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Plant's Diseases Detection and Pest Control Based On Deep Learning

Bhagyashree Bais

St. Vincent Pallotti College of ngineering and Technology Nagpur, India

salonibais3@gmail.com

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***Abstract—** Invasive organisms and Plant disorder have a big influence on output and quality. By employing digital image processing, scholars can precisely detect these problems. Researchers are looking into using deep learning to identify pests and agricultural diseases since recent developments in the field have outperformed more conventional approaches. This paper provides an overview of the issue, contrasts deep learning with traditional approaches, and summarizes current work on segmentation, detection, and classification networks. Performance assessments and common datasets are addressed. Research directions and possible answers are discussed, as well as challenges in practical application. The paper concludes with a summary of upcoming developments in deep learning-based agricultural disease and pest detection. The process of detecting agricultural diseases entails locating illnesses in crops. There are two phases to it: feature extraction for picture analysis and classification, and segmentation to identify impacted regions.*

Keywords— Plant disease, Deep learning,

I. INTRODUCTION

Plant's ailments and pests pose significant threats to the regular growth of vegetation, potentially leading to plant demise throughout the entire growth cycle, from seed development to seedling emergence. Human experience concepts will be utilized to describe plant afflictions and pests in imaginative and anticipatory tasks. Given the dearth of comprehensive and precise information on techniques for detecting plant's diseases and pests based on deep learning, this study compiles and scrutinizes relevant literature from 2014 to 2020, aiming to assist researchers in swiftly and comprehensively understanding applicable methodologies and technologies in this field. The study is organized as follows: The "Definition of plant's diseases and pests detection problem" section provides the definition of the problem; the "Image recognition technology based on deep learning" section focuses on the introduction of such technology; the "Plant's diseases and pests detection techniques based on deep learning" section analyzes three types of techniques according to network structure; the "Dataset and performance evaluation" section introduces datasets and compares performance; the "Challenges" section discusses challenging conditions; and the "Conclusions and future guidelines" section offers prospects. Traditional vision-based approaches for detecting plant's diseases and pests often rely on conventional image processing algorithms or manual feature extraction with classifiers. While carefully constructed imaging schemes can reduce algorithmic complexity, they may increase software costs. Natural environments pose challenges such as small lesion area differences, low contrast, and varied lighting conditions, making detection difficult with classical methods. Deep learning, particularly convolutional neural networks, has shown promise in various computer vision fields. Several deep learning-based detection strategies have been applied in agriculture, indicating significant academic and market potential.

II. LITERATURE REVIEW

[1] Used backpropagation neural networks and digital image processing to address plant disease detection (BPNN). To divide affected leaf sections, they used a variety of methods, such as border detections and Otsu's thresholding. For the purpose of classifying diseases, features such as color, texture, morphology, and edges were then extracted. BPNN was applied in order to diagnose

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diseases.

[2] Investigated numerous image processing algorithms for identifying plant ailments. They examined both surface and color properties and ran their algorithms on a batch of 110 RGB photographs. The features comprised the mean and standard deviation of the RGB and YCbCr channels, GCLM features, and the mean and standard deviation of pictures convolved using Gabor filters. Support vector machines were used for classification. They discovered that GCLM features are good for recognizing healthy leaves, but colour and Gabor filter features are better for detecting anthracnose and leaf spot, respectively. Their technique had a maximum accuracy of 83.34% when all characteristics were retrieved.

[3] The study verified the use of VNIR and SWIR spectrums in hyperspectral imaging to identify plant diseases. The researchers presented a unique grid removal approach and employed k-means clustering for leaf segmentation. With VNIR vegetation indices, they were 83% accurate, and with full spectrum, they were 93% accurate. But the technique needs an expensive 324-spectral-band hyperspectral camera.

[4] A Bacterial Blight detection method for Pomegranate plants was created by Sharath D. M. and colleagues by utilizing a variety of variables, including color, mean, homogeneity, SD, variance, correlation, entropy, and edges. They used the Canny edge detector to extract edges and GrabCut segmentation to isolate the region of interest. The degree of infection in the fruit is accurately predicted by the method.

[5] Using a dataset of 3000 high-resolution RGB photos, Garima Shrestha and colleagues used a convolutional neural network to identify plant illnesses, and they were able to categorize 12 diseases with 88% accuracy. Comprising three blocks of convolution and pooling layers, the network has a high computational cost. The model's F1 score, however, is poor at 0.12 because there are more false negative predictions than true ones.

III. PROPOSED SYSTEM ANALYSIS AND DESIGN

Analysis

The current method of plant disease detection relies on visual observation by specialists, requiring significant manpower and expenses, particularly for large-scale farms. However, in many regions, access to experts is limited, and consulting them is both costly and time-consuming. In such scenarios, an automated detection method is proposed, utilizing image-based analysis of plant leaves for more efficient and cost-effective disease detection. While visual inspection by humans is challenging and less accurate, automated detection reduces effort, time, and improves accuracy. Common diseases such as brown and yellow spots, early and late scorch, as well as fungal, viral, and bacterial infections, can be detected using photo processing to measure affected guidance.

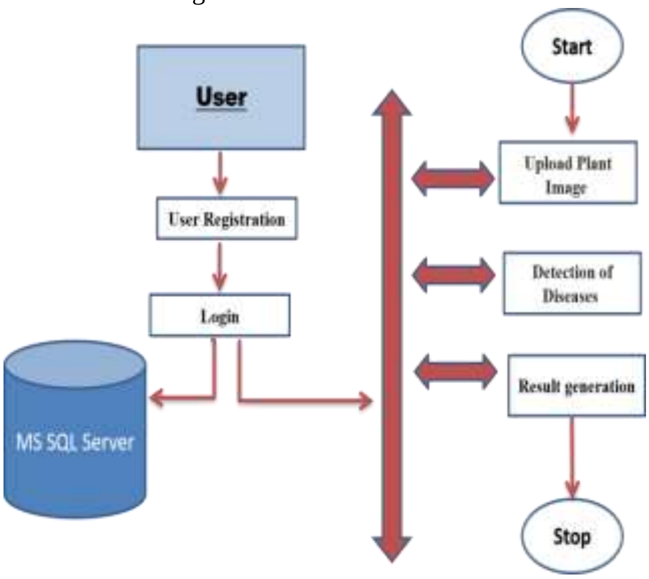

Fig: System Flow Diagram

IV. RESEARCH METHODOLY

1. **Data Collection**:- Gather a diverse dataset of images containing Plants that are healthy and those that have been infected with different illnesses.
   - Ensure that the dataset covers different plant species, growth stages, lighting conditions, and disease severities. - Annotate the images with labels indicating the presence of diseases.

2. **Data Preprocessing**:- Resize and normalize the images to a consistent size and color space.
   -Augment the dataset with techniques such as rotation, flipping, and zooming to increase its diversity and robustness.
   -Divide the dataset into training, validation, and testing sets.

3. **Feature Extraction:** Identify relevant characteristics from photos to represent their characteristics.
   -Common techniques include color histogram, texture analysis, and deep feature extraction using pretrained convolutional neural networks (CNNs) like VGG, ResNet, Inception.

4. **Model Selection and Training**:- Select an adequate machine or deep learning model for classification, such as SVM, Random Forest, or CNNs.
   - Train the chosen model using the training dataset, optimizing its hyperparameters through techniques like cross-validation.
   - Fine-tune the model using transfer learning if using pretrained CNNs.

5. **Model Examination**:- Using the validation dataset, figure out the trained model's performance by assessing measures like as accuracy, precision, recall, and F1-score.
   - Fine-tune the model further based on validation results to improve its performance.

6. **Model Testing and Validation:**- Test final model using test dataset to assess a generalization ability on unseen data.
   -Validate the model's predictions against ground truth labels to ensure its reliability and effectiveness.

7. **Deployment and Integration:**- Deploy the trained model into a production environment, either as a standalone application or integrated into existing agricultural systems.
   - Implement an intuitive user interface for interacting with the model, allowing users to upload images and receive disease detection results.

8. **Monitoring and Maintenance**:- Monitor the deployed system's performance over time, collecting feedback and data for continuous improvement.
   - Update the model periodically with new data and retrain it to adapt to evolving disease patterns and environmental conditions.

9. **Community Engagement and Collaboration**:- Foster collaboration with domain experts, agricultural researchers, and farmers to gather domain-specific knowledge, validate model outputs, and incorporate feedback into the system.

V. OBJECTIVES

1. It is used to detect unhealthy regions of plant leaves.
2. The classification of diseases affecting plant leaves.
3. To investigate leaf infection.
4. To give the user remedy information.

VI. SYSTEM IPLEMENTATION AND TESTING

SETTING ENVIRONMENT

Technology Used:

Python

Python is a famous programming language.

It became created by means of Guido van Rossum, and released in 1991.

Tool VS Code:

Redefined and improved for creating and debugging contemporary online applications, Visual Studio Code is a code editor.

VS code runs on various operating system macOS, Linux, and Windows.

Flask Python:

Flask is a internet framework, it is a module of python that helps to increase internet programs effortlessly.

It’s has a small and easy-to-amplify centre: it’s a micro framework that doesn’t include an ORM (object Relational manager) or such functions.
It does have many cool abilities like URL routing, template engine. it's miles a WSGI net app framework.

Implementation Details:

Importing necessary libraries:

The script starts by importing the required libraries, such as TensorFlow, Keras, NumPy, Pandas, OpenCV, Matplotlib, and Scikit-learn.

Loading and preprocessing the dataset:

The script loads a CSV file containing information about the dataset, including the image file paths and their corresponding labels. It then maps the labels to binary and string values for binary classification and human-readable interpretation. Next, the dataset is split into stratified train, validation, and test sets using the Scikit-learn library. The images are then copied to their respective directories for processing with the KerasImageDataGenerator.

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Building the CNN model:

The script builds a simple CNN model with three convolutional layers and one fully connected layer. The model uses rectified linear unit (ReLU) activation functions, max pooling layers, and batch normalization layers to enhance the training process.

Compiling and training the CNN model:

The script compiles the CNN model with the Adam optimizer, and accuracy metric. It then trains the model for 30 epochs using the fit method of the model object.

Saving the CNN model:

The script saves the trained CNN model to a file named "64x3-CNN.model" using the save method of the model object.

Evaluating the CNN model:

The script evaluates the trained CNN model using the evaluate_generator method of the model object with the test data. The loss and accuracy metrics are then printed to the console.

Defining a prediction function:

The script defines a predict_class function that takes a path to an image file and outputs the predicted class (Normal or Tuberculosis). The function reads the image file with OpenCV, resizes it, and converts it to RGB format. It then normalizes the pixel values and feeds the image to the saved model for prediction. The function uses the argmax method of NumPy to determine the predicted class index and prints the corresponding label to the console.

Explanation of the model: The CNN architecture used in this code consists of four convolutional layers with increasing filter sizes (8, 16, and 32), followed by max

pooling layers and batch normalization layers. The first convolutional layer has a filter size of (3, 3) and an input shape of (224, 224, 3) representing an RGB image with a resolution of 224x224 pixels. The second convolutional layer has a filter size of (3, 3), and the third convolutional layer has a filter size of (4, 4). All convolutional layers use a rectified linear unit (ReLU) activation function.

After the final convolutional layer, there is a flatten layer that reshapes the output into a 1D array, which is then passed through two dense (fully connected) layers with ReLU activation functions. The last dense layer has two units (one for each class), and uses a softmax activation function to generate class probabilities. The model is trained using binary cross-entropy loss and the Adam optimizer with a learning rate of 1e-5. The model is evaluated using the accuracy metric. During training, the model is trained on the train set and validated on the validation set for 30 epochs.

CONCLUSION

In contrast to traditional image manipulation techniques, which deal with plant diseases and pest identifying duties in numerous steps and hyperlinks, plant ailments and pests detection strategies based on deep analysis combine them into stop-to-forestall feature extraction, which has enormous improvement opportunities and brilliant capacity. No matter the reality that plant sicknesses and pests detection generation is growing abruptly, it is been shifting from instructional studies to agricultural software, there may be nevertheless a sure distance from the mature application inside the actual natural surroundings.

In end, plant ailment detection and pest manipulate play important roles in ensuring the fitness and productiveness of agricultural vegetation. those practices provide several benefits, which includes early detection, targeted interventions, reduced economic losses, increased crop yield, prevention of ailment spread, and advanced aid management. They make contributions to better decision making, more desirable crop fine, environmental sustainability, and the implementation of integrated pest management techniques.

but, there also are vital considerations and ability negative aspects related to plant sickness detection and pest control. those consist of the value of implementation, constrained accessibility to advanced technologies, the possibility of fake positives/negatives, the want for technical understanding, time-ingesting tactics, complexity in diagnosing sicknesses, and infrastructure requirements.

similarly, pest manage efforts have advantages together with crop protection, expanded productiveness, protection of the meals delivers, disorder prevention, reduced pesticide use, preservation of herbal ecosystems, value savings, lengthy-term sustainability, minimized fitness risks, and compliance with guidelines. however, additionally they gift disadvantages, inclusive of environmental impacts, development of resistance, harm to useful organisms, health risks, financial fees, complex pest dynamics, confined efficacy, regulatory compliance demanding situations, potential for pesticide residues, and influences on herbal enemies.

To make sure a hit plant sickness detection and pest manage projects, it's miles critical to strike a stability between the benefits and disadvantages. Implementing sustainable and included procedures, incorporating medical studies, selling schooling and education, and adhering to safety pointers are important for effective sickness detection, pest manipulate, and the long-time period sustainability of agricultural systems. with the aid of addressing those challenges and embracing progressive answers, we can attempt for

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healthful plants, reduced environmental effect, and progressed meals protection for the destiny.

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