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Efficient Deep Learning Technique for Detecting and Classifying Plant Leaf Diseases

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ABSTRACT

Agriculture accepts a basic part by virtue of the quick improvement of the general population and extended interest in food in India. Hence, it is required to increase harvest yield. One serious cause of low collect yield is an infection brought about by microorganisms, infection, and organisms. Plant disease investigation is one of the major and essential tasks in the part of cultivating. It tends to be forestalled by utilizing plant disease detection techniques. To monitor, observe or take care of plant diseases manually is a very complex task. It requires gigantic proportions of work, and moreover needs outrageous planning time; consequently, image processing is utilized to distinguish diseases of plants. Plant disease classification can be done by using machine learning algorithms which include steps like dataset creation, load pictures, pre-preparing, segmentation, feature extraction, training classifier, and classification. The main objective of this research is to construct one model, which classifies the healthy and diseased harvest leaves and predicts diseases of plants. In this paper, the researchers have trained a model to recognize some unique harvests and 26 diseases from the public dataset which contains 54,306 images of the diseases and healthy plant leaves that are collected under controlled conditions. This paper worked on the InceptionV3 Architecture algorithm. A residual InceptionV3 Architecture is a subpart of the artificial neural network (ANN). ResNet algorithm contains a residual block that can be used to solve the problem of vanishing/exploding gradient. InceptionV3 algorithm is also used for creating Residual Network. For the image classification, InceptionV3 Architecture a much well result. The ResNets techniques applied some of the parameters like scheduling learning rate, gradient clipping, and weight decay. Using the InceptionV3 Architecture, the researchers expect high accuracy results and detecting more diseases from the various harvests.

Keywords: ResNet, artificial neural network

I.INTRODUCTION

In India, for economic development, agriculture is a valuable source. To increase the production of food, the agriculture industries keep on searching for efficient methods to protect crops from damages. This makes researchers search for new efficient, and precise technologies for high productivity. The diseases on crops give low production and economic losses to farmers and agricultural industries.

For a successful farming system, one of the essential things is disease identification. In general, by using eye observations, a farmer observes symptoms of disease in plants that need continuous monitoring. Different types of disease kill leaves in a plant. For identifying these diseases, farmers get more difficulties.

For disease detection, the image processing methods are suitable and efficient with the help of plant leaf images. Though continuously monitoring of health and disease detection of plant increase the quality and quantity of the yield, it is costly. Machine learning algorithms are experimented due to their better accuracy. However, selection of classification algorithms appears to be a difficult task as the accuracy varies for different input data. The objectives are to detect leaf disease portion from the image, extract features of an exposed part of the leaf, and recognize disease.

Various efforts have been developed to prevent crop loss due to diseases. Historical approaches of widespread application of pesticides have in the past decade increasingly been supplemented by integrated pest management (IPM) approaches (Ehler, 2006). Independent of the approach, identifying a disease correctly when it first appears is a crucial step for efficient disease management.

Image processing algorithms encompass a broad spectrum of techniques designed to manipulate and analyze digital images. These algorithms serve a multitude of purposes, from fundamental tasks such as image resizing and noise reduction to more intricate operations like object detection and facial recognition. Image enhancement algorithms work to refine image quality by adjusting contrast, equalizing histograms, and correcting gamma levels.

Filtering algorithms, both linear and non-linear, are employed to enhance or suppress certain features in an image, while edge detection algorithms, like the Canny edge detector, pinpoint edges and boundaries. Further, segmentation algorithms help divide an image into meaningful regions, and feature extraction methods yield valuable data from these regions. These algorithms, often powered by computer vision and machine learning, play a pivotal role in diverse applications, from medical imaging to autonomous vehicles and beyond.

In plant disease detection, the CNN algorithm operates as the cornerstone of accurate and efficient image analysis. It starts with the collection of a diverse dataset, encompasses data preprocessing to ensure consistency and quality, and involves the creation of a CNN model architecture, which learns to extract crucial features from the images.

The training process refines the model's ability to distinguish between healthy and diseased plants, and extensive validation and testing validate its performance. Once deployed, this algorithm proves invaluable, enabling the software to swiftly and accurately detect and diagnose plant diseases. It contributes significantly to improved crop management and healthier plant life by providing early and reliable disease identification.

II.RELATED WORKS

Researchers have long been engaged in the development of automated systems to detect crop diseases accurately and in real-time. One of the earliest approaches involved basic image processing techniques that included color transformation and thresholding to detect the presence of infected areas on leaves. These methods, though simple, provided a base for further explorations into more advanced technologies. Subsequent developments focused on extracting features from infected areas of the leaf using methods like GLCM (Gray Level Co-occurrence Matrix), color histograms, and texture analysis. These techniques aimed to capture the unique visual patterns present in diseased regions. However, feature-based systems were often sensitive to noise and lighting variations in the images. The introduction of machine learning provided a significant advancement in disease classification tasks. Algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Decision Trees were applied to classify plant diseases using features extracted from images. These models showed improvements in accuracy but required careful tuning and pre-processing of data. In an attempt to improve reliability, ensemble learning techniques were introduced. These combined the predictions from multiple classifiers to enhance the overall accuracy. Bagging and boosting methods, such as Random Forest and AdaBoost, proved effective in handling variability across datasets, thereby offering better generalization. Researchers explored the use of Artificial Neural Networks (ANNs) as an alternative, capable of learning patterns directly from data. Though ANNs performed reasonably well, their performance was limited by the availability of training data and the complexity of leaf disease patterns. With the emergence of Convolutional Neural Networks (CNNs), a new era of plant disease detection began. CNNs automatically learn hierarchical features from raw image data, eliminating the need for manual feature extraction. Their ability to process large datasets and learn complex visual patterns makes them ideal for image classification tasks. Several studies have demonstrated the effectiveness of CNN-based models for plant disease detection. For example, models trained on datasets like PlantVillage, which includes tens of thousands of annotated images of diseased and healthy leaves, achieved accuracy rates above 95%, showcasing the potential of deep learning in agriculture. Despite high accuracy in controlled environments, CNN models often struggle when deployed in real-world conditions. Factors such as background clutter, different lighting conditions, and leaf occlusions impact performance. To address this, researchers have developed data augmentation techniques to make models more robust and adaptable. Transfer learning has also been utilized, wherein pre-trained models like VGGNet, ResNet, and Inception are fine-tuned on plant disease datasets. This reduces the need for large datasets and computational resources while still achieving high accuracy in classification tasks. To further enhance detection capabilities, researchers have integrated image segmentation algorithms with CNNs. Techniques like U-Net and Mask R-CNN help in isolating infected regions from the leaf, allowing for more precise classification and severity assessment of the disease. Beyond detection, some systems aim to identify the exact disease type, severity level, and suggest treatment options. These systems combine image classification with expert systems or rule-based modules that provide recommendations based on detected symptoms. Edge computing and mobile deployment of plant disease detection systems have gained traction in recent years. Lightweight CNN models, such as MobileNet, are now used to deploy disease detection applications on smartphones, enabling farmers to diagnose diseases in real-time from the field. In addition to CNNs, Generative Adversarial Networks (GANs) have been explored to generate synthetic images for training purposes. This helps in balancing datasets that might otherwise be skewed toward certain disease types or conditions. A few studies have introduced hybrid models that combine CNNs with other techniques like fuzzy logic or Bayesian networks to improve interpretability and trustworthiness of the diagnosis. These models not only predict the disease but also provide confidence scores and explanations. Cloud-based systems have also been developed to centralize disease detection and provide analytics services to agricultural stakeholders. These platforms collect data from multiple sources and use cloud processing to analyze and generate insights for crop management. Some research has focused on multi-modal approaches that combine visual data with sensor data (e.g., temperature, humidity, and soil moisture) to improve detection accuracy. Such holistic systems take into account both visual symptoms and environmental conditions that influence disease prevalence. Recent works emphasize explainable AI (XAI) for plant disease detection. Visualization techniques like Grad-CAM are used to highlight regions of the image that influenced the model's prediction, helping users understand and trust the system’s output. Another avenue of exploration includes real-time disease monitoring systems using drones equipped with cameras. These systems scan entire fields, capture images from different altitudes, and send them to centralized servers for disease analysis and crop health monitoring. Finally, efforts are underway to develop open-source platforms and datasets to encourage collaboration in this domain. Benchmarking datasets and shared models allow researchers worldwide to build upon existing work, refine methodologies, and push the boundaries of automated disease detection in agriculture.

III.PROPOSED SYSTEM

Plant disease identification by sight is a more time-consuming and inaccurate task that can only be performed in limited locations. Automatic detection, on the other hand, requires fewer efforts, takes less time, and is more accurate. Brown and yellow spots, early and late scorch, and fungal, viral, and bacterial infections are some of the common diseases encountered in plants. Image processing is used to detect the difference in colour of the affected region and to measure the affected area's impacted area. In the process of tree identification from pictures of leaves in a natural background, retrieving an accurate contour is a challenging and crucial issue. In this project we implement a method designed to deal with the obstacles raised by such complex images, for simple and lobed tree leaves. A first segmentation step based on a light polygonal leaf model is first performed, and later used to guide the evolution of an active contour. Combining global shape descriptors given by the polygonal model with local curvature-based features, the leaves are then classified over leaf datasets. And implement classification algorithm which includes Convolutional neural network algorithm to classify the diseases and recommend the fertilizers to affected leaves. Based on CNN algorithm, model file build and in future analysis predict the disease with improved accuracy rate

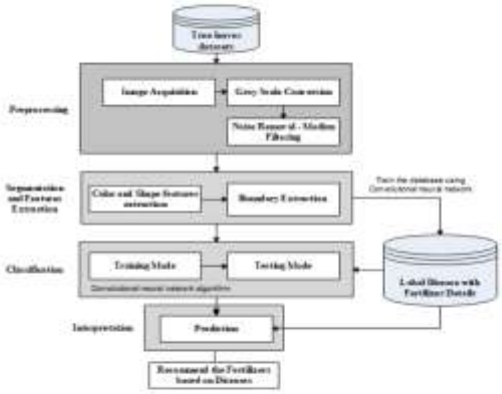

Figure 1: System Architecture of proposed system

IV. MODULES

LEAF IMAGE ACQUISITION

Leaves are structures specialized for photosynthesis and are arranged on the tree in such a way as to maximize their exposure to light without shading each other. In this module, we can upload the leaf images from the datasets. This database called LEAF was originally created for experiments with recognition of wood species based on a leaf shape. It contains leaves of species growing in the Czech Republic, both trees and bushes; native, invasive and imported (only those imported species which are common in parks are included). The number of samples (leaves) of one species varies from 2 to 25; their total number in the database is 795. The leaves were scanned with 300 dpi, threshold (binarized) , preprocessed (denoising and cleaning) and saved in PNG format. In this module, we can input the corn leaf image datasets.

IMAGE PREPROCESSING

In this module convert the RGB image into gray scale image. The colors of leaves are always green shades and the variety of changes in atmosphere cause the color feature having low reliability. Therefore, to recognize various plants using their leaves, the obtained leaf image in RGB format will be converted to gray scale before pre-processing.

where R, G, B correspond to the color of the pixel, respectively.

Then remove the noises from images by using filter techniques. The goal of the filter is to filter out noise that has corrupted image. It is based on a statistical approach. Typical filters are designed for a desired frequency response. Filtering is a nonlinear operation often used in image processing to reduce "salt and pepper" noise. A median filter is more effective than convolution when the goal is to simultaneously reduce noise and preserve edges. And implement image binarization tasks. Document Image Binarization is performed in the preprocessing stage for document analysis and it aims to segment the foreground text from the document background. A fast and accurate document image binarization technique is important for the ensuing document image processing tasks.

IMAGE SEGMENTATION

In this module, we can implement CNN algorithm with automatic descriptors. CNN algorithm is to pass the preprocessed image through a series of convolutional layers. These layers perform feature extraction by applying a set of filters to the image. Each filter produces a feature map that highlights a particular feature in the image, such as edges or corners. After each convolutional layer, a pooling layer is added to reduce the spatial dimensions of the feature maps. This helps to decrease the number of parameters and also helps to generalize the features by reducing the noise. In order to get the original image size after the pooling layer, the upsampling layer is added which increases the spatial dimensions of the feature maps. The decoder layers take the upsampled feature maps and combine them to create the final segmentation mask. The activation function is applied to the output of each layer to introduce non-linearity. Finally, a loss function is applied to the output segmentation mask and the ground truth mask to calculate the error between them. The error is then backpropagated through the network to update the weights.

CLASSIFICATION:

Leaves are affected by bacteria, fungi, virus and other insects. In this module implement Convolutional neural network algorithm with multi-class to classify the leaf image as normal or affected. Layers are constructed based leaf features such as color, shape, textures. Then layers can be constructed with conditions to categorize the preprocessed leaves.

CNN has multiple layers that process and extract important features from the image. There are mainly 4 steps to how CNN works

Step : 1 Convolution Operation with Relu Activation Function

The objective of the Convolution operation is to find features in the image using feature detectors to preserve the special relationship between pixels. Relu activation function is used to break linearity and want to increase non-linearity because images are themselves are highly non-linear.

Step: 2 Pooling

Pooling is a down-sampling operation that reduces dimensions and computation, reduces overfitting as there are fewer parameters and the model is tolerant towards variation and distortion.

Step: 3 Flattening

Flattening is used to put pooling output into one dimension matrix before further processing.

Step: 4 Fully Connected Layer

A fully connected layer forms when the flattening output is fed into a neural network which further classifies and recognized images. And also implement multiclass classifier; we can predict diseases in leaf images with improved accuracy.

WORKING OF CNN

A Convolutional Neural Network (CNN) is a deep learning architecture designed for processing and interpreting visual data, particularly images and videos. It has had a transformative impact on computer vision and pattern recognition tasks. CNNs are characterized by their intricate network of layers that collectively enable the automatic extraction of meaningful features from input data, allowing the network to understand and classify complex visual information.

In the context of plant disease detection, Convolutional Neural Networks (CNNs) play a pivotal role in automating the process of identifying and classifying plant diseases based on leaf images.

This technology leverages its deep learning capabilities to extract intricate visual features from the input images, enabling it to discern subtle differences between healthy and diseased plant leaves. With an extensive dataset that includes a diverse range of plant species and disease types, CNNs are trained to learn and recognize unique patterns and signatures associated with various diseases. Through multiple layers of convolutional and pooling operations, the model identifies local and global features, ultimately making informed predictions about the presence and type of disease.

The versatility and accuracy of CNNs have made them an invaluable tool in modern agriculture, assisting farmers and researchers in early disease detection and crop management, ultimately contributing to healthier and more productive crops.

CNN (Convolution Neural Network) is one of the methods to detect whether the plant has a particular disease by taking a picture of the plant leaves and feeding it to a model to know the results. Using CNN the disease in the plants is identified and has proven the results with high accuracy.

V.RESULTS AND DISCUSSION

The results from various studies indicate that image processing combined with machine learning, particularly Convolutional Neural Networks (CNNs), significantly enhances the accuracy and efficiency of plant disease detection. These approaches outperform traditional manual methods by enabling early, automated, and precise identification of diseases, ultimately leading to improved crop management and reduced losses. However, challenges remain in real-world application due to environmental variability, limited datasets, and computational demands. Continued advancements in model robustness, mobile deployment, and integration with sensor data are essential for making these technologies more accessible and practical for widespread use in agriculture.

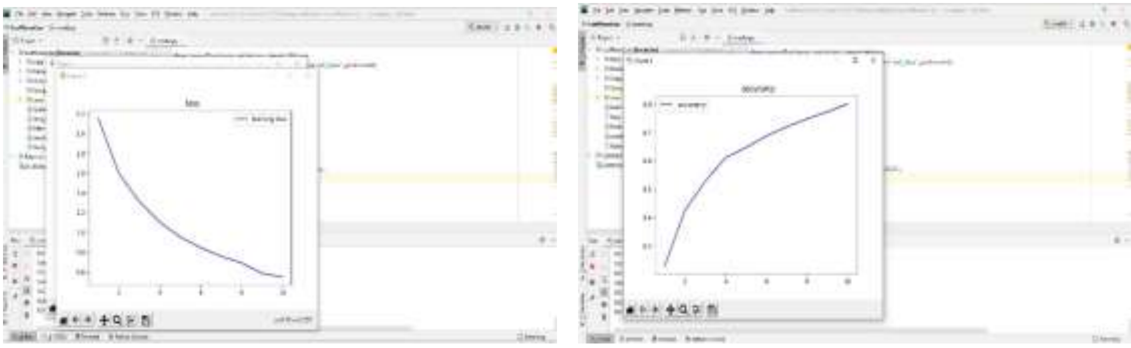

Fig:2Loss And Accuracy

VI.CONCLUSION

In conclusion, image processing and machine learning techniques, especially CNNs, offer a powerful solution for accurate plant disease detection. These methods improve yield quality by enabling early diagnosis and reducing crop loss. Future work should focus on real-world adaptability and farmer-friendly implementations.

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