PLANT DISEASE CLASSIFICATION SYSTEM USING AI

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Abstract- **Farmers must detect and treat plant, leaf, and fruit diseases early in order to increase agricultural production. The utilization of contemporary farming technology can assist them in achieving this goal. Farmers can limit the danger of disease transmission and crop loss by utilizing a variety of approaches and keeping a careful check on things on a regular basis. Detecting plant leaf disease is an important stage in farming because it can save a farmer a lot of money. Keeping a close check on your crops at all phases of development is critical if you want to maximize your output. Because human diagnosis of leaf diseases can be difficult, an automated approach to disease detection and categorization is especially desired.**

INTRODUCTION

I.Project Description

Plant diseases can have a significant impact on crop yields, food security, and the viability of agriculture in addition to crop yields. For effective disease control and the most effective reduction of crop losses, these diseases must be accurately and quickly detected. The subject of diagnosing plant diseases has undergone a radical transformation in recent years as a result of advancements in artificial intelligence (AI), particularly in machine learning techniques like convolutional neural networks (CNNs). Systems powered by artificial intelligence may examine images of plants to find signs of disease. This offers an immediate, precise, and scalable answer.early diagnosis of the illness

Key features of using AI for plant disease detection:

Image analysis, first Convolutional neural networks are utilized. Due to their higher performance in image recognition tasks, CNN models are crucial for AI-based plant disease detection. With the help of enormous amounts of tagged plant image training data, these deep learning algorithms are able to recognize and distinguish between disease patterns.

2. The Generation of Huge Datasets In.orderto.train CNNs properly, it is.necessaryto,have huge datasets that contain both healthy and ill plant examples. These datasets are absolutely necessary in,order to guarantee that,themodel,is generalizable over a.widevariety,of plant species and diseases.

3. Early identification of Disease: AI models have the ability to identify disease symptoms in plants even before,they are evident to the human eye. This enables early identification and appropriate action to avoid the spread of illness

. 4. great Accuracy and Objectivity: Systems based on AI offer great accuracy in disease identification, hence reducing the likelihood of receiving an incorrect diagnosis. The method is objective and consistent, which removes the possibility of human bias and subjective judgements

5. Real-Time Monitoring: Real-time monitoring of plant health is made possible by merging AI-based disease detection with sensors and cameras located in the field. Farmers are able to receive quick notifications regarding the outbreak of diseases, which enables them to take immediate action.

6. extremely Scalable and Efficient for huge-Scale Agricultural Operations Because AI-based systems can process a huge number of plant photos in a short amount of time, they are extremely scalable and efficient for large-scale agricultural operations.

7. User-Friendly Interfaces: Plant disease detection utilising AI frequently incorporates userfriendly interfaces, which enable farmers and agronomists to simply upload photographs and obtain disease assessments without requiring a significant amount of specialised technical expertise.

Literature survey

II.Existing system

Plant pathologists and agronomists manually examine plants for disease. They examine the plants for pests, lesions, wilting, discoloration, and other issues. This method has a number of shortcomings that may decrease its accuracy and effectiveness:

III.Limtations

1. Subjectivity: Conventional techniques heavily rely on the perceptions and expertise of the observers. Different agronomists may interpret symptoms differently, which might influence the diagnosis and management of illnesses.

IV.Proposed system

AI-based plant disease detection automates the identification of plant diseases using machine learning methods like CNNs. To swiftly and accurately diagnose sickness, the technology examines images of plants.

Advantages

1. Early Detection: AI-based systems are capable of identifying diseases and their symptoms before they become visible. Crop losses are reduced through early detection.

2. High Accuracy: AI models, particularly CNNs, can reliably identify diseases. They are able to recognize subtle patterns and abnormalities, reducing false positives.

3. Efficiency and Speed AI-based identification is much quicker than visual assessment. For real-time sickness detection, the technology quickly scans several pictures. Assessment

SYSTEM.REQUIREMENTS

Users

Agriculture and plant health stakeholders would employ a CNN-based plant disease prediction system. CNN-based disease prediction systems assist farmers and agronomists diagnose and manage plant diseases early. This system's main users are:

1. Farmers and crop growers would use the plant disease prediction system most. The device can detect agricultural illnesses early in the season. Early detection allows targeted pesticide use or disease-resistant crop cultivars.

2. Agronomists and Plant Pathologists: The system supports field observations and diagnosis for plant health and disease management specialists. The system can help diagnose disorders.

3. Agricultural Extension Officers: They educate farmers on best practises. The disease prediction system can teach farmers about common plant illnesses, prevention, and sustainable disease management.

4. Research Institutions and Scientists: Researchers in agriculture and plant pathology can help system developers test CNN model correctness and efficacy. They can help the system predict and generalise across locations and crops.

Functional.requirements

Acquiring and Cleaning the Data: Specify the Data Sources and Collection Methods. Please detail the necessary data cleansing, transformation, and normalization preparatory methods. Training, validation, and testing data will need to be sampled and divided in different ways.

Model creation and training: Define the machine learning models or algorithms to be employed.Get a handle on the hyper parameters and training-optimization algorithms. Establish the measurements and criteria to evaluate the model's performance.Provide details on how to pick and engineer features.

Inference and Prediction: Specify the Types of Inputs Needed to Make Predictions and What Kinds of Data Are Needed. To what extent will you be making predictions in real time, or in batches? choose how prediction results will be shown after being generated.

Model Integration and Deployment : Target deployment environment (cloud, on-premises, edge devices, etc.) must be specified. Create the application programming interfaces (APIs) that will allow the machine learning model to be used in other software. Find out what kind of performance and scalability your model deployment needs

Non-Functional Requirements

Efficiency: Define the utmost permissible response time for training, prediction, and inference of models.-Throughput:-Specify,the.number,of queries or predictions per unit of time that,the system should be.able to process.-Scalability: Determine the system's capacity to accommodate growing data volumes or user demand.

Precision and Dependability:-Accuracy of the Model: Specify the acceptable level of accuracy or performance metrics (e.g., accuracy, precision, recall) for the machine learning model.-Robustness: Define the system's capacity to deal with chaotic, absent, or anomalous

V.Tools and Technologies

Introduction to Python

Python is a well-known interpreted high-level programming language because it is simple to learn and versatile in a variety of settings. Important Python traits include the following:

Python's grammar prioritizes code readability by having a straightforward and uncomplicated structure. Consistently indented coding blocks are simpler to read, understand, and update.

Python is a dynamically typed language, meaning that variable types are decided at runtime. Variables may be assigned to many types without making a specific type declaration, allowing for more flexible code and quicker development.

Python can be used right away because it is an interpreted language, so there is no need to first compile it. This expedites prototyping and testing because the code can be run without being first compiled**.**

Flask Architecture:

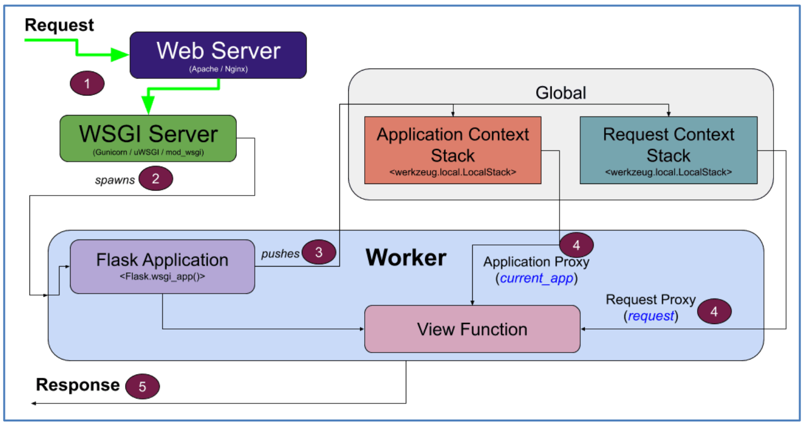

Figure 2.3.7;Architectural view of Flask

VI.Hardware and Software Requirements

Hardware Specification

- Processor : Intel Core i3
- RAM : 4GB or Higher
- Hard disk : 500 GB

Software Specification

- Front end : Bootstrap Framework
- Back end : Python
- Web frame work : Flask
- Operating System : Windows 10 or Any Compatible
- IDE : Anaconda, vscode

VII.Architecture Diagram

System Architecture

1. Input Layer: An image's data is sent to the input layer as a matrix of pixel values. Each pixel indicates a different aspect of the image, such as the grayscale value or color saturation.

2. Convolutional Layer: The convolutional layer transforms the input image using a number of learnable filters, also referred to as kernels. Every filter carries out a convolution operation, sliding across the image while computing the dot products between the filter weights and corresponding pixel values. This method aids in the identification of various visual patterns and features in the image.

3. Activation Function: To inject non-linearities into the network, an activation function is used after each convolution operation. Typical activation functions include sigmoid, tanh, and ReLU (Rectified Linear Unit). In order to introduce non-linear interactions between the input and output, activation functions

4. Pooling Layer: The pooling layer downsamples the feature maps produced by the convolutional layer. It reduces the spatial dimensions of the features while preserving important information. Popular pooling techniques include max pooling and average pooling, which select the maximum or average value within each pooling region, respectively.

5. Fully Connected Layer: The fully connected layer receives the flattened feature maps from the pooling layer and connects every neuron to every neuron in the previous layer. This layer acts as a classifier, learning high-level representations and making predictions based on the extracted features.

6. Output Layer: The.outputlayer.produces the final predictions based.onthe.learned representations. The number of neurons in the output layer corresponds to.the.number of classes or categories being predicted. For example, in bird breed classification, each neuron in the output layer might represent a specific bird breed, and the highest activation value indicates the predicted breed.

7. Training and Optimization: CNNs are trained using backpropagation, where the network's weights are adjusted to minimize,the,difference between the predicted output and the actual output (target labels). This optimization is achieved by minimizing a loss function, such as categorical cross-entropy or mean squared error, using gradient descent-based optimization algorithms.

8. Evaluation and Prediction: Once the CNN is trained, it can be evaluated on new, unseen data to assess its performance. The input images are,fed,through the network, and the output layer produces class probabilities or predicted labels. The predicted labels are compared to the ground truth labels to measure the accuracy and performance of the model

6.2 Screen shots

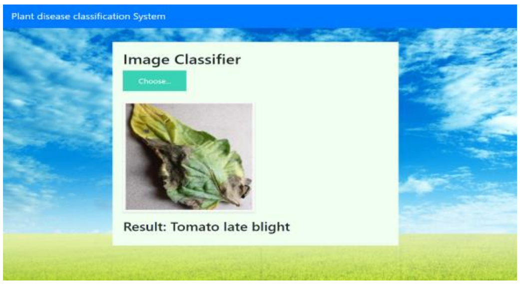

Figure 6.2.1: input the tomato bacterial spot image for prediction

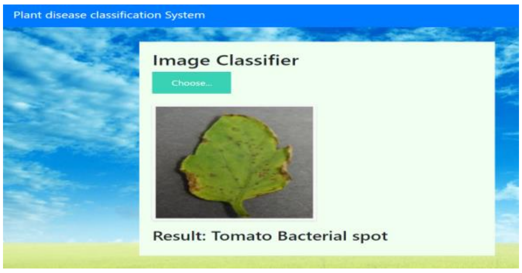

Figure6.2.2: Input tomato late blight image for prediction

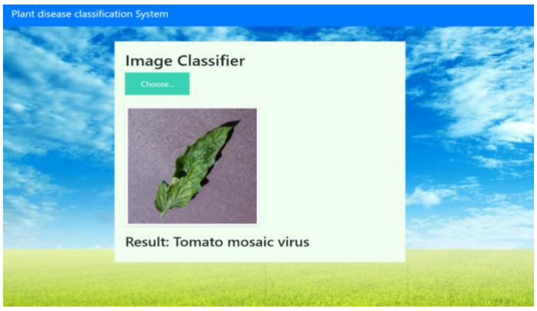

Figure6.2.3: Input tomato mosaic virus image for prediction

VIII.SOFTWARE TESTING

1. Data Gathering: The system begins by compiling a substantial and diverse collection of images of legitimate and counterfeit money from a variety of sources, including central banks, financial institutions, and law enforcement agencies. The collection was put together utilizing images of different coins, bills, and denominations, as well as updates to printing specifications and security measures.

2. Data preparation: Data augmentation, normalization, and resizing processes are used during the preparation of the currency pictures. These procedures ensure that the images are suitable for CNN model training. Data augmentation makes use of the diversity of the dataset to increase the richness of the images by applying adjustments like rotation, flipping, and scaling to build versions of the original photos.

3. CNN Model Development: To recognize and classify images, the system must select or develop an appropriate CNN architecture. The chosen architecture must be capable of identifying the intricate patterns and traits that distinguish real currency from counterfeit.

For the fourth phase, model training, the preprocessed dataset is divided into training and validation sets. The CNN model is then instructed using the training set to recognize the characteristics that separate authentic currency from fake currency. The model's parameters are iteratively changed based on training data during the training phase to decrease the classification error.

5. Model Evaluation and Optimization: - The system assesses the CNN model's performance on the validation set following training to determine its accuracy and generalizability. - Hyperparameter tweaking and optimization approaches may be used to increase the model's precision if it does not match the desired performance criteria.

6. Model Deployment: Once the CNN model reaches an acceptable level of accuracy, it is put into use in a production setting for batch or real-time processing of money images. The system makes sure the model is usable and expandable to accommodate numerous users and incoming money images.

IX.CONCLUSION

"Plant disease classification using AI" is a development in plant health management and agriculture. Utilizing artificial intelligence (AI) and cutting-edge methods like convolutional neural networks (CNN), this strategy may revolutionize the detection, diagnosis, and treatment of plant diseases.
The application of AI to plant disease categorization increases the precision and effectiveness of disease detection in agriculture. The system can swiftly identify disease trends, enabling early interventions and prevention, by analyzing vast datasets of plant pictures and training CNN models.

Plant diseases identified by AI offer significant advantages. It aids in crop health monitoring, boosting yields, lowering losses, and enhancing farm profitability. Early disease detection and precise diagnosis enable focused treatments, such as precise pesticide application, crop rotation, and disease-resistant varieties, to lessen the impact of farming on the environment.

This technique could increase food security by ensuring healthy crop output. By reducing disease outbreaks and improving agricultural management, AI-driven disease classification increases the stability of the food supply chain.

Implementing AI-based plant disease classification is still challenging. For model accuracy and generalization across geographies and crop kinds, well-rounded datasets are crucial. The technology must be available and inexpensive to farmers, especially in developing nations, in order to have the greatest impact on global agriculture.

By assuring healthy crop output, this technology could improve food security. AI-driven disease classification improves food supply chain stability by preventing disease outbreaks and optimising agricultural management.

AI-based plant disease classification is still difficult to implement. High-quality and diversified datasets are essential for model accuracy and generalisation across geographies and crop varieties. For maximum influence on global agriculture, the technology must be accessible and affordable to farmers, especially in developing regions. As AI advances, agricultural professionals, data scientists, and technology developers must collaborate to improve disease classification algorithms.

To create trust in AI in agriculture, ethical, data privacy, and regulatory issues must be addressed. "Plant disease classification using AI" can revolutionise agriculture and plant health management. AI can make farming more sustainable, efficient, and resilient, helping achieve global,foodsecurity,and sustainable agricultural growth

X.FUTURE ENHANCEMENTS

1. Multi-Spectral Imaging: The illness classification approach can be made more accurate by including multi- or hyperspectral imaging. These sophisticated imaging methods can identify early-stage infections and subtle disease symptoms that are invisible to the naked eye.
2. Few-Shot and Transfer Learning: These learning techniques enhance models for classifying illnesses. By transferring knowledge from pre-trained models on large datasets to smaller, domain-specific datasets, the technique can increase accuracy for novel diseases or crop varieties with little to no training data.
3. Field-based disease monitoring is made possible by sensor technology and IoT gadgets. AI-powered image analysis and local sensors immediately identify disease outbreaks, reducing agricultural losses.
4. Mobile Applications and Edge Computing: Farmers' smartphones or tablets can classify diseases using mobile apps or AI models on edge devices.

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