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IOT-driven precision agriculture: A comprehensive review of machine learning techniques for rice plant disease diagnosis and nutrient deficiency detection using IOT sensor data

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Abstract: *In many nations, rice is the primary agricultural product. On the other hand, illnesses on rice plants may cause the crop to produce less rice overall and of lower quality. Consequently, early identification of plant diseases will aid in shielding rice from serious infection and minimizing crop loss. The recent utilization of GPS and a camera in agricultural monitoring is a substitute tool for gathering data in large area fast and independently. This review describes existing systems based on Internet of Things (IoT) which uses real-time information, including acquisition utilizing image processing techniques to perform rice disease diagnosis and classification in order to improve rice yield. The IoT sensors employed in such systems continuously monitor crucial environmental parameters, including soil moisture, temperature, and nutrient levels, providing real-time data for analysis. The system can map the location of diseased rice plants on rice fields and present the analytical technique by using a sensor to detect the position in real-time. The aims of these systems are to function as a prototype for an early and real-time disease detection system based on the Internet of Things.*

Key Words: *Rice Plant disease, Machine Learning (ML), Deep Learning (DL), Internet of Things (IoT), CNN, GPS, Sensor.*

1. INTRODUCTION

Crop diseases and pests that damage crops and greatly reduce agricultural productivity are the two main factors contributing to the depletion of food supply, according to statistical data. Insufficient soil nutrients, variable weather patterns that promote plant diseases and ultimately lower production, and poor water management are the main causes. Farmers can make better decisions if decision support systems are developed to help them act morally and increase agricultural productivity. Thus, one of the most important factors in guaranteeing high productivity and quality is the automatic and precise diagnosis of plant diseases [1]. Additionally, it removes the requirement for fieldwork to manually identify plant diseases [2]. Many studies are currently being conducted on the automatic diagnosis and analysis of plant diseases using image processing techniques. Treatment of pesticides, illness prediction, and early illness diagnosis are a few potential applications.

The agriculture sector benefits greatly from rice farming. In terms of quantity consumed in metric tonnes, it is one of the most extensively used cereal crops worldwide; 486.62 million metric tonnes were consumed in 2018–2019 and 496.30 million metric tonnes in 2019–2020. It is expected that as rice production rates rise, so will rice consumption. Unfortunately, due to inadequate field surveillance, disease-related issues often result in the destruction of a significant volume of rice. The production of rice is frequently plagued by a number of ailments that cause large financial losses. The agriculture sector benefits greatly from rice farming. It is one of the most widely utilized cereal crops in the world when considering the volume consumed in metric tonnes (486.62 million metric tonnes in 2018–2019 and 496.30 million metric tonnes in 2019–2020). These symptoms can be recognized by their texture, colour, and form [3]. Currently used methods for detecting rice diseases include automated detection, querying rice disease maps, and artificial identification.

In recent years, there has been a notable improvement in the efficiency of computing power, and a multitude of data from many sources is easily accessible to enhance our comprehension of the agriculture sector. The fields of deep learning and IoT research have created new opportunities for agricultural anomaly identification. Three major categories can be used to classify disease surveillance: spectral and digital image analysis, soil sensor measurements, and climatic normal analysis [4]. Thus, by using ML and DL algorithms, farmers can increase their profit margin while conserving land resources when creating an integrated management system for crop diseases [5].

1.1 Types of Rice Plant diseases

In the world, including India, rice is the food that is consumed the most. Rice plants are susceptible to over forty different forms of genetically related diseases. The most frequent illnesses that cause rapid damage to rice plants include sheath blight, rice blast, leaf smut, bacterial leaf blight, and narrow brown spot. Several paddy crop diseases are depicted in Fig. 1. Comprehending the structural features of mature rice plants is crucial for precise disease infection detection and localization. Grain particles, a sheath, a leaf, a stem, and a root make up a rice plant illnesses connected to every section of the rice plant, along with their signs and causes [8].

1.1.1 Rice Blast

Magnaporthe Grisea, a fungus that grows on the leaf and sheath of rice plants, is the cause of rice blast, the most common and damaging disease to affect them. Green-grey specks on the sick leaf are surrounded by a dark green border. The late mature stage is characterized by the dots changing into an oval structure and the dark green outline turning reddish brown. There are some lesions or patches that resemble diamonds. Later on, the lesions or spots multiply endlessly, causing the entire leaf to deteriorate.

1.1.2 Bacterial Blight of Rice

The bacteria Xanthomonas Oryzae are the cause of bacterial leaf blight. The most common symptom is a transparent spot that appears on the leaf and gives it a pale-yellow tinge. Rolling, drooping, and fading leaves are just a few of the cascade symptoms that the plant experiences before dying as the disease progresses.

1.1.3 Tungro Disease

Tungro disease is brought on by the Bacilliform virus, which damages the rice plant's sheath and leaves. The hue of the leaves appears to be yellow or yellowish orange. From the apex of the leaf to the bottom, the tungro illness spreads widely [6]. Plant hoppers are drawn to the rust-colored patch and its striped look, which lowers the crop's overall quality and output.

1.1.4 Brown Spot

Rice plants typically have brown patches on their leaves and sheaths. Soil that is poorly drained and lacking in nutrients is the main cause of brown spots on leaves. The rice plant's coleoptiles become infected with tiny, spherical lesions that have a yellowish-brown or brown color during the seedling stage. Initially appearing dark brown, the lesions eventually turned reddish brown with dots around a grey centre.

1.1.5 Grain Discoloration

At the panicle initiation stage, the grain's typical hue turns brownish-white. Discoloration of the grain signifies low quality, which lowers yield. Grains that are discolored are frequently subjected to storage infection fungus like Aspergillus and Fusarium species.

1.1.6 False Smut

This illness, which is brought on by the fungus Claviceps virens, is thought to be a sign of strong crop output because of the favourable weather. Only a few of the panicle's grains are affected by the disease; the remaining grains are unaffected. The infected plant's rice grain has a 1 cm-diameter smut ball of velvety spores [7]. The enclosure of floral components results from the formation of velvety spores. Underdeveloped spores have a smooth, flattened yellowish hue and are hidden by a membrane. Likewise, fungus-caused leaf smut is observed, exhibiting black dots throughout the leaves.

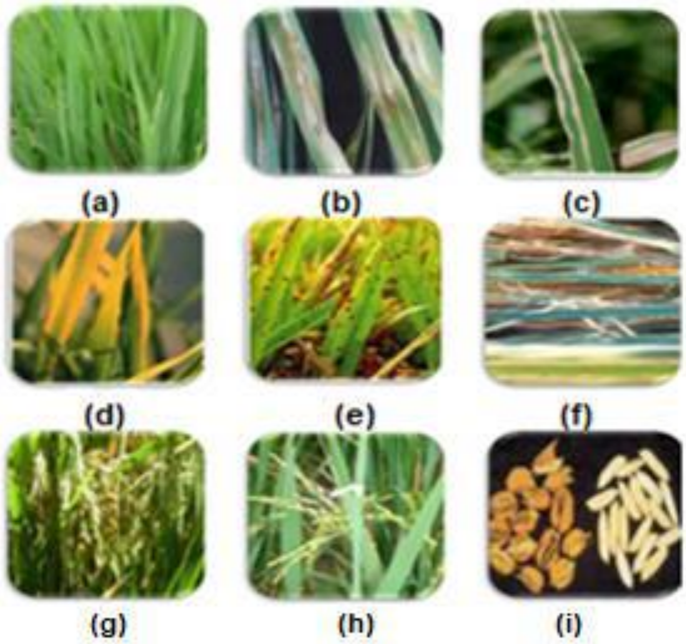

Fig. 1 Various crop leaf diseases: a) healthy leaf, b) rice blast, c) bacterial leaf blight, d) tungro disease, e) brown spot, f) narrow brown spot, g) Healthy grain, h) Grain discoloration, and i) false smut [8]

1.1.7 Stem Blast

Greyish-brown lesions in the nodes and compression of the panicle are the results of a node infection. These infections result in low-quality grain later on and in grain loss during the milky stage. Stem splitting is not brought on by the blast. Stem borers are the cause at the boring point. In addition to the stem borers, the blast also produced whiteheads.

1.1.8 Stem Rot

Numerous microscopic black and white sclerotia and mycelium round the diseased culms. The affected culms exhibit symptoms such as chalky grain and empty panicles. On the leaf sheath along the water's edge, there are small black lesions that get bigger as the illness progresses. When the infection gets serious, Tiller dies.

1.1.9 Stem Dwarf

The afflicted plants become small and have pale green leaves due to stem dwarfism. The over-tilting causes the leaves to progressively deteriorate and droop. Significant damage is done to the root's growth, and chlorosis develops and extends to the leaf sheath [9].

1.1.10 Stem Grassy Shunt

The decaying plants grow upright and stunted, with growth patterns resembling rosettes. Even with an adequate amount of nitrogen fertilizer, the leaves appear yellowish green and are significantly reduced in size. Tiny patches of rust on leaves reduce the formation of panicles. When all of these patches combine, mottled leaf blotches are created [10].

1.1.11 Root Rot

The afflicted plants appear odd, thinner, and somewhat taller than the healthy ones due to root rot. Because of an excess of root lesions, infected seedlings die earlier, often even before they are transplanted. The leaves have a light, yellowish green color. The plant develops white chalky growth either below or above the ground node.

1.2 IoT sensors

Over the last few decades, farming has undergone numerous technical changes and is increasingly industrialized and technology-driven. The development of smart agricultural devices has allowed farmers to better manage the growth of their crops and efficiently care for their livestock. Every aspect of our lives, including health care, automation, cars, smart cities, and logistics, has begun to see the introduction of Internet of Things-based gadgets. All services based on technological innovations and digital systems that meet modern farmers' demands for optimizing yield, cutting waste, and preserving environmental quality are together referred to as precision agriculture. Along with the following assistance, farmers can use IoT sensors in their crops to help them allocate fertilizer and pesticides correctly.

- Optimizing harvesting time
- The health of the crop
- Monitoring humidity, light, and temperature in greenhouses
- Determining the moisture content and soil quality

There are many smartphone applications that combine data aggregation, process speed, and Internet of Things (IoT) principles. As a result, the information may be updated and small farmers may receive information on fertilization, weeding, sowing, and watering. Data from these sensors is being gathered by these applications, particularly from weather stations and distant sensors. In the wake of IoT technology advancement and deployment, seeding is no longer purely speculative. The precise location where a seed should be sown and grown can be determined by the programmed smart gadget. When the harvest is ready, the clever tractors harvest the crops with even greater care and efficiency. Currently, fixing tractor damage consumes 80–90% of the energy needed to cultivate crops utilizing the G.P.S. controlled steering system and route planning based on the supplied data.

- Reducing erosion by monitoring the route of vehicles
- Steep cost cutting
- An increase in operational accuracy

Small-scale farmers may benefit from the applications designed for them in a number of ways. The plant ailments were diagnosed and sent to specialists for correction. Based on soil quality and leaf color, fertilizers need different amounts of nutrients. Other characteristics that can be measured include the pH level of the soil. The observations performed on the leaves of the plants allowed for the determination of their water requirements. By harvesting crops when they are ready and using UV and white light-based photography, ripeness can be prevented.

2. Related Work

It is important to emphasize current existing research and advancements in this field as we examine related works on rice plant disease diagnosis and nutrient insufficiency based on IoT sensor data. Here are some key points for this:

Dhaka et. al. (2023) [11] showed that one of the main obstacles to precision and smart farming is the autonomous identification, visualization, and categorization of plant diseases using picture databases. The technical solutions thus far showcased the efficiency of deep learning models for self-governing feature extraction and selection, as well as the remarkable capabilities of the Internet of Things for gathering, storing, and transmitting data. This means that the combination of these technologies is becoming an increasingly important tool for monitoring, gathering information, predicting, identifying, and classifying plant diseases from farm images. Plant disease monitoring and categorization using deep learning models and the Internet of Things are thoroughly evaluated in this issue. The comparison provides information on how to choose the best deep learning models based on factors including dataset size, anticipated response time, and computing and storage resources. In order to create hybrid and optimized models for the classification of plant diseases.

Ahmad et. al. (2023) [12] studied that several factors associated with disease diagnosis in plants using deep learning techniques must be considered to develop a robust system for accurate disease management. A substantial amount of investigation has looked into how deep learning methods might be applied to precision farming. There are still a lot of research gaps on plant diseases to aid in disease control on farms, despite the wide range of applications. Therefore, identifying potential and issues as well as building a knowledge base of present uses are essential to advancing the development of tools that meet farmer desires. This is an in-depth analysis of studies on deep learning technologies and the most recent developments in their application to the diagnosis and treatment of agricultural diseases. The study covers seven primary topics: deep learning methodology, generalization of deep learning models, imaging sensors and data collection platforms, needs, accessibility, and usefulness of datasets, and sickness severity estimation. This makes it possible to evaluate thoroughly and take into account the creation of deep learning-based instruments for the diagnosis of plant diseases.

Patil et. al. (2022) [13] analyzed that rice leaf infections are a common hazard to rice production, affecting many farmers all over the world. To support the establishment of healthy rice plants and guarantee a sufficient supply for the world's fastest growing population, rice leaf infections must be identified and treated. In order to resolve the problems previously mentioned, the popular Convolution Neural Network design offers a diagnostic and information extraction from images. Nevertheless, this technique performs poorly on real-time images and works best on segmented images. Here, a paradigm shift is being facilitated by the Internet of Things, which is collecting agro-meteorological data that may be utilized to precisely diagnose rice ailments. Rice-Fusion, a novel multimodal data fusion system powered by agricultural IoT and CNN models, is proposed as a diagnosis tool for rice sickness. Combining multiple modalities is necessary for the diagnosis of rice sickness since an insufficient diagnosis from a single modality may occur. This ensures a solid and trustworthy disease diagnosis. This adds another level of complexity to the field of diagnosing rice diseases. Using a camera and agro-meteorological sensors, 3200 rice health category samples were manually gathered for the dataset. Initially, the Rice-Fusion framework takes agro-meteorological data that is gathered from sensors and extracts its numerical properties.

Ouhami et. al. (2021) [14] conducted studies and revealed that crop diseases constitute a serious issue in agriculture, affecting both quality and quantity of agriculture production. Studies on disease control have been conducted in a variety of scientific and technological fields. Artificial intelligence, data storage, sensors, and computer power have all demonstrated significant promise for successful disease control. An increasing amount of study acknowledges the advantages of utilizing machine learning techniques and data from many sensor kinds to create models for analysis, assessment, prediction, and other applications. The study looked into cutting-edge machine learning techniques that diagnose plant diseases by utilizing many data sources. The four primary modalities of data acquisition are satellite imaging, Internet of Things imaging, unmanned aerial vehicle imaging, and terrestrial imaging. Deep learning and conventional learning approaches are listed for each of these modalities. It describes the main challenges and highlights the advantages of combining data from several sources using intelligent data fusion techniques to enhance plant health status prediction.

Zhang et. al. (2020) [15] examined that the detection, quantification, diagnosis, and identification of plant diseases is particularly crucial for precision agriculture. The increasing demands of precision agriculture information have resulted in constraints for traditional visual evaluation technology. Hyper spectral technology is becoming more popular as a typical non-invasive technique. The numerous advantages of hyper spectral technology for plant disease diagnosis are explained by this study solely taking into account pathogen types and host-pathogen interaction mechanisms. Moreover, it is proposed that the main obstacles to initiating a customized response are the identification of various pathogens, the distinction between biotic and abiotic stressors, the early diagnosis of plant diseases, and the application of satellite-based hyper spectral technologies. This is based on an analysis of the primary issues that currently surround the use of hyper spectral technology in plant disease diagnosis.

Anamisa et. al. (2019) [16] tried to determine the technologies which have been applied for the detection system, such as web-based, mobile-based, and internet of things. The methods that are most frequently employed include deep learning and expert systems. In previous studies, the most regularly used techniques were incremental learning, fuzzy models, Bayesian networks, K-means clustering, genetic algorithms, and backward and forward chaining. On the other hand, the least used methods were Decision Trees, Convolution Neural Networks, and Naïve Bayes and Certainty Factors. The analysis also showed that there isn't a single optimum technology or method for creating precise pest or disease detection systems. Rather, the fusion of technologies, techniques, and strategies led to disparities in accuracy and performance. This could be explained by the fact that the systems are used to identify, manage, and keep an eye on a variety of plants, including flowers, corn, onions, wheat, rice, mangoes, and other unique plants. This work makes a contribution by offering techniques, strategies, and technology for the plant disease and pest detection system.

Rau et. al. (2017) [17]highlighted a few key problems that paddy farmers currently face after conferring with the Kerala Rice Research Station, Vytilla, and Kerala Agricultural University, Mannuthy. It covers the issue of either over- or under-watering as well as the requirement for consistent hand irrigation. Furthermore, there is no system in place to automatically keep an eye out for illnesses specific to the rice species and determine whether the crop is receiving enough nutrients. Rice is the major crop of Kerala. In this study, they have developed an automated irrigation and fertigation system that is affordable, and they have also used image processing to detect nutrient deficits and rice diseases. Here, they are emphasizing the importance of two nutrients: nitrogen and magnesium. The components include solenoid valves, a Raspberry Pi, and a DHT11 temperature and humidity sensor.

Mahlein et. al. (2016) [18]carried out studies and found that early and accurate detection and diagnosis of plant diseases are key factors in plant production and the reduction of both qualitative and quantitative losses in crop yield. Optical approaches like chlorophyll fluorescence, RGB imaging, thermography, multi- and hyper-spectral sensors, and thermography have shown promise in automated, objective, and repeatable detection systems for the early diagnosis and assessment of plant diseases. More recently, an optical test called 3D scanning was developed to provide more details on agricultural plant viability. There are systems available for multi-scale monitoring of individual crop organs or entire fields, ranging from local to remote sensing. Extensive and innovative data processing techniques that yield new insights from sensor data for complex plant-pathogen systems enable accurate and dependable disease detection. Plant disease assessment using non destructive, sensor-based techniques complements and extends the use of optical and/or molecular approaches. Precision farming and plant phenotyping are the most pertinent applications of sensor-based analysis.

Table 1: Comparison of literature review

Study	**Focus**	**Findings and Solutions**
Dhaka et. al. (2023) [11]	Using picture databases, automatically identify, visualize, and classify plant diseases for precision and intelligent farming.	Emphasizing the Internet of Things (IoT) for data collection, storage, and transmission, and deep learning models' superiority for autonomous feature extraction. Combining deep learning models and IoT for surveillance, data acquisition, forecasting, identification, and categorization of plant ailments. Provides insights into selecting optimum deep learning models based on dataset size, expected response time, and available computational resources.
Ahmad et. al. (2023) [12]	Factors related to plant disease diagnosis with deep learning strategies for effective disease control in precision farming.	Despite numerous studies, research gaps exist in understanding plant diseases. The requirement to establish a knowledge base of existing applications, as well as to pinpoint issues and possibilities, for instruments meeting farmers' needs. Focuses on seven key questions related to dataset requirements, imaging sensors, deep learning techniques, generalization of models, and disease severity estimation.
Patil et. al. (2022) [13]	Crop of rice leaf diseases that have an impact on rice production worldwide and the application of Rice-Fusion, a multimodal data fusion platform, for precise diagnosis.	Robust image backgrounds hinder diagnosis with computer assistance. Introducing Rice-Fusion, a multimodal data fusion system that combines agricultural IoT with models from Convolution Neural Networks to provide precise diagnosis. Real-time image processing issues and the necessity of data fusion for solid and trustworthy disease diagnosis. Highlights the complexity of diagnosing rice diseases and the importance of using multiple modalities for appropriate diagnosis.
Ouhami et. al. (2021) [14]	Crop diseases' impact on agriculture production quality and quantity, exploring machine learning techniques and data fusion for disease control.	The AI, data storage, sensors, and machine learning for disease control. And investigates machine learning methods for imagery from satellites, planes, unmanned aerial vehicles, and Internet of Things. Intelligent data fusion techniques can be used to improve the prediction of plant health status. Presents the main challenges facing the field of disease detection and emphasizes the importance of ongoing research.

Zhang et. al. (2020) [15]	Essential components of precision agriculture include the use of hyper-spectral technologies for the detection, measurement, diagnosis, and identification of plant diseases.	Hyper-spectral technology gains attention for its non-invasive nature in plant disease detection. Explores the advantages of using hyper-spectral technology in relation to the different types of infections and the ways in which they interact with hosts.
Anamisa et. al. (2019) [16]	Application of various technologies (web-based, mobile-based, IoT) and dominant approaches (expert system and deep learning) for plant disease detection.	Describes the application of web-based, mobile-based, and IoT technologies for plant disease detection. Lists commonly used techniques, including backward chaining, forward chaining, fuzzy models, genetic algorithms, and K-means clustering. Emphasizes the fusion of technologies, techniques, and strategies, leading to disparities in accuracy and performance.
Rau et. al. (2017) [17]	Development issues in technology for Indian agriculture, addressing problems in paddy farming and proposing an automated irrigation and fertigation system.	Highlights the limited development in technology for Indian agriculture. Addresses problems of over- or under-watering, lack of automated disease monitoring, and nutrient assessment in paddy farming. Proposes an affordable automated irrigation and fertigation system using image processing for nutrient deficiency and disease detection. Emphasizes the importance of two nutrients: nitrogen and magnesium. Includes solenoid valves, a Raspberry Pi, and a DHT11 temperature and humidity sensor.
Mahlein et. al. (2016) [18]	Optical techniques, multi- and hyper-spectral sensors, thermography, 3D scanning, sensor-based analysis, precision farming, plant phenotyping, sensor-based technology, and chlorophyll fluorescence.	Investigates optical techniques for the detection of plant diseases, such as thermography, RGB imaging, multi- and hyper-spectral sensors, and chlorophyll fluorescence explains how sensor-based analysis is crucial for precision farming.

3. Detecting Disease in Bio Medical Imaging: A Comprehensive Overview

For detection of diseases the primary image has been segmented into a number of sub images, each containing a region of interest or features. These features are further extracted to reduce the number of variable characteristics that are actually needed for sickness identification. Features can be grouped using edges, colors, textures, and shapes. The following measurements are part of the feature form: color, axis length, solidity, concavity, perimeter, roundness, eccentricity, elongation, circumference, length, breadth, and elongation. The texture consists of the following: mean, energy, entropy, contrast, variance, correlation, and moment of inertia.

3.1 Color Based feature: The color co-occurrence approach and the color moment method (CMM) are frequently used to extract color data from photographs. The RGB color space must first be translated to the HIS color space in order to extract the color information from CMM. Three color moments exist for each plane: skewness, standard deviation, and mean.

3.2 Texture Based feature: An object's texture is defined as a region's spatial arrangement of different entities with distinct shapes, colors, or intensities. Similar pixel values indicate smooth texture, but highly varying pixel values constitute rough texture.

Table 2: Various feature extraction techniques used for plant disease detection

Plant	Disease	Feature	Feature extraction Reference technique	Reference
Moth orchid (Phalaenopsis sp.)	Bacterial soft rot, Bacterial brown spot, and Phytophthora black rot	Texture	GLCM	[19]

Maize seedlings	Corn leaf blight, Sheath blight, Southern leaf blight	Texture and color	SGDM	[20]
Grapes	Downey mildew and Powdery mildew	Texture and color	GLCM and SGDM	[21]
Bean	Cercospora leaf spot	Texture and color	SGDM	[22]
Tomato	Nutrient Deficiency (N and K)	Color and Texture	Percent histogram difference operator, Fourier transform and wavelet packet decomposition	[23]
Soya bean	Bacterial leaf spot, frog eye spot and rust	Lesion size, shape, color and texture	Discrete cosine transformation (DCT)	[24]
Rice	Brown spot, blast, bacterial leaf blight, and Tungro disease	Texture	Fourier based fractal descriptors	[25]
Rice	Blight, blast and sheath blight	Shape	Minimum closing rectangle	[26]

3.3 Shape Based feature: The area and perimeter of the input image are rotated at the same angle to obtain the minimum enclosing rectangles (MER) of lesions or spots. This approach can be used to determine several shape properties, such as elongation, compactness, rectangularity, and solidarity, by utilizing the area, perimeter, and MER. Table 2 has an enumeration of further feature extraction methods.

Table 3: List of some classifiers used in diseases of rice

Disease	**Classifier**	**Accuracy**	**Reference**
Blast and brown spot	Self-organizing map neural network SOM-NN	92 %	[27]
Blast, narrow brown spot, and brown spot	Production Rules with orward chaining method	94.7 %	[28]
Blast and healthy leaf	Fuzzy-C-mean clustering	85 %	[29]
Bacterial leaf blight	PNN	96.25 %	[26]
Brown spot and Blast disease	Rule mining technique	92.29 %	[30]
Brown spot, leaf blast and bacterial blight	KNN	93.3 %	[31]
Bacterial blight, brown spot, leaf smut	Alex Net	>99%	[32]
Blast	Convolution neural network (CNN)	99.6 %	[33]

The majority of studies looked at individual nutrient deficiencies, primarily nitrogen, affected leaf spectra, while others created models using spectral indices to identify other nutrients in addition to nitrogen. A selection of noteworthy studies on the application of imaging technology to analyses nutrient content or detect nutrient deficiencies in plants are shown in Table 4 below.

Table 4: List of some imaging method used for detection of nutrient deficiencies in Crops

Crop	**Method used**	**Nutrient**	**Country**	**Reference**
Rice	RGB	N, P, K	China	[34]
Rice	RGB	N, P, K	China	[35]
Rice	Hyper Spectral Imaging	N	Japan, China	[36]
Tomato	RGB	N, K	China	[24]
Corn	RGB	N	USA	[37]
Potato	Multispectral Image	N	USA	[38]

4. Challenges of Crop Disease Detection

Nevertheless, several factors can diminish the efficiency of disease detection mechanisms. The following is a discussion of those attention-grabbing tasks that will test the performance of the system:

4.1 Disease Symptom Variations

Variations in color, size, and form ultimately alter the characteristics of disease symptoms. The identification of diseases gets more difficult when several symptoms appear under various circumstances. A number of variables, including temperature, wind, humidity, sunshine exposure, plant genotype, and the color of healthy plants, have a significant impact on disease features.

4.2. Diseases of Similar Patterns

The presence of several diseases with comparable symptoms and patterns significantly reduces the accuracy of disease identification and categorization. The methods employed have an impact, and there is considerable variation in the complexity of classifying and distinguishing disease symptoms. The traditional method fails to distinguish between diseases with comparable symptoms because it uses a visible spectrum in the detecting sensor. In the meantime, it is discovered that infrared spectrum-based sensors are expensive, difficult, and prone to mistakes.

4.3 Symptom Segmentation

Disorders with similar symptoms are challenging to segment. In digital image processing, an intrinsic component of symptom segmentation is frequently utilized. However, the segmentation procedure is complicated by illnesses that include time-varying symptoms, overlapping disease symptoms, and imprecise edge symptoms. This problem can be solved by integrating a different segment symptom correction technique with the current model. Image cropping with background noise: Segmentation is not too tough if the crop image has a black-and-white background. Nonetheless, the inclusion of a multi colored picture background with foliage, grass, dirt, etc.

4.4 Image Background Criteria

Due to a number of variables, including temperature, humidity, wetness, light intensity, and image angle, it might be difficult to get comparable photos. Therefore, in order to improve the training dataset, it is necessary to take pictures at various times of the day, in various environments, and from all angles.

5. Conclusion

This review study demonstrated the use of drone’s facilitated faster field surveying in wide areas that enables real-time image collecting mechanism, where obtained photos are analyzed on a server. Additionally, researchers also suggest a rice disease detection system that makes use of the HSV color space, which is useful for disease segmentation. The continuous monitoring of environmental factors through IoT sensors, coupled with advanced analytics and machine learning approaches, enables early detection of diseases and precise identification of nutrition deficiencies. This real-time data not only facilitates proactive interventions but also allows for the optimization of resource usage, contributing to sustainable and efficient farming practices. The remote monitoring capabilities empower farmers to make informed decisions from any location, enhancing overall operational efficiency. With the help of this the diseased leaf's location was identified, and the initial step of early disease detection's direction was visible. They will think about that will operate the drone so that it can fly and scan the rice field to collect on-demand imagery. After that, this drone technology will be used to capture aerial photos of the plants in order to further aid in the prediction of rice diseases. By extracting the color and texture pattern features, this method can also classify the sort of diseases that manifest on leaves.

6. Future scope

The future scope of rice plant disease diagnosis and nutrition deficiency management leveraging IoT sensor data promises a paradigm shift in agriculture. Farmers can transition to precision agriculture where real-time data on environmental variables, like soil moisture, temperature, and nutrient levels by integrating advanced sensor technologies. Thanks to powerful analytics and machine learning algorithms, this abundance of data makes it possible to diagnose diseases and nutritional deficiencies early on. Automated systems can not only identify subtle signs of distress in rice plants but also offer precise interventions, optimizing resource utilization and minimizing environmental impact. Remote monitoring and control, facilitated by IoT platforms, empower farmers to manage their fields from anywhere, fostering efficiency and convenience. The synergy of IoT with data analytics opens avenues for predictive modelling, allowing farmers to anticipate and mitigate potential issues before they escalate. Moreover, the adaptability of these systems to changing climate conditions ensures resilience in agriculture. Collaboration among farmers, researchers, and agricultural experts is facilitated, promoting knowledge sharing and the development of best practices and technologically advanced agricultural landscape, where IoT sensor data plays a pivotal role in maximizing yields while minimizing resource usage and environmental impact.

Declarations

Conflict of Interest: The authors declare that they have no conflict of interest.

Data Availability: Data sharing not applicable to this article as no datasets were generated or analyzed during the current study

REFERENCES

1. Patil, R. R., & Kumar, S. (2020). A Bibliometric Survey on the Diagnosis of Plant Leaf Diseases using Artifificial Intelligence. *Library Philosophy and Practice*, 1-26.
2. Pantazi, X. E., Moshou, D., &Tamouridou, A. A. (2019). Automated leaf disease detection in different crop species through image features analysis and One Class Classifiers. *Computers and electronics in agriculture*, *156*, 96-104.
3. Zarbafi, S. S., & Ham, J. H. (2019). An overview of rice QTLs associated with disease resistance to three major rice diseases: blast, sheath blight, and bacterial panicle blight. *Agronomy*, *9*(4), 177
4. Lary, D. J., Alavi, A. H., Gandomi, A. H., & Walker, A. L. (2016). Machine learning in geosciences and remote sensing. *Geoscience Frontiers*, *7*(1), 3-10.
5. Golhani, K., Balasundram, S. K., Vadamalai, G., & Pradhan, B. (2018). A review of neural networks in plant disease detection using hyperspectral data. *Information Processing in Agriculture*, *5*(3), 354-371.
6. Shivappa, R., Navadagi, D. B., Baite, M. S., Yadav, M. K., Rathinam, P. S., Umapathy, K., ... & Rath, P. C. (2021). Emerging minor diseases of rice in india: losses and management strategies. *Integrative Advances in Rice Research*.
7. Raghu, S., Baite, M. S., Patil, N. B., Sanghamitra, P., Yadav, M. K., Prabhukarthikeyan, S. R., ... & Rath, P. C. (2020). Grain discoloration in popular rice varieties (Oryza sativa L) in eastern India, associated mycoflora, quality losses and management using selected biocontrol agents. *Journal of Stored Products Research*, *88*, 101682.
8. M. Karthick, D. Vijayalakshmi, Malaya Kumar Nath, M. Mathumathi (2022, Dec). Machine Learning Approaches for Automatic Disease Detection from Paddy Crops.International Journal of Engineering Trends and Technology
9. Katsantonis, D., Kadoglidou, K., Dramalis, C., &Puigdollers, P. (2017). Rice blast forecasting models and their practical value: a review. *PhytopathologiaMediterranea*, 187-216.
10. Johannes, A., Picon, A., Alvarez-Gila, A., Echazarra, J., Rodriguez-Vaamonde, S., Navajas, A. D., & Ortiz-Barredo, A. (2017). Automatic plant disease diagnosis using mobile capture devices, applied on a wheat use case. *Computers and electronics in agriculture*, *138*, 200-209.
11. Dhaka, V. S., Kundu, N., Rani, G., Zumpano, E., & Vocaturo, E. (2023). Role of Internet of Things and Deep Learning Techniques in Plant Disease Detection and Classification: A Focused Review. *Sensors*, *23*(18), 7877.
12. Ahmad, A., Saraswat, D., & El Gamal, A. (2023). A survey on using deep learning techniques for plant disease diagnosis and recommendations for development of appropriate tools. *Smart Agricultural Technology*, *3*, 100083.
13. Patil, R. R., & Kumar, S. (2022). Rice-fusion: A multimodality data fusion framework for rice disease diagnosis. *IEEE Access*, *10*, 5207-5222.
14. Ouhami, M., Hafiane, A., Es-Saady, Y., El Hajji, M., & Canals, R. (2021). Computer vision, IoT and data fusion for crop disease detection using machine learning: A survey and ongoing research. *Remote Sensing*, *13*(13), 2486.
15. Zhang, N., Yang, G., Pan, Y., Yang, X., Chen, L., & Zhao, C. (2020). A review of advanced technologies and development for hyperspectral-based plant disease detection in the past three decades. *Remote Sensing*, *12*(19), 3188.
16. Anamisa, D. R., Yusuf, M., Agustiono, W., &Svarief, M. (2019, September). Technologies. Methods, and Approaches on Detection System of Plant Pests and Diseases. In *2019 6th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI)* (pp. 163-170). IEEE.

17. Rau, A. J., Sankar, J., Mohan, A. R., Krishna, D. D., & Mathew, J. (2017, July). IoT based smart irrigation system and nutrient detection with disease analysis. In *2017 IEEE Region 10 Symposium (TENSYMP)* (pp. 1-4). IEEE.
18. Mahlein, A. K. (2016). Plant disease detection by imaging sensors–parallels and specific demands for precision agriculture and plant phenotyping. *Plant disease*, *100*(2), 241-251.
19. Huang, K. Y. (2007). Application of artificial neural network for detecting Phalaenopsis seedling diseases using color and texture features. *Computers and Electronics in agriculture*, *57*(1), 3-11.
20. Kai, S., Zhikun, L., Hang, S., &Chunhong, G. (2011, January). A research of maize disease image recognition of corn based on BP networks. In *2011 third international conference on measuring technology and mechatronics automation* (Vol. 1, pp. 246-249). IEEE.
21. Sannakki, S. S., Rajpurohit, V. S., Nargund, V. B., & Kulkarni, P. (2013, July). Diagnosis and classification of grape leaf diseases using neural networks. In *2013 Fourth International Conference on Computing, Communications and Networking Technologies (ICCCNT)* (pp. 1-5). IEEE.
22. Arivazhagan, S., Shebiah, R. N., Ananthi, S., &Varthini, S. V. (2013). Detection of unhealthy region of plant leaves and classification of plant leaf diseases using texture features. *Agricultural Engineering International: CIGR Journal*, *15*(1), 211-217.
23. Xu, G., Zhang, F., Shah, S. G., Ye, Y., & Mao, H. (2011). Use of leaf color images to identify nitrogen and potassium deficient tomatoes. *Pattern Recognition Letters*, *32*(11), 1584-1590.
24. Shrivastava, S., Singh, S. K., & Hooda, D. S. (2014). Statistical texture and normalized discrete cosine transform-based automatic soya plant foliar infection cataloguing. *British Journal of Mathematics & Computer Science*, *4*(20), 2901.
25. Asfarian, A., Herdiyeni, Y., Rauf, A., &Mutaqin, K. H. (2013, November). Paddy diseases identification with texture analysis using fractal descriptors based on fourier spectrum. In *2013 International Conference on Computer, Control, Informatics and Its Applications (IC3INA)* (pp. 77-81). IEEE.
26. Tian, Y., & Zhang, L. (2012). Study on the methods of detecting cucumber downy mildew using hyperspectral imaging technology. *Physics Procedia*, *33*, 743-750.
27. Phadikar, S., & Sil, J. (2008, December). Rice disease identification using pattern recognition techniques. In *2008 11th International Conference on Computer and Information Technology* (pp. 420-423). IEEE.
28. Kurniawati, N. N., Abdullah, S. N. H. S., Abdullah, S., & Abdullah, S. (2009, December). Investigation on image processing techniques for diagnosing paddy diseases. In *2009 international conference of soft computing and pattern recognition* (pp. 272-277). IEEE.
29. Verma, T., Satpathy, S. K., Nagwanshi, K. K., & Sharma, L. K. (2011). Loss Estimation by Fuzzy C-Means Clustering Algorithm in Rice Farming Caused by Leaf Blast Diseases. *International Journal of Computer Information Systems*, 21-27.
30. Phadikar, S., Sil, J., & Das, A. K. (2013). Rice diseases classification using feature selection and rule generation techniques. *Computers and electronics in agriculture*, *90*, 76-85.
31. Matin, M. M. H., Khatun, A., Moazzam, M. G., & Uddin, M. S. (2020). An efficient disease detection technique of rice leaf using AlexNet. *Journal of Computer and Communications*, *8*(12), 49-57.
32. Rathore, N. P. S., & Prasad, L. (2020). Automatic rice plant disease recognition and identification using convolutional neural network. *Journal of critical reviews*, *7*(15), 6076-6086.
33. Sun, Y., Gao, J., Wang, K., Shen, Z., & Chen, L. (2018). Utilization of machine vision to monitor the dynamic responses of rice leaf morphology and colour to nitrogen, phosphorus, and potassium deficiencies. *Journal of Spectroscopy*, *2018*.
34. Chen, L., Lin, L., Cai, G., Sun, Y., Huang, T., Wang, K., & Deng, J. (2014). Identification of nitrogen, phosphorus, and potassium deficiencies in rice based on static scanning technology and hierarchical identification method. *PloS one*, *9*(11), e113200.
35. Sayeed, M. A., Shashikala, G., Pandey, S., Jain, R., & Kumar, S. N. (2016). Estimation of nitrogen in rice plant using image processing and artificial neural networks. *Imperial Jurnal of Interdisciplinary research (IJIR)*, *2*.
36. Rorie, R. L., Purcell, L. C., Karcher, D. E., & King, C. A. (2011). The assessment of leaf nitrogen in corn from digital images. *Crop Science*, *51*(5), 2174-2180.
37. Borhan, M. S., Panigrahi, S., Satter, M. A., & Gu, H. (2017). Evaluation of computer imaging technique for predicting the SPAD readings in potato leaves. *Information processing in agriculture*, *4*(4), 275-282.
38. Barbedo, J. G. A. (2016). A review on the main challenges in automatic plant disease identification based on visible range images. *Biosystems engineering*, *144*, 52-60.