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Leaf Disease Detection Using CNN Algorithm and AI/ML Methods

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Abstract: The use of artificial intelligence and machine learning techniques for the identification and categorization of plant leaf diseases has gained popularity in recent years [1][2][3][4]. The early detection of diseases made possible by this technology has the potential to completely transform the agricultural industry by reducing crop losses and enhancing plant health in general. The labour-intensive and time-consuming nature of the traditional manual techniques of disease detection causes delays in diagnosis and treatment. Researchers have been using AI and ML methods, particularly convolutional neural networks, which have demonstrated remarkable promise in picture recognition and classification applications, to solve these difficulties.
Keywords: Artificial Intelligence, Machine Learning, Plant Leaf Diseases, Disease Detection, Agriculture, Crop Loss Reduction, Plant Health,

INTRODUCTION

Plant diseases pose a serious risk to the world's food security because they lower crop yields and cause farmers to suffer large financial losses. Expert visual inspection is the basis of traditional plant disease detection techniques, which can be laborious, subjective, and prone to human error. Automatic and precise plant disease detection systems are becoming a reality because to the advancements in artificial intelligence (AI) and machine learning (ML). Convolutional Neural Networks (CNNs) are a popular AI and ML technology that has demonstrated exceptional performance in computer vision applications, which makes them a perfect fit for plant disease diagnosis.[5][6][7]

In this study, we primarily concentrate on the identification of leaf diseases in plants utilizing CNNs for plant disease detection. We will go over the fundamentals of CNNs, how they are used in plant pathology, and how to create a system for detecting leaf diseases. We will also examine the data gathering and preprocessing procedures needed to develop a reliable and precise CNN-based plant disease detection system.

LITERATURE REVIEW

Convolutional neural networks, in particular, are one of the AI and ML techniques that researchers are actively investigating for the detection of leaf illness. For example, Spasojevic et al. used ANN technology to construct a tea leaf disease recognizer [1]. To identify disorders, they used a neural network ensemble to recognize patterns in tea leaves. Similar to this, deep convolutional networks have been used by other researchers to identify diseases and classify leaf images [2–3]. These studies have shown how well AI and ML systems work for precisely identifying and categorizing leaf diseases.

METHODOLOGY

The methodology employed in leaf's disease detection using the CNN algorithms and AI/ML methods typically involves the following steps:

1. Data Collection: High-resolution images of plant leaves displaying various diseases are collected.
2. Preprocessing: The collected images are pre-processed to enhance their quality and remove any noise or artifacts.
3. Feature Extraction: Features such as colour, texture, and shape are extracted from the pre-processed images to represent the unique characteristics of different leaf diseases.
4. Classification: The extracted features are used as input to a convolutional neural network, which is trained on a dataset of labelled leaf images. The CNN learns to recognize patterns and identify different leaf diseases based on the training data. [8]
5. Expected Results: The expected results of leaf's disease detection using CNN algorithms and AI/ML methods are improved accuracy and efficiency in disease identification and classification. This can lead to early detection and timely treatment of leaf diseases, reducing crop losses and improving overall plant health.

6. Future Improvement Requirements: Although the application of CNN algorithms and AI/ML techniques to the diagnosis of leaf disease has enormous promise, there are still a number of areas in need of development. First, in order to train the CNN model, a more extensive and varied dataset must be created. This will guarantee that a variety of leaf diseases can be accurately identified by the model. To further enhance the CNN model's accuracy and computing efficiency, additional optimizations can be made.

Figure 1: Apple leaf with scab

Figure 2: rust on corn leaf

Figure 3: Grape leaf with esca

Understanding Convolutional Neural Networks

Plant diseases pose a serious risk to the world's food security because they lower crop yields and cause farmers to suffer large financial losses. Expert visual inspection is the basis of traditional plant disease detection techniques, which can be laborious, subjective, and prone to human error[5]. Automatic and precise plant disease detection systems are becoming a reality because to the advancements in artificial intelligence (AI) and machine learning (ML). Convolutional Neural Networks (CNNs) are a popular AI and ML technology that have demonstrated exceptional performance in computer vision applications, which makes them a perfect fit for plant disease diagnosis. In this research paper, we focus on using CNNs for plant disease detection, specifically for identifying leaf diseases.

Ai And Ml Techniques in Plant Pathology

In order to improve disease detection and diagnosis, plant pathology is using more and more AI and ML techniques. CNNs have demonstrated exceptional success among these methods because of their capacity to automatically identify and extract pertinent features from input images. Additional AI and ML methods for plant pathology include:

- Image Segmentation: This method allows for more precise illness quantification by dividing the unhealthy areas of an image from the healthy ones [9]. Image segmentation can be accomplished using a variety of techniques, including thresholding, edge detection, region growth, and watershed transformation.
- Feature Extraction: From input photos, machine learning models can identify and extract pertinent features that can be utilized for classification. For feature extraction, methods such as Scale-Invariant Feature Transform (SIFT) [11], Local Binary Patterns (LBP) [10], and Histogram of Oriented Gradients (HOG) [11] can be employed.
- Support Vector Machines (SVM): SVMs are a popular ML technique for plant disease classification, where the extracted features are used to train a binary or multi-class SVM classifier.

Data Collection and Preprocessing for Disease Detection

Data collection and preprocessing are crucial steps in developing a successful plant disease detection system. To create a robust and diverse dataset, consider the following:

- Data Sources: Gather images from a variety of sources, including online repositories, research papers, and real-world field data.[23]
- Disease Representation: Make sure that the dataset includes a wide variety of plant diseases, with a balanced representation of healthy and diseased samples.
- Image Quality: Ensuring that the images are of high quality, with minimal noise and sufficient resolution to capture relevant features.[25]
- Preprocessing: Preprocess the images by resizing them to a uniform size, normalizing the pixel values [9], and applying data augmentation techniques to increase the dataset's size and diversity.

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```
Out[47]:  {0: 'Apple___Apple_scab',
            1: 'Apple___Black_rot',
            2: 'Apple___Cedar_apple_rust',
            3: 'Apple___healthy',
            4: 'Background_without_leaves',
            5: 'Blueberry___healthy',
            6: 'Cherry___Powdery_mildew',
            7: 'Cherry___healthy',
            8: 'Corn___Cercospora_leaf_spot Gray_leaf_spot',
            9: 'Corn___Common_rust',
            10: 'Corn___Northern_Leaf_Blight',
            11: 'Corn___healthy',
            12: 'Grape___Black_rot',
            13: 'Grape___Esca_(Black_Measles)',
            14: 'Grape___Leaf_blight_(Isariopsis_Leaf_Spot)',
            15: 'Grape___healthy',
            16: 'Orange___Haunglongbing_(Citrus_greening)',
            17: 'Peach___Bacterial_spot',
            18: 'Peach___healthy',
            19: 'Pepper,_bell___Bacterial_spot',
            20: 'Pepper,_bell___healthy',
            21: 'Potato___Early_blight',
            22: 'Potato___Late_blight',
            23: 'Potato___healthy',
            24: 'Raspberry___healthy',
            25: 'Soybean___healthy',
            26: 'Squash___Powdery_mildew',
            27: 'Strawberry___Leaf_scorch',
            28: 'Strawberry___healthy',
            29: 'Tomato___Bacterial_spot',
            30: 'Tomato___Early_blight',
            31: 'Tomato___Late_blight',
            32: 'Tomato___Leaf_Mold',
            33: 'Tomato___Septoria_leaf_spot',
            34: 'Tomato___Spider_mites Two-spotted_spider_mite',
            35: 'Tomato___Target_Spot',
            36: 'Tomato___Tomato_Yellow_Leaf_Curl_Virus',
            37: 'Tomato___Tomato_mosaic_virus',
            38: 'Tomato___healthy'}
```

Figure 4: Indexing and preprocessing of data

Training Cnn Models for Disease Identification

The design of the model, which mimics the brain's capacity to process picture input effectively while maintaining essential properties, is modelled after biological nerve systems in the training process of Convolutional Neural Networks (CNN) for illness identification [12]. The structure of CNN consists of three layers: the Output Layer, which uses logistic functions like sigmoid or SoftMax for class probability scores, Hidden Layers, which introduce non-linearity through matrix multiplication and activation functions, and Input Layers, where the total number of neurons matches the data features. The role of clustering and classification is pivotal in achieving precise and automated diagnosis. In a proposed approach, the picture processing system and k-means clustering algorithm were employed to diagnose various pathogens affecting leaves. MATLAB software facilitated training and testing using mat files, with the neural network consisting of 10 hidden layers and three leaf clusters. The forward backpropagation algorithm and Mean Square Error (MSE) calculation contributed to improved accuracy, with 2000 epochs enhancing performance. This systematic integration of clustering and classification techniques underscores their crucial role in refining the training process [13][14] and optimizing disease identification outcomes in CNN models.

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1        [-1, 32, 224, 224]             896
              ReLU-2        [-1, 32, 224, 224]               0
       BatchNorm2d-3        [-1, 32, 224, 224]              64
            Conv2d-4        [-1, 32, 224, 224]           9,248
              ReLU-5        [-1, 32, 224, 224]               0
       BatchNorm2d-6        [-1, 32, 224, 224]              64
         MaxPool2d-7        [-1, 32, 112, 112]               0
            Conv2d-8        [-1, 64, 112, 112]          18,496
              ReLU-9        [-1, 64, 112, 112]               0
      BatchNorm2d-10        [-1, 64, 112, 112]             128
           Conv2d-11        [-1, 64, 112, 112]          36,928
             ReLU-12        [-1, 64, 112, 112]               0
      BatchNorm2d-13        [-1, 64, 112, 112]             128
        MaxPool2d-14          [-1, 64, 56, 56]               0
           Conv2d-15         [-1, 128, 56, 56]          73,856
             ReLU-16         [-1, 128, 56, 56]               0
      BatchNorm2d-17         [-1, 128, 56, 56]             256
           Conv2d-18         [-1, 128, 56, 56]         147,584
             ReLU-19         [-1, 128, 56, 56]               0
      BatchNorm2d-20         [-1, 128, 56, 56]             256
        MaxPool2d-21         [-1, 128, 28, 28]               0
           Conv2d-22         [-1, 256, 28, 28]         295,168
             ReLU-23         [-1, 256, 28, 28]               0
      BatchNorm2d-24         [-1, 256, 28, 28]             512
           Conv2d-25         [-1, 256, 28, 28]         590,080
             ReLU-26         [-1, 256, 28, 28]               0
      BatchNorm2d-27         [-1, 256, 28, 28]             512
        MaxPool2d-28         [-1, 256, 14, 14]               0
          Dropout-29               [-1, 50176]               0
           Linear-30                [-1, 1024]      51,381,248
             ReLU-31                [-1, 1024]               0
          Dropout-32                [-1, 1024]               0
           Linear-33                  [-1, 39]          39,975
================================================================
Total params: 52,595,399
Trainable params: 52,595,399
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.57
Forward/backward pass size (MB): 143.96
Params size (MB): 200.64
Estimated Total Size (MB): 345.17
----------------------------------------------------------------
```

Figure 5: Training model for Plant-Disease Detection

Expected Results of Cnn-Based Leaf Disease Detection

Numerous investigations have examined various approaches to identify leaf disease, with each study exhibiting unique accuracy levels. 90% identification of Alfalfa diseases was accomplished in one method using a combination of K-Means Clustering, KNN algorithm, and Local Binary Pattern. Another study classified infection intensity at percentages of 20%, 40%, and 75% while maintaining an undisclosed solution accuracy. It did this by using Canny edge detection and the Gaussian mixture model. SVM models achieved accuracy rates above 90% in many studies; a CNN-based experiment yielded the best result, which was 98.60%. Innovative methods, such a web-based program that combined Support Vector Machine and Kmeans clustering, demonstrated 82% accuracy in diagnosing fruit infections. Other techniques including SVM, ANN, deep learning, and image processing showed accuracy between 80% and 100%. The integration of IoT in a Leaf Disease Estimation using the Deep Learning Principle (LDEDLP) achieved an impressive 99% accuracy. These findings showcase the diverse landscape of leaf disease detection methodologies, with accuracy rates varying based on the adopted techniques and models.

The accuracy of several strategies in the field of leaf disease detection highlights the significance of customized approaches. SVM and CNN are two examples of techniques that often show excellent accuracy, demonstrating their dependability in disease identification. As demonstrated by LDEDLP, the fusion of cutting-edge ideas like the Internet of Things (IoT) with deep learning principles pushes the envelope of accuracy, achieving an astounding 99% accuracy. Furthermore, group techniques like Random Forest work well and achieve a 97% classification accuracy. The dynamic nature of the field is reflected in the diversity of approaches used, which highlights the importance of having a detailed understanding of individual plant diseases and their traits in order to get the best possible detection results. As researchers continue to innovate, these findings contribute to the broader understanding of leaf disease detection, paving the way for improved agricultural practices and crop management.

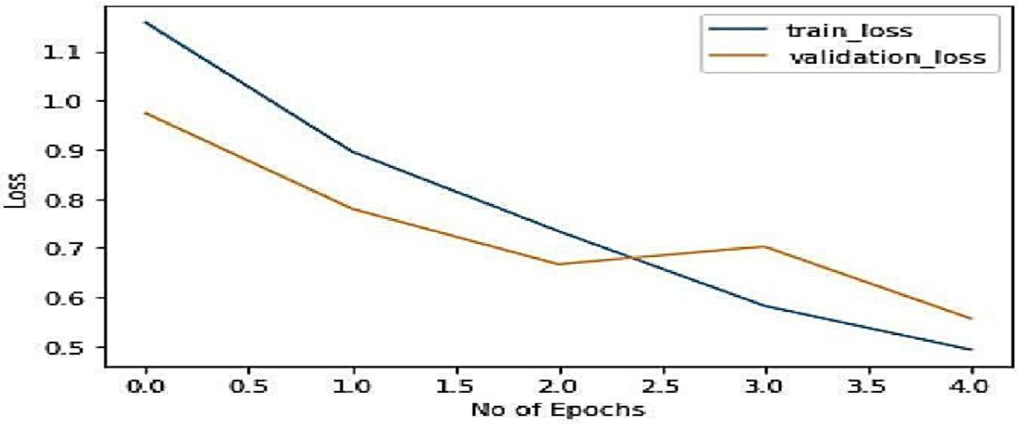

Figure 6: Plotting the various losses during the training

Challenges In Current Disease Detection Methods

Although manual observation is still a feasible method, it is expensive and time-consuming. Prompt and precise disease diagnosis is essential for agricultural development. Plant diseases can be identified and categorized with the use of image processing, which makes use of digital cameras and learning algorithms. Current approaches, however, still have shortcomings [15]. Lack of technical know-how in image processing methods affects computer vision system performance [16]. Because of the large volume of data, processing speed is an issue that requires effective feature extraction and selection strategies [17]. In realworld applications, tight setup requirements—like regulated lighting conditions—present difficulties and compromise algorithm accuracy. A lack of thorough information about image-capturing conditions undermines data trustworthiness and makes result validation more difficult. Since current techniques are sometimes limited to a single disease kind, creating a universal strategy for recognizing different plant leaf diseases continues to be difficult [18]. Writers' ought to devote greater effort to comprehending and elaborating on the technologies they have selected, offering lucidity Procedure, apparatus, and experimental results. To solve these enduring issues, sustained research efforts are needed to develop comprehensive and generally applicable systems for plant disease diagnosis.

Future Directions for Ai in Plant Disease Management

Overcoming obstacles in obtaining a variety of training images is a necessary step towards the future directions of AI for plant disease control. The shapes, sizes, backgrounds, and orientations of images are among the variables that researchers should address while studying picture variability. As Ethiopia shown in 2019, using high-resolution satellite images[19] has the potential to improve deep learning methods. Developing more machine learning techniques to improve accuracy and putting GPU clusters for big datasets into practice are further developments. Farmers can be empowered by real-time applications for live photo analysis, which allow for quick disease identification [20], providing a proactive method of evaluating crop health [21][22]. These projects represent significant advancements toward a more complete and successful AI driven plant disease control system.

CONCLUSION AND IMPLICATIONS FOR AGRICULTURE TECHNOLOGY

In summary, our research lays a robust foundation for the potential implementation of a deep learning-based CNN model in leaf disease detection. While our current progress includes successful experimentation with Python, Keras, and Jupyter, the envisioned model promises to yield optimal outcomes by fine-tuning parameters such as dataset color, epochs, and regularization methods. Anticipated results suggest that the optimized RGB-colored image dataset, coupled with augmentation, could enhance the model's performance. The expected efficiency, though not achieved yet, holds promise for aiding farmers in identifying and managing leaf diseases, ultimately contributing to advancements in agriculture technology and mitigating economic losses.

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