



Analysis of Plant Leaf Disease Detection

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Abstract : With the increasing requirement for sustainable farming practices that can satisfy food needs of the world, the adoption of new age technologies for agricultural field has gained momentum. Deep learning algorithms are widely considered to be among the most potent techniques for automated plant disorders' detection and provide rapid and accurate identification of crop diseases.

IndexTerms – Automated Plant Disease Detection, Deep Learning Methods, Neural Network Topologies

I. INTRODUCTION

Plant diseases have a detrimental effect on agricultural productivity. Food instability will rise if plant diseases are not identified in timely manner. Plant diseases are largely controlled and prevented by early identification, which is also why they are so important for agricultural production management and decision-making. Plant disease identification has become a critical issue in recent years. Plants with diseases typically have visible lesions or marks on their leaves, stems, blooms, or fruits. Generally speaking, every illness or pest problem has a distinct outward pattern that can be utilized to identify anomalies. Plant illnesses are typically primarily identified by looking at the leaves of the plants, as most disease signs can first be seen on the leaves. Deep learning technology has advanced more recently in the field of plant disease identification research. Deep learning (DL) technology is transparent to the user; plant protection and statistics researchers have a low professional level. It can automatically extract image features and classify plant disease spots, doing away with the labor-intensive feature extraction and classifier design processes of traditional image recognition technology.

II. LITERATURE SURVEY

Plant diseases are significant elements in agriculture production because they can lead to a considerable drop in crop quality and quantity. The identification and categorization of diseases is therefore a crucial and pressing issue. Farmers have historically used the method of visual observation to identify illnesses. Experts using this method can visually various specialists can identify the same area as a distinct illness. The paper grid approach is employed to improve accuracy. One disadvantage of this approach is its painstaking nature. Therefore, it is necessary to recognize plant diseases quickly and accurately.

The methods for VOC sampling and analysis for both in-situ and some field trials were provided by the authors. The current paper focuses on the use of plant VOC profile monitoring for plant disease detection. When a plant becomes diseased, its physiology changes, which affects the volatile organic compounds (VOCs) that the plant releases. It is anticipated that these emissions will differ from the VOCs emitted in the context of a typical plant. By making it easier to identify plant diseases in real time, this technology may help stop plant diseases from spreading. These methods will help our economy expand and prosper financially and in the agriculture sector [1]. Garcia and Lee examine performance improvement and scalability strategies for digital commerce platforms. The article addresses techniques including load balancing, caching, horizontal infrastructure scaling, and performance maximizing the efficiency to handle different traffic patterns and guarantee the best conceivable user experience.

A variety of plant volatiles that are generated by plants as a result of biotic and abiotic interactions were evaluated by Dudareva et al. (2006). Terpenoids, volatile fatty acids (trans-2-hexenal, cis-3-hexenol, and methyl jasmonate), phenylpropanoids, benzenoids, and amino acid volatiles (aldehydes, alcohols, esters, acids, and volatiles containing nitrogen and sulfur that are derived from amino acids) are a few of the frequently found secondary plant volatiles.

Li et al. (2009b) employed a Cyranose® 320, an array of 32 conducting polymer-based sensors, to identify fungal illness that occurs after blueberries are harvested. Ethanol was used to destroy any naturally occurring bacteria and fungus spores from the blueberries. The blueberries were infected with spore suspensions of three fungal species: Botrytis cinerea, Colletotrichum gloeosporioides, and Alternaria spp., after they had been rinsed with deionized water to eliminate any remaining ethanol.

A technique for identifying and categorizing paddy illness was presented by Nunik Noviana Kurniawati et al. [3]. This method uses a median filter to eliminate unwanted spots and Otsu threshold for disease spot detection.

Neural network classifiers based on statistical classification were created by Dheeb Al Bashish et al. and were successful in detecting and classifying the diseases with a precision of about 93% maize illness image detection of corn based on BP networks, where YCbCr Disease spots are segmented using color space technology, the texture feature of the spots is extracted using the Co-occurrence matrix (CCM) spatial gray level layer, and the maize disease is classified using a BP neural network.

The next step of feature extraction is to measure certain aspects or attributes of each segmented region, including color, texture, or form, in order to reduce the amount of image data. The process will be carried out in two stages: spot extraction and spot isolation. Spot isolation will be accomplished using the component labeling technique. As previously stated in the study, values for different leaf image attributes are recovered in the feature extraction process and summarized as unique entries for each illness in a database table. A way to express and work with uncertainty and ambiguity is given by fuzzy set theory. Fuzzy clustering thus proves to be especially useful for segmenting plant picture data. The fuzzy cmeans (FCM) method will be employed. The most widely utilized algorithm is Bezdek's FCM.

III. PROPOSED SYSTEM

A. Abstract

The proposed methodology strives to develop deep learning methods to excel at this significant task of identifying plant leaf diseases in a timely and accurate manner. Traditional methods for diagnosing plant diseases are often time consuming, inaccurate, and labor-intensive. Yet with large leaf image datasets and deep neural networks architectures, deep learning can be one of the promising solution for this process automation. The proposed system consists of the following key components; data collection, preprocessing, training models, and generating inference. The entire dataset is first built with thoroughly labelled traditional leaf photos collected from various sources, such as drones relating to digital cameras. Image preprocessing then occurs in the form of noise reduction, augmentation, and normalization. Transfer learning techniques can be used to use pre-trained models to improve performance with less data. Given an input leaf image, the trained model is then used to recognize whether the image corresponds to a healthy or diseased leaf for real-time detection and diagnosis. Quick response Capabilities Scriptbased robots are getting used to process large volumes of data to convert it to knowledge for decision making.

B. Problem Overview

Plant diseases are a significant threat to agricultural productivity and global food security. Traditional approaches to diagnosing diseases can be labor-intensive, slow and imprecise at times. To address the limitations of existing methods, this paper suggests a deep learning system for automated plant leaf disease recognition. CNNs are used to detect disease indicators in an accurate and efficient manner by analyzing the data from an image of the leaf. This paper presents a complete discussion of what problem the suggested system should solve, all the disadvantages of the available detection approaches, the reasons to apply deep learning to this problem, and the main advantages of the suggested approach. Moreover, it describes an outline of the main characteristics and features of the proposed system, providing an avenue for future research and develop.

C. Existing System

Teaching a model to recognize patterns in images of both healthy and diseased leaves is the first step in using deep learning to detect plant leaf diseases. An active deep learning system for detecting plant leaf diseases is briefly described here. compile a substantial collection of images illustrating both healthy and diseased leaves. A large range of images is necessary for the model to learn to generalize correctly. Before including the images into the deep learning model, preprocess them to ensure consistency and enhance model performance. This could entail splitting the dataset into training, validation, and testing sets in order to expand its size, as well as scaling, normalizing, and enriching the dataset (for example, by flipping, rotating, or adding noise). Choose the deep learning architecture that best fits the issue. CNNs are used widely in image classification applications due to their ability in automatically extracting important properties from images. Using pre-trained models on CNN as VGGor ResNet or inception of Xception and fine-tuned on your dataset or you can start-from-scratch and design your CNN architecture yourself and train. Fit the chosen model on the preprocessed dataset. During training, the model learns to distinguish between healthy and unhealthy leaves by changing its parameters to lower the classification error. Text heads organize the topics on a relational, hierarchical basis.



Fig.1 : CNN based banana leaf disease detection using deep learning

D. Objectives

- 1) One of the main objectives is to extract meaningful features from plant leaves. These may be color, pattern, shape,

and other visual characteristics. When deep learning models can automatically extract meaningful features from raw images of leaves, they perform better than manually extracted features.

2) The second objective is to classify what disease the leaf is suffering from. Deep learning models, like CNNs, can be trained to classify leaves into categories that are either healthy or ill depending upon the data that were collected.

3) The methodology is to classify diseases the moment they are detected into individual categories (like bacterial blight, rust, powdery mildew, etc.). Deep learning models can be trained to distinguish between different diseases by searching for patterns from the leaf images.

These are techniques that can be employed to make the model's decision-making process more transparent. Acknowledge the limitations and hurdles that the venture presented. This could include data quality issues within the dataset, class imbalance, computing resources, or interpretability of the model. Discuss potential means of evading these limitations

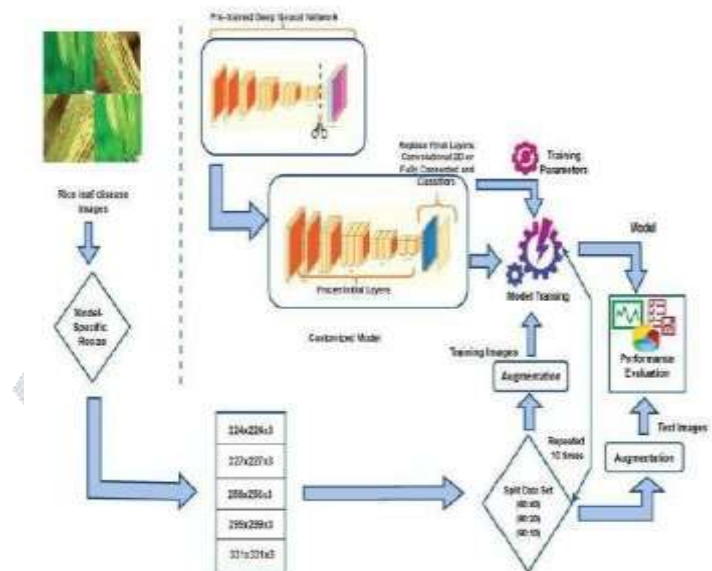


Fig.2 : Deep Learning Based Workflow

in future attempts. Test the usability of the model in real agricultural environments. Alleviate issues such as computability efficiency, scalability, and ease of interfacing with current infrastructure, and ease of use in the interface . areas and innovations.

$$Z_{i,j}^{(k)} = \sum_{m=1}^M \sum_{n=1}^N X_{i+m,j+n} \cdot K_{m,n}^{(k)}$$

This equation represents the convolution operation used in convolutional neural networks (CNNs), where X is the input image, $K^{(k)}$ is the kernel for the k -th feature map, and $Z^{(k)}$ is the resulting feature map.

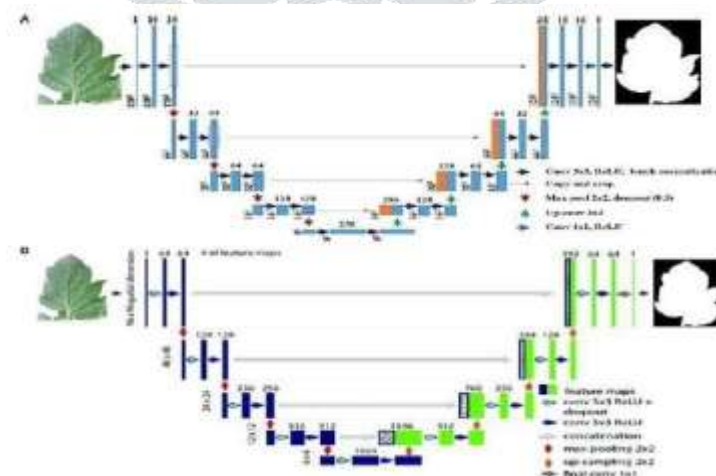


Fig.3 : Comparing U net designs for the segmentation of leaf

IV. Result and Discussions

It is also necessary to present issues concerning the project and examine the results following the installation of a deep learning plant leaf disease detection system. Below is a list of the potential discussion points and results section. Present your deep

learning model's performance metrics first. Report performance metrics such as accuracy, precision, recall, and F1-score. Interpret how these numbers indicate the program's ability to detect plant leaf diseases. Describe a comparison of your deep learning model's performance with baseline models or traditional machine learning algorithms, if any. Draw attention to the deep learning strengths to this task, i.e., the capability of automatically learning hierarchical features from raw data. This research can continue to prove how challenging diagnosing certain sicknesses is. Test how effective the model was against slight change, leaf rotation, and occlusion. Detail how data augmentations helped generalize the model and whether further progress in the same is possible. Detail how much interpretable the decision of the model is. Is the pathological classification of a single leaf possible to explain from the model? Experiment with methods such as feature maps and attention visualization.

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Vaidehi Sharma is currently pursuing a Bachelor of Engineering in Computer Science Engineering (Honors) with a specialization in Artificial Intelligence and Machine Learning at Chandigarh University, India. With a strong academic foundation and a passion for emerging technologies, she is actively shaping her journey toward becoming a future leader in AI innovation. She is an enthusiastic member and volunteer at the IEEE Robotics and Automation Society (RAS) Student Branch, where she contributes to research initiatives, technical workshops, and community outreach programs. Her involvement reflects a commitment to collaborative learning and advancing the frontiers of intelligent systems. Her long-term vision is to contribute to ethical AI research, human-centered design, and technological solutions that address global challenges. With a blend of technical expertise, collaborative spirit, and a growth mindset, Vaidehi is poised to make meaningful contributions to the world of Artificial Intelligence.



Navjot Singh Talwandi is a dynamic and accomplished student at Chandigarh University, specializing in Artificial Intelligence (AI), Machine Learning (ML), Cybersecurity, and Data Science. With a deep passion for technology and innovation, Navjot is dedicated to pushing the boundaries of these cutting-edge fields. In AI and ML, Navjot excels in developing intelligent algorithms and automation systems, enhancing decision-making processes through predictive modeling, natural language processing (NLP), and computer vision. Their research and hands-on implementations have contributed significantly to advancements in smart technology solutions. As a Cybersecurity expert, Navjot is committed to fortifying digital infrastructures, safeguarding systems against evolving cyber threats. Their expertise in threat intelligence, security protocols, and vulnerability assessment ensures robust protection for organizations in an increasingly complex cyber landscape.