International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Plant Disease Detection Using Deep Learning

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ABSTRACT :

Throughout human history, agriculture has played a crucial role. difficulties like dropping agricultural prices, irrigation issues, and pest problems are among the many concerns of farmers. A major problem for farmers nowadays is the rise in plant diseases. Minimizing output losses requires early detection and treatment of plant diseases. Deep learning a subset of machine learning techniques utilizes neural network architecture to examine data sets and identifies the plant diseases. Datasets were acquired from the Plant Village Dataset, which comprises images of disease free and affected plant leaves, together with their labels. Convolutional Neural Networks (CNN), a deep learning system, can detect diseases based on leaf image inputs. Various phases of image processing is carried out until the desired patterns are discovered. This study evaluates, compares, and examines the performance of multiple CNN architectures, specifically VGG16 and ResNet with respect to a particular dataset. Farmers prioritize using efficient techniques to detect infections and avoid crop losses.

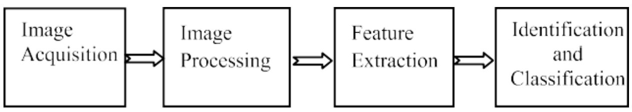
Keywords: Plant disease detection, deep learning, Convolutional Neural Networks (CNN), VGG 16, ResNet .

1. Introduction :

In order to maintain life on Earth, plants are essential since they are the main source of food, oxygen, and ecosystem stability. Their health is threatened by a number of issues, though, which results in large crop losses. The global food supply chain can be disrupted and farmers negatively impacted by factors like pest infestations, natural catastrophes, and delayed disease diagnosis. In order to reduce these dangers, early diagnosis of plant diseases is essential.

Manual inspection is a major component of traditional diagnostic techniques, although it can be labor-intensive, time-consuming, and prone to human mistake. Consequently, there may be a considerable delay in responding to plant infections, which can worsen the spread of illnesses and increase financial losses for farmers and the agricultural industry. More effective and trustworthy detection techniques are desperately needed to meet these difficulties.

Fig. 1. Traditional image recognition processing



Technological developments have opened the door for creative approaches to plant disease diagnosis. Technologies for image identification processing, especially those that use computer vision and neural networks, have showed promise in automating plant disease diagnosis. These techniques enable faster and more precise evaluations by using pictures of plant leaves and other tissues to spot disease symptoms.

Several crucial phases are involved in the typical process for diagnosing plant diseases using common image recognition techniques. First, cameras or smartphones are used to take high-quality pictures of plants. To ensure clearer data for analysis, the photos are then preprocessed to improve characteristics and eliminate noise. After that, important details about health and illness symptoms are taken out of the pictures.

Following feature extraction, deep learning models are used to classify the photos according to the attributes found, identifying whether a plant is healthy or sick. Lastly, farmers and agricultural professionals receive the results, allowing for prompt management plans and actions. The fundamental process for utilizing these sophisticated image recognition systems to diagnose plant diseases is shown in Fig.1. We can greatly increase the precision and effectiveness of plant disease diagnostics by utilizing technology, which will ultimately benefit farmers and promote global food security.

With its ability to quickly and accurately identify diseases, deep learning is helping to support plant protection, especially when models are trained on huge datasets. Deep learning, in contrast to conventional techniques, automates the disease diagnosis process, allowing for faster detection and intervention. As a result, there is a decrease in the need for chemical treatments, less labor, and healthier crops. Agriculture can effectively monitor plant health by integrating deep learning into its operations, which will eventually reduce crop losses.

Deep learning has promise as an ultimate solution for improving agriculture's resilience and sustainability in the face of growing global issues. Rapid plant disease detection can assist farmers in making early decisions that protect their crops and increase productivity. The process for recognizing plant diseases using deep learning algorithms is shown in Fig. 2, demonstrating the creative methods being used in contemporary agriculture.

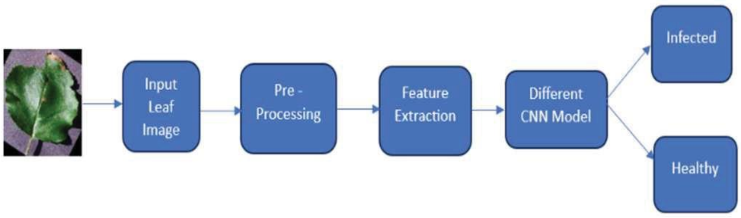


Fig. 2. Deep Learning image recognition processing

Furthermore, these deep learning models have been greatly improved by the incorporation of transfer learning. This method makes it simpler to apply current models to various agricultural contexts by enabling models to adapt to new datasets with little retraining. The advantages of transfer learning include reducing reliance on big datasets, which can be a barrier to creating reliable machine learning solutions, as well as speeding up the deployment of these models.

2. Literature Survey :

[1] Recent research has demonstrated the exceptional accuracy rates attained by deep learning models such as ResNet-50 in the diagnosis of plant diseases. For example, one study showed the model's resilience in early disease detection with an accuracy of 99.3% on a dataset of more than 32,000 photos. ResNet-50 is perfect for identifying subtle disease symptoms since it can learn complex image features without the vanishing gradient problem because to its use of residual connections. This excellent performance points to the possibility of using it with a variety of crops and environmental circumstances. By incorporating ResNet-50 into remote sensing or mobile devices, disease detection may become easier to access, allowing farmers to act quickly and enhance crop health, eventually promoting sustainable agriculture .

[2] In a different study, the efficacy of CNN, VGG16, and VGG19 models in plant disease identification was assessed using a dataset of 9,127 pictures. A thorough understanding of each model's performance was provided by this analysis, which contrasted the models according to accuracy, precision, recall, and F1 score. Because of their deeper architectures, which enable more thorough feature extraction, VGG16 and VGG19 fared better in terms of precision and recall than CNN, despite CNN's efficient accuracy. The resilience of VGG16 and VGG19 in processing intricate plant disease data was demonstrated by the F1 score, a balanced indicator of precision and recall. These results imply that deeper CNN architectures, such as VGG16 and VGG19, can provide more reliability for accurate disease diagnosis, which is essential for targeted treatments and early intervention in agriculture.

[3] On the PlantVillage dataset, the research obtained 98.27% accuracy using CNNs and pre-trained models. Because to the implementation of various methods for data augmentation and transfer learning that have enhanced model performance, early diagnosis of plant diseases is now feasible. The results demonstrate how well CNN architectures are able to extract complex features from both healthy and sick crop images. This reduces crop loss by automating early disease diagnosis and facilitating timely agricultural practice improvement. The high accuracy of deep learning models highlights their robustness for real-world use.

[4] Because deep learning-based models, such as CNNs, can accurately classify plant leaf images by extracting complicated features, they have shown promise in the diagnosis of plant diseases using image classification. When refined on datasets like PlantVillage, pre-trained architectures like DenseNet-121, ResNet-50, VGG-16, and Inception V4 have shown progress; nevertheless, they are computationally costly because to their high GPU requirements and large data sets. Training from scratch takes a lot of time, and these models are prone to overfitting on small or less diverse datasets, which might limit real-world performance. By using pre-trained models that attain high accuracy with less datasets and fewer resources, transfer learning overcomes these difficulties.

[5] Additionally, by training on more than 50,000 photos and including pesticide recommendations depending on the diseases found, a customized 15-layer CNN model has successfully diagnosed diseases across ten different plant species. This model demonstrates its adaptability in examining a broad range of plant diseases, enabling precise categorization and prompt symptom recognition in actual agricultural environments. The model's functionality is improved by the inclusion of pesticide recommendations, which enable farmers to make well-informed decisions more rapidly and use less broad-spectrum pesticides, thus encouraging sustainable practices.

[6] Through the analysis of leaf pictures, deep learning models particularly convolutional neural networks (CNNs) are widely employed for the detection and classification of plant diseases. With datasets like PlantVillage, a variety of architectures, including AlexNet, VGG, ResNet, and custom CNNs, achieve great accuracy. However, these models might not function effectively in real-world situations with different conditions and need a lot of high-quality training data. Furthermore, DL models can overfit with little or non-diverse datasets and frequently require a large amount of processing resources. CNNs continuously outperform conventional machine learning techniques, providing quick and accurate disease categorization in spite of these difficulties.

[7] Using a sizable dataset of plant leaf photos, the study investigates the application of deep learning models more especially, ResNet-34 for the detection of plant leaf diseases, showing an astounding 98.7% accuracy rate. The main goal is to improve disease management procedures and advance agricultural sustainability by offering quick and precise diagnosis via a web interface. But in order to reach such high accuracy, deep learning models like ResNet-34 usually need a lot of computing power and big datasets, which can make it difficult to use in many agricultural contexts. Furthermore, the efficacy of the model may be impacted in a variety of scenarios if it is used on real-world photos that differ greatly from the training data.

[8] The study uses pre-trained models such as EfficientNetV2S that have been optimized for efficient performance in noisy situations to identify plant illnesses from photographs of leaves using deep learning models, namely convolutional neural networks (CNNs). Based on the examined picture data, these models are intended to categorize plant diseases into different groups. However, these models' efficacy depends on the availability of high-quality, labeled datasets for precise classification, since performance might drastically deteriorate when working with low-resolution or noisy images. Furthermore, limitations in the training datasets make it difficult to generalize across different kinds of plant diseases.

[9] Convolutional Neural Networks (CNNs) are used in plant disease detection to train deep learning models to categorize leaf images according to their visual symptoms. For training and validation to be successful, a reliable dataset of healthy and diseased plant images is needed. By facilitating early and precise detection, which is essential for avoiding crop loss, this automated method seeks to support agricultural operations. CNN models, however, require enormous collections of high-quality images, which makes data collecting and curation difficult. Additionally, they are computationally demanding, needing a large amount of memory and processing power, which may restrict their use on edge devices. Additionally, when confronted with novel or undiscovered plant disease variants, CNNs might have trouble generalizing.

[10] With fewer parameters than more intricate models, the proposed 2D CNN Model is a lightweight architecture created especially for the classification of illnesses in cotton and tomato plants. It can successfully identify 12 infected classes and 2 healthy ones. The deep CNN models VGG16 and VGG19, on the other hand, are renowned for their strong feature extraction skills; nevertheless, their large number of parameters causes lengthy training durations and expensive storage needs. By using multi-scale convolution layers, InceptionV3 improves classification performance and can extract a variety of features from images. Despite its excellent accuracy and quick classification times, the proposed 2D CNN might have trouble extrapolating to new crops or diseases that aren't included in the existing dataset.

[11] Pre-trained models like DenseNet-121 and Inception V4 have shown optimal accuracy for multi-class classification tasks in a variety of applications, including the identification of plant diseases. These models are especially well-suited for agricultural jobs since they use deep learning techniques to efficiently learn and categorize complicated information from photos.

[12] A revised Convolutional Neural Network (CNN) model outperformed other models in the same classification test, achieving an amazing 98.70% accuracy on a Kaggle dataset in recent studies. This demonstrates how deep learning approaches may increase the diagnostic precision of plant disease detection, enabling prompt management plans and actions.

[13] To improve training accuracy, data augmentation approaches were applied in studies regarding illnesses of apples plants.

[14] With 5,170 annotated photos of tropical crops, the FieldPlant collection offers useful real-world information.

[15] A novel lightweight CNN architecture has demonstrated success in resource-constrained scenarios by reducing parameters while preserving performance. Because it enables efficient disease identification without the need for expensive hardware, this method is especially advantageous for applications in areas with limited computational resources.

[16] A newly created lightweight CNN architecture was introduced in [16] with the goal of functioning well in settings with limited resources. The model's efficacy in automating early disease identification was demonstrated by its 94% success rate in identifying illnesses in a variety of crops. Reducing the amount of parameters keeps the model computationally efficient and accurate. This method increases crop yield by enabling early intervention without requiring a lot of hardware resources. The outcomes demonstrate its applicability in actual agricultural situations.

[17] Furthermore, it has been demonstrated that combining local binary patterns (LBP) with deep CNNs improves classification performance on a variety of datasets by utilizing both the CNN's feature extraction capabilities and LBP's capacity to capture texture features. This hybrid method has shown promise in identifying small differences in plant disease symptoms that are frequently hard for regular CNN models to pick up on their own.

[18] With models like Inception V3 and AlexNet, transfer learning has further accelerated improvements in early crop disease identification, reaching up to 99.57% accuracy. These models are feasible for practical usage in agricultural applications because they use pre-trained weights, which reduces the amount of training data and processing resources needed. Proactive disease management is made possible by this high degree of accuracy, which lowers crop losses and increases productivity. By incorporating these models into smart farming technologies, farmers may be able to monitor crops in real time and take early action, which would help them manage crop health more effectively.

[19] For real-time classification, advanced architectures such as YOLOv3 and EfficientDet-D2 are used, improving illness identification.

[20] A 147,500-image augmented dataset was used to build and train a 14-layer deep CNN architecture.The application of sophisticated data augmentation techniques significantly increases the model's effectiveness in identifying plant diseases. CNN becomes increasingly accurate and resistant to overfitting when the variety of training data is increased. This approach enables more precise disease classification, which is advantageous for large-scale agricultural applications. Deeper architectures' ability to manage intricate image datasets is demonstrated in this work.

3. Methodology :

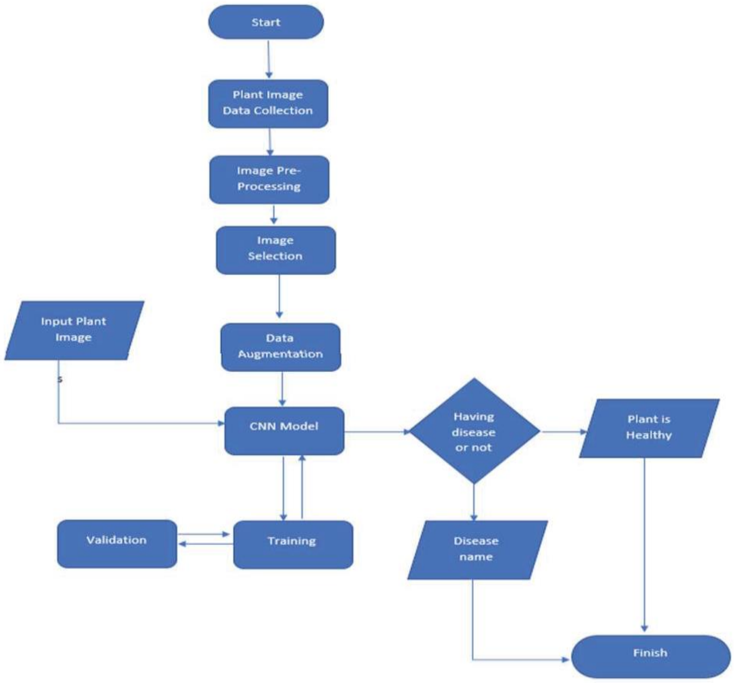
To reduce crop losses and allow for appropriate intervention, plant diseases must be identified quickly and accurately. In this work, deep learning models specifically CNN, VGG16, and ResNet applied to leaf photos are used to automatically identify and categorize plant diseases. Using characteristics like color, texture, and patterns that frequently indicate the kind and existence of disease, these algorithms may identify disease symptoms by examining photographs of leaves.

By evaluating each model's effectiveness in terms of accuracy, precision, recall, and F1 score, the combination of these models offers a thorough comparison. This research attempts to give farmers and agricultural specialists a tool for early, accurate diagnosis by automating disease identification through deep learning. This will lessen the need for manual inspection and eventually support sustainable agricultural practices.

The task of detecting plant diseases benefits greatly from each of the selected architectures. As a foundational model, CNN provides effective processing and sets a baseline accuracy appropriate for simple picture classification applications. It is helpful for real-time applications because of its comparatively basic structure, which allows for rapid training and execution. VGG16 is very good at identifying complex disease patterns and minute changes in leaf textures because of its much deeper layers, which enable it to extract complex information with ease. VGG16 can examine more intricate features like colour gradients and subtle pattern variations linked to certain plant diseases thanks to this depth. ResNet, on the other hand, offers a residual learning framework that lessens the vanishing gradient problem that deep networks frequently face.

3.1 CNN

Fig. 3. Methodology of CNN



One kind of deep learning model specifically made for image analysis and tasks involving spatial data, such object recognition and classification, is the Convolutional Neural Network (CNN). They are made up of layers that use filters to identify elements in pictures, moving from basic patterns (such colors or edges) to complex shapes. The main building blocks of CNNs are convolutional layers, which use these filters to create "activation maps" that emphasize important features in certain areas. Pooling layers, which frequently use max or average pooling to preserve important information, come next. These layers decrease the spatial size of these maps and improve the model's resilience to slight changes or transformations in the input. The final classification or prediction is produced by integrating these extracted information through fully connected layers.

The first step in the Convolutional Neural Network (CNN) plant disease detection process is the systematic gathering of a wide range of plant photos. Frequently collected from fields or agricultural databases, these photos feature samples of both healthy and diseased plants. By ensuring that these samples are diverse, the model can better generalize and distinguish between healthy and unhealthy plants, even when fresh data is added. The foundation of a trustworthy dataset is created by this first collection, which is essential for creating a useful diagnostic tool.

The photos undergo a number of pre-processing stages after capture in order to get them ready for training. In order to standardize inputs for the CNN model and enable effective batch processing, all photos are first scaled to a uniform size. Normalization is then used, which usually involves scaling pixel values to a range of 0 to 1. Training becomes quicker and more reliable as a result of this stabilization of the learning process. Additionally, noise reduction techniques are used to eliminate any unwanted or unnecessary visual information that could impair the model's capacity to identify patterns.

Only high-quality photographs are kept after pre-processing due to a selection procedure. Samples that are vague or ambiguous are eliminated throughout this selection process to prevent the model from becoming confused. Training results are more accurate since the data quality is preserved by concentrating on distinct, pertinent samples.

Data augmentation strategies are used to further enhance the dataset and make it more representative.

These methods, which include cropping, scaling, flipping, and rotating, produce different versions of every image. In addition to expanding the dataset, data augmentation exposes the model to a variety of viewpoints and angles, improving its capacity to identify diseases from a range of perspectives. This helps the model better generalize to real-world situations by keeping it from being overly specific to the training images.

Ultimately, the CNN model is trained using the prepared dataset, which is separated into training and validation sets. The model optimizes itself through several iterations as it learns to identify complex patterns linked to different plant diseases. The model can correctly categorize fresh plant photos after it has been trained. The model finds and labels any diseases seen in an input image; if not, it verifies the health of the plant. In addition to facilitating early disease detection, this automated diagnosis procedure helps farmers and agricultural specialists manage crops in a timely and educated manner.

3.2 VGG

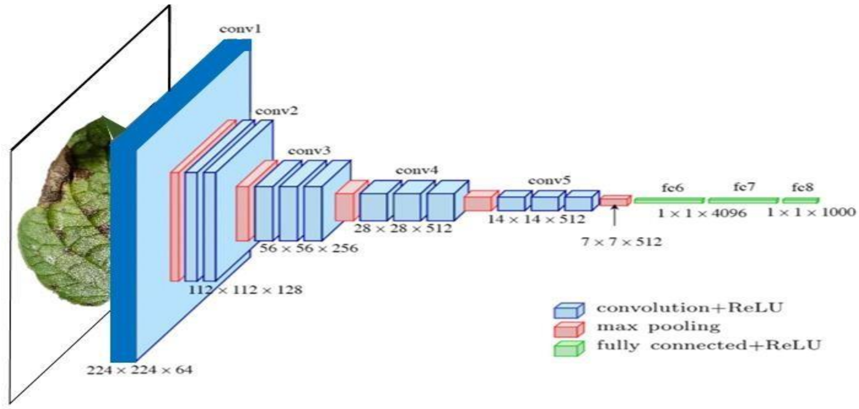


Fig. 4. Methodology of VGG

High-accuracy picture identification is the goal of the deep convolutional neural network architecture known as VGG16, or Visual Geometry Group with 16 layers. For large-scale image classification problems like those in the ImageNet competition, it gained notoriety for its simple yet efficient architecture. VGG16's architecture comprises 16 weighted layers, including 3 fully linked layers at the end and 13 convolutional layers that make use of tiny 3x3 filters. The model can identify fine-grained patterns in the input image thanks to the tiny filter design choice, and as the layers get deeper.

A 224 x 224 RGB image is usually used as the input to VGG16. It is first processed using a number of convolutional layers. The feature maps in these layers gradually get deeper, with the deepest layers having 512 channels and the first layers having 64 channels. A rectified linear unit (ReLU) activation function comes after each convolutional layer, adding non-linearity to aid in the model's learning of increasingly intricate patterns. By taking the maximum value within a limited window, max pooling layers are positioned after convolution sets to lower the spatial dimensions and assist control the computational load while maintaining important characteristics.

The multi-dimensional feature maps undergo three fully connected layers after being flattened into a single vector following all convolutional procedures. The network can learn global patterns and integrate the data retrieved from previous convolutional layers due to the huge number of neurons (usually 4096) in the first two of these layers. The softmax classifier, which generates a probability distribution across the output classes, comes after the third and last fully connected layer. In multi-class issues, like the 1000-class ImageNet dataset, where each output category denotes a distinct class label, this classifier is typically employed.

VGG16 is highly effective for tasks requiring high-resolution feature extraction and classification because of its depth, which allows it to learn complex, hierarchical patterns. VGG16 has been a key component in picture classification and transfer learning, while being computationally more expensive due to its large number of parameters. VGG16 is frequently utilized in different applications such as object detection, picture segmentation, and even medical imaging analysis due to its pre-trained weights and efficient feature extraction capabilities. Its architecture influenced later models by acting as a standard for creating deep convolutional networks.

3.3 ResNet

A novel deep learning architecture called the Residual Network (ResNet) was created to train extremely deep neural networks without running into the vanishing gradient issue. By adding residual blocks, which enable the network to skip specific layers via shortcut (or skip) connections, ResNet accomplishes this. The model retains knowledge as it becomes deeper due to these connections, which allow the network to learn residual functions that directly reference input data from earlier levels. ResNet can stack hundreds of layers using this method, learning complex patterns without experiencing gradient decline.

In order to capture broad features across a vast receptive field, ResNet starts its image-processing architecture with a 7x7 convolutional layer set with stride of 2 and 64 filters. This layer uses the stride parameter to reduce the size of the input image while applying a high-level feature extraction. A 3x3 max pooling layer comes next, which condenses information and further minimizes spatial dimensions. In order to prepare the image for more precise feature extraction in the deeper layers, this first portion of the network helps strike a compromise between the image's spatial resolution and computational efficiency.

ResNet's residual blocks, which usually comprise a collection of three convolutional layers with 1x1, 3x3, and 1x1 filters, are its fundamental component. While the 3x3 convolutions capture spatial characteristics within the residual block, the 1x1 convolutions are crucial because they reduce and then restore dimensions. At each level of the network's depth, the spatial dimensions are decreased while the number of filters is progressively increased in a succession of 64, 128, 256, and 512 filters. With the help of this design, the network can recognize ever more intricate patterns in the visual data, enabling it to collect both low- and high-level information as it becomes more sophisticated.

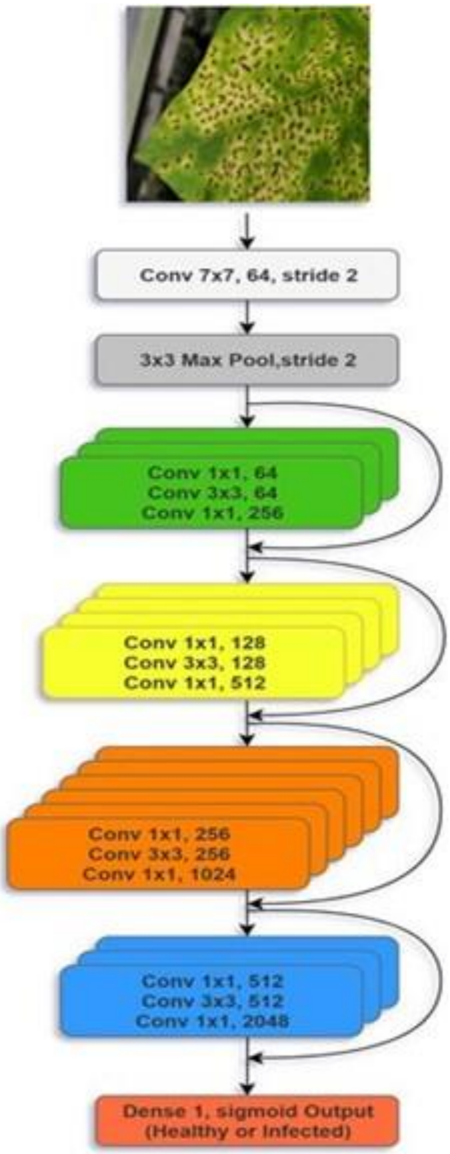


Fig. 5. Methodology of ResNet

Each residual block includes a skip connection that connects the block's input to its output immediately, avoiding intermediary layers as the data moves through these layers. This characteristic is essential to ResNet's performance since it guarantees that gradients can move freely throughout the network, keeping them from disappearing even in extremely deep networks. It would be challenging to train hundreds of layers in typical architectures, but our design enables ResNet to do it efficiently. By allowing gradients to "skip" specific levels, these skip connections protect learning signals and let the model continue to train steadily throughout incredibly deep networks.

High-level characteristics that have been collected from earlier layers are processed by a fully connected (or dense) layer at the conclusion of the ResNet to get a final classification result. A softmax classifier, which offers probabilities for each class, is usually the last layer in image classification projects such as ImageNet. With designs like ResNet-50, ResNet-101, and ResNet-152 delivering outstanding results across a variety of areas, ResNet's novel method with residual blocks has established new benchmarks in deep learning. ResNet is essential for tasks requiring sophisticated feature extraction, such as image classification, object identification, and medical image analysis, because of its capacity to efficiently train very deep networks.

4. Results and Discussion :

Based on accuracy, precision, recall, and F1-score, this study compares CNN, VGG16, and ResNet34 in detail, showing that ResNet34 performs best across the board. ResNet34's high accuracy, precision, recall, and F1-score, which are consistently around 97%, highlight its powerful generalization and prediction skills for the diagnosis of plant diseases. The architecture is particularly good at identifying minute changes in disease symptoms because of its residual learning framework, which preserves important information and avoids gradient problems.

Despite ResNet34's superior performance, VGG16 comes in second with comparable outcomes, especially in precision and F1-score. This implies that whilst VGG16's architecture is a little simpler than ResNet34's, it can still be a dependable choice, particularly when computational resources are an issue. On the other hand, CNN performs poorly, particularly in recall and F1-score, suggesting that it might not be able to identify every case of illness and might even miss some or incorrectly classify some.

All things considered, these results demonstrate ResNet34's resilience and suitability for precise and early plant disease detection, establishing it as a useful instrument in precision farming. It is perfect for a variety of agricultural applications where crop loss can be avoided by early intervention due to its great generalization capacity, which implies that it can adapt effectively to various plant species and disease kinds. ResNet34 practical application could give farmers a dependable, automated way to handle diseases in a timely manner, ultimately promoting sustainable farming methods.

To further improve model resilience and adaptability, future research in this area may investigate the integration of bigger, more varied datasets including a range of plant species, disease stages, and environmental circumstances. Furthermore, using sophisticated regularization strategies like dropout, data augmentation, and early preventing may lessen overfitting and improve the model's ability to generalize to new data. In order to make the model more accessible for real-time applications on mobile and edge devices, lowering the computing load is also a major area of study. Deep learning-based plant disease detection may become more effective with methods like model trimming, quantization, or the use of lightweight architectures, allowing for useful implementation in environments with restricted resources.

Model	Accuracy	Precision	Recall	F1-score
CNN	96.22%	94.60%	95.78%	95.06%
VGG16	96.16%	95.54%	95.32%	95.32%
ResNet34	97.04%	97.11%	97.04%	97.05%

Table : Comparison among various methods

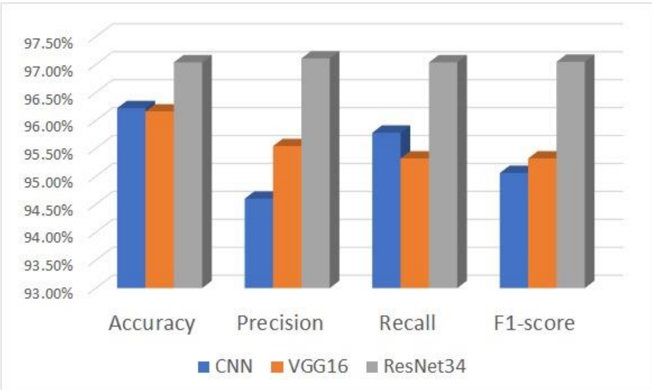


Fig. 6. Graphical representation of various performance metrics

5. Conclusion :

Applications in the agricultural industry, which give farmers vital tools to prevent crop loss, have become the focus of more and more research on the early diagnosis of plant diseases. Because they mostly rely on manual examination and expert assessment, traditional methods for detecting plant diseases are usually time-consuming and prone to human error. To reduce damage, early intervention is essential, but it calls for precise, quick, and easily accessible detection techniques. A promising solution that allows for highly accurate automatic detection is deep learning. With its combination of accuracy and computing economy, the ResNet-34 model is a strong choice in this regard and has the potential to greatly simplify illness identification in agricultural contexts.

ResNet-34's high performance stems from its capacity to extract intricate patterns from data while preserving a small architecture. The model is a useful tool for farmers because of this special combination, which enables it to precisely identify plant illnesses. Models like ResNet-34 are positioned to be crucial in strengthening disease management tactics and raising overall agricultural efficiency as agriculture increasingly embraces technology-driven solutions.

In the end, the development of automated disease detection technologies has the potential to revolutionize farming methods. Farmers will be better able to protect their plants from illnesses by using deep learning into crop management, which will increase productivity and promote sustainability. In addition to helping individual farmers, technological developments in this area also make agricultural systems more resilient globally, guaranteeing a more stable supply of food in the future.

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