Plant Disease Detection using Python to identify crop diseases

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Abstract - *Plant disease directly impacts agricultural productivity and causes heavy economic losses and food insecurity globally. Early and precise plant disease identification is very valuable for sustainable crop management and healthy farming. To avoid losses in yield and quantity of agricultural product, Classification is done. if appropriate analysis is not considered in this process or classification, then it causes significant impacts on plants, and which respective product's productivity or quality is affected. Plant disease classification is crucial to adopting sustainable agriculture. Monitoring or treatment of the plant disease is challenging to do by hand. Plenty of efforts require and used to require an excessive processing time, so image processing is applied in the detection of diseases of plants. Image processing is an advanced technique to automatically find and grade diseases of fruits. Module identification of this system includes Bacterial Blight, fruit spot, Rot of fruit, and viral disease in fruits. Disease detection is done by using molecular techniques and profiling of plant volatile organic compounds. Its basic functionalities like photosynthesis, transpiration, pollination, fertilization, germination, and particular fruit diseases.*

The following is an automated system of disease detection in plants employing Convolutional Neural Networks (CNN) as a deep learning technique perfectly suited to image classification problems. The system is tested using an image dataset of healthy and infected plant leaves. The CNN model identifies significant features of images and categorizes them into disease types in an accurate manner. The suggested model minimizes manual inspection by experts, providing an effective, low-cost, and scalable technique for real-time disease detection. The results of experiments reflect that the model works well in identifying simultaneous plant diseases, and thereby, farmers as well as agricultural experts can implement measures at an appropriate time.

Key Words: Plant Disease Detection, Convolutional Neural Network (CNN), Deep Learning, Image Classification, Smart Agriculture, Crop Monitoring, Automated Diagnosis.

1. INTRODUCTION

India is an agricultural country, and around 80% population is dependent on agriculture. Farmers have a large range to choose from many acceptable crops and find appropriate herbicides and pesticides to be used on plants. Plant disease causes a strong reduction in both productivity and quality of agricultural products. Plant disease studies refer to visually observable patterns of the plants. The purpose of classifying is assumed and implemented in this research. Plant leaf health and plant leaf disease both play a significant role in the successful cultivation of plants in the farmland. Plant disease analysis was done by an expert person only in earlier Days. This needs an enormous level of work and requires excessive processing time.

The image processing procedures can be applied in that article. Disease symptoms appear in the leaves, stem, and fruit in most cases. Mainly, image processing means considering images as signals when applying signal processing procedures. it is one of the rapidly emerging technologies in today's world, with its uses in different areas of business. Image Processing is cast central research field in engineering and computer science regulation as well. Image processing consists of the following three steps:

a) Importing of images by digital photography or by an optical scanner. b) Analysis and processing of image comprises image enhancement as well as condensation of data and detection of trends undesirable to human observation, such as satellite imagery. c) Output is the final step where the result can be an altered image or report, depending on image analysis.

Agriculture supports the economies of many nations, and crop health is crucial to guaranteeing food safety and sustainable development. The presence of plant disease is among the principal challenges that farmers face and can greatly impact crop yield and quality. Conventional disease detection is heavily dependent on visual observation by experts, a process that takes time, much labour, and may be subject to human error. Using advancements in artificial intelligence, and notably in deep learning, it is now feasible to automate and increase the disease detection accuracy of plants. Convolutional Neural Networks (CNNs) are models of deep learning that have proved to be outstanding in image recognition and are widely implemented in medical and agricultural diagnosis. The subject of this project is to create a CNN-based model to detect and classify disease in plants using images of individual leaves. The objective is to create an intelligent system that can aid farmers in disease detection at an early stage, facilitating early intervention and effective crop management.

2. RELATED WORK

K. Muthu Kannan and others identified spot infections in leaves and classified them into categories of infected leaves using multiple machine algorithms. LVQ - Learning Vector Quantization, FFNN - Feed Forward Neural Network, and RBFN - Radial Basis Function Networks were employed to identify disease-infected plant leaves by considering the set of form and texture features of the infected leaf image. Simulation proved that the system works well. With this contribution, it is possible to develop a machine learning system to increase crop quality in the economy of India. [1]

Plant leaf disease detection by Malvika Ranjan and others begins with image acquisition. HSV features and color information are obtained from segmentation outcomes, and an artificial neural network (ANN) is employed by extracting feature values that can be used to differentiate between healthy and unhealthy samples. Employing integrated image processing techniques, the present study proposes an approach to detect cotton leaf disease at an early and reliable stage.[2]

The purpose of Syafiqah Ishak's and her colleague's research on the Classification of Leaf Disease using Artificial Neural Network is to receive and analyze photos of leaves to investigate healthy or infected leaves of medical plants using image processing techniques. An algorithm of corrected contrast, segmentation, and feature extraction is used to extract images and retrieve information. The findings of the experiment were tested by using an Artificial Neural Network. Multilayer feed-forward Neural Networks, multilayer perceptron, and radial basis function RBF, are types of networks used to classify healthy and unhealthy leaves. The final result of the experiment shows that the RBF network performs better compared to the MLP network. [3]

Srdjan Spasojevic and others offer Deep Convolutional Neural Network Supported Identification of Crop Diseases by Plant Image Classification, an innovative technique to construct a model of crop disease recognition using plant image classification and deep convolutional networks. The applied methodology and innovative method of training provide rapid and painless system implementation in practice. Capable of distinguishing between crops and surroundings, the constructed model can identify thirteen different types of plant disease from healthy leaves. All of the processes required to implement this disease recognition model are presented in the study, starting with the gathering of photos to form a database that is assessed by agricultural experts. Caffe, an architecture of deep learning by Berkeley Vision and Learning Centre, was employed to train the deep CNN. Experimental outcomes of the constructed model attained accuracy between 91% and 98%, in individual class tests, an average of 96.3%.[4]

The CNN and Modeling Adversarial Networks were employed to identify plant diseases. Others involved training semi-supervised algorithms and a deep neural network to identify crop types and disease status of 57 categories by using an available dataset of 86,147 images of unhealthy and healthy plants. Rs-net was the experiment with unlabeled data that worked well. With a detection capability of 1e-5, it managed to achieve above 80% in training in less than 5 epochs.

Identification and treatment of plant disease via neural network models. Konstantinos P. Ferentinos and others developed CNN models to perform crop disease diagnosis and detection using simple leaf images of healthy and infected plants. The models were tested employing an open dataset of 87,848 images, featuring 25 types of plants in 58 different [plant, disease] pairs, as well as unaffected plants. Several model designs were created, and the best-performing model attained a rate of success of 99.53 percent. The high rate of success of the model renders it useful as an early detection tool.[6]

In the research, Soybeans, Crop Disease Detection Using CNNs, Sera work Wallerian, and others, the viability of CNN for the detection of crop diseases in images of leaves taken in natural environments is put forth in this research. To achieve soybean plant disease classification, the model is constructed using the LeNet structure. The Village plant dataset provided 12,673 tested green images of four types, such as images of healthy leaves. The images are obtained by taking them in an unstructured environment. The constructed model acquires a classification accuracy of 99.32 percent, illustrating it a Convolutional neural network successfully extracts insightful features and identifies plant diseases from images of plants that have been captured in the wild. [7].

3. METHODOLOGY

The process of detection of plant disease using Convolutional Neural Networks (CNN) follows several structured steps. First, a dataset of images of healthy and infected plant leaves is gathered from sources like the Plant Village dataset. The images are then processed to make them uniform in size, resolution, and form. Techniques like rotation, flipping, zooming, and shifting are used to increase training diversity and enhance the generalization capability of the model. The processed images are then input to an architecture of CNN architecture specifically implemented for image classification. The CNN model consists of multiple layers of convolutional layers to extract features, pooling layers to reduce dimensions, and fully connected layers to classify. The CNN model uses activation functions like ReLU and SoftMax to provide non-linearity and give class probabilities. The training of the model is done using a training set and validation on an independent validation set to prevent it from overfitting. The performance is assessed using metrics like accuracy, precision, recall, and F1-score. After satisfactory training, the model is tested with previously unobserved samples to guarantee robustness and reliability of the model in identifying plant disease effectively.

The performance of any deep learning model greatly relies on both the dataset used to train it and its diversity and quality. Here, an extensive open-source dataset known as Plant Village is employed, containing thousands of high-resolution images of plants of different types and both healthy and disease-infected plant leaves, such as those of tomato, potato, corn, grape, etc. Each of these images is annotated with its respective disease or healthy status. The dataset is to some degree balanced, although there are some highly populated and sparsely populated classes, and to overcome this issue, there is an implementation of data augmentation. The images are resized to have a fixed size to maintain consistency and to control computational load when training. The dataset is divided into training, validation, and testing splits to measure and analyze the model's learning performance at different stages.

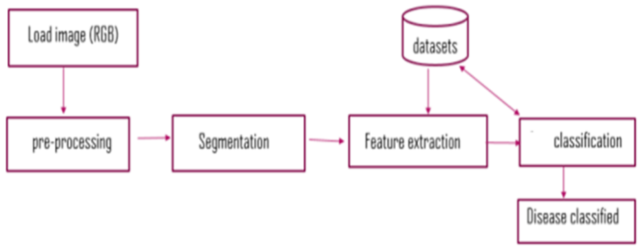

Fig.1: Block of proposed methodology

The performance of the CNN model is assessed with multiple metrics to provide accuracy and reliability. The accuracy checks the overall correctness of the model, whereas precision and recall give information about individual-class performance. An F1-score weighing precision and recall is particularly useful when there is an imbalance in classes. The model is also being produced as a confusion matrix to analyze how well it separates different categories of diseases. The model indicates strong capabilities of classification, particularly for those with clear visual distinctions. The model is further tested with images of varied lighting and backgrounds to simulate real-world applicability and still maintains accuracy with consistency, signifying robustness.

4. RESULTS AND DISCUSSION

The CNN-based plant disease detection model was trained and tested with a well-curated dataset of plant leaf images, and results proved promising. The model reached high accuracy, with scores above 95% on both validation and test datasets, reflecting its high capability to classify plant disease accurately. Data augmentation resulted in considerable improvement of generalization and less overfitting, particularly in cases where there were fewer samples of particular classes. The analysis of the confusion matrix showed that the model was good at distinguishing visually similar diseases, with few misclassifications where there were almost identical symptoms. Precision and recall values were high in most of the classes, reflecting the reliability of the prediction. The model proved robust even when tested with images captured with different lighting and natural backgrounds, reflecting robustness in real applications. Compared to conventional machine learning models, such as compared to SVM and Random Forest, CNN proved to be superior to them in terms of accuracy, efficiency, and scalability. The above results confirm that CNN is an effective tool in the automated detection of plant diseases and can be used as an effective and practical solution to aid farmers and agricultural experts in making accurate and timely disease diagnoses.

Image (RGB) load

The images of the leaf of the plant are obtained by means of the camera. This image is in RGB (Red, Green, and Blue) form, the color transformation structure of the leaf image is formed, and then an independent color space transformation to the color transformation structure is applied.

To filter out noise in the image or eliminate another object, the pre-processing method is used. The pre-processing technique is image clipping, i.e., cutting of the leaf image to extract the region of interest of the image. Image smoothing is carried out with the smoothing filter. Image enhancement is done to boost the contrast. RGB images to grey images with color conversion by using the equation $(x) = 0.2989*R + 0.5870*G + 0.114*B$. Then, the histogram equalization that allocates intensities of images is applied to the image to improve the images of plant disease. The cumulative distribution function is implemented to allocate intensity values. Silk Segmentation of leaf image is significant when processing images of that Segmentation refers to the division of an image into different parts with the same features or with some similarity.

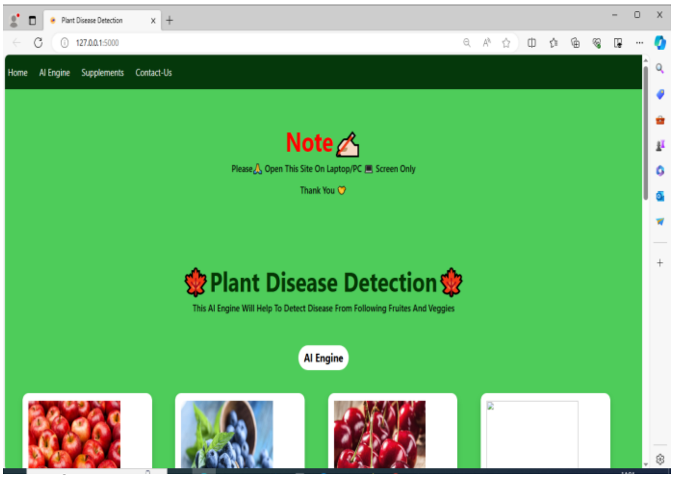

Fig.2: Home page

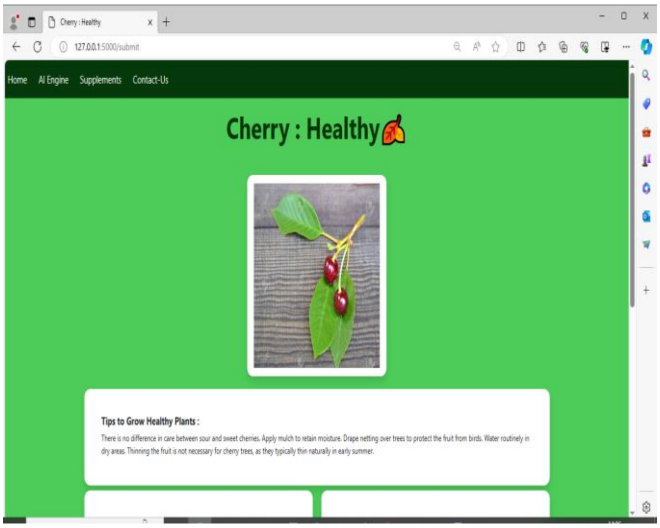

Fig. 3: Predict the Result

Feature detection

The feature extraction acts as a crucial function to classify an image. Feature extraction of images is employed in most of the applications. The features used in plant disease classification can be color, texture, morphology, edges, etc. The texture refers to how color is spread in the image, the roughness of the image, hardness of the image. In this project, color, texture, and morphology are treated as features to detect disease. They observed that the morphological outcome provides an improved outcome as compared to other features. It can be utilized to detect infected plant leaves of classify plant images.

5. CONCLUSIONS

In this project, a deep learning-based approach using Convolutional Neural Networks (CNN) was successfully implemented for the detection and classification of plant diseases from leaf images. The model demonstrated high accuracy and robustness, proving its effectiveness in identifying a wide range of plant diseases with minimal human intervention. By automating the detection process, this system offers a reliable and efficient solution for farmers, enabling early diagnosis and timely action to prevent crop loss. The use of image preprocessing and data augmentation significantly enhanced the model's performance, and the results confirmed that CNNs are well-suited for complex image classification tasks in agriculture. Although the model performs well, future improvements such as real-time deployment via mobile applications, integration with IoT sensors, and expanding the dataset with real-world images can further enhance its practical applicability. Overall, this work highlights the potential of deep learning to transform traditional agricultural practices and support precision farming through intelligent disease detection.

Although the current CNN-based plant disease detection system has shown excellent performance, there is still room for further enhancement to improve its real-world usability and accuracy. One of the key improvements could be the development of a mobile or web-based application that allows farmers to capture leaf images in real-time and receive instant disease diagnosis along with recommended remedies. Integrating the model with Internet of Things (IoT) devices and smart cameras in agricultural fields can enable continuous crop monitoring and automated alerts. Additionally, expanding the dataset with more real-world images captured under varying environmental conditions will improve the model's robustness and generalizability. The use of advanced deep learning architectures like Efficient Net, Dense Net, or hybrid models can also be explored to enhance prediction accuracy and reduce computational cost. Furthermore, the system can be extended to detect nutrient deficiencies and pest infestations, making it a more comprehensive tool for precision agriculture.

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