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Plantify: A Mobile Application for Intelligent Plant Disease Detection Using Deep-Learning Algorithms

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A B S T R A C T

Plant diseases have a significant impact on the quality and productivity of plants. The identification of plant diseases may be done via digital image processing. Deep learning has significantly outperformed conventional approaches in the field of digital image processing in recent years. The study of plant diseases using deep learning technologies has grown to be a major research priority for scientists. This review defines the challenge with detecting plant diseases and compares it to conventional techniques for doing so. This study describes the research on deep learning-based plant disease detection in recent years from three perspectives: classification network, detection network, and segmentation network. Each strategy's advantages and disadvantages are briefly examined. Common datasets are presented, and the effectiveness of previous studies is contrasted. Based on this, this article explores potential difficulties with deep learning-based plant disease identification in real-world applications. In addition, a number of recommendations are made as well as potential research directions and remedies for the problems. Finally, this paper analyses and predicts the future direction of deep learning-based plant disease detection.

Keywords: Deep learning, Convolutional neural network, Plant diseases, Classification, Object detection, Segmentation

1. Introduction

Detecting plant diseases early is critical for efficient crop yield and preventing economic losses in the agriculture industry. Manual disease detection by human experts is a common practice, but it can be time-consuming and error-prone. The use of expensive approaches and pesticides to combat plant diseases is also damaging to the plant and the environment. With the advancements in technology, automatic detection of plant diseases through computer vision and artificial intelligence research is possible. Image processing techniques are widely used in agriculture for detecting and recognizing weeds, fruit grading, and identifying disease infestations of plants. Deep learning methods, particularly convolutional neural networks (CNN), are popular for image processing in agriculture. This paper aims to explore the use of pre-trained CNN models to detect plant diseases from raw images.

The study will utilize a dataset from the Plant Village dataset and will involve three key stages: data acquisition, pre-processing, and image classification. The results of the study will provide insights into the effectiveness of pre-trained CNN models for plant disease detection and could potentially pave the way for more efficient and cost-effective approaches to managing plant diseases.

Convolutional Neural Network

Artificial neural networks (ANNs) are used in deep learning, a branch of machine learning and artificial intelligence, to analyze data. In deep learning, models are trained to automatically extract features and classify data. This technology finds a wide range of applications, including computer vision, image classification, speech recognition, video analysis, and more. Convolutional neural networks (CNNs) are a type of deep learning algorithm that are highly effective in image processing and recognition tasks. The CNN architecture consists of four layers: the input image layer, convolutional layer and pooling layer, fully connected layers, and output layer. CNNs can efficiently evaluate graphical images and extract essential features using their multi-layered structure. As shown in Figure 1, CNNs are capable of detecting and categorizing images with high accuracy, making them a popular choice for image classification tasks.

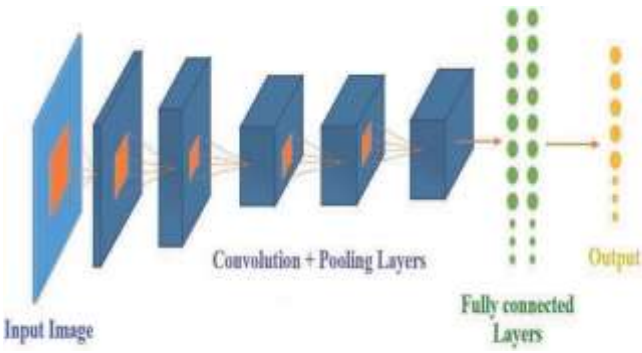

Fig 1. Illustration of Convolutional Neural Network Architecture

A. Convolutional Layer

A convolutional layer is a core component of convolutional neural networks (CNNs), which are a popular class of deep learning algorithms used for image and video processing. In CNNs, the convolutional layer applies a set of learned filters (also known as kernels or weights) to the input image. The filter slides or convolves over the image, performing element-wise multiplication at each location and then summing up the results to

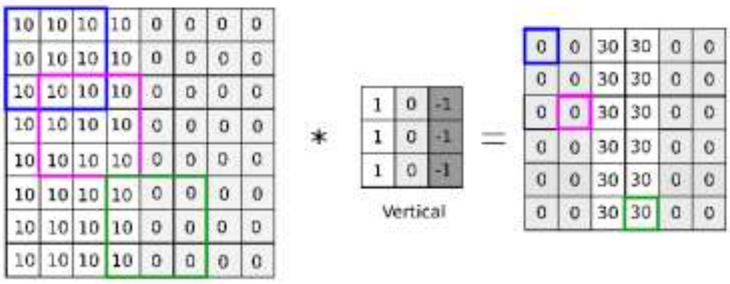

Fig.2 8x8 input and 3x3 filter operation of convolution layer.

B. Pooling Layer

In a CNN, the pooling layer is a way to reduce the size of the feature maps that are outputted by the convolutional layers. This is useful because it can help to decrease the computational cost of the network and also prevent overfitting. The pooling layer works by taking a small region of the input feature map, known as a pool, and replacing it with a single value. This can be done using various operations, such as max pooling or average pooling. For example, in max pooling, the maximum value of the pool is taken as the output, while in average pooling, the average value is used. By using pooling, the spatial resolution of the feature maps is reduced, making the network more efficient. However, it's important to use pooling carefully since too much pooling can also lead to loss of important information in the input. The size and operation of the pooling layer should be chosen based on the specific task and data to optimize performance.

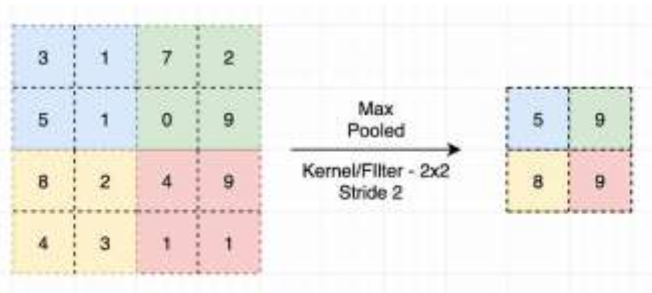

Fig. 3. Pooling operation

C. Activation Layer

The activation layer in a CNN is a non-linear transformation applied to the output of a convolutional or fully connected layer. This transformation introduces non-linearity to the network, which allows it to learn more complex relationships between the input and output. The activation layer applies a mathematical function to each element of the output feature map. There are several activation functions that can be used in CNNs, including the Rectified Linear Unit (ReLU), Sigmoid, and Hyperbolic Tangent (tanh). ReLU is the most commonly used activation function because it is computationally efficient and allows the network to learn quickly. If the input is positive, the result is returned; else, it returns 0., and 0 otherwise. Sigmoid and tanh activation functions were commonly used in the past, but they have some limitations. Sigmoid maps the input to a value between 0 and 1, which can be interpreted as a probability, but it has a tendency to cause the vanishing gradient problem. Tanh maps the input to a value between -1 and 1, which makes it a good choice for outputs that can have negative values, but it is computationally more expensive than ReLU. The unique job and data must be considered while selecting the activation function. It is important to experiment with different activation functions to find the one that works best for the problem at hand.

D. Fully Connected Layer

A fully connected layer in a convolutional neural network (CNN) is a layer in which every neuron is connected to every neuron in the previous layer. In a CNN, fully connected layers are typically used at the end of the network to map the output of the convolutional and pooling layers to a desired output shape, such as a classification or regression output. The input to a fully connected layer is a vector that has been flattened from the output feature map of the previous layer. For example, if the output feature map has dimensions 4x4x64, the input to the fully connected layer will be a vector of length 1024 (4x4x64=1024). Each neuron in the fully connected layer is then connected to each element of this input vector. The weights and biases of the fully connected layer are learned through backpropagation during training, just like the convolutional and pooling layers. The output of the fully connected layer is computed by taking a weighted sum of the input, adding a bias term, and applying an activation function. The most commonly used activation function in fully connected layers is the Rectified Linear Unit (ReLU), although other functions like sigmoid or tanh can also be used. The number of neurons in the fully connected layer is a hyper parameter that must be chosen by the user. This number depends on the complexity of the problem being solved and the size of the input feature map. In general, more neurons will allow the network to learn more complex relationships, but may also lead to overfitting if the network is too large.

Methodology

A block diagram presented in Fig. 4 shows the Input Dataset, Image Acquisition, Image pre-processing and Classification.

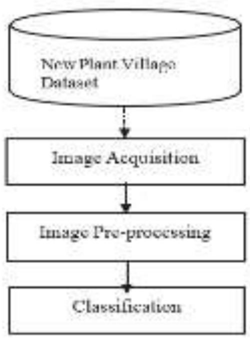

Fig. 4 Plant leaf disease recognition methodology

A. Image Acquisition

The New Plant Village dataset was used to obtain the image collection that was used to train the algorithm [11]. The pictures of the plant diseases were downloaded from the source using a python script. About 65,000 images from 11 distinct groups of plant types and diseases make up the collected collection.

B. Image Pre-processing

Pre-processed photographs have their image sizes lowered and have been cropped to fit an input. The image is improved and processed to the required colour scale. The research processes coloured, 256x256 resolution photographs that have been resized.

C. Classification

Fully connected layers are used for classification, whereas convolutional and pooling layers are used for feature extraction. The classification procedure determines the kind of plant disease and classifies the plant leaf according to whether it is diseased or not.

2. Dataset Description

The dataset consists of approximately 75,000 images containing 2 different types of potato leaf diseases, 3 different types of apple leaf diseases, 4 different types of corn leaf diseases, 3 different types of grape leaf diseases,1 type of cherry disease, 3 different types of cotton leaf diseases, 1 type of peach leaf disease, 1 type of bell pepper leaf disease, 2 different types of rose leaf diseases, 4 different types of tomato leaf diseases, 1 type of strawberry leaf disease. The CNN model is integrated with Android application. All the image dataset was used for training and testing uses multiple images that was taken from the field. The every single plant CNN model is trained for 15 epochs using a batch size of 32. All the experimentations were performed on ASUS ROG Ryzen 7 processor and memory size of 16GB.

3. Results and Analysis

A 97.5% accuracy rate was achieved using 15 epochs during the training of the model. When put to the test against random photos of different plant species and illnesses, the model's accuracy rate at its highest level was 100%. The visualization of plots of training and validation accuracy is described in Fig. 5 demonstrates how well the model detects and recognizes plant illnesses. Fig. 6 shows an accuracy rate of 100% recognition of healthy plant leaf on the left image and 100% affected with early blight disease on the right image. Fig. 7 shows a 100% confidence rate that it is infected with a cedar apple rust disease on the right image and 100% recognition of healthy plant leaf on the left image Fig. 8 shows a 100% rate that the leaf is infected with a common rust disease on the left image and 99.82% recognition healthy plant leaf on the right image. Fig. 9 shows a 100% confidence rate that it is infected with a black rot disease on the left image and 100% recognition of healthy plant leaf on the right image. Fig. 10 shows a 100% accuracy rate that it is infected with a bacterial spot disease on the right image and 100% recognition of healthy plant leaf on the left image.

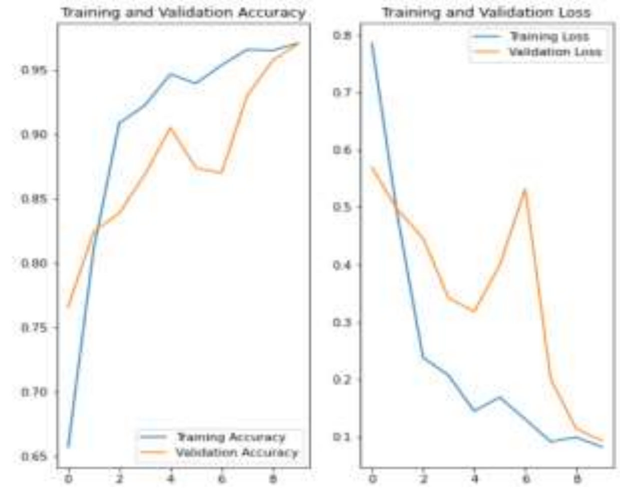

Fig. 5 Training and Validation graph for Accuracy and loss

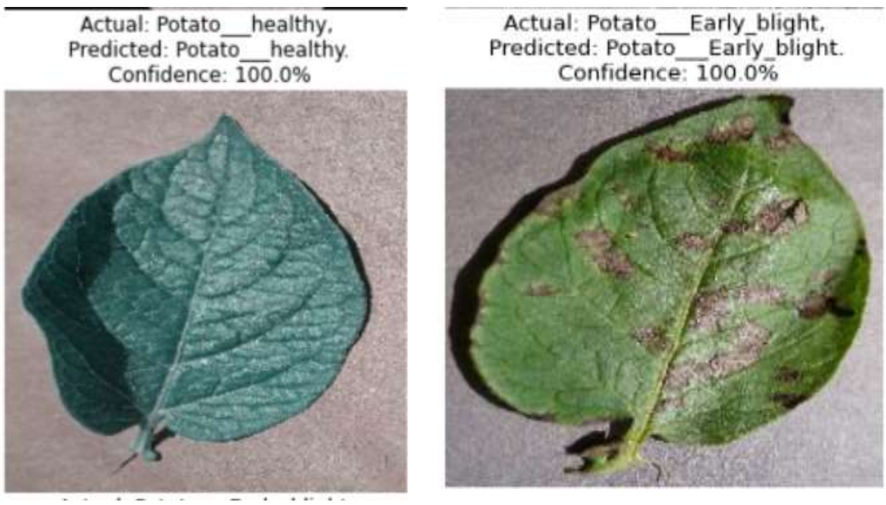

Fig.6 Result of detection and recognition of a Potato plant leaf infected with early blight disease with 100% confidence and predicted a healthy plant leaf on the left image with 100% confidence.

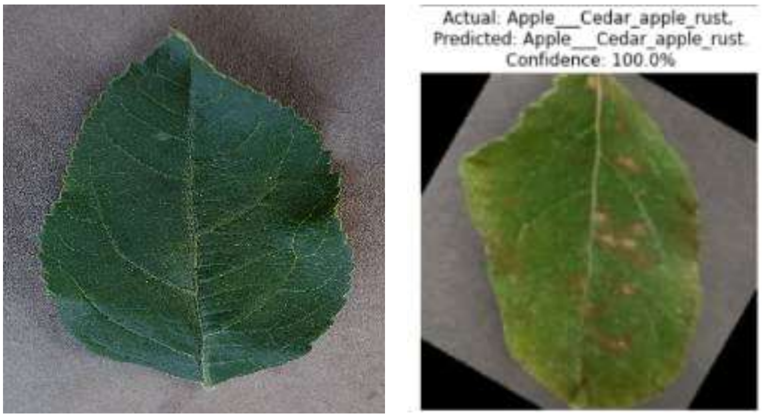

Fig.7 Result of detection and recognition of an apple plant leaf infected with a cedar apple rust disease on the left image with 100% confidence and predicted a healthy leaf on the left image.

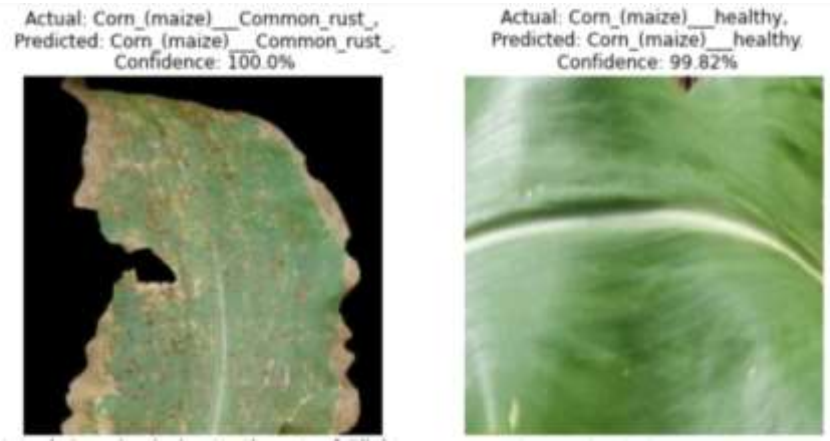

Fig.8 Result of detection and recognition of an corn plant leaf infected with a common rust disease on the left image with 100% confidence and predicted a healthy leaf on the right image with 99.82% confidence.

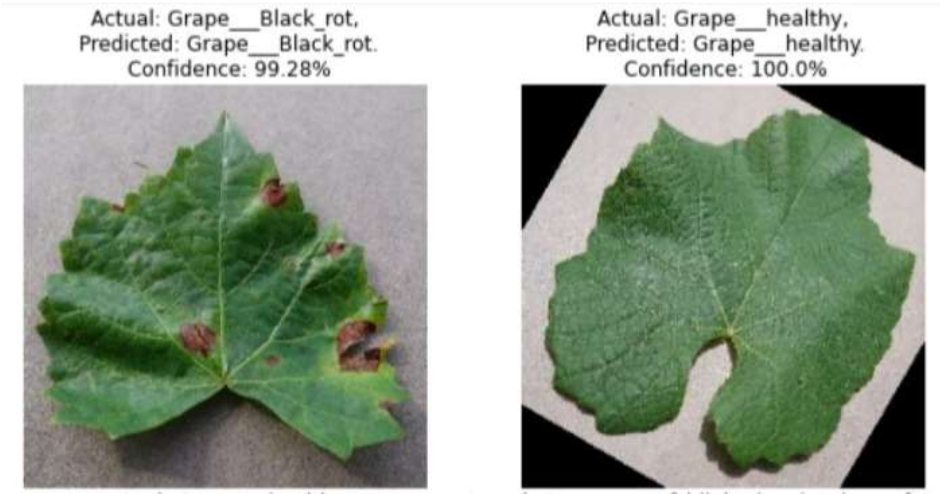

Fig.9 Result of detection and recognition of an Grape plant leaf infected with a Black root disease on the left image with 99.28% confidence and predicted a healthy leaf on the right image with 100% confidence..

Fig.10 Result of detection and recognition of an peach plant leaf infected with a Bacterial spot disease on the right image with 100 % confidence and predicted a healthy leaf on the left image with 100% confidence.

4. Conclusion

The agricultural industry is one of the most vital industries, and crops are a necessity for providing food to people all over the world. The agriculture sector depends heavily on early illness detection and identification. This study successfully used a convolutional neural network to identify and detect 17 different plant kinds and plant illnesses. Real-time photos may be tested using the trained model to find and identify plant diseases. To boost the trained models for future work, the present dataset may be expanded to cover more plant species and other plant illnesses. Other CNN designs could also experiment with different learning rates and optimizers to see how the model performs and how accurate it is. With a 96.5% accuracy rate, the suggested approach can help farmers identify and detect plant illnesses.

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