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Plant Disease Identification using Deep Learning

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Plant diseases are a major threat to the world's agricultural industry, resulting in crop loss, financial hardships, and worries about food security. To lessen the effects of these disorders, prompt detection and treatment are essential. Identifying plant diseases with deep learning uses cutting-edge technologies to automate the process, including deep learning and computer vision. An overview of the strategy is given in this abstract, with special attention to its methodology, importance, and results. The use of convolutional neural networks (CNNs) in the identification of plant diseases is investigated in this paper. The procedure includes gathering a large dataset of photos showing both healthy and sick plants, preprocessing the information to guarantee consistency, and using a CNN-based model to accurately classify the diseases. The accuracy, precision, recall, and F1-score are among the important evaluation metrics used to evaluate the model's performance.

Keywords: CNN, BPNN, GCLM and DL.

1. Introduction

An inventive and useful use of computer vision and machine learning techniques is plant disease diagnosis in DEEPLEARNING. It makes use of the flexibility of Python as well as numerous libraries and frameworks to automate the identification and diagnosis of illnesses that impact plants. With the ability to detect diseases early and treat them specifically, this technology will have a big impact on agriculture by eventually increasing crop yields and food security. The foundation of the economy is agriculture. The economy of our nation is, first and foremost, heavily reliant on agriculture. When it comes to picking crops and convenient herbicides and pesticides, farmers are spoiled with choice. Consequently, crop damage may lead to unforeseen losses that have an effect on farming industry output, which in turn has an effect on the economy. The economy of our nation is, first and foremost, heavily reliant on agriculture. Farmers may choose from a wide variety of crops and practical herbicides and pesticides to employ.

Consequently, our automated method is developed through the use of deep learning image processing techniques. Farmers choose monoculture because of its advantages, which are covered in the sections that follow. As a result, the monoculture agricultural sector is growing in importance today. The framers would benefit from this document, which will serve as a kind of guide. Numerous methods have been created to carry out the detection of plant diseases; in this work, we focus on the most often used method, image processing. It is critical to identify plant diseases in order to minimize yield losses. Manually observing plant diseases is quite tough. It requires a significant amount of effort, knowledge of plant diseases, and a lengthy period of time. Therefore, the diagnosis of plant diseases may be accomplished through the use of image processing and machine learning models.The factors for categorization include leaf color, leaf area, leaf damage, and leaf texture. In order to attain the highest accuracy, we have examined many picture characteristics or features in this research to identify various plant leaf diseases. In the past, professionals would visually check the leaves to discover plant diseases, or they would use chemical techniques. This requires a sizable team of specialists and ongoing plant monitoring, both of which are expensive when dealing with huge farms. Under these circumstances, the suggested approach works well fora keeping an eye on big agricultural fields. Automatic illness identification by only observing the symptoms on

1.Python's Function

2.Important Elements

3.Challenges

4.Benefits

5.Applications.

2. LITERATURE SURVEY

Using back propagation neural networks (BPNNs) and digital image processing techniques, S.Khirade. handled the challenge of plant disease identification in 2015 [1].

Several methods for identifying plant diseases using leaf photos have been developed by authors. To separate the affected portion of the leaf, they have used Otsu's thresholding in conjunction with border detection and spot detection algorithms. Subsequently, characteristics including color, texture, morphology, edges, and so on were retrieved in order to classify plant diseases. In order to classify, or identify plant diseases, BPNN is employed. In this study, Shiroop Madiwalar and Medha Wyawahare examined several image processing techniques for the identification of plant diseases. In order to identify plant diseases, the authors examined the color and textural characteristics Their methods using the 110 RGB image dataset. The mean and standard deviation of the RGB and YCbCr channels, the grey level cooccurrence matrix (GLCM) features, and the mean and standard deviation of the picture convolved with the Gabor filter were the features retrieved for classification. For classification, a support vector machine classifier was employed. The authors came to the conclusion that normal leaves may be identified using GCLM traits. On the other hand, it is thought that color features and Gabor filter features work best for identifying leaf spots and anthracnoseaffected leaves, respectively[3].

Using every characteristic that was retrieved, they were able to attain the greatest accuracy of 73.34%. The use of hyperspectral imaging in the job of plant disease detection was proven by Peyman Moghadam. The authors' accuracy with vegetation indices in the VNIR spectral band was 73%, while their accuracy with complete spectrum was 93%.Even if the suggested approach produced better accuracy, the solution becomes unaffordable since it needs a hyperspectral camera with 324 spectral bands. The Bacterial Blight detection method for Pomegranate plants was created by Sharath D.M. utilizing characteristics like color, mean, homogeneity, SD, variance, correlation, entropy, edges, etc. With an accuracy rate of 88.80%, the authors have correctly categorized 12 plant diseases[5].

For the experiments, a dataset of 3000 RGB high quality photos was employed. There are three convolution and pooling layer blocks in the network. As a result, the network has high computational costs. Additionally, the model's F1 score is 0.12, which is extremely poor due to the increased quantity of incorrect negative predictions. Deep learning approaches for recognizing images DL techniques have emerged as a viable way to find plant lesions[6].

These RNN-based methods have shown successful in recognizing different plant lesions from images with a high degree of accuracy. DL models reduce the requirement for human feature engineering by properly identifying and classifying various illness signs by automatically learning features from the photos. These models are also capable of processing massive volumes of data, which makes them ideal for large-scale plant lesion identification. Deep learning theory In a 2006 Science publication, Iqbal made the term "Deep Learning" widely known (DL). The process of converting high-dimensional data into low-dimensional codes via "autoencoder" networks is explained in the article. These networks consist of low-parameter layers that are trained to produce high-dimensional input vectors. Gradient descent is one technique for fine-tuning the network's weights although it works best when the baseline weights are close to an acceptable solution. They've carried out trials. Gradient descent is one technique for fine-tuning the network's weights, DL-based models are used for tasks such as language translation, text summarization, and sentiment analysis[9].

3. PRE-PROCESSING TECHNIQUE

In the discipline of image processing, data preparation is a crucial step that entails organizing, cleaning, and converting raw data into a format that can be used for analysis or model training. Data pretreatment is a critical step in the image processing process that improves the caliber and efficiency of later image processing operations. This article examines important methods used in data preparation and discusses its importance in the field of picture processing.

Resizing

Normalization

Mean Subtraction and Standardization

Data Augmentation

Contrast Enhancement

Noise Reduction

Cropping

Grayscale Conversion

Histogram Equalization

Pre-trained Models and Transfer Learning

Put strong preprocessing methods into practice to get the picture data ready for analysis. To increase model performance, this entails scaling photos to a constant resolution, eliminating noise, and improving image quality.

4. EXISTING SYSTEM

The effective use of deep learning technology in plant disease categorization in recent years has given researchers a fresh perspective on the field. Nevertheless, interpretability and transparency are lacking in DL classifiers. DL classifiers are occasionally regarded as" black boxes" since the bracket system isn't explained or handed with any specifics. In addition to being essential for classifying plant diseases, high accuracy also requires knowledge of the plant's symptoms and the method used for diagnosis. In order

to get a better understanding of the diagnosis of plant diseases, several researchers have dedicated themselves to the study of visualization approaches in recent years, such as the creation of visual heat maps and salient maps. Among these are the works of and are crucial to understanding how CNN recognizes disease from images. The system is made available to the intended audience, which may consist of farmers, agricultural specialists, or researchers. It offers them an important tool for crop management and early disease diagnosis. It's crucial to remember that the selection of machine learning algorithms, the quality and variety of the dataset, and continuous maintenance and updates all affect how effective these systems are. Future developments in deep learning and computer vision might result in more precise and effective methods for identifying plant diseases.

5. PROPOSED SYSTEM

One of the most important jobs in the world is agriculture. It is quite important. as food is a necessity for all living things in the world. Region Based Convolutional Neural Networks (R-CNN), a deep learning technique, are used in this suggested method for identification. The training phase and the testing phase are their two stages. They acquired photos, preprocessed them, and trained the images using R CNN. Classification and identification of the leaf disease are done in the second step. While real-time photos can be utilized for testing, photographs from the dataset are used for training. Images that are submitted to the system or stored in the database are used to diagnose leaf disease. In the event that real-time information is obtained from the environment, preprocessing of the picture and feature categorization are required. Diseases are identified and their names are gained via diagnosis.

Architecture Model :

Choose a deep literacy armature, similar as Convolutional Neural Networks(CNNs), that's applicable for image categorization tasks. suppose about using trained models, similar as VGG16, ResNet, or Inception, and modify them for the particular splint complaint discovery job. To enhance performance, fine- tune the pre-trained model using the target dataset.

Training :

Training Split the dataset into training, confirmation, and test sets. Train the model on the training set, validate its performance on the confirmation set, and fine-tune consequently. Monitor for over fitting and adjust hyper parameters to achieve a balance between accuracy and generalization.

Block diagram :

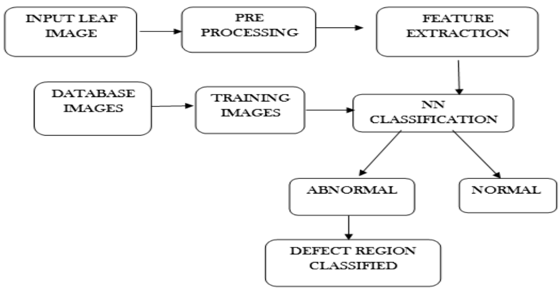

Figure 1. Block diagram to identify plant disease

Steps to identify plant disease

1.Data Collection:

Compile a collection of pictures showing both healthy and unhealthy plants. The plants and illnesses you wish to identify should be represented in this dataset, which should be varied.

2. Data Preprocessing:

To guarantee consistency, clean and prepare the photos. To enhance model generalization, this might involve data augmentation, standardization, and scaling.

3. Model Selection:

Select a deep learning model that is appropriate for classifying images.Because Convolutional Neural Networks (CNNs) are so good at capturing picture characteristics, they are frequently utilized for this kind of job.

4. Model Training:

Using an appropriate optimizer and loss function, divide the dataset into training and validation sets. In order to minimize the loss function, the model's weights are updated during the training phase.

5. Model Evaluation:

On a different test dataset, evaluate the model's performance using evaluation measures including accuracy, precision, recall, and F1-score. This stage aids in evaluating the model's precision in identifying plant diseases.

6. Deployment:

After the model performs well enough, you may use it to diagnose plant diseases inpractical situations. This may be done using a mobile or online application.

6. RESULT AND DISCUSSIONS

Design of input page

While the deep literacy- grounded factory complaint opinion model presented in this exploration may overcome environmental complexity and increase identification delicacy, there are still a many issues that need to be addressed. For instance, the Chan-Vese technique requires lengthy computations that must be repeated iteratively, which hinders the method's ability to identify results quickly. In subsequent studies, we will employ the neural network to produce a zero starting set that corresponds to various leaves.

This will raise the Chan-Vese algorithm's end of calculation limit, accelerate training, and terminate the iteration early.

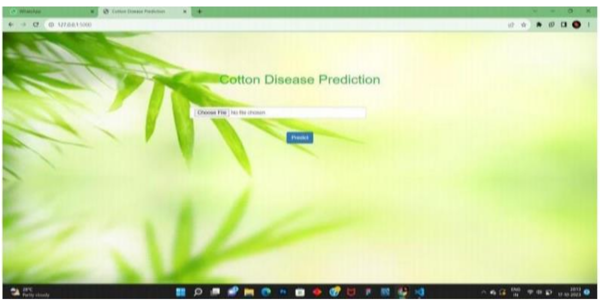

Figure 2. Web Page

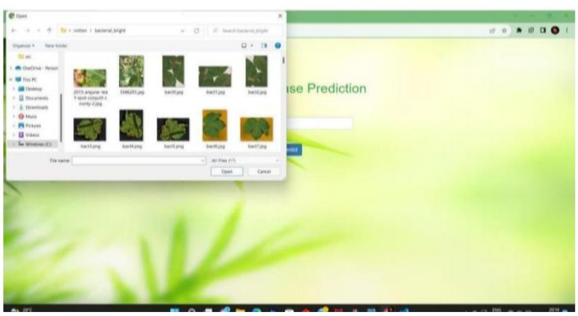

Figure 3. Choosing image

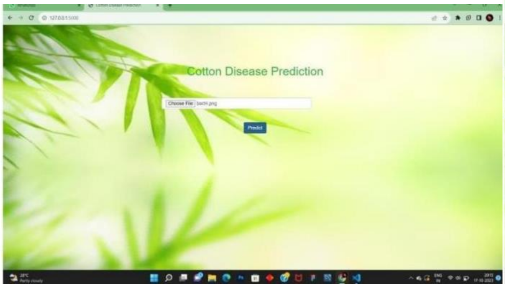

Figure 4. Image Uploaded

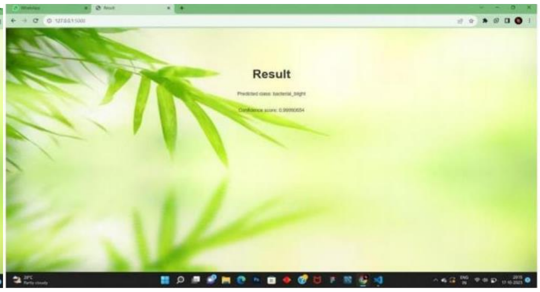

Figure 5. Result Page

Plant diseases change over time, therefore you might need to update your model to account for new strains or illnesses. Maintaining accuracy requires retraining the model and updating the dataset on a regular basis.

7. CONCLUSION AND FUTURE SCOPE

Conclusion

This program description gives a thorough rundown of the features, advantages, and possible future improvements of the Plant Disease Identification program. It provides as a framework for comprehending the features and importance of the software in the agriculture industry. The easiest way to maintain an effective yield is to identify plant diseases using image processing. This paper's major objective was to demonstrate how an image processing tool may help farmers increase yields by helping to ensure reliable findings about plant disease identification. By the project's conclusion, we had succeeded in achieving the goal, which was to use image processing to the detection of plant diseases. Additionally, developing the stand-alone application will increase farmers' access to and use of this technology. Consequently, a standalone application for distinguishing between healthy and diseased plants has been created. Future research also aims to develop a smart phone application to facilitate the procedure for farmers and employ drones to increase the amount of training picture dataset and boost the precision of our suggested solution.

Future Scope

It is advised that future studies employ bigger datasets with more pictures in order to assess CNN models' performance in greater detail. To further increase classification accuracy, more computationally robust deep learning architectures may be investigated. The development of more precise and effective agricultural disease detection techniques may benefit from these advancements. With the continuous advancement of technology, it is plausible that in the future, location and time data may be added to picture data obtained from cell phones for image classification jobs. It could be able to improve crop disease detection accuracy and dependability even further by adding this more data. Such study might lead to the development of a smart phone assisted crop disease diagnostic system.

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