JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Deep Leaf: A Comprehensive Analysis of Deep Learning Technique CNN For plant Diseases Diagnosis and Remedies

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Abstract—The world's food supply is greatly dependent on plants. Plant diseases are caused by a variety of environmental variables, which cause large losses in productivity. Plant disease identification by hand, however, is a laborious and prone to error procedure. It may not always be an accurate way to recognize plant diseases and stop them from spreading. By making early plant disease detection possible, the adoption of cutting-edge technologies like machine learning (ML) and deep learning (DL) can aid in overcoming these obstacles. The most current developments in the application of ML and DL methods for plant disease identification are examined. The study's studies show how these strategies can be used to increase the precision and productivity of plant disease detection, and the research is centered on publications from 2015 to 2022. This paper also discusses the difficulties and restrictions involved in applying ML and DL for the identification of plant diseases, including problems with data accessibility, imaging quality, and the capacity to distinguish between healthy and diseased plants. This paper presents a comprehensive approach to plant disease detection and gives remedies using deep learning methodologies, focusing on the utilization of VGG19 and ResNet architectures for feature extraction and classification. The proposed system involves several key components: preprocessing of input images, feature extraction through pre-trained CNN models, selection of appropriate activation functions for classification, and performance evaluation metrics to assess the model's effectiveness.A user-friendly plant disease detection system that can examine leaf photos and classify them according to the particular illness present is the desired outcome.The proposed system is able to detect the disease of plant with cnn model vgg19 and resnet-9 with accuracy 86.42 % and 94.86 % respectively.

Index Terms—Deep learning ,VGG19, Resnet, Activation function, plant disease detection, image processing ,convolutional neural networks, performance evaluation,pytorch Framework

I. Introduction

India is an agricultural country wherein most of the population depends on agriculture. Research in agriculture is aimed towards increase of productivity and food quality at reduced expenditure, with increased profit. Agricultural production system is an outcome of a complex interaction of soil, seed, and agro chemicals. Vegetables and fruits are the most important agricultural products The potential to generate enough food to suit the needs of more than 7 billion people has been provided by modern technologies. Intergovernmental Science-Policy Platform on Biodiversity Ecosystem and Services on the work of its fourth session plant diseases and other factors continue to pose a threat to food security. However, these threats are not new and they include climate change, pollinator decline, and other threats. In addition to posing a threat to global food security, plant diseases can have catastrophic effects on smallholder farmers whose livelihoods depend on robust crops. More than 80 % of agricultural production in the developing world is produced by smallholder farmers and reports of yield loss many initiatives have been created to stop crop loss from diseases. Integrated pest management (IPM) approaches have replaced traditional methods of pesticide broad administration in the last ten years Whatever the method, the first step in effective illness management is accurate disease identification when it first manifests. Historically, institutions like local plant clinics or agricultural extension agencies have assisted disease identification. More recently, these initiatives have also been helped by the availability of online resources for disease detection, taking advantage of the global increase in Internet usage.

Even more recently, mobile phone-based tools have emerged, capitalizing on the historically unprecedented global adoption of mobile phone technology.Due to their powerful computers, sharp screens, and broad built-in accessory sets, such as high-definition cameras, smartphones in particular provide very innovative methods to aid in the identification of diseases. Between 5 and 6 billion cellphones are expected to be in use worldwide by 2020. In 2015, 69% of the world's population had access to mobile broadband, a 12fold increase from 2007. By the end of the year, mobile broadband penetration had reached 47 %. The confluence of factors included makes it possible for disease diagnosis based on automatic picture identification to be made available at an unprecedented scale, if technically achievable. Here, we use 54,306 photos of 14 crop species with 26 illnesses (or healthy) from the new plant disease Dataset project to show the technical viability of a deep learning approach.

In many different fields, deep neural networks have lately been successfully used as examples of end-to-end learning. A mapping between an input—such as a picture of a sick plant—and an output—such as a crop-disease pair—is provided by neural networks. The mathematical nodes in a neural network receive numerical inputs from the incoming edges and output numerical results as the outgoing edges. A sequence of stacked layers of nodes in deep neural networks simply map the input layer to the output layer. The difficult part of building a deep network is making sure that the network's structure, functions (nodes), and edge weights accurately map the input to the output.Deep neural networks are trained by adjusting the network parameters so that the mapping gets better during the course of training. This computationally difficult technique has recently seen significant improvements because to a number of conceptual and engineering advancements.

We required a sizable, validated dataset of photos of damaged and healthy plants in order to create accurate image classifiers for plant disease diagnosis. Such a dataset did not exist, and even smaller datasets were not openly accessible, until quite recently. To solve this issue, the new plant disease dataset project has started gathering tens of thousands of photographs of both healthy and damaged crop plants and has made them openly and freely accessible Here, we report on a convolutional neural network-based analysis of 54,306 pictures to classify 26 illnesses across 14 crop species. By predicting the right crop-disease match out of 38 different classes, our models' performance is evaluated.

II. Background And Related Work

As stated in the project's above introduction, our goal is to identify research gaps and conduct a unique examination of certain literature reviews.

A. Literature Review

Our innovative "Plant Diseases Diagnosis and Remedies" project proposal is supported by a literature review that cites a wide range of sources, including books, journals, research papers, and articles. Authorship, publication year, methodology, results, and future directions are highlighted in *Table I*.

A thorough evaluation of 13 literature publications from diverse sources serves as foundation for our research on "Plant Diseases Diagnosis and Remedies". Through a methodical examination of authors, study periods, methodology, results, and real-world applications, we were able to identify significant

TABLE I Literature Review

Author and Year	Methods	Result	Future Scope
Prof. Ujwalla Gawande. et al [1] 2014	Radial Basis, PNN, KNN, BPN, SVM	It gives 60% accuracy	Enhanced Machine CNNs or RNNs to improve the accuracy.
S. Samundeswari et al [2] 2020	HOG, GLCM, KNN	It gives 80% accuracy	IoT devices can be used.
Muhammad Shoaib1 et al. [3] 2022	U-Net CNN, Inception Net CNN	It achieves 99.95% accuracy	Improved accuracy and efficiency
Sharada Prasanna Mohanty et al. [4] 2016	AlexNet, GoogleNet	Great accurac 85.53% to 99.34%	Expand the collection to include more varied.
Vijai Singh et al. [5] 2017	Genetic algorithm, KMean, SVM	Accuracy is 95.71%.	To improve recognition rate in classification process ANN
Ganesh Bahadur Singh [6] 2021	Alexnet, CNN, Computer Vision	Accuracy is 85.53%	Real time Monitoring and improve the accuracy.
Pranesh Kulkarni et al.[7] 2021	Digital image processing, K-fold cross	Detect 20 different diseases of 5 common plants with 93% accuracy.	Make application is easy to use improve identification accuracy.
Shan-e-Ahmed Raza et al. [8] 2015	Principal component analysis (PCA), SVM, NCA	Average accuracy of more than 75 %	Commercial setting in future.
Aravind Krishnaswamy Rangarajan et al. [9] 2018	AlexNet, VGG16 net	The accuracy is 97.49% and 97.23%	Other user-friendly tools for farmers.
Paul Shekonya Kanda et al. [10] 2022	K-means algorithm, SVM, CNNs	Highest F1 score of 99.5%	If data augmentation also proved to be effective.
Lili Li et al. [11] 2021	GANs, R-CNN	Accuracy is average	Better robustness DL models are needed
Davinder Singh et al. [12] 2019	Deep Learning, Object Detection.	Average Accuracy	Applying image segmentation techniques.
Shima Ramesh et al. [13] 2018	Random forest, Feature extraction.	Accuracy is 70.14%	The accuracy will be increase.

research gaps that highlight the distinctiveness of our work and provide fresh perspectives for the machine learning and artificial intelligence Plant Diseases Diagnosis and Remedies fields. To sum up, our research is a noteworthy and unique addition to this developing field of inquiry.

III. Methodology

A. Plant Diseases Dataset

For this project we have used public dataset for plant leaf disease detection called new plant diseases dataset is available on kaggle website This dataset is recreated using offline augmentation from the original dataset. The original dataset can be found on this github repo. This dataset consists of about 87K rgb images of healthy and diseased crop leaves which is categorized into 38 different classes. The total dataset is divided into 80/20 ratio of training and validation set preserving the directory structure. A new directory containing 33 test images is created later for prediction purpose.

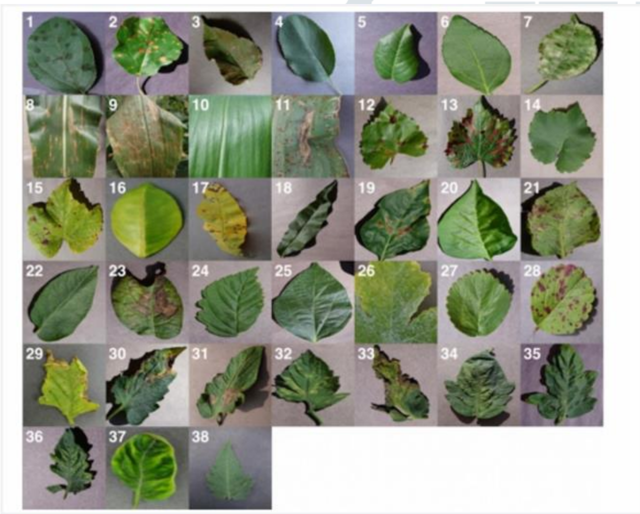

Fig. 1. Plant Leaves

TABLE II Dataset

Plants	Disease	No. of images
	scab	2016
	rot	1987
	apple rust	1760
	blight	1851
	blight	1920
	leaf spot	1745
	leaf curl virus	1961
	Healthy Apple Black Cedar 2008	1702
	Healthy Late Early Septorial Yellow Bacterial Target Tomat Leaf 1926 1741	
	Healthy Early Late 1824	
	Healthy 1692	
	spot	1827
	mosaic virus	1790
	mold	1882
	Spider mites Two	–
	spotted spider mite blight	
		1939
	blight	1939
	Leaf blight (Isariopsis Leaf spot)	1722
	Black rot	1888
	Esca (Black Measles)	1920

TABLE III
Dataset

Plants	Disease	No. of images
	Healthy 2022	
	Healthy Bacterial 1728	
	Healthy 1816	1838
	Healthy 1824	
	Healthy 1781	
Corn (Mazie)	(Including sour) ealthy H	1826
	(Including sour) owderymildew P	1683
	Healthy	1859
	Northern Leaf Blight	1908
	Cercospora Leaf spot Gray Leaf sp	ot1642
	Commopn Rust	1907
Paper bell	Healthy	1988
	Bacterial spot	1913
Orange	Haunglongbing (Citrus greening)	2010
Squash	Powdery mildew	1736

B. Proposed System

There are five main steps used for the detection of plant leaf diseases as shown in fig.3.The processing scheme consists of image acquisition through digital camera or web, image pre-processing includes image enhancement and image segmentation where the affected and useful area are segmented, feature extraction and classification. Finally the presence of diseases on the plant leaf will be identified. In the initial step, RGB images of leaf samples were picked up. The step-by-step procedure as shown below:

- RGB image acquisition;
- convert the input image into color space;
- Segment the components;
- obtain the useful segments;
- Computing the texture features;
- Configuring the deep neural networks for recognition.
- Give the remedy.

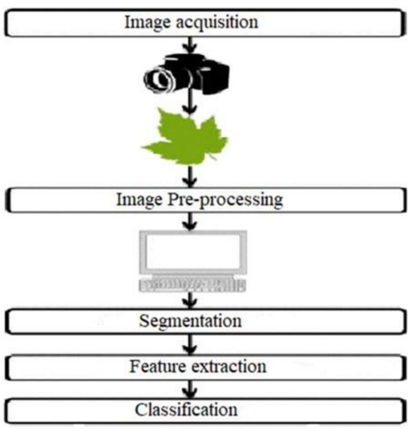

Fig. 2. Implementation

1) Image Acquisition: Firstly, the images of various leaves acquired using a digital camera with required resolution for better quality The initial process is to collect the data from the public repository. It takes the image as input for further processing. We have taken most popular image domains so that we can take any formats like .bmp, .jpg, .gif as input to our process. The image is captured, scanned and converted into a manageable entity. This process is known as image acquisition. During a test-phase, we acquire a series of color images using a digital scanner so as to acquire a single image of leaf. The color images were digitized to produce RGB digital color images.

2) Image Pre-processing: In the second step, this image is pre-processed to improve the image data that suppress undesired distortions, enhances some image features important for further processing andanalysis task. It includes color space conversion, image enhancement, and image segmentation. The RGB images of leaves are converted into color space representation. The purpose of the color space is to facilitate the specification of colors in some standard accepted way. RGB images converted into Hue Saturation Value (HSV) color space representation. Because RGB is for color generation and his for color descriptor. HSV model is an ideal tool for color perception. Hue is a color attribute that describes pure color as perceived by an observer. Saturation termed as relative purity or the amount of white light added to hue and value means amplitude of light. After the color space transformation process, hue component used for further analysis. Saturation and value are dropped since it does not give extra information.

3) Segmentation: Image segmentation is the process of reducing the complexity of an image's representation so that it may be examined more closely and with greater ease. Image segmentation is one of the core techniques of digital image processing, serving as the foundation for feature extraction and pattern identification. Below is a discussion of several image segmentation methods.

- Region based:
  This method groups pixels that are connected to an object. Closing the identified segmentation area is necessary. There won't be a gap in this region-based segmentation because of the missing edge pixels. For segmentation, the boundaries are determined. At least one pixel is connected to the region and taken into account in each stage. The edge flow is transformed into a vector when the color and texture changes are recognized. These edges are then found for additional segmentation.

- Edge based:
  Edge detection algorithms can also be used for segmentation. Numerous methods exist, including gradient, log, canny, sobel, laplacian, and Robert. This method identifies the boundary to segment. To find the discontinuities in the image, edges are recognized. They employ both fixed and adaptive support vector machine features for classification.

- Threshold based:
  This method of segmentation is the simplest. In this case, the original image's edges 'histogram is used to determine the threshold values, which are then used to segment the image. Thus, the threshold should also be correct if the edge detections are. Thresholding-based segmentation requires less computations than other methods. This segmentation technique's drawback is that it isn't appropriate for complex images.

4) Feature Extraction: Feature extraction involves taking each segment of the image and extracting features from it,such as texture features, color histograms, form descriptors, etc. These characteristics aid in the segmented regions' characterization and offer useful data for disease classification.

- Feature Representation:
  Features are traits or qualities of the picture that help differentiate between several classes (e.g., healthy vs. ill plants). Aspects of the image such as color, texture,

shape, and spatial relationships can be used to determine features.

- Color Features:
  The intensity and distribution of colors in the image are captured by color characteristics. Color histograms, which show the frequency of occurrence of various color values in the image, are examples of common color features. A more thorough description of color distributions can be achieved by using additional color descriptors, such as color moments or color consistency vectors.

- Features of Texture:
  The spatial arrangement of the image's pixels is described by texture features, which also reveal details about structures and patterns. Textural descriptors quantify characteristics like smoothness, roughness, or regularity within different sections of the image. Examples of these descriptors are Gabor filters, local binary patterns (LBP), and gray-level co-occurrence matrices (GLCM). These characteristics are especially helpful in capturing minute variations in appearance brought on by illnesses or other anomalies.

- Feature Selection and Reduction of Dimensions: In actuality, not every trait that has been extracted will be useful or instructive for the particular goal of disease identification. To find the most discriminative features, one can employ feature selection techniques like filter methods (like correlation analysis) or wrapper methods (like recursive feature removal). To decrease the dimensionality of feature spaces while keeping the most important information, t-distributed stochastic neighbor embedding (t-SNE) or principal component analysis (PCA) might be used.

C. Classification

After segmentation and feature extraction, machine learning or deep learning models are trained to classify the segmented regions into different disease classes.

- Convolutional Neural Network: CNNs are a type of deep learning model that are best suited for image classification tasks like diagnosing leaf disease.The design of the CNN is composed of multiple layers, including maxpooling, normalization, and fully connected layers.
  The input layer is the first layer of a CNN. It has data in the form of an image.The image's RGB dimensions—height, width, depth, and color—are included in the parameters. The input size is fixed at 224 x 224 RGB. While most CNNs have convolutional layers as their second layer, which extract features from images by applying different kinds of 2D filters, the number of images increases, which can subsequently lead to dimensionally reduced pooling—also known as down sampling layers—which produces a more compact representation of the image. The term "learnable features" refers to the fully connected (FC) layers in a CNN, where the extracted features are processed for learning and weight optimization.Additionally, these layers are in charge of creating classifications that are used to identify different plant diseases.
  The first step in the learning process of a CNN model is training. Images and their labels are fed into the model, and once training is complete, the model can detect different illness kinds. Upon receiving an image of a leaf, a CNN begins its decision-making process for the diagnosis of leaf diseases.After that, the picture is sent through the convolutional layers, which extract features.Following that, the feature vectors are processed by pooling layers, which lower the spatial dimensions.Following transmission of the feature vectors via the FC levels, a determination is made regarding the existence of a disease or pest.The odds that the leaf is ill or healthy are output by the models.Because of their architecture, which consists of up-sampling, downsampling, and learnable layers, CNNs are highly suited for the identification of leaf diseases. CNNs are trained through the use of tagged photos of both healthy and diseased plants. framework for using leaf data to categorize plants into normal and pathological plants.The framework uses a number of distinct Inception architectures, and a bagging-based method is used to make the ultimate conclusion.

D. Algorithms

1) *Transfer Learning:* In DL networks, transfer learning—using the taught item to retrain the other objects—is frequently employed. Transfer learning comes in four kinds: feature-based, parameter-based, relationship-based, and case-based. It goes without saying that selecting the training parameters for the optimal classification system is difficult. In this case, the network parameters must be redicted for the new input data and a suitable network architecture must be addressed. To increase performance, the new network must then be adjusted. This work used the parameter-based transfer learning approach to categorize illnesses of plant leaves. To improve categorization, the VGG-19 network will specifically freeze the convolution layers and retrain the fully connected layers. . Furthermore, we also adjust the batch size, epoch, and learning rate to choose the best network.

2) *VGG19:* VGG19 is a 19 layers deep convolutional neural network. The network is capable of categorizing photographs into 1000 different object categories, including keyboards, mouse, pencils, and other animals.Other VGG variations include VGG11, VGG16, and more. There are 19.6 billion FLOPs in VGG19.Herein, we apply VGG-19 to train theNew Plant Diseases Dataset. VGG has an architecture of a CNN network, and VGG-19 is one of the VGG-based architectures. The VGG-19 is a deep-learning neural network with 19 connection layers, including 16 convolution layers and 3 fully connected layers,5 MaxPool layers and 1 SoftMax

output layer. The convolution layers will extract features of the input images, and the fully connected layers will classify the leaf images for those features. In addition, the max-pooling layers will reduce the features and avoid overfitting, as described in Figure 3

Architecture of VGG19

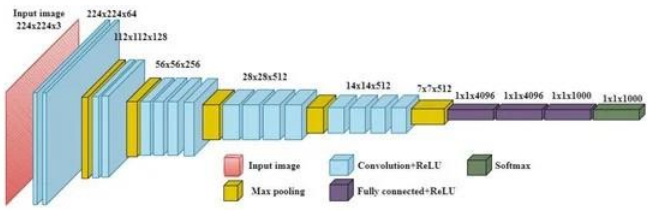

Fig. 3. The network architecture of VGG19 model

- As input, this network was given a specific size (224 * 224) RGB image, implying that the matrix was of configuration (224,224,3).
- The only pre-processing was eliminated from the mean RGB value from each pixel, which was estimated for the entire training set.
- To cover the complete visual notion, they employed kernels with a size of (3 * 3) and strides of 1 pixel.
- Spatial padding was used to maintain the image's spatial resolution.
- Optimal pooling was obtained with sride 2 over a 2 × 2-pixel window.
- The Rectified linear unit (ReLu) was introduced to incorporate non-linearity into the model in order to enhance categorization and reduce processing time, whereas previous models used tanh or sigmoid functions.
- The initial two fully linked layers were 4096 in size, followed by a layer of 1000 cha The VGG19 model is a variation of the VGG model with 19 layers (16 convolution layers, 3 Fully connected layer, 5 MaxPool layers and 1 SoftMax layer). nnels for 1000-way ILSVRC classification, and finally a softmax function.

3) ResNet-9 Architecture: ResNet-9 architecture Residual networks (ResNet) is a classic neural network which allows for deep training of neural networks. ResNet 9 architecture, which has 9 layers, can be seen in Figure 4. ResNet-9 has a pretrained network that can classify images of up to 1,000 object categories which makes the network used to learn good feature representation for various images. ResNet 9 can be used as an image classification. ResNet 9 architecture has the concept of short connections, which will forward the input of each layer to the next layer. This concept will reduce the occurrence of errors or loss of features in the convolutional stage. ResNet 9 has 5 stages in the residual layer and is processed convolutionally and will be forwarded to the max pooling and fully connected layer.

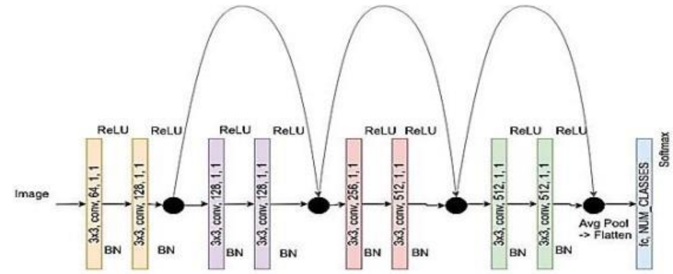

Fig. 4. ResNet-9 Architecture

E. Evaluation Metrics, Results, and Discussion

This section presents the metrics used in evaluating the results of this research, the detailed results, and relevant discussion.

1) Evaluation Metrics: The accuracy, precision, recall, and f1-score of the proposed method were all evaluated. The proposed plant recognition system's accuracy has been calculated using the following expression, which incorporates numerical details such as true positive (TP) (the number of correctly identified leaf images), false positive (FP) (the number of incorrectly detected leaves), true negative (TN) (the number of correctly detected leaf images), and false negative (FN) (it is a parameter for representation of the number of leaf images that are correctly recognized).

- Accuracy: Accuracy is the number of right predictions that are made by the model with respect to the total number of predictions that were made. It is mathematically represented by Equation (1).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

- Precision: Precision is defined as the number of true positive results (TP) divided by the number of positive results (TP + FP) that are predicted by the model. The range of the precision is between 0 and 1 and is calculated using Equation (2). It is used to find the proportion of positive identifications that is true.

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

- Recall: The recall is the number of true positives (TP) divided by the number of all relevant sample data (TP + FN). Equation (3) represents the mode of calculation of the recall. It is used to determine the proportion of actual positives that were correctly identified. These concepts are represented mathematically by Equations (2) and (3), respectively:

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

- F1 Score: Being one of the widely used metrics for the performance evaluation of machine learning algorithms, the F1 score is the harmonic mean of precision and recall. The range of the F1 score is between 0 and 1, and it is calculated as shown by Equation (4). It reflects the number of instances that are correctly classified by the learning model.

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} = \frac{2 * TP}{2 * TP + FP + FN} \quad (4)$$

IV. Results

Our VGG19 and ResNet-9-based plant leaf disease detection system performed admirably. The models demonstrated great accuracy in classifying leaf images into healthy and diseased categories following their training on our dataset. In particular, ResNet-9 obtained an accuracy of 94.86 % on the test set, whereas VGG19 obtained an accuracy of 86.42 %. This illustrates how well plant diseases can be identified from leaf photos using deep convolutional neural networks.

TABLE IV
Result

CNN Model	Accuracy (%)	F-1 Score(%)
VGG-19	86.42	94
ResNet-9	94.86	97

Graphical representation of Result is,

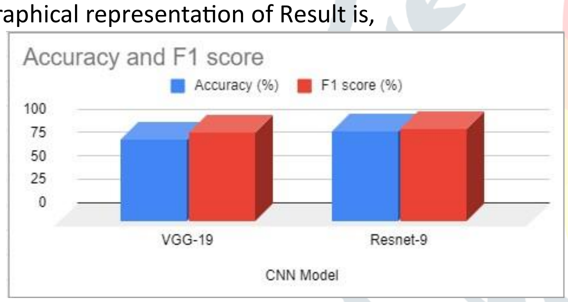

Fig. 5. Accuracy

V. Conclusion

Our work shows that we have successfully developed plant leaf disease detection with deep learning models like VGG19 and ResNet-9 is both feasible and effective with accuracy 86.42% and 94.86 % respectively. Farmers and agricultural specialists can more efficiently identify and treat plant illnesses with the use of these models, which can reliably classify photos of leaves. Our technology is not only capable of detecting problems but also making recommendations for their treatment, giving farmers important knowledge about how to care for their plants. As time goes on, more advancements can be achieved by model optimization, dataset expansion, and investigation of alternative deep learning architectures. In general, this effort advances agricultural technology, which may result in higher crop yields and greater food security.

Acknowledgment

The authors would like to express their sincere gratitude to everyone whose help and efforts have enabled the publishing of this research. First and foremost, we would like to sincerely thank our distinguished supervisor/advisor for all of their help and support during the study process, as well as for their mentorship and unwavering dedication to quality. We sincerely thank the research participants for their important collaboration and insights that have enhanced our study and advanced its conclusions.

We owe SSPM's College of Engineering a huge debt of gratitude for providing the tools, space, and intellectual atmosphere that have supported our research projects.We are grateful for the tremendous help and cooperation of our peers and colleagues, whose encouraging words, helpful criticism, and helpful discussions have greatly influenced the course and results of our work.

We are incredibly grateful to our families and loved ones for their unfailing understanding, support, and encouragement during this adventure. Finally, we would like to thank readers, reviewers, and the larger academic community for their participation, suggestions, and encouragement that have helped us improve and share our research findings. We are extremely grateful to all of the people and things listed above for their crucial contributions to the completion of this research article.

References

[1] Ms Gavhale and Ujwalla Gawande. An overview of the research on plant leaves disease detection using image processing techniques. *IOSR Journal of Computer Engineering*, 16:10–16, 01 2014.

[2] G. Geetha, S. Samundeswari, G. Saranya, K. Meenakshi, and M. Nithya. Plant leaf disease classification and detection system using machine learning. *Journal of Physics: Conference Series*, 1712(1):012012, dec 2020.

[3] Muhammad Shoaib, Tariq Hussain, Babar Shah, Ihsan Ullah, Sayyed Mudassar Shah, Farman Ali, and Sang Hyun Park. Deep learning-based segmentation and classification of leaf images for detection of tomato plant disease. *Frontiers in Plant Science*, 13, 2022.

[4] Sharada Prasanna Mohanty, David Hughes, and Marcel Salathe. Using deep learning for image-based plant disease detection, 2016.

[5] Vijai Singh and A.K. Misra. Detection of plant leaf diseases using image segmentation and soft computing techniques. *Information Processing in Agriculture*, 4(1):41–49, 2017.

[6] Ganesh Bahadur Singh, Rajneesh Rani, Nonita Sharma, and Deepti Kakkar. Identification of tomato leaf diseases using deep convolutional neural networks. *International Journal of Agricultural and Environmental Information Systems (IJAEIS)*, 12(4):1–22, 2021.

[7] Pranesh Kulkarni, Atharva Karwande, Tejas Kolhe, Soham Kamble, Akshay Joshi, and Medha Wyawahare. Plant disease detection using image processing and machine learning. *arXiv preprint arXiv:2106.10698*, 2021.

[8] Shan-e-Ahmed Raza, Gillian Prince, John P Clarkson, and Nasir M Rajpoot. Automatic detection of diseased tomato plants using thermal and stereo visible light images. *PloS one*, 10(4):e0123262, 2015.

[9] Aravind Krishnaswamy Rangarajan, Raja Purushothaman, and Aniirudh Ramesh. Tomato crop disease classification using pre-trained deep learning algorithm. *Procedia computer science*, 133:1040–1047, 2018.

[10] Paul Shekonya Kanda, Kewen Xia, Anastasiia Kyslytysna, and Eunice Oluwabunmi Owoola. Tomato leaf disease recognition on leaf images based on fine-tuned residual neural networks. *Plants*, 11(21):2935, 2022.

[11] Lili Li, Shujuan Zhang, and Bin Wang. Plant disease detection and classification by deep learning—a review. *IEEE Access*, 9:56683–56698, 2021.

[12] Davinder Singh, Naman Jain, Pranjali Jain, Pratik Kayal, Sudhakar Kumawat, and Nipun Batra. Plantdoc: A dataset for visual plant disease detection. In *Proceedings of the 7th ACM IKDD CoDS and 25th COMAD*, pages 249–253. 2020.

[13] Shima Ramesh, Ramachandra Hebbar, Niveditha M., Pooja R., Prasad Bhat N., Shashank N., and Vinod P.V. Plant disease detection using machine learning. In *2018 International Conference on Design Innovations for 3Cs Compute Communicate Control (ICDI3C)*, pages 41–45, 2018.