Plant Disease Recognition From Leaf Images Using CNN

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Abstract — Determining the crucial aspects that impact crop output or plant development is made possible by the identification of plant diseases, making this a significant area of research. According to recent studies, 14.1% of plants perish from plant disease. It's a significant issue that could affect people's health as well. The greatest number of plants can be utilised to create medications. This implies that it's critical to identify plant illnesses early on. This publication offers a helpful method for identifying illnesses in various plant species. Other from tomatoes. A wide range of plant species, including sugarcane, potatoes, apples, grapes, and maize, are recognised and detectable by the system. With camera-captured images serving as the basis, plant disease detection and treatment are now possible because to deep learning's recent advancements in computervision.

Keywords *— Plant disease, CNN (Convolutional Neural Network), VGG16, Resnet34, Flask*

I. INTRODUCTION

Agriculture is the foundation of our nation. In our country, agriculture is well-known. It's very possible that Indians are interested in agriculture. It has a significant impact on the Indian economy. Agriculture makes up little more than 70% of rural areas. Sixty percent of the population has access to jobs thanks to GDP, which obtains seventeen percent of its earnings[1]. Therefore, in agriculture, it is crucial to recognize plant illnesses. Farmers have several options when it comes to choosing different crops and figuring out which pesticides work best for their specific plants. Plant diseases significantly reduce the amount and quality of agricultural production. Plant disease studies are the examination of patterns on plants that are visible to the naked eye.

Watching for plant health issues and diseases is essential to growing food on a farm. In the past, the expert in that field would personally keep an eye on and assess plant diseases. This requires a large amount of labour as well as a lengthy processing time. Plant issues can be diagnosed using image processing techniques.Disease indications are frequently found in fruit, stems, and leaves[2]. When diagnosing the disease, consideration is given to the plant leaf displaying the symptoms.

Techniques for digital image processing (DIP), machine learning (ML), and artificial intelligence (AI) have all advanced significantly in the last several years. In order to support farmers, it is essential to identify different plant diseases early on. As a result, it is crucial to incorporate this new technology into current methods. Crop yield will decrease as a result of the spread of plant diseases. These illnesses can harm plants, alter a plant's shape, alter the color and texture of its leaves, affect fruit, and more. This makes it very difficult for farmers to diagnose diseases in plants with their unaided eyes and makes it tough for them to fully understand how serious the situation is. This can occasionally result in incorrect disease diagnosis. The treatment of plant infections might be challenging due to inexperienced or inexperienced farmers[3]. Consequently, developing methods to assist farmers in identifying diseases early on and providing treatment for such ailments is crucial.

Visual Geometry Group, or VGG for short, is a multi-layered, conventional deep Convolutional Neural Network (CNN) architecture. With VGG-16 or VGG-19, which are composed of 16 and 19 convolutional layers, the term "deep" refers to the quantity of layers. Innovative object identification models are built on top of the VGG architecture. The VGGNet, designed as a deep neural network, outperforms baselines on a wide range of tasks and datasets, going beyond ImageNet. Furthermore, it remains one of the most widely used image recognition architectures to this day shown in below figure1 and figure 2.

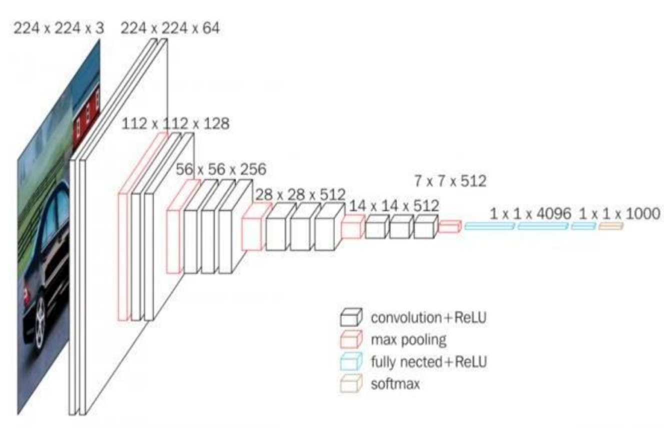

Fig1: VGGNet-16 Architecture

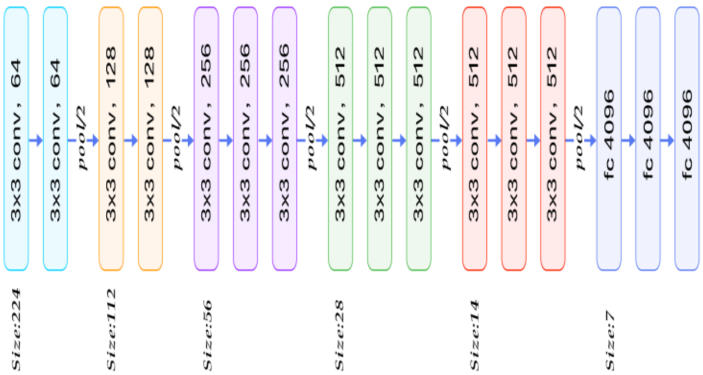

Fig2: VGGNet16 contains 16 layers

Provide a State-of-the-Art Plant Disease Detection System:

- Construct a state-of-the-art deep learning system that employs deep convolutional networks (CNN) for accurate plant disease diagnosis and treatment.
- Expand the number of species that disease detection covers to 38 distinct plant diseases.
- Increase the Recognition to 14 Different Plant Species. Enable User-Friendly Usability using an Online Application:
- Create and deploy an intuitive Flask web application that farmers and agricultural professionals may easily access.
- Facilitate early disease detection in an effort to lower crop losses and increase agricultural output.

II. Literature Review

The authors of this paper [1] assess different deep learning models that are already in use for plant disease diagnosis when low resolution data is employed. Their main field of study is deep convolutional neural networks (DCNNs), which are frequently used with picture data. Furthermore, as it is well known that DCNN performs better the deeper the networks, they propose a novel DCNN architecture that combines two branches of concatenated residual networks.

This study [2] employed Random Forest to separate healthy from unhealthy leaves based on the data gathered. It goes through several stages of implementation, such as feature extraction, dataset construction, classifier training, and classification. To categorize the photos of damaged and healthy leaves, a Random Forest collective training method is employed to acquire datasets of healthy and diseased leaves. We employ the Histogram of an Oriented Gradient (HOG) method to extract features from images.

[3] Identification of plant diseases and health surveillance are critical to sustainable agriculture. Observing plant diseases by hand is very difficult. It takes a lot of work, extended processing times, and knowledge of plant diseases. Thus, image processing is used to identify plant illnesses. Disease detection involves multiple stages, such as image collection, feature extraction, segmentation, classification, and pre-processing. Convolutional Neural Networks accurately detect more diseases in a variety of crops[4].

Erroneous information and delayed disease identification are major problems for many farmers who raise food in remote regions of the world because they rely on manual monitoring of grains and vegetables. Using digital farming techniques is an interesting way to quickly and easily diagnose plant problems [8]. This study provides a method for identifying plant leaf diseases and putting preventative measures in place in the agricultural sector. It combines image processing with the popular convolutional neural network (CNN) models AlexNet and ResNet-50 to achieve this.

A novel design for the efficient classification of plant diseases was suggested by this work [7]. Apart from our sense of sight, people can generally recognise, though not always with ease, plants that are sick with specific illnesses. If proper care and prompt action are not given, the entire production area may become infected with a disease, or plants in close proximity may spread the ailment to one another. Thus, the authors proposed a paradigm for the efficient diagnosis of plant illnesses based on modern computer technology and early plant disease detection. This research [7] explores the significance of plant diseases in agriculture, highlighting their high degree of naturalness and the potential harm that plants may suffer if they are ignored, which could lead to a decrease in productivity, quality, or quantity. Leaf disease detection and accurate diagnosis are critical to preventing productivity losses and decreases in agricultural output. Automated plant disease detection methods are advantageous because they minimize the need for extensive plant monitoring and identify disease symptoms at an early stage.

III. Proposed System

This starts with image gathering and moves through testing, model development, and model building using several architectures. In order to gather data and get related preventive measures for recognized plant ailments, the last stage entails using the model within the Flask frontend. Class Diagram.

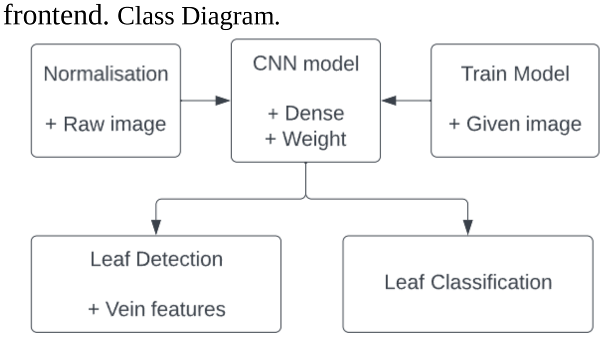

Fig3. Class Diagram

The procedure is shown in Figure 3 above, and it also entails normalizing the input image, extracting features from the preprocessed image using the CNN model, training the model with image-label pairs, identifying leaves in the input image, identifying traits from the veins in the leaves, and classifying the plant disease based on those traits.

IV. METHODOLOGY

Convolutional neural networks, or CNNs for short, are a particular type of neural network designed to handle inputs with shapes similar to 2D matrices, like pictures.

CNNs are commonly employed in the detection and categorization of images. Images are 2D matrices of pixels that we use to identify or recognize them using CNN[5]. Determine whether a picture is of a person, an automobile, or just the numbers on an address. Similar to Neural Networks, CNN is driven by the brain. We employ the Hubel and Wiesel object recognition model.

An input, I, and an argument, kernel K, are used in the mathematical operation of convolution to produce an output, which represents how the shape of one is changed by another.

Let's illustrate using an illustration.

Feature maps are the results of performing a mathematical operation to an image (x), which is a 2D array of pixels with distinct color channels (Red, Green, and Blue-RGB), and a feature detector (w) is shown in below figure 4 of convolution function.

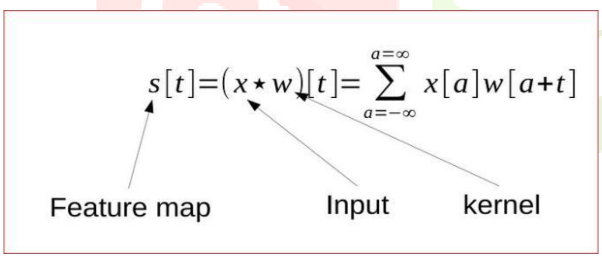

Fig4: Convolution function

The goal is to develop an advanced plant disease detection system that uses deep convolutional networks (CNN) to precisely identify 38 plant diseases that affect 14 different species. Together with the creation of an intuitive Flask web application, this increase in disease detection capabilities guarantees accessibility for farmers and agricultural Professionals[5]. Enabling early disease identification, reducing crop losses, and increasing agricultural productivity are the main objectives. This program not only helps with the pressing demand for accurate disease control, but it also advances sustainable farming methods that raise industry productivity levels.

1. Dataset

In this project, a plant disease diagnostic model based on leaf image categorization is being created using deep convolutional networks. The suggested model can distinguish 38 types of plant diseases among 14 different plant species. (3, 128, 128) = (number_of_channels, image_width, image_height,) is the form of each image.

Fig4. Different dataset images

A. A sample of leaf pictures utilized for image classification in disease detection.

Image Preprocessing:

Downsizing

The supplied image is resized to a predetermined size using this transformation. In this instance, the image gets resized to 128x128 pixels, which is a square. To standardise the proportions of the input image, resizing is frequently done. For many deep learning models to analyse input photos effectively, they must all be the same size[5]. This guarantees that the data that the model gets is consistent.

1. Reverse

The "RandomHorizontalFlip" transformation randomly flips the image horizontally with a given probability. Given that the probability in this case is set to 0.5, the likelihood of the image being horizontally mirrored is 50%. This data augmentation strategy adds diversity to the training data. The model's generalisation is enhanced by exposing it to both the original and mirrored copies of the image. Jittering

B. The Jitter transformation adds arbitrary changes to the image's colour characteristics. It has the following specifications:

Brightness: Modifies the image's brightness in an arbitrary manner. With the setting set to 0.2, the greatest change in brightness allowed is ±20%. Contrast: Modifies the image's contrast in an arbitrary manner. Like brightness, this parameter has a maximum contrast change of ±20% and is set at 0.2.

Saturation: A maximum variance of ±20% is introduced, resulting in random shifts in colour saturation. Hue: Modifies the image's hue. The "hue" parameter produces colour alterations that are barely noticeable, with a range of ±0.1.

Tensoring:
This procedure converts the image to a PyTorch tensor. Deep learning frameworks such as PyTorch require the presence of tensor-formatted data in order to process it[5]. Using this transformation, the image is converted from its original format (such as JPEG or PNG) into a numerical representation that can be input into a neural network.

Pre-Instructed Models
Pre-trained neural network models are ones that have been trained on large datasets for specific tasks, such as image classification or natural language processing. These models serve as a foundation or a starting point for the creation of more specialized machine learning models.[4] This is how machine learning and fine-tuning leverage pre-trained models. Pre-trained models used for transfer learning are used to refine machine learning plant leaf recognition algorithms. These models include:

The term "Residual Network with 34 layers," or ResNet-34, refers to a deep convolutional neural network architecture that understands that a recognized path and a residual path are the two primary paths that make up a residual block. Bypassing one or more convolutional layers and going straight from the input to the output, the identity path is a shortcut connection. In order to reduce the number of parameters, a bottleneck block features three convolutional layers (1x1, 3x3, and 1x1) instead of the two 3x3 convolutional layers found in a regular residual block. Activation functions (usually ReLU) inside these layers, batch normalisation, and several convolutions are used by the network to extract features from input images.

E. Use of the GPU Although Central Processing Units (CPUs) are capable of handling machine learning tasks, GPUs have the capacity to handle data more concurrently than CPUs. This constraint might cause training times to increase dramatically when working with large datasets or sophisticated models. Training with just a CPU is not feasible since processing big datasets requires more time and computing resources. Online GPU services, which are cloud-based platforms, provide users with powerful GPUs that are perfect for machine learning and deep learning applications.

F. Neural Convolution Architecture In machine learning, convolutional neural networks are employed. One type of deep learning network design that is capable of quickly acquiring new information from previously gathered data is the convolutional neural network. CNNs are a kind of network design that are particularly useful for pixel-level tasks in deep learning algorithms, such as image identification. CNNs can identify a broad range of objects, classes, and categories by applying all layers to the images and looking for patterns within them. CNN's numerous layers may convert a three-dimensional input volume into an output volume.

CNN layers are defined as follows: 1. Input Layer We get the input images and their pixel values from the input layer. These pictures are matrices that depict brain tumors. Second Convolutional Layer convolution Neural Nets (CNN) use different kernels to convert the entire object into convolutional layers[6].

Four convolution layers are used in the suggested approach. Ten filters with a 3*3 diameter and "the same padding" were employed in the first convolution layer. The same padding was established, as seen by the padding applied to the input edges, therefore the size of the input and output would be the same. In the second convolution layer, 20 filters of 3*3 dimensions and "identical" padding were used[6].

1. The Layer of Activation The hyperbolic tangent or sigmoid of the artificial neural network has a nonlinear translation function. Rectified Linear Units (ReLU), one of the various activation function types used in this layer, are the most well-known, and we employed them in our investigation.

2. The Swimming Layer The pooling layer is one additional CNN component. It usually happens after the convolutional layer and is used to reduce the size of feature maps and the network's parameters so that nearby pixels are taken into account when measuring these maps. The two most widely used methods are average pooling and maximal pooling. Completely Networked Layer A fully connected layer normally acts as the direct connection between two surrounding levels in the network since the final layers of a CNN are frequently entirely linked layers. The SoftMax Layer The neural network's output could be challenging to understand. The SoftMax is frequently where convolution neural networks (CNNs) stop. layer in programmes that use classification. When the result values are in the [0,1] range, the CNN model that was used is more suitable for the majority of classes or measures since binary categorization is prevented. After the data have been retrieved in a fully linked phase, each process will be assigned the SoftMax layer based on the previously collected characteristics.

F. Counterfeit Code:
The functions include some of the following:

G. the training_step() method A method defined inside the PyTorch LightningModule class is the training_step function. It is in charge of carrying out the model's single training step. The function returns a loss value after receiving a batch of data as input.

H. validation_step(): this function evaluates the model's performance using validation data during training. It is possible to log and monitor the model's development using the dictionary that is returned, which includes the accuracy and loss.

I. The function validation_epoch_end() examines the outputs from several validation stages, determines the average accuracy and loss for the full validation epoch, and provides a dictionary with these average values.

J. epoch_end(): By presenting the important performance metrics for every epoch, the epoch_end function helps to monitor and convey the status of the training procedure.

K. accuracy(): To ascertain the correctness of the model's predictions, the accuracy function compares the predicted classes to the ground truth labels.

L. Fully Connected Layers: This component has two fully linked layers. The first layer takes the flattened output of the AdaptiveAvgPool2d layer and uses it to produce a vector with 128 dimensions. The CNN model is meant to classify plant diseases using RGB images of plant leaves. After the network component extracts features from the pictures, the fully connected layers learn to classify the features according to the ailment labels.

V. RESULT DISCUSSION

Analysis of various algorithms is shown below in the Table 1.1.

Authors & year	Goals	Future perspective
[1] Savita N. Ghaiwat et al., Detection and classification of plant leaf diseases using image processing techniques: a review (2014)	Review of ANN, SVM, PNN, SELF ORG MAPS and fuzzy logic	In neural network it's difficult to understand structure of algorithm and to determine optimal parameters when training data is not linearly separable
[2] Prof. Sanjay B. et al., Agricultural plant leaf disease detection using image processing (2013)	Vision-based detection algorithm with masking the green-pixels and color co-occurrence method	NN's can be used to increase the recognition rate of classification process
[3] Mrunalini R. et al., An application of K-means clustering and artificial intelligence in pattern recognition for crop diseases (2011)	K-means clustering algorithm with neural networks for automatic detection of leaves diseases	Artificial neural network and fuzzy logic with other soft computing technique can be used to classify the crop diseases
[4] S. Arivazhagan et al., Detection of unhealthy region of plant leaves and classification of plant leaf diseases using texture features (2013)	Color co-occurrence method with SVM classifier	The training samples can be increased and shape feature and color feature along with the optimal features can be given as input condition of disease identification
[5] Anand H. Kulkarni et al., Applying image processing technique to detect plant diseases (2012)	Gabor filter for feature extraction and ANN classifier for classification	Recognition rate can be increased
[6] Sabah Bashir et al., Remote area plant disease detection using image processing (2012)	Texture segmentation by co-occurrence matrix method and K-means clustering technique	Bayes classifier, K-means clustering and principal component classifier can be used to classify various plant diseases
[7] Smita Naikwadi et al., Advances in image processing for detection of plant diseases (2013)	The color co-occurrence texture analysis method was developed through the use of spatial gray-level dependence matrices	Better result of detection can be obtained with the large database and advance feature of color extraction
[8] Sanjay B. Patil et al., Leaf disease severity measurement using image processing (2011)	Simple threshold and triangle thresholding segmentation methods	Nil
[9] Piyush Chaudhary et al., Color transform based approach for disease spot detection on plant leaf (2012)	Median filter is used for image smoothing and threshold can be calculated by applying Otsu method	Disease spot area can be computed for assessment of loss in agriculture crop. Disease can be classified by calculating dimensions of disease spot
[10] Arti N. Rathod et al., Image processing techniques for detection of leaf disease (2013)	Survey of different techniques for leaf disease detection	Development of hybrid algorithms & neural networks in order to increase the recognition rate of final classification process

Table 1.1. Analysis of various algorithms.

Fig. 1. Input and output image of banana leaf and output diseases is early scorch disease.

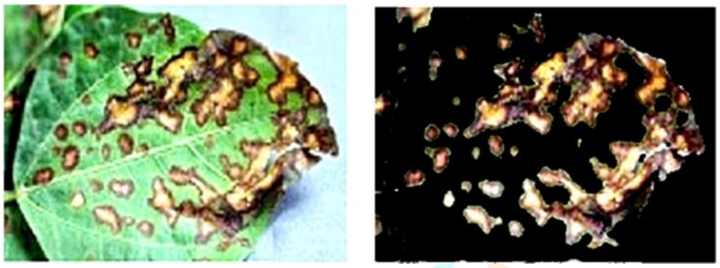

Fig. 2. Input and output image of beans leaf and output diseases is bacterial leaf spot.

Fig. 3. Input and output image of rose leaf and output diseases is bacterial leaf spot.

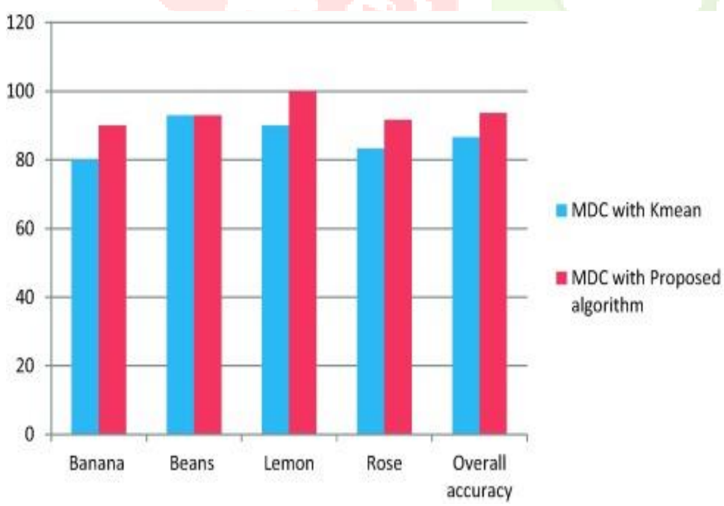

Fig. 4. Comparison of results.

VI. CONCLUSION

The earlier difficulties were successfully resolved with the development of a tailored CNN system. Comparing this newly developed model to previous models reveals a significant improvement. Agriculture is one of the most important economic sectors in India. Any country wishing to achieve economic progress must be able to identify crop ailments. The suggested technique classifies the various plant diseases taken from the Plant leaves image collection using a CNN model. pre-trained models, such as VGG16 and Resnet. 34 have also been made use of. Moreover, our proposed method can help detect plant diseases early and offers a helpful means of anticipating them. Furthermore, the development of a user- friendly front-end interface using Flask allows users to promptly upload leaf photographs and receive accurate disease diagnosis along with practical preventive measures.

VII. FUTURE SCOPE

Image processing-based plant disease classification has the potential to revolutionize agriculture by facilitating early disease identification, enhancing crop management, and promoting efficient and sustainable food production. Public access to the system will enable the system to be improved and welcomed food security to be guaranteed. Additionally, by changing the internal architecture, customized CNN can be improved to yield better results and boost accuracy.Additionally, user- friendly smartphone applications that can interface with IoT (Internet of Things) devices for real-time leaf picture collecting and disease diagnosis should be created in order to improve the system's comfort and accessibility for farmers and agricultural experts in remote locations.

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