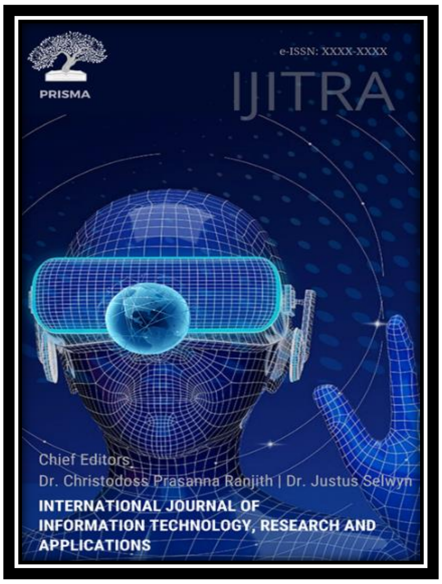

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Smart Agriculture: A Comprehensive Survey on IoT-Enabled Plant Disease Detection and Agricultural Automation

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ABSTRACT

This research paper is dedicated to the comprehensive review and discussion of diverse techniques employed in plant disease detection within the realm of agriculture. Emphasizing notable contributions and showcasing innovative methodologies, the research work takes a critical turn to address the myriad issues and challenges intricately woven into the integration of IoT data analytics in agriculture. The paper meticulously unravels the complexities associated with plant disease detection in the era dominated by IoT and data analytics. Serving as more than just a repository of current methodologies and technologies, this work actively illuminates the challenges that await further exploration. The insights derived from this exploration will provide a substantial foundation for emerging researchers. By shedding light on the evolving landscape of plant disease detection and the nuances of IoT integration in agriculture, this paper empowers researchers to actively contribute to the resilience and sustainability of agricultural practices in the face of ongoing challenges.

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1.0 Introduction

Agriculture, rooted in the Latin terms 'Agri' and 'Culture,' denoting 'Land' and 'Cultivation,' respectively, stands as a cornerstone of human civilization. Addressing hunger and enhancing agri-food systems' efficiency, inclusiveness, strength, and sustainability are pivotal goals outlined by the United Nations' Food and Agriculture Organization (FAO). The pursuit of the Four Betters—better production, better nutrition, a better environment, and a better life for all—drives these efforts. With approximately 70% of the Indian economy relying on agriculture, the demand for both quality and quantity in food production has escalated, necessitating industrial growth and advanced agricultural practices.

This paper focuses on IoT-enabled smart farming solutions, a system designed to monitor crop fields through sensors (light, humidity, temperature, soil moisture, crop health, etc.) and automate irrigation. Providing farmers with remote field condition monitoring, the smart agriculture system ensures 24/7 surveillance of irrigation, soil monitoring, heightened productivity, accurate crop disease detection and prevention, and overall food security. Employing various sensors, data is collected, stored in the cloud, and analyzed using suitable analytical techniques. The objective of this paper is to review and discuss various techniques of plant disease detection in agriculture. The paper is organized into the following sections. First section gives a brief introduction to the importance of agriculture. Second section discusses the image processing techniques. The third section includes the existing work carried out recently in this area. Lastly, fourth section concludes this paper along with future directions. The primary aim of this paper is to comprehensively review and discuss diverse techniques for plant disease detection in agriculture. The paper is structured as follows: the first section introduces the significance of agriculture; the second section delves into image processing techniques; the third section explores recent developments in this field; and finally, the fourth section concludes the paper, providing insights into future directions.

1.2 Basic Steps of Image Processing

1.2.1 Types of Plant Diseases

Plant disease, an impairment of a plant's normal state affecting vital functions, occurs due to infections by bacteria and viruses and disorders in normal growth. The impact on plant leaves ranges from discoloration to mortality. Biotic diseases, caused by factors such as viruses, bacteria, fungus, protozoa, and nematodes, and abiotic diseases, influenced by factors like temperature, rainfall, humidity, and nutrient deficiency, contribute to plant diseases and types Fig 1.

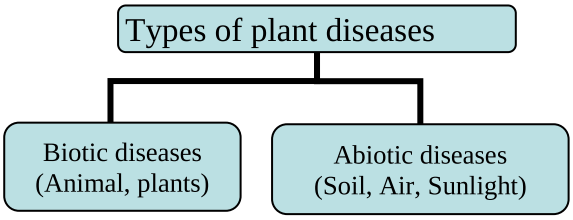

Fig 1: Types of plant diseases

1.2.2 Plant Disease Detection

An IoT-based disease detection system is developed using sensors for temperature, humidity, and color, based on variations in plant leaf health conditions. Values derived from temperature, humidity, and color parameters identify the presence of plant diseases. The process involves image acquisition, pre-processing, segmentation, feature extraction, classification, and detection of plant leaf diseases.

1.2.3 Image Acquisition

Image acquisition involves capturing digital images, converting optical images into numerical data for manipulation on a computer. Sub-processes include image capturing and digitization.

1.2.4 Image Pre-processing

Image pre-processing formats images before model training and inference. Techniques such as Gaussian, average, and medial filters are applied to eliminate unwanted or noisy data.

1.2.5 Image Segmentation

Image segmentation divides an image into regions or categories, allocating pixels to different objects or parts. CNN is a widely-used algorithm for accurate image segmentation.

1.2.6 Feature Extraction

Feature extraction transforms raw data into numerical features, describing the infected area. Approaches include non-linear and linear feature transformation.

1.2.7 Classification and Detection

Image classification categories and assigns labels to pixels or vectors based on specific rules. Techniques, such as supervised and unsupervised image classification, are employed for categorization

2.0 Literature Review

In recent years, numerous studies have explored innovative approaches to plant disease detection, leveraging artificial intelligence, machine learning, and Internet of Things (IoT) technologies. The following literature review provides a comprehensive overview of key contributions in this field.

2.1 AI-Based Disease Detection Systems:

S. M. Shahidur Harun Rumy et al. [1] introduced a rice leaf disease detection system based on artificial intelligence. By pre-processing data and employing machine learning algorithms, diseases like brown spot, HI spa, and Leaf Blast were accurately classified, with the Random Forest model achieving an impressive 97.50% accuracy.

George Stamoulis et al. [2] proposed a solution for plant disease detection, utilizing Artificial Intelligence, Disease Diagnosis Support System, and Convolutional Neural Networks. Their Disease Diagnosis Support System demonstrated a classification rate of 98%, showcasing the efficacy of their multi-faceted approach.

R. Deepika Devi et al. [3] presented an IoT-based technique for detecting bunchy top and sigatoka diseases in hill banana plants. Using GLCM features and Random Forest Classification, their system achieved an outstanding overall detection accuracy of approximately 99%.

2.2 Advanced Techniques and Technologies:

Sammy V. Militante et al. [4] proposed a plant diseases recognition system employing Convolutional Neural Network techniques, achieving a high precision rate of 96.5%. Laha Ale et al. [LAH 19] explored deep learning methods, employing transfer learning with Dense Net deployed in IoT devices.

Safish Mary et al. [5] developed a technique using Content-Based Image Retrieval for disease detection, utilizing a Support Vector Machine classifier. The proposed method effectively segmented images, aiding in the accurate identification and classification of diseases.

Sathiyamoorthy et al. [6] focused on sugarcane disease detection, favouring the K-means algorithm. They conducted a comprehensive analysis, including Root Mean Square Error and Mean Absolute Error measurements, comparing results with J48 pruned tree and Multilayer Perceptron algorithms.

Ahmed Gamal et al. [7] implemented smart technologies with sensors and Wireless Sensor Networks for pest monitoring. The proposed model demonstrated superior accuracy compared to existing techniques, offering farmers features such as availability, accuracy, and dependability.

2.3 Sensor Networks and Agriculture:

Sangeetha Kumari et al. [8] utilized sensor networks for automatic measurement of moisture, temperature, and humidity. By interfacing cameras with Raspberry Pi, they detected leaf diseases and communicated real-time environmental changes to farmers through WIFI Server.

Farooq et al. [9] proposed machine learning techniques for classifying IoT data at different levels, achieving integration from device to cloud. Their approach, utilizing K-means, Naïve Bayes, and Random Forest, demonstrated successful integration across multiple IoT levels.

Sherly Pushpa et al. [10] developed an AI technique for automatic tomato leaf disease detection, combining image pre-processing, segmentation, feature extraction, and classification. The proposed technique achieved a noteworthy classification accuracy of 94.1%.

2.4 IoT in Agriculture and Data Analytics:

Rao et al. [11] studied large-scale farming through IoT and data analytics, addressing rising power consumption with a centralized sensor control unit. Zigbee connectivity was found to be superior to Wi-Fi, highlighting the potential of centralized platforms.

Liu et al. [12] innovatively combined smart agriculture with clean energy consumption, exploring the synergies between agriculture and clean energy systems. Their review examined technologies, feasibilities, and advantages, offering insights for the development of integrated systems.

Li et al. [13] conducted agricultural machinery failure analysis using big data technology, providing a platform for data analysis, fault detection, and maintenance requirements. The platform, with access to 100 million data points, showcased significant potential for improving agricultural machinery management.

Chen, J., & Yang A. et al. [14] proposed a smart agricultural system using IoT, incorporating data visualization and cluster analysis. Their intelligent agriculture system aimed to enhance production, improve product quality, and optimize agricultural activities through accurate sensing, identification, monitoring, and feedback.

2.5 Advanced Techniques in Disease Identification:

Sharma et al. [15] introduced a novel method using computer vision techniques for plant disease detection. Their approach, utilizing color segmentation and CNN classification, demonstrated a 75.59% detection rate for diseased parts, showcasing effectiveness in complex backgrounds.

Singh et al. [16] employed particle swarm optimization for image segmentation in sunflower leaf disease detection. By combining color and texture features, their technique achieved accurate segmentation and classification with a 91.22% accuracy.

Vibhor et al. [17] proposed a technique for detecting fungal diseases in soybean leaves, utilizing KNN and SVM classifiers. Their approach, combining image pre-processing, clustering, and feature extraction, achieved accuracy rates of 83.6% and 87.3% for KNN and SVM, respectively.

Iqbal et al. [18] developed an automatic system for potato leaf disease identification, integrating image segmentation and machine learning techniques. Their approach, employing global descriptors and classifiers such as Random Forest, Logistic Regression, and SVM, demonstrated successful disease detection.

2.6 Machine Learning and Crop Disease Detection:

Panigrahi et al. [19] focused on classifying leaf diseases in maize plants using supervised learning algorithms. Random Forest classification outperformed other techniques, achieving an accuracy of 79.23%, showcasing its effectiveness in disease detection datasets.

Al-Bayati et al. [20] proposed a deep neural network-based technique for identifying apple plant leaf diseases, combining SURF feature extraction with Grasshopper Optimization Algorithm. Their method demonstrated improved detection and classification accuracy.

Alex et al. [21] employed thermal camera images for banana tree disease detection, utilizing multilevel thresholding. Their method achieved high precision and accuracy, providing valuable insights for disease identification in banana trees.

Laha et al. [22] proposed a minimum cross entropy-based multi-level thresholding technique for crop image segmentation, incorporating the bacterial foraging optimization algorithm. The technique exhibited enhanced segmentation results.

Kumari et al. [23] developed an algorithm for crop disease detection and classification using local information from leaf images. Utilizing region growing and multilayer perception models, their technique achieved a commendable classification accuracy of 91.22%.

Hasan et al. [24] formulated a methodology for tomato leaf disease detection, combining image analysis and pattern recognition. Employing segmentation algorithms, color moments, and classifiers such as multilayer perceptron, KNN, and SVM, their approach demonstrated effective disease recognition.

Dhiman et al. [25] proposed a spot tagging leaf disease detection model with persistent feature selection, achieving a remarkable 97% classification accuracy. Their method utilized energy, homogeneity, correlation, mean, variance, and standard deviation features for accurate predictions.

Table 1: Comparative Study and Summary of Research Work

Reference and Year	Objectives	Datasets	Technique Used	Outcomes	Advantages	Disadvantages
S.M. Shahidur Harun Rumy et al., 2021	Detection of rice leaves disease	Rice Leaves	Pre-Processing, Machine learning algorithm, Random Forest classifier	Accuracy of 97.50%	Categorized rice plant diseases	Difficult to prepare, unstable training and testing process
George Stamoulis et al., 2021	Recognition	Leaf	Disease diagnosis support system, Artificial intelligence, Convolutional neural network algorithm	Precision rate of 98%	Early disease detection, Control potential production damages	Detection of multiple diseases not simultaneously
R. Deepika Devi et al., 2020	Sigatoka diseases detected	Banana	Gray level co-occurrence matrix	Accuracy of 99%	Identifying and classifying bunchy top and sigatoka diseases	Climate changes impact, Inaccuracy with various sensors
Sammy V. Militante et al., 2019	Recognition and classification	Plant diseases	Classification, Deep learning models, Convolutional neural network	Accuracy of 96.5%	Detection and classification of diseases in multiple plant species	Inability to detect multiple diseases simultaneously
Laha Ale et al., 2019	Plant diseases detection	Disease-affected leaves	Internet of Things, Dense Net, DNN	Accuracy 87%	Transfer learning for detecting diseases affected areas	Limited to identifying diseases in leaves affected areas
Sherly Pushpa et al., 2019	Finding bacterial spot, late blight, tomato mosaic	Tomato leaves dataset	Image pre-processing, Segmentation, feature extraction, image classification	Accuracy 94.1%	Detection of bacterial spot, late blight, tomato mosaic	Optimization techniques not employed
Sasikala Vallabha et al., 2020	Automatic plant diseases detection	Plant village dataset	Deep ensemble neural network (DENN)	Accuracy for 14 crops using pre-trained models	Utilizes pre-trained models for better accuracy	Focuses on pre-trained models only
Minu Eliz Pothen et al., 2020	Find rice diseases to increase production	Rice leaf	Classification using Otsu’s method	Accuracy of 94.6%	Segmentation using LOP and HOG	Classifies bacterial, smut, and brown spot diseases only
Nanehkaran et al., 2020	Identify plant disease using computer vision	Diseased leaf	CNN using classification	Accuracy of 75.59%	HIS and LAB color segmentation achieves higher classification	Detection of diseases with complex background methods
Sachin et al., 2019	Detect and classify	Soybean leaf dataset	GLCM, KNN, SVM for classification	KNN 83.6%,	Utilizes K-means clustering	KNN, SVM only used for

	fungal diseases			SVM 87.3%	for feature extraction	detection and classification
Panigrahi et al., 2020	Focus on supervised algorithm for maize diseases	Maize plants	Random forest classification techniques	Accuracy 79.23%	Implementation with high-dimensional datasets and other models	Segmentation not followed in this work
Anasta et al., 2020	Thermal camera image for detecting diseases	Banana trees	Multilevel thresholding techniques	Recall 85.4%, Precision 89.3%, F-measure 87.3%, Accuracy 92.8%	Utilizes multilevel thresholding for performance measurement	Utilizes thermal camera images for disease detection
Nazki et al. (2020)	Detection of leaf disease	2789 tomato plant disease images	Generative Adversarial Network and Deep CNN	Accuracy 86.1%	Demonstrates information appropriation and GAN versatility	Difficult to prepare, unstable training process, Mode Collapse
Zhang et al. (2019)	Detection of leaf disease	600 cucumber sick leaves of 6 cucumber varieties	GPDCNN	Accuracy 94.65%	GPDCNN is robust compared to other strategies	Fully connected layer has many parameters, reduces training speed, and causes overfitting
Vijai Singh (2019)	Detection of Sunflower leaf disease (6 diseases)	Sunflower leaves	Particle Swarm Optimization Algorithm	Accuracy 98%	PSO is easy to implement, performs better than GA	PSO application for this issue is not complex
Agarwal et al. (2019)	Detection of Tomato leaf disease	Plant Village dataset	Convolution Neural Network	Avg. Accuracy for disease 91.2%	Proposed model storage space 1.5MB, pre-prepared models require 100MB	CNN slower due to operation like pooling

3.0 Statement of Research Problem

Plant diseases is one of the major problems that affects the production and quality of crops. Its Losses due to plant diseases may be catastrophic or chronic. The farmers spend large amount of money on disease management, often without adequate technical support, resulting in poor disease control and harmful consequences. Much greater emphasis is required to detect and prevent the diseases so as to increase the yield. This research focuses on narrowing this gap by deploying IoT technology to get prior information on plant health.

4.0 Research Motivation

Farmers find it difficult to diagnose the diseases in plants which result in crop losses. The crop losses further increase the financial burden of low-income farmers. In addition to that, Laboratory tests are expensive and often time-consuming. Research is needed for early detection of diseases and reduction of yield losses through appropriate technology like IoT. This requirement has motivated to undertake this research work.

5.0 Issues and Challenges in IoT Data Analytics for Agriculture

IoT and data analytics applications have gained significant traction in various organizations, yet these technologies are still in their nascent stages, posing numerous unresolved challenges. In the realm of IoT data analytics for agriculture, several critical issues persist.

5.1 Data Collection Challenges:

A primary hurdle in agricultural IoT is the effective collection of data. Deploying sensors across the farm enables comprehensive tracking, from soil moisture levels to crop health. This data, crucial for informed decision-making on irrigation, fertilization, and pesticide use, remains a substantial challenge in terms of seamless aggregation.

5.2 Enhancing Data Quality:

The abundance of real-time data empowers farmers to monitor their crops continuously, facilitating the early detection of issues. This proactive approach enables corrective measures before problems escalate, leading to healthier crops and improved overall yield quality.

5.3 Risk Mitigation through Weather Tracking:

IoT plays a pivotal role in risk reduction for farmers, particularly in monitoring weather conditions. Armed with precise weather data, farmers can optimize planting and harvesting schedules, minimizing the risk of crop losses due to adverse weather events.

5.4 Business Automation Advantages:

Automation is a significant benefit brought about by IoT in agriculture. Tasks ranging from irrigation management to other agricultural processes can be automated, resulting in time and cost savings. For instance, automatic irrigation systems adjust water flow based on real-time soil moisture levels, ensuring optimal water usage without wastage.

5.5 Remote Monitoring Capabilities:

The advent of smart farming systems enables farmers to remotely track their crops' progress through various devices, such as computers or mobile devices. Alerts and notifications regarding soil conditions, seed health, and other critical factors provide farmers with immediate insights into their crops.

5.6 Improved Return on Investment (ROI):

IoT-driven automation directly influences operational costs, enhancing overall farm efficiency. Through the utilization of sensors and data analytics, farmers can reduce water consumption, energy usage, and input materials like fertilizers, resulting in improved resource utilization and increased productivity.

5.7 Drought Monitoring Solutions:

Addressing drought conditions remains a significant challenge for farmers. IoT solutions contribute by detecting water shortages before they escalate into critical issues. Some advanced systems even offer insights into optimal irrigation timing and locations to maximize the efficiency of crop watering.

5.8 Harvesting Automation with Robotics:

The integration of robotics in agricultural harvesting tasks presents an innovative solution. This not only reduces labor costs but also ensures a consistent and higher quality of harvested products. The automation of harvesting processes is becoming increasingly prevalent, further streamlining agricultural operations.

6. Conclusion

In the agricultural domain, the pivotal task of plant disease detection takes center stage. This compilation provides a comprehensive overview of diverse research endeavors focused on the implementation of IoT in plant disease detection and classification systems, leveraging computer vision and machine learning techniques. In the context of India, where mitigating agricultural losses is paramount, the need for robust plant disease detection solutions is acutely felt. This survey encapsulates a range of well-established methodologies employed across the entire process, encompassing image acquisition, pre-processing modules, feature extraction, and ultimately, the application of classifiers. The early detection of diseases is of paramount importance to curtail their spread to neighboring plants, making disease classification a proactive solution. Furthermore, the document delves into the limitations inherent in existing systems, shedding light on areas ripe for improvement.

The insights derived from this survey are poised to serve as a valuable resource for upcoming emerging researchers, offering a platform to build upon and enhance the performance of future plant disease detection systems. By assimilating the knowledge gleaned from these diverse research works, the agricultural community is better equipped to tackle the challenges associated with plant diseases, ultimately contributing to the resilience and sustainability of agriculture.

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