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CROP DISEASE DETECTION USING CNN

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Abstract : Crop diseases are a major challenge in agriculture, causing significant yield losses and threatening global food security. In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown great promise in detecting crop diseases. we propose a deep learning approach for crop disease detection using CNNs. Our method is trained on a large dataset of labeled images of healthy and diseased crops and optimized using backpropagation and stochastic gradient descent. We evaluate our approach on several crop types and disease categories and compare its performance with traditional methods. Our experimental results demonstrate that the proposed approach achieves high accuracy and outperforms traditional methods in detecting crop diseases. Moreover, the approach is shown to be robust and effective across different crop types and disease categories, indicating its potential for real-world applications. Overall, our proposed approach provides an effective and efficient solution for crop disease detection, which can help farmers make timely decisions and take necessary actions to prevent yield losses and ensure food security.

INTRODUCTION- Crop disease detection is a critical aspect of modern agriculture that plays a vital role in ensuring food security and preventing substantial economic losses. With the increase in global population and the growing demand for agricultural

products, the timely and accurate identification of crop diseases is of utmost importance. Conventionally, farmers have relied on visual inspection and expert knowledge to diagnose and mitigate diseases. However, this manual approach is subjective, time-consuming, and often prone to errors. To overcome these limitations, advanced technologies, such as Convolutional Neural Networks (CNNs), have emerged as powerful tools for automated crop disease detection. The rise of CNNs, a type of deep learning algorithm inspired by the functioning of the human visual system, has revolutionized the field of image classification. CNNs excel at extracting meaningful features from images and are particularly well-suited for tasks involving pattern recognition. In the context of crop disease detection, CNNs can effectively analyze digital images of plant leaves, stems, or fruits and accurately identify the presence of diseases or abnormalities. This technology offers several advantages over traditional methods, including increased accuracy, speed, and scalability. By leveraging large datasets of labeled plant images, CNN models can be trained to learn the distinctive patterns and characteristics associated with different crop diseases. Once trained, these models can then be applied to new, unseen images to automatically classify and diagnose the presence of diseases. Additionally, the continuous advancements in computing power and the availability of powerful GPUs have made it feasible to deploy CNN-based disease detection systems on portable devices, enabling farmers to access real-time information in the field. Overall, the application of CNNs in crop disease detection has the potential to revolutionize agricultural practices, empower farmers, and contribute to sustainable food production in a rapidly changing world.

METHODOLOGY:

CNNs (Convolutional Neural Networks) can be used for plant yield detection in various ways. Here are a few steps that can be taken to use CNNs for plant yield detection: Data Collection, Data Preparation, Architecture, etc. Overall, CNNs can be a powerful tool for plant yield detection, enabling growers to optimize their crop yield and improve their bottom line. In deep learning, Convolutional Neural Networks (CNNs) are a type of artificial neural network commonly used for image and video recognition tasks. They are inspired by the structure and function of the visual cortex in animals, which is specialized to detect patterns in visual stimuli.

A CNN consists of a series of convolutional layers, which apply filters to the input data in order to extract features, followed by one or more fully connected layers, which perform classification or regression based on the extracted features. The convolutional layers are responsible for learning local features such as edges, corners, and textures, while the fully connected layers use these features to make predictions. The key advantage of CNNs over traditional machine learning methods for image recognition tasks is their ability to automatically learn features from the data, rather than relying on hand-engineered features. This makes them more flexible and scalable, as they can be trained on large datasets without requiring extensive feature engineering . We have used Convolutional neural networks (CNNs) use self-optimizing artificial neurons that work similarly to convolutional neural networks (ANNs). CNN has three layers: a convolutional layer, a pooling layer, and a fully connected layer. Convolutional layers have as their main purpose the generation of features for an image by sliding a smaller matrix (a filter or kernel) over the entire image and generating feature maps. Reducing the feature maps kept the most critical features of the data. To continue to the output layer, which will output the prediction, we flatten the previous layer's input matrix by linking the bottom-most neurons in the previous layer to the top-most neurons in the next layer. The model's architecture will allow it to train using fewer datasets, which reduces the amount of parameter learning required. CNN has been very good at machine learning applications, and it improves the accuracy and efficiency of applications. In a classification query, feature extraction is a more critical task for image recognition.

CONVOLUTION LAYER: • A convolutional layer is the main building block of a CNN. • It contains a set of filters (or kernels), parameters of which are to be learned throughout the training. • The size of the filters is usually smaller than the actual image.

ACTIVATION-RELU LAYER: • A non-linearity layer in a convolutional neural networkconsists of an activation function that takes the feature map generated by the convolutional layer and creates the activation map as its output • In crop disease detection, ReLU can be used in the convolutional neural network (CNN) layers to extract features from the input images. The ReLU activation function can help to identify the areas of the input image that are important for distinguishing between healthy and diseased crops

MAXPOOLING: Pooling layers are used to reduce the dimensions of the feature maps. Thus, it reduces the number of parameters to learn and the amount of computation performed in the network

FULLY-CONNECTED LAYER: A fully connected layer refers to a neural network in which each neuron applies a linear transformation to the input vector through a weights matrix. As a result, all possible connections layer-to-layer are present, meaning every input of the input vector influences every output of the output vector.

MATHEMATICAL MODEL:

Convolution:
The convolution operation in CNNs is used to extract features from input images. Given an input image and a set of learnable filters (kernels), the convolution operation is defined as follows: Output feature map (activation map) at position (i, j) = sum of element-wise multiplication between the filter and the input image patch centered at position (i, j).

This can be expressed mathematically as:

$$H(i\,,j)=\sum m\sum n\; I(i+m\,,j+n).k(m\,,n)$$

where H(i, j) is the value in the output feature map at position (i, j), I(i+m, j+n) represents the pixel value in the input image at position (i+m, j+n), and K(m, n) represents the corresponding filter coefficient at position (m, n).

Pooling:
Pooling operations, such as max pooling or average pooling, are used to down sample the feature maps and reduce the spatial dimensionality. The pooling operation computes a single output value for a region of the input feature map. The mathematical formulas for max pooling and average pooling are as follows:

$$H(i\,,j)=max\ m\ max\ n\ F(i+m\,,j+n)$$

Max pooling:

$$H(i\,,j)=max\ m\ max\ n\ F(i+m\,,j+n)$$

Average pooling:

$$H(i\,,j)= 1/m\text{-}n \sum m\sum n\ F(i+m\,,j+n)$$

Activation functions:
Activation functions introduce non-linearity into the CNN model and help in capturing complex patterns. Some Unit), sigmoid, and tanh. The mathematical formulas for these activation functions are:

Rectified Linear Unit (ReLU): ReLU is the most popular activation function in CNNs. It sets all commonly used activation functions in CNNs include ReLU .

Sigmoid: The sigmoid activation function squashes the input values between 0 and 1. It is defined as f(x) = 1 / (1 + exp(-x)). Sigmoid is useful in models where we want to interpret the output as probabilities.

Hyperbolic Tangent (Tanh): Tanh is similar to the sigmoid function but squashes the input values between -1 and 1. It is defined as f(x) = (exp(x) - exp(-x)) / (exp(x) + exp(-x)). Tanh is centered at 0 and is sometimes preferred over sigmoid as it provides stronger gradients.

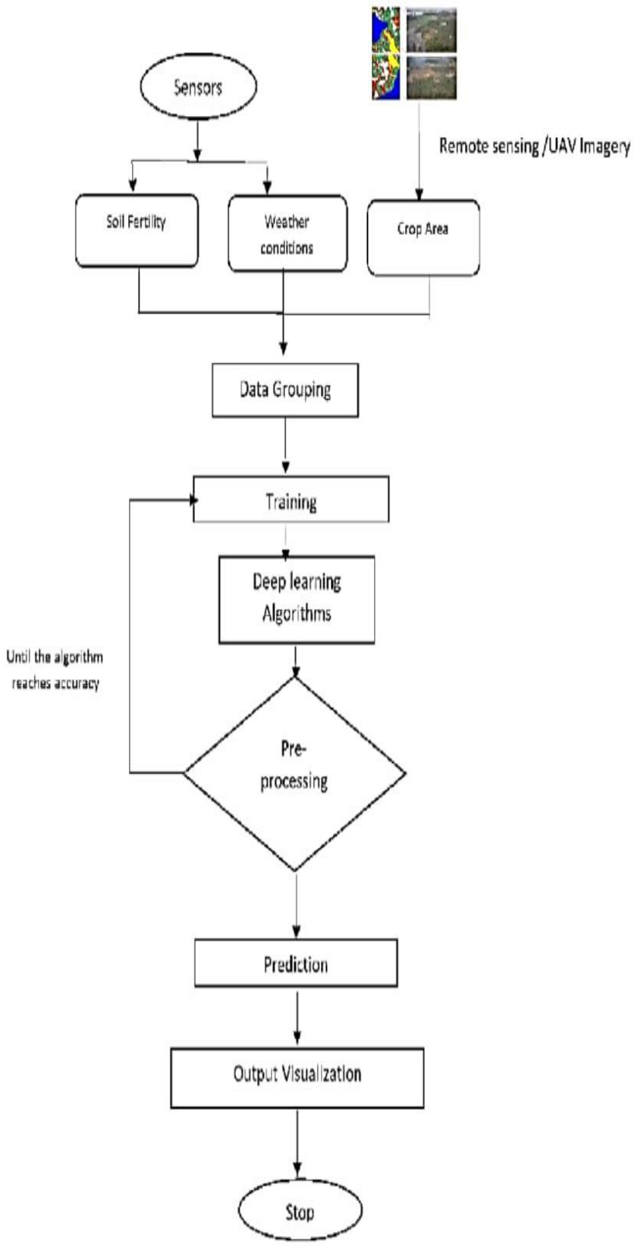
Softmax: Softmax is commonly used as the activation function in the output layer of a CNN for multi-class classification problems. It transforms the logits (raw output) into probabilities. Softmax is defined as f(x) =

exp(x) / sum(exp(x)) for each element in the output vector.

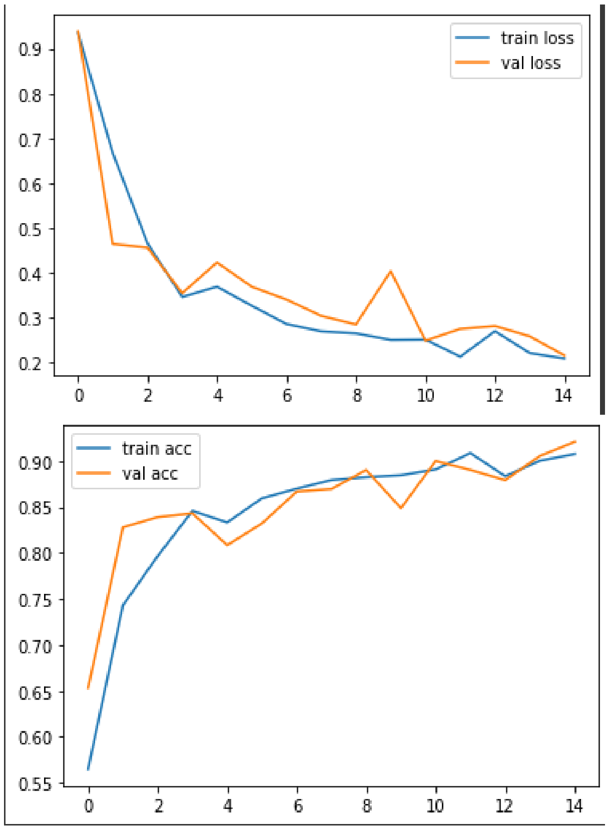
Relu:
F(x)=max(0,x)

Sigmoid:
F(x)=1/ 1+e^-x

FLOW CHART:



Results:



```
if result[0]<0:
    print("The image classified is faulty crop")
else:
    print("The image classified is normal crop")
```

The image classified is faulty crop

CONCLUSION:

In conclusion, crop disease detection using deep learning is a promising approach to improve agricultural productivity and food security. The proposed methodology involves collecting a large and diverse dataset of labeled images of healthy and diseased crops, environmental factors, and historical data, preprocessing the dataset, selecting a suitable deep learning model, training the model, evaluating its performance, deploying it into a user-friendly interface, and collecting user feedback and maintaining the system. A well-designed deep learning system can detect and classify crop diseases accurately, predict their occurrences based on environmental factors and historical data, and provide diagnostic recommendations and management strategies to farmers and agricultural experts. This can reduce the use of pesticides and increase the yield and quality of crops, leading to more sustainable and profitable agriculture. The proposed system also has some limitations and challenges, such as the need for high-quality and diverse data, the requirement for computational resources, and the potential biases and errors in the model. These limitations should be addressed through careful dataset curation, model selection, training, and evaluation, as well as ongoing maintenance and update.

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