Image
Anthracnose	Plants with this fungal disease will wilt and eventually become brown because the infection attacks the veins and the leaves. In addition, both reticulate and parallel venation damage may result in anthracnose.	
Leaf spot	Circular patches with sharp borders appear on the leaves of infected plants due to microbial or fungal disease. In addition, both reticulate and parallel venation patterns may get damaged, leading to the onset of leaf spots.	
Downy mildew	Fungi cause yellow patches on leaves and stems, which ultimately become brown, resulting from this illness. In addition, plants' reticulate and parallel venation patterns may both be harmed, which can lead to downy mildew development.	
Powdery mildew	This white powdery substance appears on the leaves of infected plants due to a fungal disease. Both reticulate and parallel venation patterns may be damaged, leading to powdery mildew.	
Rust	Spots of orange, yellow, or brown appear on the leaves of infected plants due to fungus disease. Damage to either the reticulate or parallel venation patterns might lead to rust.	

Identification of venation damage on parallel and reticulate leaf patterns[9,10,11] is a critical component of plant pathology [12] in order to diagnose and prevent diseases that could hinder the growth and productivity of the plant. Regretfully, the traditional method of identifying leaf venation damage requires a great deal of work and plant pathology expertise. Therefore, it is necessary to have an automated system that can recognize these flaws with speed and accuracy.

That's where the intelligent DL model comes in. In this type of artificial intelligence, computer systems use pre-existing neural networks to find patterns in vast volumes of incoming data and take advantage of them. In this case, the deep-learning model is trained using a set of images showing both healthy and damaged leaves with parallel and reticulate venation patterns[13,14]. By identifying the changes in venation patterns brought on by injury, the model is trained to discriminate between leaves that are healthy and those that are damaged. Because of their improved processing speed and accuracy, DL models have gained popularity in plant pathology in recent years [15,16]. Even variations in venation patterns that are not visible to the naked eye might be detected by the advanced deep learning model. This increases the likelihood that potential problems can be identified early and treated or averted. Using the proposed paradigm instead of more traditional methods has various advantages. It doesn't require any prior understanding of plant pathology and is quick, accurate, and completely automated. The model may be integrated into already-existing disease surveillance networks and is flexible enough to be used in a variety of settings, such as farming, floriculture, and forestry.

Then, taking into account the following key factors, the MCNN-based classification model is trained and tested for the detection of damaged leaves:

1. A disease's severity can be determined automatically, allowing for prompt, efficient therapy to be started in advance.
2. This can also help determine the type of disease and how it progresses, which can help determine who is vulnerable to it.
3. As a result, this research suggests using a deep learning model called MCNN to classify disease-infected leaves.
4. The suggested approach can contribute to determine the ecological and financial benefits of the trees and its yields since it is automatic, economical and computationally.

1.1 Significance of Plant disease detection

If identified with DL, venation damage to a plant can significantly affect its overall health and yield [17,18,19]. Vein damage in plants is typically a sign of impending problems, such as a disease or pest invasion. Early damage assessment enables the implementation of preventative measures, hence reducing the risk of the disease spreading to other plants. Massive datasets analyzed by DL models may reveal venation pattern alterations that are not immediately visible to the human eye. Consequently, the margin for error in disease diagnosis is reduced. The traditional method of venation damage detection requires extensive plant pathology expertise and labor. DL models have the potential to increase the speed and accuracy of illness detection because they can assess images in real-time and produce results immediately. DL models have the potential to automate disease identification, reducing the need for human labor and knowledge [15,16]. If this trend keeps up, farmers, gardeners, and foresters could wind up saving a significant amount of money over time [20]. Early disease detection and treatment can lead to increased agricultural production and output. Food safety might be enhanced by technology, and there could be enough food to meet growing demand.

1.2 Problem Statements

The following problem was tried to be resolved by detecting disease on plant. An automated, precise, and fast method based on a clever deep learning model is desperately needed to detect disease problems classification in leaves [17]. This research proposes a clever solution to address this issue by training a deep learning model to classify plant disease in 38 classes pictures of both healthy and disease leaves, the model provides an automated and precise method of classifying healthy and disease leaves from 38 classes [18].

1.3 Motivation

An intelligent deep learning algorithm has been employed by researchers to scan leaf patterns for indications of deterioration. This facilitates the early detection of venation faults and increases automation. Unfortunately, using the current methods for diagnosing venation issues requires a great deal of time, effort, and expertise of plant pathology. Furthermore, a delay in diagnosis could contribute to the spread of diseases and pests, which would lower productivity and output in agriculture. Therefore, it's imperative to create a more efficient method for the early detection of venation damage so that it can be promptly treated and avoided. This problem is solved by the proposed smart DL model, which makes use of AI principles to learn and identify patterns in data.

In order for the model to distinguish between healthy and injured leaves and identify the alterations in venation patterns brought about by damage, it is trained using images of both leaves with parallel and reticulate venation patterns. Because the model's automatic and precise method of identifying venation damage issues reduces the need for pesticides and other chemicals, it increases crop yield and production while minimizing the detrimental effects of agricultural activities on the environment. The main goal of this study is to create a more effective, long-term plant pathology strategy that will benefit farmers, gardeners, and foresters greatly.

1.4 Objectives

The goal of this effort is to use deep learning techniques to construct an extremely accurate and efficient system for the automatic identification and classification of plant diseases. The study's specific objectives are to:

1. **Create a Multilayer Convolutional Neural Network (MCNN):** Create and apply an MCNN model specifically designed to accurately identify healthy and damaged plant leaves.

2. Utilize a Comprehensive Real-Time Dataset: Utilize a substantial dataset that includes more than 87,000 RGB photos of plant leaves from 38 distinct classes in order to train and test the model. This dataset encompasses both healthy and damaged leaves in order to provide a thorough assessment of the model's functionality.

3. Put into Practice Efficient Data Augmentation Strategies: Enhance the dataset using offline augmentation techniques, making sure the model is trained on a variety of images to increase its generalization capacity.

4. Optimize the Training and Validation Process: To efficiently train the model and assess its performance, divide the dataset into 80/20 training and validation sets.

5. Create a Test Set for Assessment: To evaluate the model's predictive power independently after training, create a separate directory with 38 test photos in it.

6. Attain Greater Classification Accuracy: Show how well the MCNN model performs in comparison to other cutting-edge techniques and show how well it can classify plant diseases.

The ultimate objective is to advance agricultural informatics by offering a dependable, automated method for early disease identification in crops, which would increase food security and agricultural output.

IV. MATERIALS AND METHODS :

A. DATASET :

One database repositories have been employed in the proposed work from Kaggle Having leaves from various plants. 70295 photographs in all were used in this work; all of those were self-acquired photos taken in a real-time setting, These photos were divided into thirty eight groups: photographs of thirty eight groups leaves showing disease, images showing disease-free leaves, and images showing many plants showing illness and disease-free leaves.

These photos have labels assigned to them based on the categories. As illustrated in Figure 1. the example dataset comprises thirty eight photos of leaves captured in their natural state . The image details are displayed below.

The Number of Images in Tomato___Late_blight: 1851

The Number of Images in Tomato___healthy: 1926

The Number of Images in Grape___healthy: 1692

The Number of Images in Orange___Haunglongbing_(Citrus_greening): 2010

The Number of Images in Soybean___healthy: 2022

The Number of Images in Squash___Powdery_mildew: 1736

The Number of Images in Potato___healthy: 1824

The Number of Images in Corn_(maize)___Northern_Leaf_Blight: 1908

The Number of Images in Tomato___Early_blight: 1920

The Number of Images in Tomato___Septoria_leaf_spot: 1745

The Number of Images in Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot: 1642

The Number of Images in Strawberry___Leaf_scorch: 1774

The Number of Images in Peach___healthy: 1728

The Number of Images in Apple___Apple_scab: 2016

The Number of Images in Tomato___Tomato_Yellow_Leaf_Curl_Virus: 1961

The Number of Images in Tomato___Bacterial_spot: 1702

The Number of Images in Apple___Black_rot: 1987

The Number of Images in Blueberry___healthy: 1816

The Number of Images in Cherry_(including_sour)___Powdery_mildew: 1683

The Number of Images in Peach___Bacterial_spot: 1838

The Number of Images in Apple___Cedar_apple_rust: 1760

The Number of Images in Tomato___Target_Spot: 1827

The Number of Images in Pepper,_bell___healthy: 1988

The Number of Images in Grape___Leaf_blight_(Isariopsis_Leaf_Spot): 1722

The Number of Images in Potato___Late_blight: 1939

The Number of Images in Tomato___Tomato_mosaic_virus: 1790

The Number of Images in Strawberry___healthy: 1824

The Number of Images in Apple___healthy: 2008

The Number of Images in Grape___Black_rot: 1888

The Number of Images in Potato___Early_blight: 1939

The Number of Images in Cherry_(including_sour)___healthy: 1826

The Number of Images in Corn_(maize)___Common_rust_: 1907

The Number of Images in Grape___Esca_(Black_Measles): 1920

The Number of Images in Raspberry___healthy: 1781

The Number of Images in Tomato___Leaf_Mold: 1882

The Number of Images in Tomato___Spider_mites Two-spotted_spider_mite: 1741

The Number of Images in Pepper,_bell___Bacterial_spot: 1913

The Number of Images in Corn_(maize)___healthy: 1859

Total Number of Images in Directory: 70295

With the indicators of Accuracy, we can assess the performance of the models by taking

Accuracy = $(TP + TN)/(TP + TN + FP + FN)$

C. CONVOLUTION NEURAL NETWORK:

The advancement of computationally efficient devices like Graphics Processing Units (GPUs) has led to an exponential surge in the development of deep learning applications. The classic artificial neural network served as the model for the deep learning idea. The deep learning model is made up of several preprocessing layers that gather data from the unprocessed input and produce an output tailored to the job at hand. Since Convolutional Neural Networks (CNN) were introduced and demonstrated to have excellent accuracy in image classification on the dataset, as suggested [25], deep learning methods have become increasingly popular.

Deep learning has since been used in many fields, including object identification, pattern recognition, voice recognition, and image categorization[26]. One kind of deep learning model that is particularly useful for solving challenging pattern recognition and classification issues is the convolutional neural network.. There are numerous CNN models available, including AlexNet, VGG, GoogLeNet, and ResNet. These models differ with respect to their number of units, depth, configurations, and nonlinear function. To solve complex processing difficulties in pattern recognition and classification, characteristics like learning rate and dropout rate can be adjusted.

The subject of computer vision was greatly advanced by the groundbreaking deep convolutional neural network known as AlexNet, which was first introduced in 2012. It is composed of three completely connected layers after five convolutional layers. ReLU (Rectified Linear Units) activations were used by AlexNet, which aided in training more quickly than more conventional activation functions like sigmoid or tanh [27,28]. In order to prevent overfitting, dropout layers were also used in the fully connected layers. Max-pooling layers were also employed by the network to decrease the data's spatial dimensions. Through the use of augmentation techniques, like picture translations and reflections, AlexNet was able to significantly expand the training dataset. [29].

The Visual Geometry Group created VGG in 2014, and it is well known for its consistent architecture and simplicity. A stack of tiny, uniformly sized 3x3 convolutional layers is used in VGG networks, like VGG-16 and VGG-19. While VGG-19 adds 16 convolutional layers, VGG-16 only has 13 convolutional layers and three fully linked layers. ReLU activations and max-pooling layers are used for downsampling in both versions [30,31].

With the introduction of its inception modules in 2014, GoogLeNet (Inception Network) provided a fresh approach to the field by enabling the execution of numerous convolutional and pooling processes in parallel inside the same layer. The network was able to more effectively capture features at different scales because to its creative design. Known by another name, Inception v1, GoogLeNet is a 22-layer network that uses auxiliary classifiers in intermediary layers to help with faster convergence and address the vanishing gradient issue. [32,33,34].

With its residual learning framework, ResNet (Residual Network), which was introduced in 2015, completely changed deep learning. ResNet successfully solved the vanishing gradient issue by employing residual blocks, which combine the input of a layer with the output of a few layers ahead, allowing for the training

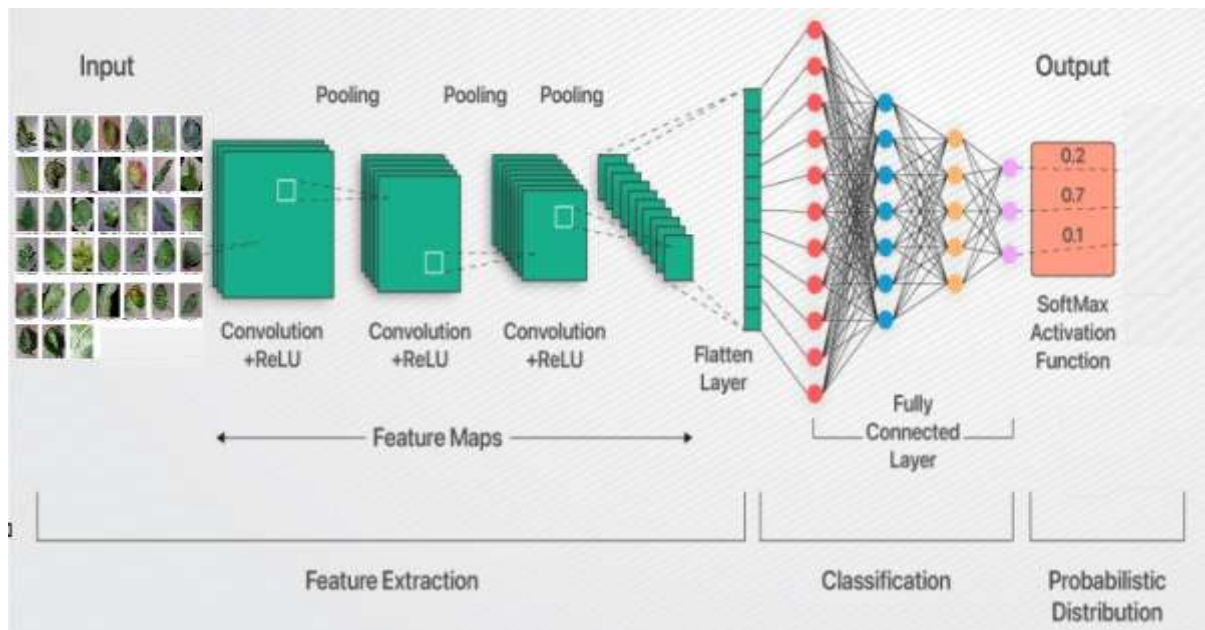
of extremely deep networks. ResNet architectures are named according to their depth; examples of these include ResNet-50, ResNet-101, and ResNet-152. Gradients could now travel directly across the network because to the addition of skip connections, which greatly improved training stability and convergence[35,36]. ResNet also made considerable use of batch normalization to enhance training dynamics..

Below diagram provide the details of our designed model.

```
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 128, 128, 32)	896
conv2d_1 (Conv2D)	(None, 126, 126, 32)	9248
max_pooling2d (MaxPooling2D)	(None, 63, 63, 32)	0
conv2d_2 (Conv2D)	(None, 63, 63, 64)	18496
conv2d_3 (Conv2D)	(None, 61, 61, 64)	36928
max_pooling2d_1 (MaxPooling2D)	(None, 30, 30, 64)	0
conv2d_4 (Conv2D)	(None, 30, 30, 128)	73856
conv2d_5 (Conv2D)	(None, 28, 28, 128)	147584
max_pooling2d_2 (MaxPooling2D)	(None, 14, 14, 128)	0
conv2d_6 (Conv2D)	(None, 14, 14, 256)	295168
conv2d_7 (Conv2D)	(None, 12, 12, 256)	590080
max_pooling2d_3 (MaxPooling2D)	(None, 6, 6, 256)	0
dropout (Dropout)	(None, 6, 6, 256)	0
flatten (Flatten)	(None, 9216)	0
dense (Dense)	(None, 1500)	13825500
dropout_1 (Dropout)	(None, 1500)	0
dense_1 (Dense)	(None, 38)	57038
=====		
Total params: 15,054,794		
Trainable params: 15,054,794		
Non-trainable params: 0		



1. The model is a sequential model that consists of multiple layers designed to transform a standard size image into a feature set that can be used for subsequent processing.
2. The initial first layer and second layer of model consist of a convolutional layer of 32 filters and utilizing the Rectified Linear Unit (ReLU) as the activation function with third layer is the max pooling layer which will downsize the convoluted image by a factor of (2, 2).
3. Additionally, The fourth layer and fifth layer of model consist of a convolutional layer of 64 filters and utilizing the Rectified Linear Unit (ReLU) as the activation function with sixth layer is the max pooling layer which will downsize the convoluted image by a factor of (2, 2).
4. Additionally, The seventh layer and eighth layer of model consist of a convolutional layer of 128 filters and utilizing the Rectified Linear Unit (ReLU) as the activation function with ninth layer is the max pooling layer which will downsize the convoluted image by a factor of (2, 2).
5. Additionally, The tenth layer and eleventh layer of model consist of a convolutional layer of 256 filters and utilizing the Rectified Linear Unit (ReLU) as the activation function with twelfth layer is the max pooling layer which will downsize the convoluted image by a factor of (2, 2).
6. Additionally, The thirteenth layer and fourteenth layer of model consist of a convolutional layer of 64 filters and utilizing the Rectified Linear Unit (ReLU) as the activation function with fifteenth layer is the max pooling layer which will downsize the convoluted image by a factor of (2, 2), which is then followed by a dropout rate of 0.25.
7. This model has subsequently incorporated an additional layer to transform the output of the previously constructed convolutional neural network model into a flattened format.
8. This process of flattening will produce the feature set for each image as output. This model contains dense layer with of 1500 hidden neurons and the Rectified Linear Unit (ReLU) as the activation function, which is then followed by a dropout rate of 0.4.
9. This model is set up so that every input neuron forms a completely linked layer with every other hidden neuron connected to it. SoftMax is the activation function that is being used. This layer's output is the expected 38 class label, which is a gauge of the overall accuracy of the suggested model.

D. TRAINING AND TESTING :

Accuracy and loss of different approaches after 30 epoch training. [46]

Pre-trained model	10 epochs Training accuracy %	Validation accuracy %	Training loss	Validation loss	30 epochs Training accuracy %	Validation accuracy %	Training loss	Validation loss
Dense Net-201	80.27	76.33	0.5726	0.4323	84.13	79	0.4451	0.4987
ResNet-50	65.19	64.67	1.0028	0.9310	70.41	69.67	0.8338	0.8442
Inception V3	85.56	82.33	0.4087	0.2783	92.14	85	0.2576	0.3717
VGGNet-19	65.19	66.67	1.164	0.8784	74.2	74.83	0.9026	0.9162
Proposed Method	97.02	94.58	0.1059	0.2494	96.56	92.35	0.2156	0.5674

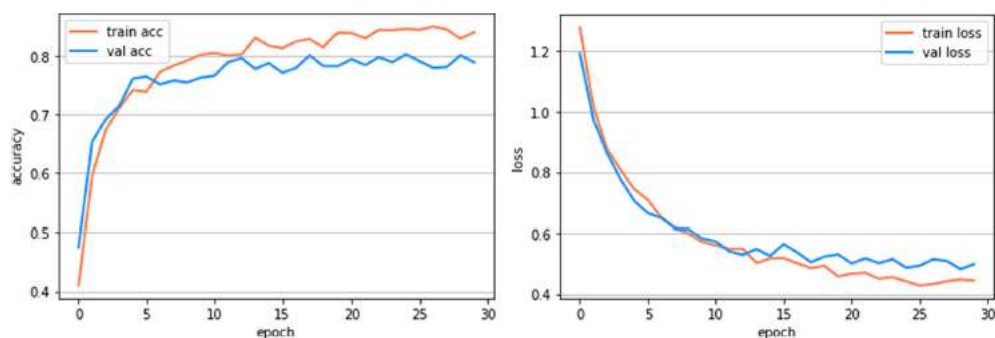


Fig. 7. DenseNet-201, left is the accuracy and right depicts the loss of the model.

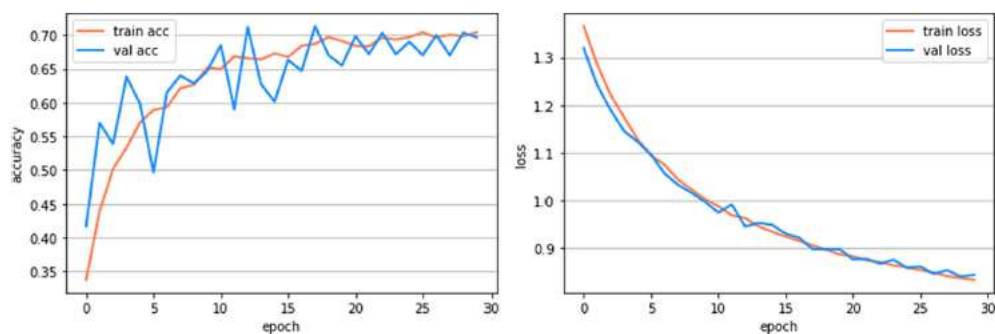


Fig. 8. ResNet-50, left is the accuracy and right depicts the loss of the model.

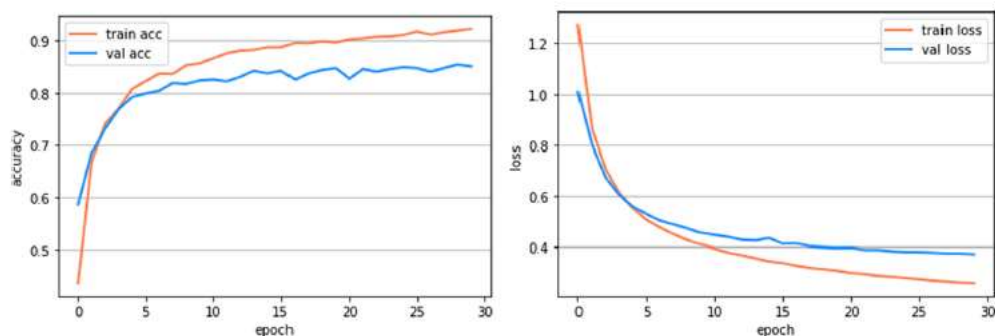


Fig. 9. Inception V3, left is the accuracy and right depicts the loss of the model.

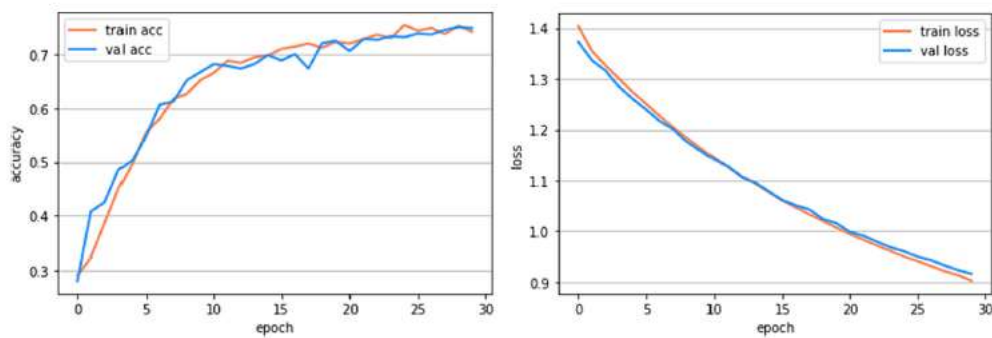
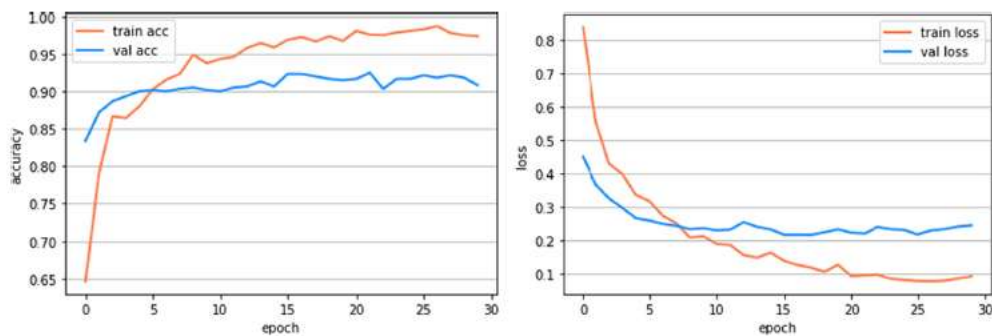
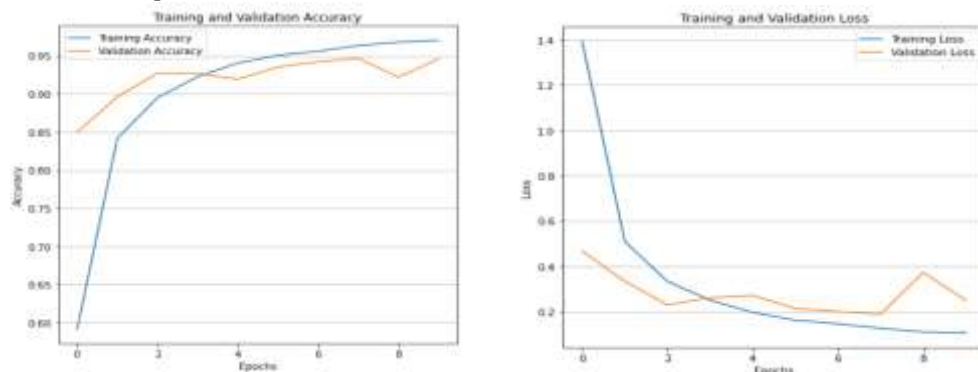


Fig. 10. VGGNet-19, left is the accuracy and right depicts the loss of the model.



Our Proposed model Graph :



V. RESULTS :

At an astounding 97.02% accuracy rate, the model developed to identify plant diseases using the "New Plant Diseases Dataset" performed admirably. This high degree of accuracy shows how reliable and efficient the model is in accurately classifying different plant diseases from the given photos. The model's performance indicates that it may find useful applications in agriculture, where crop management and yield loss prevention depend heavily on the early and precise diagnosis of plant diseases. Additional assessment and practical experimentation may confirm its applicability in automated plant disease diagnostic systems.

VI. CONCLUSION AND FUTURE WORK:

We can improve the productivity and quality of the plants and their products by managing the biotic variables that lead to significant losses in agricultural output. Pattern identification, classification, object extraction, and other plant leaf disease concerns have been better solved using computer vision and machine learning techniques[39,40]. Consequently, we present an original model in this study called MCNN for the categorization of mango leaves affected by the fungus known as anthracnose. When comparing the accuracy of the proposed work to other state-of-the-art methodologies, its greater performance is proven with a 97.02% accuracy rate. Additionally, the model is straightforward and computationally efficient. Here are some of the upcoming projects[41,42,43]:

- 1) Using a different function in place of the Softmax activation function can improve CNN performance and make it suitable for classifying a variety of disorders.
- 2) Measuring the discrepancies that arise while using real-time datasets.
- 3) Using other economically significant plants and estimating the disease's severity while taking into account the health of the plants' other components.
- 4) To develop a real-time disease monitoring system that is Web/Internet of Things (IoT) enabled.

REFERENCES:

1. Juncheng Ma et al., "A recognition method for cucumber diseases using leaf symptom images based on deep convolutional neural network," in *Computers and Electronics in Agriculture*, vol. 154, pp. 18–24, 2018, doi: 10.1016/j.compag.2018.08.048.
2. Artzai Picon et al., "Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild," in *Computers and Electronics in Agriculture*, doi: 10.1016/j.compag.2018.04.002.
3. Bhatia, A., Chug, A. and Singh, A.P. (2020a) 'Application of extreme learning machine in plant disease prediction for highly imbalanced dataset', *Journal of Statistics and Management Systems*, pp.1–10, doi: 10.1080/09720510.2020.1799504.
4. Naik, H.S., Zhang, J., Lofquist, A., Assefa, T., Sarkar, S., Ackerman, D., Singh, A., Singh, A.K. and Ganapathysubramanian, B. (2017) 'A real-time phenotyping framework using machine learning for plant stress severity rating in soybean', *Plant Methods*, Vol. 13, No. 1, p.23.
5. Mohanty, Sharada P., David P. Hughes, and Marcel Salathé. "Using deep learning for image-based plant disease detection." *Frontiers in plant science* 7 (2016): 215232.
6. Ferentinos, Konstantinos P. "Deep learning models for plant disease detection and diagnosis." *Computers and electronics in agriculture* 145 (2018): 311-318.
7. H. Durmus, E. O. Gunes and M. Kirci, "Disease detection on the leaves of the tomato plants by using deep learning," in *2017 6th International Conference on Agro-Geoinformatics*, Fairfax, VA, 2017, pp. 1-5, 2017, doi: 10.1109/Agro-Geoinformatics.2017.8047016.
8. Mohanty, Sharada P., David P. Hughes, and Marcel Salathé. "Using deep learning for image-based plant disease detection." *Frontiers in plant science* 7 (2016): 215232.
9. Ferentinos, Konstantinos P. "Deep learning models for plant disease detection and diagnosis." *Computers and electronics in agriculture* 145 (2018): 311-318.
10. Sladojevic, Srdjan, et al. "Deep neural networks based recognition of plant diseases by leaf image classification." *Computational intelligence and neuroscience* 2016 (2016).
11. Wang, Guan, Yu Sun, and Jianxin Wang. "Automatic image-based plant disease severity estimation using deep learning." *Computational intelligence and neuroscience* 2017 (2017).
12. Zhang, Xihai, et al. "Identification of maize leaf diseases using improved deep convolutional neural networks." *Ieee Access* 6 (2018): 30370-30377.
13. Saleem, Muhammad Hammad, Johan Potgieter, and Khalid Mahmood Arif. "Plant disease detection and classification by deep learning." *Plants* 8.11 (2019): 468.
14. Liu, Bin, et al. "Identification of apple leaf diseases based on deep convolutional neural networks." *Symmetry* 10.1 (2017): 11.
15. Khamparia, Aditya, et al. "Seasonal crops disease prediction and classification using deep convolutional ncoder network." *Circuits, Systems, and Signal Processing* 39 (2020): 818-836.
16. Chen, Junde, et al. "Using deep transfer learning for image-based plant disease identification." *Computers and electronics in agriculture* 173 (2020): 105393.
17. Lu, Yang, et al. "Identification of rice diseases using deep convolutional neural networks." *Neurocomputing* 267 (2017): 378-384.
18. Too, Edna Chebet, et al. "A comparative study of fine-tuning deep learning models for plant disease identification." *Computers and Electronics in Agriculture* 161 (2019): 272-279.
19. Golhani, Kamlesh, et al. "A review of neural networks in plant disease detection using hyperspectral data." *Information Processing in Agriculture* 5.3 (2018): 354-371.
20. Ramesh, Shima, et al. "Plant disease detection using machine learning." *2018 International conference on design innovations for 3Cs compute communicate control (ICDI3C)*. IEEE, 2018.
21. Singh, Uday Pratap, et al. "Multilayer convolution neural network for the classification of mango leaves infected by anthracnose disease." *Ieee access* 7 (2019): 43721-43729.
22. Toda, Yosuke, and Fumio Okura. "How convolutional neural networks diagnose plant disease." *Plant Phenomics* (2019).

23. Türkoğlu, Muammer, and Davut Hanbay. "Plant disease and pest detection using deep learning-based features." *Turkish Journal of Electrical Engineering and Computer Sciences* 27.3 (2019): 1636-1651.
24. Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." *arXiv preprint arXiv:1409.1556* (2014).
25. Nagasubramanian, Koushik, et al. "Plant disease identification using explainable 3D deep learning on hyperspectral images." *Plant methods* 15 (2019): 1-10.
26. Lee, Sue Han, et al. "New perspectives on plant disease characterization based on deep learning." *Computers and Electronics in Agriculture* 170 (2020): 105220.
27. Karlekar, Aditya, and Ayan Seal. "SoyNet: Soybean leaf diseases classification." *Computers and Electronics in Agriculture* 172 (2020): 105342.
28. Tiwari, Divyansh, et al. "Potato leaf diseases detection using deep learning." *2020 4th international conference on intelligent computing and control systems (ICICCS)*. IEEE, 2020.
29. Sanga, Sophia, et al. "Mobile-based deep learning models for banana diseases detection." *arXiv preprint arXiv:2004.03718* (2020).
30. Atila, Ümit, et al. "Plant leaf disease classification using EfficientNet deep learning model." *Ecological Informatics* 61 (2021): 101182.
31. Hassan, Sk Mahmudul, et al. "Identification of plant-leaf diseases using CNN and transfer-learning approach." *Electronics* 10.12 (2021): 1388.
32. Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "ImageNet classification with deep convolutional neural networks." *Communications of the ACM* 60.6 (2017): 84-90.
33. Prajapati, Harshadkumar B., Jitesh P. Shah, and Vipul K. Dabhi. "Detection and classification of rice plant diseases." *Intelligent Decision Technologies* 11.3 (2017): 357-373.
34. Fuentes, Alvaro, et al. "A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition." *Sensors* 17.9 (2017): 2022.
35. Kamilaris, Andreas, and Francesc X. Prenafeta-Boldú. "Deep learning in agriculture: A survey." *Computers and electronics in agriculture* 147 (2018): 70-90.
36. Bharate, Anil A., and M. S. Shirdhonkar. "A review on plant disease detection using image processing." *2017 International Conference on Intelligent Sustainable Systems (ICISS)*. IEEE, 2017.
37. Rangarajan, Aravind Krishnaswamy, Raja Purushothaman, and Anirudh Ramesh. "Tomato crop disease classification using pre-trained deep learning algorithm." *Procedia computer science* 133 (2018): 1040-1047.
38. R. Agarwal, A.K. Agrawal, H.V. Singh, S. Tyagi, A review paper on diagnosis of approximal and occlusal dental caries using digital processing of medical images, in: *2016 International Conference on Emerging Trends in Electrical Electronics & Sustainable Energy Systems, ICETEESES, IEEE, 2016*, pp. 383-385.
39. G.D. Koutsouri, E. Berdouses, E.E. Tripoliti, C. Oulis, D.I. Fotiadis, Detection of occlusal caries based on digital image processing, in: *13th IEEE International Conference on BioInformatics and BioEngineering, IEEE, 2013*, pp. 1-4.
40. H. Nascimento, A. Ramos, F. Neves, S. de Azevedo-Vaz, D. Freitas, The 'sharpen' filter improves the radiographic detection of vertical root fractures, *Int. Endodontic J.* 48 (5) (2015) 428-434.
41. M.M. Srivastava, P. Kumar, L. Pradhan, S. Varadarajan, Detection of tooth caries in bitewing radiographs using deep learning, 2017, *arXiv preprint arXiv: 1711.07312*.
42. J.-H. Lee, D.-H. Kim, S.-N. Jeong, S.-H. Choi, Detection and diagnosis of dental caries using a deep learning-based convolutional neural network algorithm, *J. Dent.* 77 (2018) 106-111.
43. V. Geetha, K. Aprameya, Textural analysis based classification of digital X-ray images for dental caries diagnosis, *Int. J. Eng. Manuf. (IJEM)* 9 (3) (2019) 44-45.
44. V. Geetha, K. Aprameya, D.M. Hinduja, Dental caries diagnosis in digital radiographs using back-propagation neural network, *Health Inf. Sci. Syst.* 8 (1) (2020) 1-14.
45. H. Yu, Z. Lin, Y. Liu, J. Su, B. Chen, G. Lu, A new technique for diagnosis of dental caries on the children's first permanent molar, *IEEE Access* 8 (2020) 185776-185785.
46. Chen, Junde, et al. "Using deep transfer learning for image-based plant disease identification." *Computers and electronics in agriculture* 173 (2020): 105393.