A Review Paper On Plant Disease Identification Using Neural Network

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ABSTRACT - Accurate identification of plant diseases is crucial for preventing reductions in agricultural productivity and quantity. Plant pathology refers to the examination and analysis of visually discernible patterns that manifest on plants, which are indicative of illnesses. Ensuring the health and detecting diseases in plants is crucial for the long- term sustainability of agriculture. Agriculture plays a vital role in ensuring both food security and economic stability, and early identification of plant diseases is crucial to minimizing crop loss. Plant disease monitoring by hand is an extremely difficult task. It requires a significant amount of work,, specialized knowledge in the field of plant diseases, and additionally it requires a substantial amount of processing time. Consequently, image processing is used to identify plant illnesses by taking leaf images and comparing them with available images. The primary objective of this paper is to a review of various methods for detecting plant diseases using neural networks and image processing. In this paper review of various neural network methods such as Probabilistic Neural Network, Alexnet, Googlenet, Resnet, and VGGNet is considered.

Keywords: Plant Disease Detection, Image Processing, Neural Network, Data Modeling, Image Translation, Real-Time Disease Monitoring

INTRODUCTION

Agriculture serves as essential support of numerous economies, supplying sustenance and unprocessed resources for diverse businesses [1]. Crop health and productivity are put in danger by a range of diseases, resulting in substantial economic losses and food scarcity. Conventional illness detection methods depend on human competance, which can be time-consuming and prone to errors [2]. Advancements in computer vision, machine learning, and deep learning have the potential to enable automated, efficient, and dependable identification of plant diseases.

India is an agrarian nation, with over 70% of its population relying on agriculture[3]. Farmers possess a wide array of options when it comes to selecting diverse and appropriate crops, as well as identifying the most suited insecticides for their plants [4]. Consequently, harm to the crops would result in significant decline in productivity and ultimately impact the economy.

The leaves, being the most susceptible portion of plants, exhibit disease symptoms at the earliest stage [5]. It isessential to continuously monitor the crops for illnesses from their first stage of growth until they are ready for harvest

Originally, the technique employed to monitor plants for illness was visually inspecting them with the naked eye [6]. This method is labor-intensive and requires skilled individuals to manually survey the crop fields. In recent years, many methodologies have been employed to create automated and semi-automated systems for detecting plant illnesses [7]. The ability to detect diseases by simply seeing symptoms on plant leaves not only simplifies the process but also reduces costs [8]. Thus far, these methods have proven to be rapid, cost-effective, and more precise compared to the conventional approach of farmers manually observing.

Disease symptoms are typically observed on the leaves , stem and fruit in the majority of instances [9]. The plant leaf used for disease detection is selected based on its manifestation of disease symptom.

There are numerous instances where farmers lack comprehensive understanding about crop cultivation and the diseases that can impact their harvests [10]. Farmers can enhance their crop productivity by utilising this article as an alternative to seeking help from experts [11].

A greenhouse, also known as a glasshouse or, if equipped with adequate heating, a hothouse, is a building constructed mostly with transparent materials, such as glass, that is used for cultivating plants that require controlled climatic conditions[12].

LITERATURE REVIEW

Dr. Sridhathan [15], uses the dimension of the region of interest (ROI) will be smaller than the original image. Gray level co-occurrence matrix (GLCM) is one of the best methods for texture analysis. k-means and GLCM technique provide 98 Banupriya . N [14] , uses the k - means clustering Algorithm to fetch the required features from the leaves. And the the features of the infected part of the leaves are enhanced by obtaining the contrast image of the leave and from the neural networks.It provides Accuracy 89.8%.

Dr. Sridhathan [15], uses the dimension of the region of interest (ROI) will be smaller than the original image. Gray level co-occurrence matrix(GLCM) is one of the best methods for texture analysis. k-means and GLCM technique provide 98% accuracy

Xuewei Wang[16], uses Classified 9 extraordinary forms of rice diseases by using the features extracted from DCNN mode. In this paper Grape lead disease dataset is used. The accuracy achieved 97.5%.

Suja radha [17], uses computing amount of disease present in the leaf, we can use sufficient amount of insecticides to efficiently manipulate the pests in flip the crop yield could be increased. We can increase this method with the aid of using the usage of distinctive algorithms for segmentation, classification It provides prediction: 49.88 %.

Comparative study of technique used in Plant Disease detection

Title	Publisher, year	Dataset	Merits	Demerits	Measuring parameter
Leaf Disease Detection using Image Processing [17]	VIT university 2017, Suja radha	Cotton leaf Dataset	By computing amount of disease present in the leaf, we can use sufficient amount of insecticides to efficiently manipulate the pests in flip the crop yield could be increased. We can increase this method with the aid of using the usage of distinctive algorithms for segmentation, classification.	The characteristic extraction is completed in RGB, HSV, YIQ and Dithered Imageswhich is time consuming	Affected area prediction: 49.88 %
Plant Infection Detection Using Image Processing[15]	IJMER,2018 Dr. Sridhathan	Plant Disease database	The dimension of the region of interest (ROI) will be smaller than the original image. Gray level co-occurrence matrix (GLCM) is one of the best methods for texture analysis	Not Easy to debug and develop,support dynamic neural network, easy to expand,modularization and low learning cost	k-means and GLCM technique : 98 % accuracy
Rice Leaf Disease Detection Using Machine Learning Techniques[22]	International Conference on, Sustainable Technologies Kawcher Ahmed,2019	IJRET	The algorithms predicted The rice leaf illnesses with various degree of accuracy.It was found that decision tree performed the best with 97.9167% accuracy on test data.	It takes more time because entropy and information Gain, standards borrowed from statistics theory, are usedfor constructing the tree	F1 score 96.5%
Plant Disease Detection using CNN[18]	Natioal college of ireland 2020 m Ema harte	Rice disease Image dataset	As a default of transfer learning, all layers except the final two layers are frozen. These incorporate new weights and are particular to the plant disorder category task. Freezing allows these layers to be disease-separately trained, without backpropagating the gradients. In precisely this way, the 1cycle coverage is	Augmentation and transfer learning in this case, proved not that beneficial to the model, helping the CNN to generalize more reliability.	Accuracy :90.34%

			used to train the very last layers		
Plant Disease Detection using Image Processing[19]	Ijert 2020, Mr.V Suresh	Plant village dataset	Proposed system havean end-to-end Android application with TFLite. Proposed system opted to broaden an Android utility that detects plant diseases.It has the algorithms and models to recognize species and diseases in the crop leaves by using Convolutional Neural Network	The signs of bacteria are often harder to detect than fungi, since bacteria are microscopic. Upon cuttingan infected stem, a milky white substance may appeared	Accuracy :90.34
Leaf Disease Detection Using Machine Learning[21]	Journal of seabold , Utkarsha Fulari,2020	Leaf dataset	In SVM, each data item is plotted as a point in n-dimensional space; the number of dimensions corresponding to the number of features being classified	Though continuous monitoring of health and Disease detection of plants increase the quality and quantity of the yield, it is costly for ML every time.	Accuracy :88%
PLANT DISEASE DETECTION USING IMAGE PROCESSING AND MACHINE LEARNING ALGORITHM[14]	Xidian University,2 022Banupri ya .N	Realtime Data	The k-means clustering algorithm is used to fetch the required features from the leaves. And the features of the infected part of the leaves are enhanced by obtaining the contrast image of the leave and from the neural networks.	Image segmentation is performed on each image using k-means clustering a sample clustered image set which consists of three other clusters, which takes more time.	Accuracy :89.8%
Plant diseases and pests detection based on deep learning [16]	Springer Nature,2022, Xuewei Wang	Grape lead disease dataset (GLDD)	Classified 9 extraordinary forms of rice diseases by using the features extracted from DCNN mode	When the quantity of plant sicknesses and pests elegance to be categorized exceed 2 class, the conventional plant diseases and pests classification network is the same as the original image classification method	the accuracy achieved 97.5%.

Table 1 Comparative study

Table 1 represent the comparative study of Different Model used in plant Diseases detection .This table represent the topic of the paper, author name, Database used ,Merits of the paper and demerits of paper. In this table there are study of 8 paper which is done .In the table it is mention in which journal it is published, it also contain the information about the database used in the particular paper also it contains the merits and demerits of the paper in merits and at last it represents the parameter in which it is taken as consideration .the parameter included is the accuracy,F1 score, prediction

Technique

Digital image processing processes images that are entered as inputs and outputs findings on extracted images. This work can be completed multiple times in a short amount of time and is done remotely. neural networks have been used to detect diseases. It featured a wide variety of algorithms that might identify ailments. A few neural network algorithms are Probabilistic Neural Network, Alexnet, Googlenet, Resnet, and VGGNet.

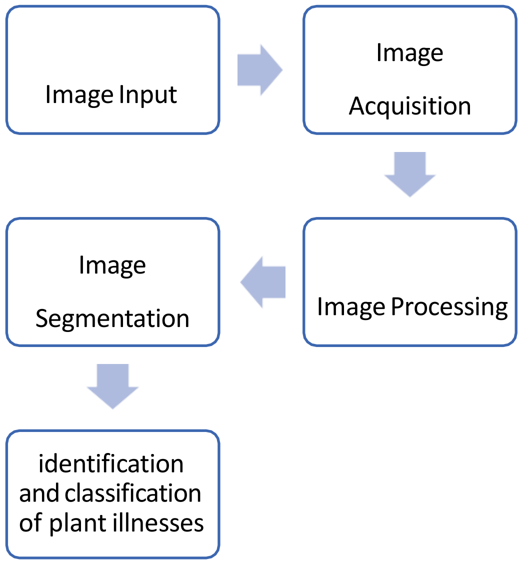

Figure 1 Process in Plant Diseases Detection

I. Image Acquisition

Digital cameras are utilized in the process of capturing images. RGB format is used for images. Many methods are used to apply color transformation structure to RGB photos of the plants.

II. Image Processing

Image preprocessing is a critical step in plant disease detection, as it involves enhancing the quality and usability of images before feeding them into machine learning models

Image Resizing

Image resizing is a critical preprocessing step in the realm of plant disease detection, serving the purpose of adjusting the dimensions of images to a standardized resolution. The primary objective is to establish a consistent size for all images, facilitating uniform processing and reducing computational complexity during subsequent stages, such as feature extraction and machine learning model training. This process involves choosing target dimensions based on the specific requirements of downstream tasks or model architectures while preserving the aspect ratio of the original images to prevent distortion. The method of resizing, including interpolation techniques like bilinear or cubic interpolation, influences the quality of the resized images. The integration of image resizing with data augmentation techniques, such as rotation and flipping, contributes to dataset diversity and enhances the robustness of the machine learning models. Careful consideration of resizing algorithms, efficiency in implementation, and documentation of the resizing parameters are crucial aspectsto ensure the effectiveness of this preprocessing step. Additionally, quality control checks verify that resized images meet desired dimensions and maintain the necessary quality for accurate disease detection. Ultimately, image resizing establishes a standardized and compatible foundation for subsequent analysis and model development in plant disease detection applications.

Color Normalization

color normalization stands as a pivotal preprocessing step, addressing the inherent challenges posed by variations in lighting conditions. This technique is instrumental in creating a standardized and consistent representation of color across diverse images within a dataset. The normalization process ensures that the impact of disparate illuminations on the visibility of disease symptoms is mitigated, providing a more uniform foundation for subsequent analyses. By harmonizing color channels, color normalization not only enhances the visual coherence of the dataset but also facilitates the effectiveness of machine learning models in recognizing genuine patterns associated with plant diseases. The calibrated color representation achieved through this preprocessing step is crucial for fostering accuracy and reliability in disease detection systems, ultimately contributing to the robustness of the overall analysis.

Noise reduction

Noise reduction is a critical preprocessing technique in the field of plant disease detection, focused on refining the quality and interpretability of captured images. In the context of agricultural imaging, sensor noise, environmental factors, and artifacts can introduce irregularities that hinder the accurate identification of disease symptoms. To address this challenge, noise reduction techniques are applied to smooth out such irregularities and enhance the clarity of relevant features. Commonly utilized filters, such as Gaussian or median filters, effectively attenuate noise, resulting in a cleaner and more refined dataset. By minimizing unwanted variations, noise reduction contributes to a higher signal-to-noise ratio, allowing machine learning models to discern genuine patterns indicative of plant diseases. This preprocessing step not only improves the overall quality of the dataset but also ensures that subsequent analyses

and disease detection algorithms operate on images with reduced interference, leading to more accurate and reliable results. Noise reduction, as an integral component of the preprocessing pipeline, plays a crucial role in optimizing the performance of plant disease detection systems in agricultural applications.

III. Image Segmentation

Image segmentation is a pivotal process in plant disease detection, providing a detailed and granular understanding of the spatial distribution of disease symptoms within plant images. This technique involves partitioning an image into multiple segments or regions, with each segment corresponding to distinct objects or areas of interest. In the context of plant pathology, segmentation is particularly valuable for isolating and delineating affected regions, such as diseased leaves or lesions, from the healthy background. Several segmentation approaches are employed, including thresholding, region-based methods, and advanced techniques like semantic segmentation using deep learning models.

Thresholding

Thresholding is a straightforward method that involves classifying pixels based on intensity values, thereby distinguishing between diseased and healthy areas. Region- based methods group pixels with similar properties, aiding in the identification of lesions or affected regions. These conventional methods, while effective, may face challenges in scenarios with complex backgrounds or varying disease presentations.

Semantic Segmentation

Semantic segmentation, powered by deep learning models, like Convolutional Neural Networks (CNNs), has emerged as a sophisticated approach in recent years. These models learn intricate patterns and hierarchies of features, enabling pixel-level classification of images. This allows for precise identification and delineation of disease symptoms with remarkable accuracy.

IV. Classification

Plant leaves are categorized according to their many morphological characteristics. Several neural network classification algorithms, include Resnet, Alexnet, Googlenet, Probabilistic Neural Network, and VGGNet can be used for classification.

Resnet

ResNet is a type of deep neural network architecture designed to address the vanishing gradient problem in very deep networks It introduces residual blocks, which contain shortcut connections allowing the gradient to flow more easily through the network. residual block typically consists of two convolutional layers, and the output of the block is the sum of the input to the block and the output of the convolutional layers. In plant disease detection, ResNet architectures such Resnet50 ,Resnet 101 are commonly used as feature extractors. Pre-trained versions of ResNet on la rge image datasets (such as ImageNet) are often employed for transfer learning. Transfer learning involves taking a pre- trained model on a large dataset (like ImageNet) and fine- tuning it on a smaller dataset specific to plant diseases. This approach leverages the knowledge the model gained during the pre-training phase, allowing it to adapt quickly to the new task. model is trained on the plant disease dataset using an appropriate loss function and optimization algorithm.

Google Net

GoogLeNet, also known as Inception, has demonstrated efficacy in the domain of plant diseases detection through its application in computer vision tasks. Leveraging the unique architecture of GoogLeNet, which incorporates inception modules with multiple filter sizes in parallel, this model proves valuable for discerning intricate patterns and features within images of plants affected by diseases. The flexibility provided by the inception modules enables the network to capture information at different scales, facilitating the identification of nuanced disease-related characteristics. employ GoogLeNet for plant diseases detection, the model is adapted by fine-tuning it on a dataset of labeled images containing both healthy plants and those affected by various diseases. The final classification layer is adjusted to match the number of distinct disease classes present in the dataset. Utilizing transfer learning, GoogLeNet benefits from pre- trained weights on large image datasets, enhancing its ability to generalize to new and diverse plant disease scenarios. Once trained, the adapted GoogLeNet can be deployed for automated plant diseases detection, contributing to precision agriculture practices by enabling timely and accurate identification of diseases in crops.

AlexNet

AlexNet, a seminal deep neural network architecture, has been applied effectively to the realm of plant disease detection. Its usage involves the adaptation of the model to the unique characteristics of plant images affected by various diseases. In the initial stages, a diverse dataset comprising labeled images of both healthy plants and those afflicted by different diseases is curated. Data preprocessing techniques are applied, including normalization and augmentation, to enhance the model's capacity to discern relevant features. The AlexNet architecture is then modified to accommodate the specifics of the plant disease detection task, with adjustments made to the final classification layer to align with the number of distinct disease classes. Leveraging transfer learning, the model benefits from pre- trained weights on large datasets, providing it with a foundational understanding of visual features. During training, the adapted AlexNet learns to associate visual patterns with specific disease categories, enhancing its ability to make accurate predictions. Va lidation on separate datasets ensures the model's generalization capabilities, while testing on independent datasets evaluates its performance in real-world scenarios. Hyperparameter tuning, such as adjusting learning rates and dropout rates, is performed to optimize the model's accuracy. The interpretability of the model's predictions is considered, shedding light on the features influencing disease identification. Once trained and validated, the adapted AlexNet becomes a valuable tool for automating the detection of plant diseases, contributing to precision agriculture practices by enabling early and accurate diagnosis.

Probabilistic Neural Network

Probabilistic Neural Networks (PNNs) are a type of neural network that provides a probabilistic interpretation of its predictions. While traditional neural networks provide point estimates for the output, PNNs offer a probability distribution over possible outcomes. PNN have emerged as promising tools in the realm of plant diseases detection, offering a unique approach that extends beyond traditional neural networks. In the context of this application, PNNs provide a probabilistic interpretation of predictions, presenting a distribution of probabilities associated with each class rather than a singular point estimate. The foundational steps involve assembling a diverse dataset of labeled plant images, encompassing both healthy specimens and those afflicted by various diseases. Through rigorous preprocessing, including resizing and augmentation, the dataset is prepared for training. The architecture of the PNN comprises layers dedicated to computing probability distributions over output classes, allowing the network to inherently capture uncertainty. During training, the model learns these probability distributions, refining its understanding of the complex relationships between input features and disease classes. The distinctive feature of PNNs lies in their ability to quantify uncertainty, providing valuable insights into cases where predictions may be ambiguous. Decision thresholds can be tailored based on the predicted probabilities, allowing for flexible and context-specific decision-making. The evaluation phase involves assessing the model's performance using standard metrics while considering the nuanced aspects of uncertainty estimation. The interpretability of the probability distributions further enhances the model's utility, aiding in decision trustworthiness. Upon successful validation, the trained PNN can be deployed for plant diseases detection, contributing to precision agriculture by delivering not only accurate predictions but also valuable information about the confidence levels associated with each prediction.

VGGNet

VGGNet is characterized by its simplicity, using 3x3 convolutional filters and max-pooling layers. It is known for its uniform architecture. VGGNet has been applied to plant disease detection tasks, often as a feature extractor in transfer learning. VGGNet follows a specific architecture, it would include convolutional layers for feature extraction, pooling layers for down sampling, and fully connected layers for classification.

CONCLUSION

An accurate and effective technique is needed to identify and categorize plant diseases, Image processing and neural network approaches can help with this. This paper reviewed a number of previously used techniques. These methods are relevant to classification, feature extraction, and segmentation. With the use of these techniques, numerous plant diseases have been accurately identified and classified. However, there are still some opportunities for advancements in the current methods.

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