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IDENTIFICATION PLANT LEAF DISEASE USING RNN AND DEEP LEARNING APPROACH

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ABSTRACT :

Agricultural productivity is something on which economy highly depends. This is the one of the reasons that disease detection in plants plays an important role in agriculture field, as having disease in plants are quite natural. If proper care is not taken in this area then it causes serious effects on plants and due to which respective product quality, quantity or productivity is affected. Detection of plant disease through some automatic technique is beneficial as it reduces a large work of monitoring in big farms of crops, and at very early stage itself it detects the symptoms of diseases i.e. when they appear on plant leaves.

This project proposes an algorithm for image segmentation technique which is used for automatic detection and classification of plant leaf diseases. It also covers survey on different diseases classification techniques that can be used for plant leaf disease detection. Image segmentation, which is an important aspect for disease detection in plant leaf disease, is done by using Recurrental neural network.

Keywords: Agricultural Productivity, Plant Disease Detection, Automatic Detection, Image Segmentation, Plant Leaf Disease, Disease Classification, Recurrent Neural Network (RNN)

1. INTRODUCTION :

Plant blade disorders significantly affect agricultural productivity, which is necessary for major financial losses and food safety problems. For heavy crop control and return adaptation, it is necessary to detect initial and accurate detection of these diseases. Traditional disease detection technology depends on professional expertise and guide inspection, which can be weakened for timing, hard work clicks and errors.With improvements in deep learning, automated plant disease detection has emerge as a promising answer. Recurrent Neural Networks (RNN) and deep studying procedures have proven superb potential in figuring out plant leaf sicknesses by using reading pics and detecting styles related to extraordinary sicknesses. While Convolutional Neural Networks (CNN) are extensively used for photograph-based type responsibilities, RNNs can beautify the process through shooting temporal dependencies in sequential data, along with leaf colour adjustments over time or multi-body photo sequences. This observe explores the use of RNNs and deep getting to know techniques for plant leaf disease identity, leveraging models together with Long Short-Term Memory (LSTM) networks and hybrid CNN-RNN architectures. By integrating deep learning methodologies, the machine goals to achieve high accuracy in disease classification, aiding farmers and agricultural experts in early disease detection and efficient crop managementaims to improve the prediction accuracy of gale pressure detection, improving the early warning systems for various industries reliant on weather situations

2.LITERATURE SURVEY :

2.1 EXISTING SYSTEM

The current agricultural system for diagnosis and handling plant blade disorders depends primarily on the manual inspection of specialists, laboratory testing and image processing and mobile apps as basic technical aids. Although these approaches offer some levels of the disease detection, they are often disabled, exposed to time -consuming and errors. Manual inspections are subject to human errors, limited by the availability of expertise, and not scalable for large areas. Laboratory tests, although accurate, expensive, slow and often inaccessible in rural areas. Technology -assisted methods such as image processing and mobile apps, while more automatic high -quality automatic images and predetermined datasets, which are not always practical under real conditions. These systems are also unable to integrate advanced data analysis or adapt to complex environmental factors affecting plant diseases, such as delayed diagnosis and under -treatment management.

2.1.1 Drawbacks of existing system

- **Dependency on manual inspection:** Subjective, incorrectly exposed and limited in scalability.
- **Laboratory and chemical test shortages**: High costs, time delay and limited access.
- **Basic technology -assisted methods:** predetermined features, poor image quality requirements and dependence on incompatible performance.

- **Lack of scalability:** Inability to monitor large areas or regional variations effectively.
- **Absence of real -time diagnosis:** Delayed analysis and reactive approach.
- **Access and strength problems:** High costs and geographical inequalities prevent a lot from using.
- **Environment and biological variability:** Failure to be responsible for ups and downs in environmental factors and overlap of the disease.
- **Data use and integration intervals:** declining forecasting insights and fragmented data sets

3. METHODS :

Data collection: Collect leaf images of different plants from different datasets or real -time images, correct dataset labels, healthy leaves with popular datasets and both affected leaves affected by the disease will include: Plant Village, Kagal Leaf Dataset, etc.
Pre-treatment of the image: Form of images for a certain dimension (eg 256x256 pixels), image enlargement technique, converter RGB image to grass scale or HSV for better convenience extraction.
Image Division: The Division is used to separate the infected area from the healthy part of the blade
The technique used: Corpus Clusting, Threadald -Segmentation, edge detection (Kan or Sobel), the growing area
Functional extraction: Remove features from fragmented images to classify different types of diseases, features: Histograms (HOG), GLCM (Grow Level CUM phenomenon matrix)
Disease classification: The model classifies leaves into various disease categories such as: bacterial stains, powder semi

4.IMPLEMENTATION :

A. The implementation phase plays an important role in identifying diseases of plant leaves using the recurrent nervous network (RNN) and deep learning techniques. The whole process is divided into several stages to ensure accurate detection and classification of plant diseases.
B. Step in the implementation

Data collection: Collect the leaf images of the plant from different sources such as: Plant Village DataSetcagal Leaf Dataset, real -time images from agricultural areas, datasets include both healthy leaves and diseased leaves, types of diseases include types of diseases
Data pre -treatment: Pre -treatment is required to improve the quality of the images before using deep learning models.
Steps involved: Image size (256x256 pixels), RGB to Gracecale or HSV converting, noise removal using Gausian filter, image improvement using histograms equal, imaging (pixel price scaling between 0 and 1)
Image Division: The division is used to separate the sick area to the magazine.
Technique to be used: K-instrument clustering, using the Otsu, Thrace holding, Growing Area Growing Algorithms, Cani Edge Detection
Functional extraction: Remove relevant features from fragmented images that help identify the type of disease.
The facilities include: Color functions (HSV colorhistograms), structured features, size functions, infected area size, edge functions using GLCM (Gray-Level CO-Event Matrix).

5.PROPOSED SYSTEM OVERVIEW :

The proposed system for detecting the plant blade disease involves a multi -phase process that begins with image collection, followed by pre -problems to increase the quality of the entrance picture and remove distortions. The image is then cut to focus on the area of interest, and the stagnation and unfavorable growth techniques are used. The system identifies and masks mostly green pixels based on a computed threshold, and the infected clusters within these pixels are removed. The relevant segments are then isolated for further analysis, which is performed using a Recurrent Neural Network (RNN) algorithm to classify leaf diseases accurately.

Proposed System Architecture:

Image collection: Blade images are collected from crop areas using digital cameras or mobile devices or plant disease data sets, the data set contains both healthy and disease affected by the correct label.
Picture Picture: Purchased images undergo pre-transcendent techniques to increase image quality and remove noise. Pre-treatment steps: Image raising (256x256 pixels or fixed dimensions), noise removal using Gausian filters, RGB to Gracecale or HSV converting, image generalization, negative increase in the use of the Histronic equation
Image Division: The division is used to separate the pathological area from the healthy part of the magazine. Segmentation technology used: the with rich grouping, the threshold of the oatsu, the growing area, detection of Canny Kant, it helps to separate the infected area for further analysis.
Functional extraction: Remove important functions from the fragmented image such as: color functions (HSV Color histograms), using GLCM (GLCM) (GLCM) (GLCM) using GLCM (Grow Level CO-Event-Matrix) using texture functions, size functions, infected area size.
Deep Learning Model Implementation: The features that have been drawn out are sent in a deep learning model, including: Convisional Neural Network (CNN): For functional extraction, recurrent nervan network (RNN): To learn sequences, LSTM (long short memory) learning, timing, juice.

6.RESULT :

In this study, the process of transmission and accuracy of automated disease detection and accuracy was identified using the recurrent nerve network (RNN) and deep learning methods. The experiment was used using a dataset with plants containing healthy and sick samples in different plant species including tomatoes, potatoes and corn.

Data set description: The dataset included 10,000 images with a balanced distribution of healthy and sick leaves. Images were prepared using revival (128x128 pixels), generalization and growth techniques to improve model generalization.

7.CONSLUSION :

This project shows that the plant disease recognition model based on deep learning has the characteristics of unsupervised, high accuracy, good universality, and high training efficiency. However, there are many challenges in accuracy practicability of plant disease detection in the complex environment. In order to solve these problems and optimize the identification method, this project proposes a recognition model integrating RNN algorithm, which can effectively solve the problem of plant disease identification in the complex environment. The model not only adapts to complex environments, but also increases the accuracy of identification. Compared with the traditional model, the model proposed in this paper not only guarantees the robustness of the recurrental neural network, but also reduces the number and quality requirements of the recurrental neural network on the data set and obtains better results. The proposed system is based on python and gives an accuracy of around 88%.The accuracy and the speed can be increased by use of Google's GPU for processing better results.

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