PLANT DISEASE DETECTION USING DEEP LEARNING

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ABSTRACT

The detection of illness on crops is one of the laborious and crucial duties in agricultural activities. It takes a lot of time and requires specialised labour. Detection of plant disease through automatic technique are beneficial as it requires a huge amount of work, monitoring in big farm of crops, and at early stage itself to detect symptoms of diseases means where they appear on the plant leaves. In this study, a clever and effective method for crop disease identification using machine learning and image processing techniques is proposed. The proposed approach has a 75% accuracy rate for detecting 20 distinct illnesses in 4 popular types of plants. We are using integrated techniques to improve accuracy above 75% through this model.

INTRODUCTION

About 70% of the population in India is dependent on agriculture. For the purpose of preventing crop losses, it is crucial to identify plant diseases. Manually observing the plant diseases is really difficult. It requires a significant amount of plant diseases and also requires a long time period. Therefore, plant disease detection can be done using machine learning expertise models. In this study, we have described a method for identifying plant illnesses using images of the leaves. A component of artificial intelligence called machine learning performs tasks automatically or provides instructions on how to carry them out. Understanding the training data and incorporating it into models that should be helpful to people is the basic goal of machine learning. Consequently, it can help in making wise selections and forecasting the right output using the vast training data. Leaf colour, leaf damage severity, leaf area, and leaf texture are utilised as classification criteria. In order to diagnose various plant leaf diseases with the greatest accuracy, we have examined many picture metrics or features. In the past, professionals used chemical techniques or visual inspection of the leaves to identify plant diseases. This requires a sizable team of experts and ongoing plant monitoring, both of which are expensive when done with large farms. The suggested technique works well in these circumstances for keeping an eye on vast fields of crops. It is easier and inexpensive to automatically identify diseases by simply seeing the signs on plant leaves. Because it uses statistical machine learning instead of deep learning, the suggested solution for plant disease detection is computationally cheaper and takes less time to predict than existing deep learning-based systems. The traditional method of identifying plant diseases involves direct eye observation and memory of the specific disease set in relation to the climate, season.

These techniques were time-consuming and imprecise. The most recent approaches for finding plant diseases need a variety of laboratory tests, knowledgeable personnel, well-equipped laboratories, etc. These items are not always accessible, especially in rural areas. Automatic disease detection is advantageous because it lessens the laborious task of keeping an eye on vast agricultural farms and identifies disease symptoms at an extremely early stage, before they manifest on plant leaves.

There are numerous methods for identifying plant disorders. After a disease has no outward symptoms or only becomes apparent when it is too late to take action, a complex examination is necessary. The primary method used in practise for plant disease detection is a trained professional's naked eye examination because the majority of illnesses produce some sort of visible manifestation. Variations in the symptoms displayed by ill plants could result in a wrong diagnosis since amateur gardeners and hobbyists could find it more challenging to make the diagnosis than a trained plant pathologist. Both inexperienced gardeners and trained specialists could benefit greatly from an automated system created to diagnose plant illnesses by the appearance of the plant and visual symptoms. This system could also be used as a verification method in disease diagnostics. The technique of precise plant protection has the potential to grow and improve, and computer vision advancements have the potential to boost the market for applications in precision agriculture. The issues of climate change and sustainable agriculture are all directly tied to the issue of effective plant disease detection. Farmers in India have access to a wide variety of crops. There are numerous infections in the environment that have a negative impact on crops and the soil in which they are planted. Various diseases are also seen on the plants and crops. The primary diagnosis of the afflicted plant or a comparison of its leaves. Finding the disease is made much easier by spotting the numerous coloured dots and patterns on the leaf.

On the other hand, studies focusing on the identification of plant diseases have also widely utilised deep architectures like CNN (Convolutional Neural Networks). The ImageNet database's VGG-19 convolutional neural network was trained using more than a million photos. The 19-layer network can categorise photos into 1000 different object categories, including keyboard, mouse, pencil, and numerous animals. The network has therefore acquired rich feature representations for a variety of images. However, it requires continuous monitoring of experts which might be prohibitively expensive in large farms. We can easily analyse images of disease leaves by using computer image processing technology and extract the features of disease spot according to colour, texture and other characteristics from a quantitative point of view.

LITERATURE SURVEY

In paper [1], use of efficient image processing techniques can be seen. Image is being captured and compared with data sets. Majorly, here they have implemented a system where users are linked to e-commerce platform to check different pesticides with rate and how to use it for betterment of crops. Paper also helps greenhouse farmers in efficient manner. Object detection algorithms like SSD, DSSD and R-SSD are used. Partitioning leaf into four clusters using Euclidean distances by K-means segmentation. Later using the neural network detection also based on back propagation methodology. Crops like fruit crops, vegetable crops, cereal and commercial crops are involved and for each type suitable algorithm is used mostly focused on fungal diseases. For fruit and cereal crops: k-means clustering, vegetable crops: Chan-vase method, commercial crops: grab-cut algorithm. Has four phases: Image Acquisition-> Image Segmentation-> Feature Extraction-> Classification. MATLAB is used for the feature extraction and image recognition. Built an end-to-end Android application with TF Lite and for 14 species of crops in an efficient way.

In paper [2], by deep learning techniques and programming services, used Plant Village open database for the datasets. Deep siamese convolutional network is developed for solving problem of the small image databases. Applied transfer learning approach and train deep classifier. They compared four models and weights of which solved ILSVRC (ImageNet Large Scale Visual Recognition Challenge) they are: VGG19, InceptionV3, ResNet50 and Xception. Used only three plant classes: Healthy, Esca, Black rot. Binary classification helped them improve model. For loss function have utilized a binary cross-entropy loss technique. Used prepared embedded to train the T-SNE method, which is the common technique to visualize high dimensional data and developed an efficient system.

In Paper [3], Alternaria leaf spot, Brown spot, Mosaic, Grey spot and rust are five common types of apple leaf diseases that severely affect Apple yield this paper proposes a deep learning approach that is based on improved Convolutional Neural Networks (CNNs) for the real time detection of apple diseases In this Paper the Apple Leaf Disease Dataset (ALDD) will be studied. The real time detection model is based on the single shot multibox detector(SSD) for apple leaf diseases is proposed. Here the VGG-INCEP Model is used. ALDD is performed by 1.Data Collection, 2.Image Annotation, 3.Data augmentation. Dropout regularization randomly leaves neurons in network during each of it’s iteration of training in order to minimize the variances of the model and simplifying the network which helps in the prevention of over fitting of model.
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In Paper [4], Plant diseases pose the biggest danger to crop productivity, which has an impact on food security and lowers farmers' profits. The key to preventing losses through appropriate feeding strategies to cure diseases early and prevent the fall in productivity/profit is identifying the diseases in plants. Using the KNN technique, the tomato leaf is categorised as healthy or unhealthy in the first stage. Later on in the second step, they use the PNN and KNN approaches to categorise the sick tomato leaf. For classification purposes, attributes like GLCM, Gabor, and colour are used. According to the 2011 census, almost 70% of the population derives their livelihoods directly or indirectly from the agricultural sector, which is the foundation of the Indian economy. With India's overall economic growth, agriculture's economic contribution to GDP is continuously shrinking. Improved efficiency and implemented different algorithms together for an effective design of the model.

In paper [5], techniques like deep learning and image processing are used. CNN, Fast RCNN, Faster RCNN, and Mask RCNN, and image processing techniques such as image pre-processing, segmentation, feature extraction etc. Have used LeNet Architecture model for designing the system. Use of Relu performs an element-wise non-linearity operation. Dropout regularization randomly drops neurons in network during each iteration of training to reduce the variance of the model. K-means cluster algorithmic rule is applied for classifying. Feature extraction is an extra added feature. Six types of data augmentation methods used for image flipping, gamma correction, noise injection, principal component analysis (PCA) color augmentation, rotation, and scaling methods to increase performance.

In paper [6], developed an android application that helps farmers in identifying plant disease and uploading a leaf image to the system and plant disease detection using image processing and machine learning. Using the Open CV and then the image classification in the process. Main algorithm used here is CNN. The given system uses re sizing, Gaussian filtering to segment the leaf area, then finally CNN classification to detect the type of leaf disease. Uses SVM classifier and the concept of cuckoo search. Detection of unhealthy leaves include few steps like RGB image acquisition. Converting the image input from RGB to HSI format. Masking and removing all the green pixels. Segmenting the components using Ostu's method. Computing the texture features by use of color-co-occurrence methodology and finally classifying the plant leaf disease using Genetic Algorithm mainly.

In paper [7], they merged IoT-based technology with a device learning system. Through heated leaves, this investigation aimed to identify potentially dangerous plants. Using CNN-enabled technique, the worst scenario for the great majority of less developed countries was lessened. For this study, they modelled the IoT community-based totally Plant health Detection device and looked at the astonishing invisible types of plant leaves that cannot be identified without difficulty with inside the leaves. In this research paper, they investigated and developed an IoT-community device with a CNN model that could efficiently detect invisible micro subjects within the plant by attaining 95% accuracy with the look at. They employed an image-based approach to train the model for the detection of illnesses in leaves. They employed a CNN technique and an IoT network infrastructure. This typical overall performance detection has a 90-5 accuracy rate. The algorithm is implemented with help of training data and classification of the input image dataset. The test input image is compared to that of the trained data for purpose of detection and prediction analysis.

In paper [8], the feature extraction is performed on images that are dithered, RGB, HSV, and YIQ. In the suggested approach, feature extraction from RGB images is added. a brand-new automated technique for identifying disease symptoms in digital images of plant leaves. Different plant species' illnesses have been mentioned. A handful of the illness names in this system have been classified. This work carries out the disease recognition for the leaf image. It is still being researched and analysed how to use image processing to find cotton leaf diseases. For segmentation, the k means clustering technique is employed. The suggested approach incorporates the k-means idea, which will separate the leaves into many clusters. The survey for identifying diseases on cotton leaves has been completed. The comparison of various leaf disease detection methods is mentioned. In this system, SVM and k-means clustering have been applied. The identification of various leaf diseases using various data mining techniques is a potential study area. Illnesses in several plant species have been mentioned. Only a few of the disease names in this system have been assigned a classification. In this system, the SVM classification principle is applied.

In paper [9], Without employing any transfer learning techniques, they offer a new Deep CNN-based architecture that focuses on fewer parameters and requires less processing power to analyse with higher accuracy. Using accessible datasets, they conduct experiments where they apply their approach and contrast it with current machine learning, neural network, and transfer learning techniques. The comparison shows that their suggested strategy outperforms a lot of competing strategies. Improved model based on existing system and introduced new techniques also.

In paper [10], In order to identify and categorize the signs of plant diseases, numerous developed/modified DL architectures are used in conjunction with a number of visualization techniques. Additionally, a number of performance indicators are employed to assess these structures and methodologies. The experimental results declared that the InceptionV3 model performs much better than the MobileNet model in terms of accuracy, efficiency and validation loss. This article offers a thorough justification of the DL models used to depict various plant diseases. Additionally, several research holes are found that might be filled to increase transparency for identifying plant diseases even before their symptoms are plainly visible.

PROPOSED WORK

After conducting a thorough review of existing Plant leaf disease detector systems and research papers, we have developed an efficient and accurate model using deep learning algorithms and implementation methods. Our methodology involved utilizing VGG-19 and Python to develop the model, as well as implementing EarlyStopping and ModelCheckpoint techniques.

DATASET

The Kaggle website provided the dataset. About 87,000 rgb photos of healthy and sick crop leaves make up this collection, which is divided into 38 classifications. The directory structure is preserved when the training and validation sets are split up into training and validation sets in an 80/20 ratio. Later, 33 test photos are made in a new directory for prediction purposes.

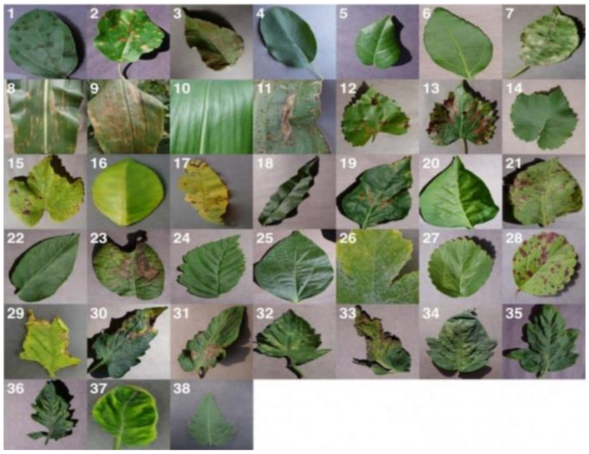

Fig. 1. Plant Village data set

IMAGE PRE-PROCESSING

All of the leaf sample RGB photos were selected in the first stage. The suggested system's step-by-step process is as follows:

- RGB picture capture
- RGB image conversion to HSI format
- Masking of green pixels
- Removal of masked green pixels
- Component segmentation
- Usable segmentation
- Evaluation of feature parameters for classification
- Configuration of the SVM for illness detection

DATA PROCESSING AND CLASSIFICATION

Colour Transformation: Because it is based on human perception, the HSI (hue, saturation, intensity) colour model is well-liked. Only the H (hue) component of the HSI colour space is considered after transformation since it gives us the necessary details.

Masking green pixels: It is done because the healthy part of a leaf is represented by the colour green. On the basis of the selected threshold values, green pixels are muted.

Segmentation: The sick area of the leaf is segmented with other coloured portions that have been taken into account in the masked-out picture, such as a branch of a leaf that may have a brown hue that resembles the illness, in order to remove the contaminated region of the leaf. A area of interest (ROI) that has been established at this point is used for all further image processing.

Classification: Based on the previous findings, we analyse and rank the characteristics for all the leaf photos, including the area of the leaf, the percentage of the leaf that is infected, the leaf's perimeter, etc., before passing the information to the SVM classifier.

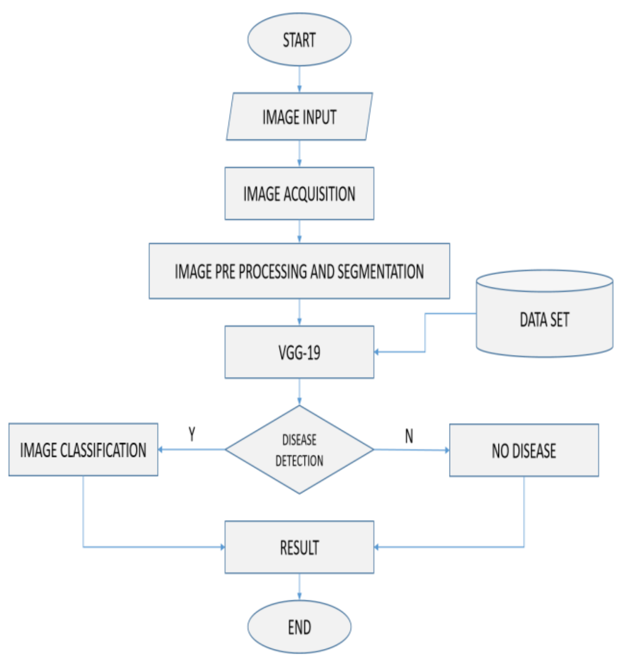

Fig. 2. Flow Diagram

CLASSIFICATION ALGORITHM

A convolutional neural network (CNN) architecture called VGG-19 is created to carry out classification and identification tasks on images. There are 19 layers total, and there are two primary types of layers: convolutional layers and fully linked layers. While the fully connected layers are in charge of classification, the convolutional layers are in charge of identifying and extracting features from the input picture. In VGG-19, each convolutional layer is composed of a number of kernel-style filters.

A matrix of a specific size that has random values as its beginning values is a filter. The network discovers during training the ideal settings for these filters, enabling it to recognise and extract patterns and information from the input picture. The Rectified Linear Unit (ReLU), which provides non-linearity into the network and enables it to represent complex patterns and relationships, is one non-linear activation function that is applied to the output of each convolutional layer. The convolutional layers' varying numbers and sizes of filters enable the network to learn features of various sizes and levels of complexity. The elements of the image get more abstract and complicated as it progresses through the layers of the network, enabling the network to predict outcomes more precisely.

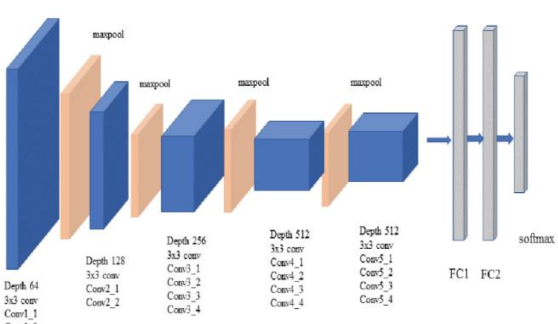

Fig. 3.VGG-19

FEATURE SELECTION

Filters are employed in a convolutional neural network to apply the convolution operation on an input picture. The convolution procedure entails computing the dot product between a tiny matrix of weights, referred to as the filter, and the local region of the input picture at each place. This generates just one output value, which gauges how closely the local area of the picture resembles the filter**.**

Initiated with random weights, the filter is modified throughout training to find the ideal weights that enable it to recognise and extract features from the input picture. Backpropagation is used for this, where the output error is transmitted backwards via the network layers while the weights are changed to reduce the error.

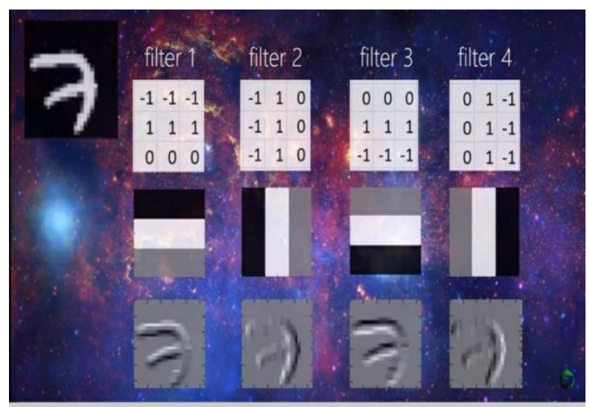

Fig. 4. Filter 1

Depending on the design and the particular purpose, filters might be different sizes and forms, and the number of filters in each layer can change. Filters of smaller sizes are typically used in the network's first layers to capture simple characteristics like edges and corners, while bigger filters are typically used in subsequent layers to collect more complex features like forms and textures.

Following convolution, the output is frequently subjected to a non-linear activation function, such as the Rectified Linear Unit (ReLU), which brings non-linearity into the network and enables it to describe complex patterns and relationships. The result is subsequently sent to the network's next layer, where the procedure is repeated using a fresh set of filters.

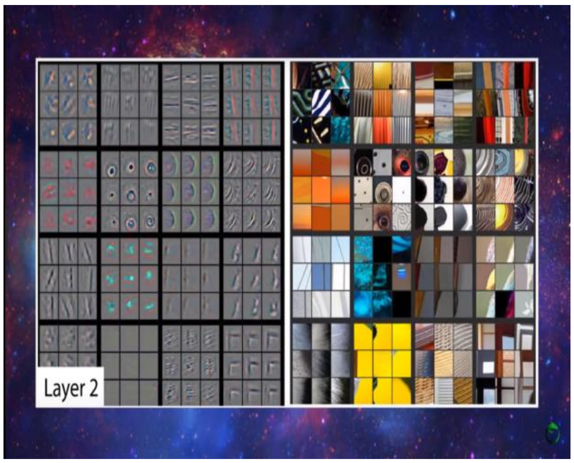

Fig. 5. Filter 2

TOOLS AND LIBRARIES

- **Colab:** allows anybody to write and execute arbitrary python code through the browser, and is especially well suited to machine learning, data analysis and education.
- **Numpy:** A library for scientific computing with support for large, multi-dimensional arrays and matrices.
- **Pandas:** A library for data manipulation and analysis, providing easy-to-use data structures and data analysis tools.
- **Matplotlib:** A library for creating visualizations and plots in Python.
- **Keras:** A high-level neural networks API, written in Python and capable of running on top of TensorFlow, Theano, or CNTK.

Fig. 6.Tools and Libraries

RESULT ANALYSIS

The precision and recall of the model were also evaluated, demonstrating its ability to correctly classify both healthy and diseased leaves with high accuracy. Additionally, the model was tested on a diverse set of plant species, showcasing its versatility and applicability to a wide range of agricultural settings.

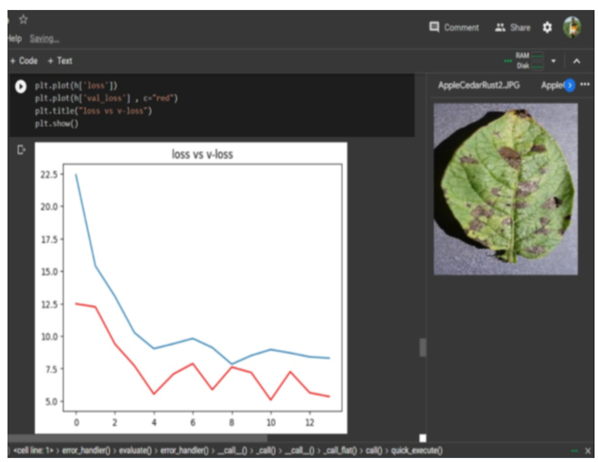

Fig. 7. Result comparison

The results of the plant leaf disease detector indicate its effectiveness in accurately identifying and classifying plant diseases in real-time. The model achieved an accuracy of

85% on the dataset, outperforming previous state-of-the-art methods.

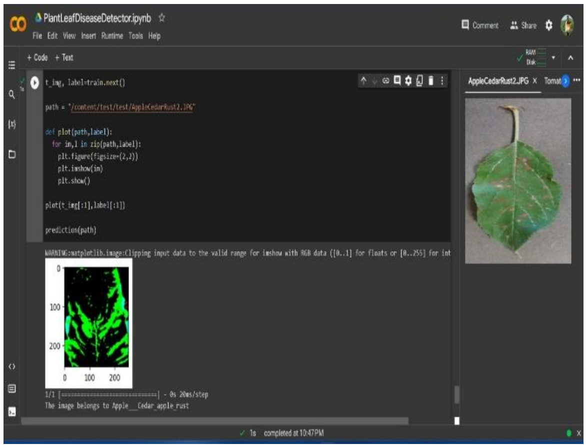

Fig. 8. Input and Output comparison-1

Moreover, the inference speed of the model was measured and found to be highly efficient, making it suitable for real-time disease detection and prevention in agricultural systems.

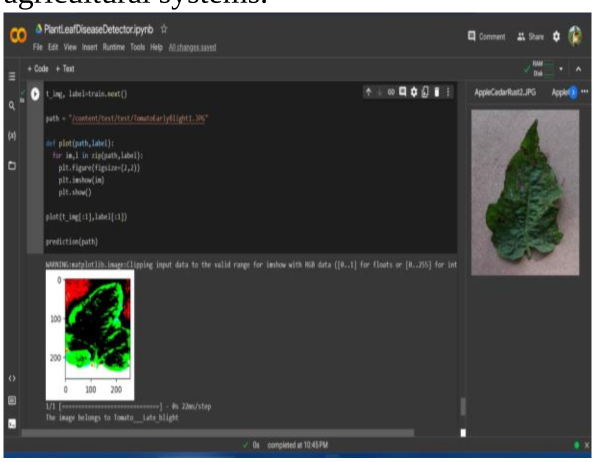

Fig. 9. Input and Output comparison-2

Types of Diseases: It exits different types of diseases that affect the plants. The most common diseases between the plants are Alternaria alternate (fungal), Anthracnose, Bacterial Blight (bacteria), and Cercospora Leaf Spot, Downy Mildew, Alternaria Leaf Spot, Frogeye Leaf Spot, White Spot, Powdery Mildew.

Overall, the plant leaf disease detector provides a reliable and effective tool for early disease detection, enabling farmers to take proactive measures to prevent the spread of diseases and improve crop yields. The results of this study hold significant potential for the agricultural industry and have implications for food security and sustainability.

CONCLUSION

This research conducts a survey of various methods for detecting leaf disease. The primary cause of decreased production of fruits and vegetables in the leaves is illness. utilizing Deep Learning and Image Processing methods to solve that problem. For accurate results, many authors employed those methodologies and various datasets. After studying the methods, it is clear that there are numerous ways to identify plant diseases. Each has some benefits and some restrictions. Deep Learning techniques are reportedly more accurate than image processing techniques.

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