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Intelligent Plant Disease Diagnosis Using Machine Learning Techniques- A Review

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ABSTRACT- No matter how we look at it, there are no chances to live without the flora surrounding us. One can be troubled by a broad range of diseases that attack the integrity of his or her health. Basically, all the plant parts are fruits, stems, roots, leaves, and so on. The time and money in terms of having successfully figured out the disease of a plant are much less than that if a diagnosis error has been made. Sustained economic losses caused by plant disease are due to the facilitation of rot production, which involves the reduction of agricultural product yields and quantities. Creating measures that would halt the destruction of crops due to plant diseases is essential since the contributing factor of 70% agricultural produce to GDP is high. This group of illnesses must be watched closely since the diseases start as soon as the plants have begun their growing process.

The conventional approach to surveillance at this point specifically is to carry out an examination, which is quite costly in terms of money. Automated for faster and more effective processing of this operation. Many researchers, by using various methods, have created networks that are mostly exemplified in diverse forms. It is also worthwhile to note that in the field of agriculture, it is very important that the plants are sorted by type. Diagnosis on pathology datasets with the aid of image feature extraction and transformation methods that are appropriate to the illness.

KEYWORDS – Intelligent, Plant Disease, Diagnosis, Machine Learning, Datasets

I. INTRODUCTION

Humans need plants in our lives. They are the main provider of nourishment. Humans and other living things depend on plants. As a result, from the roots to the leaves, theplants that are essential to human health suffer from different diseases. Each year, the agriculture sector has 20–40% losses in crop yield. because to illnesses and overuse of chemicals. Preventing the spread of illness or detecting it early on will help solve this issue and boost crop output. Determining the diseases could lead to a decrease in pesticide usage. The majority of diseases can be distinguished from one another bytheir distinguishing characteristics, such as color, texture, and shape, among others. Even while some of the difficulties with these methods, such as ambient elements including noise, lights, shadows, and inferences, may be overcome using several methods for picture enhancement. The biggest problem is deciding on the best approach. Because there is no generic approach for detecting all plant diseases, further study is required. As a result, a thorough survey was carried out using powerful machine learning algorithms.

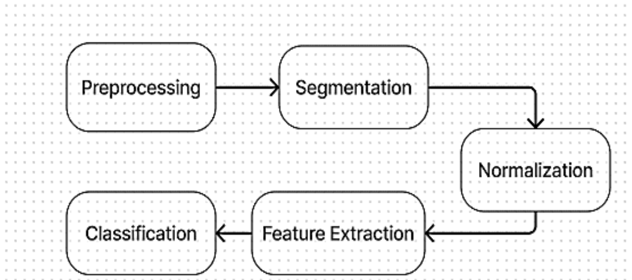

Figure 1: Primary image processing procedures

The essential stages of image processing are depicted in Fig. 1.1. Preprocessing is done on captured photos to improve the image and eliminate distortion or other interference, hence enabling precise diagnosis. Since segmentation separates the objects of interest for detection, it is a vital step in the image recognition procedure. The process of feature extraction eliminates superfluous data from the dataset. The last stage involves classifying the provided image based on our areas ofinterest. The automated creation of useful representations from data is what deep learning is. Either fresh examples or descriptive knowledge make up the generated data. This paper reviews various plant disease diagnosis techniques and discusses them according to various factors.

Numerous researchers put forth different methods for deep learning and image analysis. The most popular application of image processing is the recognition of plant illness. Machine learning techniques work well for identification in a lab setting with a consistent background. Additionally, plant illness identification can be done with the use of deep learning method advancements. The section below comprises the paper's structure.

The first part gives a quick summary of the importance of plant illness detection. The second part reviews the methods employed and talks about the recent work that has been done in this field. The basic methodology used to develop the disease detection system is covered in Section 2. This paper is concluded with future directions in the fourth section.

II. LITERATURE SURVEY

A. *Image acquisition techniques*

In earlier times Analog Imaging was used as an image acquisition technique. It refers to the traditional method of using film-based cameras or older imaging technologies. This is less common in recent years due to advancements in digital imaging.

Wankhede, D.S. et al. [1] used thermal imaging which captures infrared radiation emitted by objects. This is useful for detecting temperature variations associated with disease-infected plants. It detects and quantifies infrared energy emitted by objects. It then translates this data into an electronic image, displaying the apparent surface temperature of the object being measured.

Liu, J et al. [2] mentions the use of digital imaging. In this process, features of an image are extracted by making use of digital camera or scanner.

Zhang J et al. [3] analyzed the use of Remote Sensing technique for monitoring plant diseases. In remote sensing images are acquired from spacecraft, aircraft, and drones to monitor and manage natural and built environments. Remote sensing offers broad data coverage over large, inaccessible areas like oceans and forests. It's cost-effective, aids temporal monitoring, and provides multi spectral data for environmental analysis, hazard management, and land use studies.

Nagasubramanian, K. et al. [4] used hyper-spectral imaging of stem images, their 3D deep convolutional neural network (DCNN) achieved an impressive classification accuracy of 95.73%. It collects data across a wide range of wavelengths, enabling detailed spectral analysis. Helps identify subtle disease-related changes in plant tissues. It offers various advantages like improved object detection, 3-dimensional data cubing and rich dataset.

X-ray imaging [5] is a popular medical imaging method that creates images of the inside structures of the body using a tiny amount of ionizing radiation. It is also used by researchers to analyze agricultural products. It helps in revealing the internal plant structures and abnormalities. This method is limited by safety considerations and the use of specialized equipment.

B. *CNN / Deep Learning*

CNNs are designed to automatically learn hierarchical representations of data directly from raw pixels, eliminating the need for handcrafted features. This end-to-end learning approach allows CNNs to extract complex and discriminative features from images, leading to improved generalization and accuracy. Ability to learn from massive collection of data made CNNs particularly suitable for plant disease detection, where diverse datasets containing images of various plant species and disease types are essential.

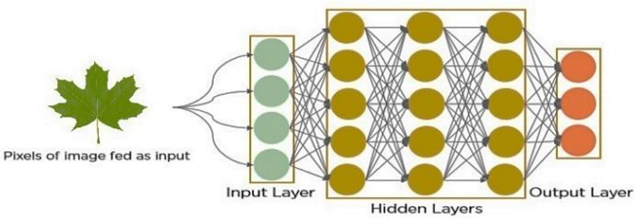

Figure 2: Layers In CNN

A., Yoon et al. [6] analyzed input photos that are classified into their respective categories using a number of CNN characteristic extractors. In their research, a team introduced a robust real-time tomato disease and pest detector based on deep learning. This innovative system offered a practical approach to identify diseases in tomato plants, distinguishing itself from conventional methods. It processed on-site images captured by various cameras in real time using GPUs, eliminating the need for physical sample collection and laboratory analysis. Their dataset included diverse challenges like lighting conditions and object variations, and they aimed to identify the best deep-learning architecture. Results showed the system successfully recognized nine disease and pest categories, even handling complex variations.

Hasan et al. [7] presented a CNN-based technique for rice virus detection that can identify eight different types. The authors used a feature learning approach to extract features, and then they trained a linear multi-class support vector machine (SVM) model with these features and their related labels. Impressively, the trained model that was produced had a validation accuracy of 97.5%.

Picon, A et al. [8] in their study, the researchers introduced three unique CNN frameworks that integrated non-image contextual metadata, such as crop-related information, into a Convolutional Neural Network. To identify 17 illnesses in five different crop types, they combined basic metadata and trained a single multi-crop model. They used a novel unified model that could manage several crops, which made it easier to categorize diseases and allowed them to simultaneously learn from the full multi-crop dataset. With contextual information incorporated by concatenation at the embedding vector level, the crop-conditional plant disease categorization network gained a remarkable accuracy of 0.98. This improvement performed better than earlier methods and resulted in a 71% decrease in misclassifications.

A. Khamparia et al [9] a hybrid approach for crop leaf disease detection was developed, utilizing convolutional neural networks. This method involved training a network to distinguish crop illness from leaf images. The research involved a dataset of 900 images, with 600 for training and 300 for testing, covering 3 crops and 5 disease types. Various convolution filters (2×2 and 3×3) were employed. Results showed accuracy variations based on the filter size and epoch count. A 97.50% accuracy was achieved with a 2×2 filter size in 100 epochs, while 100% accuracy was attained with a 3×3 filter size, surpassing traditional methods.

R. Karthik et al. [10] in the year 2020, Karthik and his team introduced two innovative deep learning methods to diagnose tomato leaf diseases, such as late blight, leaf mold, and early blight. In their first approach, they implemented residual learning within a CNN. To increase the effectiveness of feature learning, they combined residual learning with a heed procedure in the CNN in their second technique. Their research made use of the Plant Village Dataset, involving the training of their model with around 95,999 images.

Kahkashan Perveen et al [11] an inventive dual-branch network identification method for identifying illnesses of apple leaves was provided in the article. This technique effectively addressed issues related to complex backdrops and the similarity of lesions to apple leaf diseases by integrating multiple scale and multidimensional heed features from lesion images. Empirical testing validated its exceptional recognition accuracy. Additionally, they introduced a novel attention mechanism with the ability to extract three-dimensional attention features, considering channel, width, and height. Comparative experiments highlighted the method's potential to enhance recognition accuracy.

Alghamdi, et al [12] the PDD-Net, a multilevel and multiscale CNN architecture, was introduced to enhance leaf disease diagnosis. It identified intricate leaf patterns at various levels, adapting to class variations, and enabling early disease detection. Incorporating GAP in CNNs created accurate, less overfitting models with fewer parameters. Transfer learning via fine-tuning pretrained CNNs on PlantVillage and CLD datasets accelerated convergence and improved accuracy. Using CNN models with significant data optimization for the detection of plant diseases. PDD-Net achieved high precision (92.06%), recall (92.71%), F1 score (92.36%), and accuracy (93.79%) on the PlantVillage dataset. Similarly, on the cassava leaf disease dataset, PDD-Net achieved top precision (86.41%), recall (85.77%), F1 score (86.02%), and accuracy (86.98%). These findings highlight deep learning's potential in benefiting farmers, crop yield, and global food security.

Dhiman et al [13] in 2023, centered their research on the creation of a model for identifying fruit diseases using Faster-CNN in an edge computing setting. Its objective was to detect four Citrus fruit diseases precisely and efficiently. The model employed data fusion methods, combining Near-infrared (NIFR) and RGB image data to enhance recognition accuracy. To minimize the model's size without compromising accuracy, pruning and quantization processes were implemented. Pruning at 60-90% sparsity decreased the model size by 47.64% compared to the original model.

C. ANN

In 2019, Gupta and colleagues [14] identified diseases in citrus plants, employing artificial neural networks (ANN) for classification. They utilized a dataset comprising 60 images and employed image processing to extract and categorize these diseases. The proposed work achieved an accuracy of 96%.

C. U. Kumari et al [15] used k-means clustering and a neural network classifier. For cotton and tomato diseases, such as bacterial leaf spot, target spot, septoria leaf spot, and leaf mold, a variety of features were retrieved. To aid in classification, features derived from clusters afflicted by the disease were computed. Nine out of the twenty cotton samples had the bacterial leaf spot correctly identified, whereas one sample had the misclassifications. Two of the eight target spots were mistakenly recognized as bacterial leaf spots. Of the twenty tomato samples, half had leaf mold and the other half had septoria leaf spot.

Eray Önler et al [16] their work used HOG and transfer learning to combine informative vectors from two different models into a single feature set that was used to identify images of bean leaves as having angular leaf spot, bean rust, or healthy. The model had a unique structure, preprocessing methods, and input types. It had two branches, one for HOG and the other for RGB images, with a concatenation layer combining 128-neuron vectors. After passing through dropout layers using a softmax activation function for classification, dense, batch normalization, and other layers, these vectors arrived at the output layer. The feature fusion model outperformed models using only HOG or transfer learning. The research focused on bean leaf data but planned to apply the model to diverse datasets for better generalization and optimize model size for mobile applications.

D. IOT and Deep Learning

Plant disease detection has undergone a significant transformation thanks in large part to the Internet of Things (IoT), which offers data-driven insights and real-time monitoring. The Internet of Things (IoT) makes it possible to continuously monitor important environmental parameters like temperature, humidity, and soil moisture in agricultural settings by integrating sensors and smart devices. These sensors gather information and send it to a centralized system, where sophisticated algorithms examine it to look for possible indications of plant illnesses. Farmers can identify irregularities and early signs with this proactive method, which makes timely intervention and disease management possible. IoT-enabled devices can also provide predictive analytics, which enables farmers to foresee disease outbreaks based on past data and environmental factors.

Ayaz M. [17] the study utilized IoT and deep learning to optimize resource utilization in agriculture, using ten sensors for pest monitoring, soil nutrient analysis, and seed variety identification. However, challenges in real-world settings limited its effectiveness.

Nawaz et. al [18] proposed a framework for identifying the type of leaf is constructed. The suggested approach uses sensor devices to determine the leaves' temperature, stickiness, and shade. Next, in order to determine whether the gathered attributes are within the range given in the informational collection, the parameters are compared to the informational index. Different regions' ranchers, merchants, botanists, food designers, and doctors can all benefit from the proposed paradigm.

Sowmiya M. et al [19] proposed an optimized deep neural network (DNN) with tailored hyper-parameters was used in their investigation to increase DNN efficiency. Additionally, the IQWO-PCA design process was used. The researchers chose the DNN hyper-parameters, including training frequency, units for each dense layer, and drop-out rate.Zhao Y et al [20] proposed a knowledge-based fusion techniques for feature extraction, data reduction, and classification in addition to sensors to collect parametric data. Their method achieved 97.5% disease diagnosis accuracy by combining the advantages of DCNN and IoT.

E. Training Parameters Used

The configurations that the trainer specifically provides to train the machine learning model are known as training parameters. These parameters determine how the data will educate the model that will be supplied to them and how the model will be trained. Various training parameters like learning rate, epoch size, batch size, etc. are used by researchers in this field and are given below.

Learning Rate [21], determines the step size during gradient descent optimization. It controls how quickly the model updates its weights based on the gradient of the loss function. A higher learning rate may lead to faster convergence but risks overshooting the optimal solution. A lower learning rate ensures stability but may slow down training.

An epoch [22] represents one complete pass through the entire training dataset. Researchers choose the number of epochs based on the trade-off between model performance and computational resources. Too few epochs may result in underfitting, while too many epochs can lead to overfitting. Regularization methods like L1 (Lasso) and L2 (Ridge) also help prevent overfitting by adding penalty terms to the loss function. Researchers select appropriate regularization strength based on the dataset and model complexity.

[23] Batch size determines the number of training examples used in each iteration of gradient descent. Larger batch sizes provide smoother weight updates but require more memory. Smaller batch sizes introduce more noise but allow faster convergence. Researchers experiment to find an optimal balance.

Weight initialization involves setting the initial values for the model's weights before the optimization (learning) process begins. Proper weight initialization ensures that the neural network converges effectively during training. This study of Duygu Sinac Terzi [24] proposes four different transfer learning weight initialization strategies for plant disease detection: Random initialization, pre-trained model on a different domain (ImageNet), model trained on a related domain (ISIC 2019), model trained on the same domain (PlantVillage). The study shows how weight initialization impacts plant disease detection performance.

Table 1: Various techniques and diseases

Author	Crop Culture	Technique Used
Zhang J et al. [3]	Multiple Crops	Remote Sensing
Nagasubramanian, K. et al. [4]	Soyabean Genotype	3D deep learning on hyperspectral images
A. Yoon et al. [6]	Tomato plant	VGG-16, ResNet-50, ResNet-152
Hasan et al. [7]	Rice plant	CNN, SVM
A. Khamparia et al. [9]	Potato, Tomato, Maize	Deep CNN Autoencoder
D. Gupta et al. [14]	Citrus Plants	ANN
C. U. Kumari et al. [15]	Cotton, Tomato	ANN, K-means Clustering
Eray Önler et al [16]	Bean Plant	ANN, HOG, Transfer Learning
Nawaz, Amir & Khan et al [18]	Multiple Crops	IOT
Sowmiya M. a b. et al [19]	Multiple Crops	DNN, IQWO-PCA

III. CHALLENGES

i. Scientists frequently overlook the larger context in favor of identifying plant diseases and pests in particular habitats. This leads to poor recognition performance and restricted application because of occlusion problems, which include variations in leaf position, branches, illumination, and hybrid designs. Plant pests and diseases can be difficult to diagnose in harsh environments, even with the latest developments in deep learning algorithms. The underlying architecture needs to be tuned to reduce model complexity, enhance GAN exploration, and maintain detection precision in order to increase performance. The effectiveness of GAN architecture needs to be further investigated as it is still in its infancy.

ii. Domain Shift and Variability by Season Systems used to detect plant diseases in various locations or during different seasons may experience domain shift and seasonal variability. Depending on the environmental conditions and stage of plant growth, disease manifestations can differ greatly. When exposed to different conditions, models that were trained on data from a particular season or region might not function as well. Adding data from various locations and seasons can help the model be more robust and flexible in a variety of situations.

iii. Real-Time Detection Is Required Real-time disease detection is essential in agricultural settings to allow timely responses and interventions. Because traditional deep learning models can be computationally expensive, they are not as applicable in environments with limited resources, like agricultural fields. This problem can be addressed and real-time disease detection on edge devices made easier by creating lightweight models or investigating hardware-accelerated solutions like model quantization and edge computing.

iv. Deep learning models, including CNNs and RNNs, are often considered as black-box models due to their complex architectures and high dimensional representations. While these models demonstrate excellent predictive performance, their lack of interpretability can hinder the understanding of the underlying factors contributing to disease progression Interpreting the learned features and decision-making process of the model is crucial for clinical acceptance and validation.

IV. CONCLUSION

As a conclusion, the impression of image processing along with machine learning will be fruitful in providing effective air monitoring. The rise in computer learning, the Internet of Things, and other technologies has initiated a huge evolution in stand-alone plant disease detection systems. Visual inspection is among the widely used manual or subjective methods of disease detection, which is also time-consuming. One of the notable deep learning modes is convolutional neural networks (CNNs), which have shown great potential for the precise classification and identification of plant diseases from image data. They do not need handcrafted features, and due to that, they are capable of learning hierarchical representations directly from a photo.

The incorporation of sensors and cameras into Internet of Things devices has made it possible to gather a variety of data, including photos and environmental variables like pH, temperature, and humidity. When paired with deep learning algorithms, this data fusion strategy has produced high disease detection accuracy rates.

In agricultural contexts, the ability to detect diseases in real time is essential for prompt responses and interventions. In order to enable real-time detection on edge devices with restricted resources, efforts have been undertaken to develop lightweight models and investigate hardware-accelerated alternatives.

Nonetheless, there are issues that must be resolved, like model interpretability, data scarcity, and domain shift. Seasonal fluctuation and domain shift might impact how well disease detection models trained on particular regions or times of year function. In order to address the problems of data scarcity and class imbalance, large datasets with uniformly dispersed class memberships must be gathered. Additionally, because deep learning models are sometimes regarded as "black-box" models, there is concern about their interpretability. To improve model interpretability and comprehend the fundamental elements influencing the course of the disease, more investigation is required.

All things considered, by facilitating early and precise disease diagnosis, plant disease detection systems built on image processing, machine learning, and Internet of Things technologies have the potential to drastically lower agricultural losses and increase crop output.

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CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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