Automatic Plant Disease Detection and Alert System Technique for Agricultural Farms

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Abstract

Plant diseases provide the largest risk to the safety of food. The quantity and quality of agricultural goods might be drastically reduced by them. The main problem facing the agriculture industry is the identification of plant diseases. The automated detection and diagnosis of plant diseases has become a common practice in recent years thanks to the development of machine learning and computer vision techniques. Based on their ability to reliably identify and categorize damaged plants based on their visual characteristics, these strategies have demonstrated encouraging outcomes. Computer vision issues involving picture categorization can be successfully handled by convolutional neural networks (CNN). A web-based tool was created to diagnose plant diseases using faulty leaf images and a suggested model that can both detect the illness and suggest a course of action. The used images dataset includes 6697 leaf photos from three different crops such as tomato, potato, apple, corn, grape and strawberry divided into 37 different classes, including 9 classes for tomato disorders and 1 class for healthy conditions, 2 classes for potato disorders and 1 class for healthy conditions, and 3 class for pepper disorders and 1 class for healthy conditions. The suggested model, according to the findings of our experiment, has the greatest training accuracy of 98.35% and validation accuracy of 94.74%.

1. Introduction

A. Plant Disease Identification

Plant diseases are one of the major challenges faced by farmers and gardeners worldwide. Plant diseases are caused by various microorganisms such as fungi, bacteria, viruses, and nematodes, as well as by abiotic factors such as nutrient deficiencies, environmental stress, and physical damage. These diseases can cause significant losses in crop yields, quality, and profitability. Visual inspection is looking at the plant for any physical disease indicators, such as wilting, discoloration, or leaf spots. Plant tissues, soil, and water samples are examined in laboratories for the presence of pathogens or disease-causing organisms. Sensors are used in remote sensing techniques to identify changes in plant growth or health that could be signs of illness. However, these threats are not new (Tai et al., 2014), and they include climate change, pollinator decline, and other threats. In recent years, there has been a growing interest in using technology to detect plant diseases more accurately and efficiently. The development of advanced imaging technologies, machine learning algorithms, and other innovative tools has enabled the creation of automated systems for plant disease detection. The technique of spotting the presence of plant pathogens or disease signs before they seriously harm the plant is known as plant disease detection. Early disease diagnosis is essential for efficient disease management because it enables producers to take the necessary precautions to stop or slow the illness's progress.

B. Diagnosis of Plant Disease using Deep Learning

Artificial neural networks are used in deep learning to examine vast volumes of data and provide predictions or classifications. Deep learning has been utilized more and more in recent years to identify and diagnose plant diseases. Deep learning has the major benefit of being able to detect patterns and characteristics in pictures and other forms of data without having to be explicitly programmed. This is accomplished using a technique known as convolutional neural networks (CNN's), which are intended to identify patterns and characteristics in images.

With the use of vast datasets of photos of both healthy and ill plants, deep learning algorithms may be taught. The algorithm gains the ability to recognize particular characteristics in the photos that are connected to either healthy or ill plants. The algorithm may be used to accurately categorize fresh photos as healthy or unhealthy once it has been trained. Deep learning can handle enormous datasets like Plant Village and complicated photos, which is one of its benefits for detecting plant diseases. Moreover, real-time uses of this technology enable rapid and precise illness identification in the field. Here, we report on a convolutional neural network-based analysis of 54,306 pictures to classify 26 illnesses across 14 crop species. By predicting the right crop-disease match out of 38 different classes, our models' performance is evaluated.

C. Problem Statement and Overview

Agriculture is one of India's key economic sectors. Plant diseases have the potential to seriously harm crops, reducing yields and costing farmers money. To stop the spread of plant diseases and lessen their effects, early detection and management are essential. Visual inspection by professionals is a traditional way for identifying plant diseases, but it can be time-consuming, expensive, and subjective. Using cutting-edge imaging technologies and machine learning techniques, there is rising interest in creating automated systems for plant disease identification to address these issues. Advanced machine learning techniques are used to evaluate photos and data in order to create automatic plant disease detection systems that are extremely accurate.

Automated plant disease detection has the potential to be more economical than conventional techniques since it requires less manual labor and can identify diseases early. Symptoms of plant diseases are frequently seen on a plant's leaf. It takes a lot of work to manually identify plant disease using leaf photos and the assistance of experts. Therefore, it is necessary to create computational techniques that would automate the process of disease identification and classification using leaf images, resulting in greater crop production and increased farmer profitability. These images can be taken with a camera or with other sensors, and they can be analyzed using a variety of methods to extract information. Human scouting is currently an expensive and time consuming method of illness diagnosis.

2. Overview

As a result, the proposed system has the solution that will help the farmer for detecting plant disease using image processing technique which has better accuracy in predicting the disease than the existing system.

A. Convolutional Neural Network

Deep learning network architectures like convolutional neural networks (CNN or ConvNet) learn directly from data, doing away with the requirement for human feature extraction. CNN's can recognize objects, persons, and scenes in photographs by looking for patterns in the images.

B. Artificial Intelligence

The ability of machines to carry out tasks that ordinarily require human intelligence, such as sensing, reasoning, learning, and decision-making, is known as artificial intelligence, or AI. The creation of algorithms and computer systems that can analyze data, spot patterns, and make predictions based on that data is artificial intelligence (AI).

Artificial intelligence has many sub fields, including machine learning, robotics, computer vision, and natural language processing. In ML, also known as machine learning, algorithms are trained to learn from data rather than being explicitly written. Large data sets may be used by ML algorithms to identify patterns and make predictions, which enables them to get better over time as they are exposed to more data. ML is used in a wide range of applications, including image recognition, speech recognition, natural language processing, and predictive analytics.

3. Literature Review

A. A large benchmark data set, a visual area, and a loss re weighting technique

This paper by Jiang, S Liu, X., Wang, L., Min, W., Wang, L., & Mei, S. describes a novel approach for disease classification. The authors first collected a large data set of cervical images, consisting of over 10,000 images. The images were labeled with the corresponding precancerous stage, and were divided into training, validation, and test sets. This approach involves dividing each image into multiple regions, and weighting the loss function differently for each region. This allows the network to focus more on important regions of the image, and to down-weight less important regions.

B. Detecting bacterial blight in pomegranate plants using image-based methods

This paper by Prashanthi, V., & Srinivas, K. presents a novel approach for detecting bacterial blight disease in pomegranate plants using image processing techniques. The damaged fruit area's edges are determined in terms of pixels after segmentation. The percentage of fruit infections is calculated using pixel counts, and remedies such as biological and chemical ones are offered depending on the disease that the fruit is affected with

C. Black rot disease in Vitis vinifera grape vines is diagnosed using color-based segmentation and machine learning.

This paper by Rajpal, N presents a new approach for employing color-based segmentation and machine learning, a novel method for identifying the black rot disease in grape plants. Using color-based image processing techniques, plant diseases can be segregated or isolated. The color % ratio has been shown to be an effective method for detecting the disorder if the sick area has a distinct color from the unaffected area. With SVM's RBF Kernel, the system operates at its best

D. Techniques for detecting plant diseases using machine learning

This article by Raghavendra, B. K., Nagaveni, V., & Shruthi, U., provides a comprehensive review of various machine learning classification techniques that have been used for plant disease detection. The authors first provide an overview of the challenges associated with plant disease detection, such as the need for accurate and timely diagnosis to prevent the spread of disease and minimize crop losses. They then review the various machine learning techniques and deep learning methods that have been used for plant disease detection. The goal is to identify the disease at an early stage, enabling farmers to take preventive measures and reduce crop losses.

E. An approach using machine learning to detect plant illnesses in leaves

Technology is used in every facet of life, according to this paper by Deepa, R. N., and Shetty, C. Plant diseases can be difficult for farmers to manually identify. Additionally, farmers do not have easy access to professional advice. It is preferable to utilize an automated technique to find plant diseases. The recommended approach to identifying plant leaf diseases included machine learning techniques.

F. Using the KNN classifier to identify and categorize groundnut leaf diseases

This paper focuses mostly on diseases that affect groundnut crops, such as early and late spot bud necrosis and rust studied by Jothi, G. A. P., Srinivasan, P., M. P., Devi, K. S., and. Vaishnnave, With efficiency, we only distinguished between 4 different diseases. By including more classifiers in the feature extraction process for the various groundnut crop diseases, the examination work may be further expanded to reduce the likelihood of incorrect classification.

G. Using image processing and machine learning to classify plant leaf diseases

The paper by Gupta, S. C., Hans, P., and Sharma, P. presents a new approach employing machine learning and image pre processing methods, for recognizing and categorizing plant leaf diseases. Images of plant leaves both healthy and afflicted with various diseases were gathered by the authors into a data set. They then applied image pre processing techniques, including image enhancement and noise removal. The model can also contain the treatments for the ailment that is classified. The model can then be made available on both the Android and iOS platforms to reach out to farmers who can actually use the suggested system.

4. Analysis of Existing System

A. Existing System

At first, plant disease detection is done by visual inspection. The best findings are then extracted from the photos using image processing techniques. The existing system uses K-means clustering, which requires the user to manually input the number of clusters (k), has problems grouping data when the clusters sizes and densities fluctuate. This method uses five steps: picture acquisition, undesirable noise reduction, k-means segmentation, leaf feature extraction, and green pixel masking. The leaf images are initially imprisoned and gathered in the database. The RGB image acquisition is completed next. K-means clustering frequently uses image segmentation. For the image, feature extraction is suggested. The photos are taken from the database to determine the health of the leaf. The system is inaccurate, and expanding the data set requires more time. As a result, learning requires more time, and the accuracy suffers as a result. The approach provides accuracy that is 80%.

5. Analysis of Proposed System

A. Proposed System

The objective is to use image processing techniques to identify illnesses in a leaf and provide an accurate treatment by offering the crop the necessary control measure. The proposed system uses dense net architecture that builds on the idea of skip connections in residual networks, which allow the network to learn residual functions. The dense block has numerous levels, each of which accepts as input the feature maps from all layers before it. As a result, the network's connectivity pattern becomes dense, enhancing the efficiency of information transfer. In Dense Net, the feature reuse process involves concatenating each dense block's output with the subsequent dense block's input.This allows the network to reuse features more effectively and reduce the number of parameters that must be learned because each layer has direct access to the features of all levels that came before it.

6. Implementation

A CNN model is included with densenet architecture which falls among the traditional networks. The regular ResNet structure is displayed where the network is organized into blocks of layers, each of which contains multiple convolutional layers.

The input can be added directly to the output of the block which bypass portions of the convolutional layers inside a block which enables the network to learn residual functions that can be easily optimized, even in very deep networks.

A. Convolution Layer

When a feature vector or picture is entered into a neural network, it is transformed through a number of hidden layers, frequently utilizing nonlinear activation functions. Each set of neurons in each buried layer is completely linked to every other neuron in the layer below it. A neural network's last layer, which displays the network's final output classifications, is also fully linked.

Each node assigned for the inputs is divided into numerous hidden layers for classification purposes, therefore there will be a lot of weight assigned and clearly a ton of calculation. Important aspects of the image should be extracted first in order to solve this issue.

We can leave some undesirable pixels back without sacrificing the quality of our product by identifying these crucial qualities. By using this technique, we can provide the model real-world image recognition at a human level. Simply searching an image by moving a filter (kernel) across it to find various aspects of the image is convolution. Kernels are merely 2D matrices with various weights. Basically, as this kernel passes across the image, the pixel values are replaced with the average of the weighted sum of their weight for that particular section of the image.

B. Pooling Layer

Pooling layers perform spatial down sampling of an image, which reduces the computational complexity of the network and helps prevent overfitting. As part of the pooling operation, the input feature maps are divided into a number of non-overlapping regions, often squares measuring 2 by 2 or 3 by 3, and the maximum or average value from each region is used as the output.

(i) MAX POOLING

Max pooling is the most popular kind of pooling procedure, where the output is the highest value possible for each zone. By eliminating unnecessary data and lessening the impact of tiny input fluctuations, this aids in capturing the most important features of the input feature maps, such as edges and corners.

(ii) AVG POOLING

The average pooling layer's main objective is to down sample the input feature map while keeping the most crucial details. This makes the network more effective by lowering the amount of parameters and processing requirements that are needed.

C. Batch Normalization

The fundamental goal of batch normalization is to normalize each layer's output by dividing by the mini-batch of inputs' standard deviation and removing its mean. Batch normalization allows for higher learning rates, which can further speed up the training process and improve the final accuracy of the model which makes the network more stable during training.

WORKING:

- During each training iteration, a mini-batch of inputs is fed into the network
- The mean of the mini-batch is subtracted, and its standard deviation is divided, to normalize the output of each layer in the network.
- The result is then altered using gamma and beta, two learnable parameters.
- The transformed output is then passed to the next layer in the network for further processing.

7. Module Description

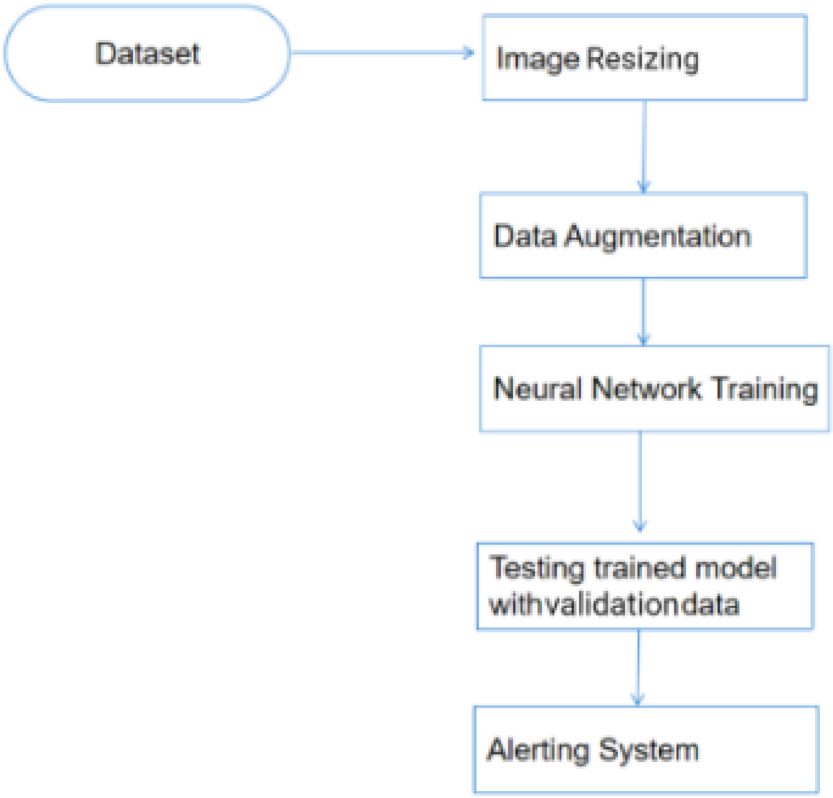

Fig. 1. Block Diagram of proposed system

1. DATASET PROCESSING

- A dataset is a collection of data that is used for training, testing, and evaluating machine learning models which typically consists of a set of input examples and their corresponding output labels

- The usage of acceptable datasets is required for both the object recognition research training phase and the assessment of the performance of recognition algorithms.
- Data wrangling, sometimes referred to as data cleaning, is the act of cleaning and manipulating raw data into a format appropriate for analysis.
- Data cleansing, data transformation, data integration, data reduction are some important steps in the pipeline for data analysis.

2. ACQUISITION OF IMAGES

In order to analyze images using image processing techniques, the process of image acquisition involves taking or gathering images using a variety of instruments. Input image is resized with the dimensionality of 160 x 160 according to the parameters mentioned. Resizing photos as part of the pre-processing step is frequently an experimental activity when CNN algorithms are used with input images. Images in large, complicated databases frequently differ in size.

3. AUGMENTATION PROCESS

The augmentation process involves applying a series of transformations to each image in the training set, such as rotation, translation, zooming, flipping, and changing brightness or contrast. These transformations create new images that are similar to the original ones but are slightly different. By adding these new images to the training set, the model learns to be more robust and generalize better to unseen data.

4. NEUTRAL NETWORK TRAINING

Neural network training is the process of adjusting the parameters of a neural network in order to minimize its error on a given dataset. This process involves feeding the network input data, computing the output, and comparing it to the desired output in order to calculate an error.

We can alter the network's functionality by changing the weights, which makes it feasible to improve it. A function that performs better than the first one is what we're looking for. The issue of training is the same as the issue of loss function minimization.

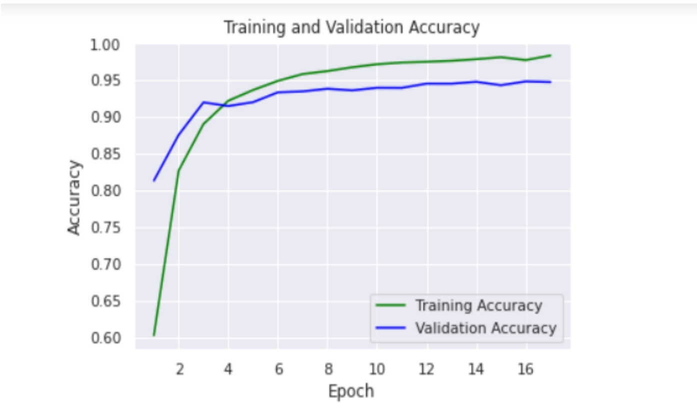

Fig. 2 - Accuracy in training and validation

Fig. 3 – Loss in learning and validation

5. RESULT ANALYSIS

Once a neural network is trained on a dataset of labeled images, it can be used to classify new, unseen images. In the case of medical imaging, the trained network can be used to identify whether an image contains a certain disease or condition.

```
Apple___Cedar_apple_rust

<matplotlib.image.AxesImage at 0x7f21ac28da10>
```

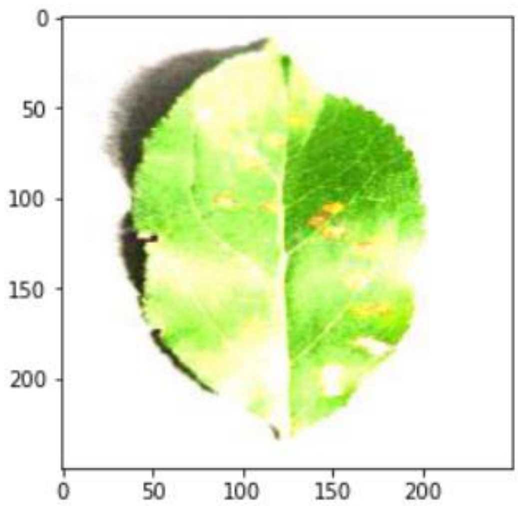

Fig.4 - Identification of disease

8. Conclusion

The identification of plant diseases is a fascinating and useful subject. However, a lack of rigorous research and a sizable dataset has prevented a thorough examination of this issue. The hardest part of creating such a dataset is giving it a structure that makes sense from both an agricultural and an image processing standpoint. Additionally, based on their individual properties, we provide a framework for plant disease recognition.

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