International Journal of Information Technology and Management
Vol. 19, Issue No. 1, February-2024, ISSN 2249-4510

DOI: https://doi.org/10.29070/fjehky26

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A Comprehensive Review of Deep Learning-Based Approaches for Rice and Wheat Leaf Disease Detection

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Abstract: Agricultural productivity is greatly influenced by various plant diseases, especially those affecting essential crops like rice and wheat. Timely and precise identification of these diseases plays a critical role in maintaining food security and enhancing crop yields. Traditional methods of detecting diseases often involve manual inspection, which is time-consuming, labor-intensive, and prone to errors. To address these challenges, there has been a growing interest in automated disease detection systems that leverage deep learning and computer vision techniques. This study focuses on utilizing image processing and machine learning to identify and classify diseases on the leaves of rice and wheat plants. The proposed system relies on a collection of images representing both healthy and diseased leaves, which are pre-processed by removing noise, enhancing contrast, and extracting relevant features. Various deep learning models, including Convolutional Neural Networks (CNNs), are employed to accurately detect and categorize the diseases. For rice, the most prevalent diseases include bacterial blight, brown spot, and blast, while wheat faces threats from diseases such as rust, powdery mildew, and leaf blight. The performance of the model is evaluated using metrics such as accuracy, precision, recall, and F1-score. Additionally, the model's robustness is assessed under varying lighting conditions, leaf orientations, and background noise. Challenges such as small datasets, diseases with similar symptoms, and the application of the same model in different climates are discussed. The findings suggest that deep learning models can significantly improve disease detection accuracy compared to traditional methods, providing farmers and agricultural experts with an efficient, cost-effective, and scalable solution.

Keywords: Deep Learning, Rice Disease Detection, Wheat Disease Detection, Image Processing, Machine Learning in Agriculture

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INTRODUCTION

Plant infections have a big impact on both the amount and quality of foods that are grown. It is important to predict and find these infections early on so that things don't get hurt and production goes up. According to [1] only 17% of India's GDP comes from farmland. Pepper, tomatoes, and potatoes are some of the most important foods that India grows [2].Environment and cross-contamination are just two of the many things that can cause diseases to start and spread in farming areas [3] In farmland, many kinds of food are grown, and we can learn about them. Pests cause about 30 to 33 percent less crops to be grown every year [4]. Molds, viruses, and bacteria can all infect plants and make them sick. To lessen the effects of infections, people who work in agriculture need help moving from one infection control method to another. This is because there are so many infections and so many things that can cause them. This situation has a direct effect on the overall quality and amount of the food that is grown. Scientists have come a long way in the past few years, but it's interesting to see that farmers still use old ways to find diseases in crops. [5] say that farmers still have to look at the products by hand to see if there are any signs of disease, even though they have modern, specialized tools. It's hard to use and has many problems in agricultural studies to judge crops based on how they look and what the farmer knows about them. In the worst case, a sickness in a crop that isn't found could kill the whole crop, which would mean less food. Symptoms of some diseases in farms are not always easy to see, which makes it tough to decide what to do. It can be tough to find the best way to decide, act, and help when things like this happen. Therefore, it becomes essential to perform advanced and comprehensive study[6].ML and DL are computer-aided automated studies that can help find diseases quickly, accurately, and early on. This is very important in agriculture today because of the problems mentioned above. Using these technologies is helpful because they can give quick and correct results by using computers to make discoveries and process pictures. AI can help farmers save money on work costs, avoid wasting time, get better crops, and get more crops in total. With the right management, it can be easier to carry out disease control plans when the most up-to-date information is used on how healthy crops are and where diseases are growing.

Wheat and rice are both the most important foods in the world. This is what more than half of the people in the world eat for breakfast. This is what one-third of the people in the world eat for breakfast. Before they are fully grown, rice leaf diseases and wheat leaf diseases can really hurt the yield of rice and wheat. So, it's important to be able to quickly and correctly name the different leaf diseases that plague wheat and rice so that they can get the right care at the right time .A lot of land, though, makes it hard to artificially find leaf diseases, so we need a picture recognition model that can fix this right away. If a certain kind of plant needs to learn how to spot leaf diseases, it will usually have its own model. But in some places, they grow wheat and rice at the same time. On both sides of the Yangtze River in China, people grow rice in the spring and wheat in the fall. Farms in this area will have trouble with both wheat and rice leaf diseases because of this. It takes 300 days for wheat to grow and 100 days for rice to grow. In other words, it's likely that both will get leaf diseases at the same time. It needs to know about both rice leaf diseases and wheat leaf diseases at this time. If rice leaf diseases and wheat leaf diseases each use their own recognition model, it will take up too much store space. Two models for spotting leaf diseases were put together to make a multi-task leaf diseases recognition model. This is possible because tasks can share features and help each other. This model not only solves the problem, but it also cuts down on clutter and improves accuracy. It is very important to make a model that can do more than one thing and find diseases on both wheat and rice leaves.

to progress in computer vision and AI, deep learning is being used more and more in picture recognition these days [7].It is the convolutional neural network (CNN) that is used most often in deep learning. CNN is great at adjusting, learning on its own, and drawing broad conclusions. A lot of people have used basic machine vision algorithms to group crop diseases into groups, such as wheat leaf diseases and rice leaf diseases. The Support Vector Machine (SVM) was used by Amit Kumar Singh et al. to tell the difference between rice leaves that were healthy and those that were sick. 82% of the time, the ranking was right [8] [9] used machine learning and hyperspectral data from wheat leaves to find wheat leaf rust. They looked at four machine learning methods and found that support vector regression worked the best (Azadbakht et al., 2019). On the other hand, the productivity is about average. With traditional machine vision algorithms, features have to be pulled and sorted by hand. CNN only needs picture data to work; it can learn on its own and will classify the images [10]For this study, CNN is used as a source.

Background

It is very difficult and often wrong to identify crop diseases by hand, so this method can only be used on small farms [10]. Automatic disease discovery, on the other hand, is much more accurate and requires less work and time [11]. Because of this, many studies [12] have been done, and we will talk about them in more detail below. This part talks about a few different ways to help find crop diseases. It also talks about the classification of these diseases and what image processing and machine learning are. It also shows how internet of things, deep learning, hyperspectral pictures, and transfer learning can be used to find diseases.

Taxonomy of Crop Diseases and Their Symptoms

It is normal for diseases to spread quickly through the leaves of plants [13]. But if steps aren't taken quickly enough to stop the disease from spreading, it affects the quality and quantity of agricultural goods in a big way [15]. Different pathogens [14], like viruses, bacteria, fungi, and shortages, can hurt crops. So, the germs that cause the disease can be put into two groups [25]: autotrophs, which live on living tissue, and saprophytes, which live on dead tissue. People can easily see the disease's signs, which hurt the growth and development of crops. Discolored leaves are the first sign that a plant is sick. The shape and feel of the leaves can also help doctors find many kinds of illnesses. By taking pictures of the leaves, different diseases like mildew, rust, and powdery mildew can be found [16].This short article will talk about the three main types of plant illnesses that are shown in Figure 1.

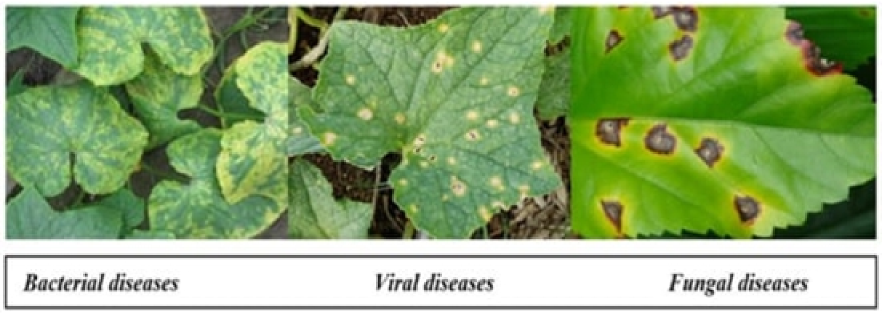


Figure 1. Different types of pathogens: viruses, fungi, and bacteria.

Virus diseases -Infection-related plant diseases are the hardest to spot and evaluate. Because there isn't a single sign that can be constantly watched, these symptoms are also often mistaken for signs of not getting enough nutrients or being hurt. Virus diseases are often spread by whiteflies, leafhoppers, aphids, and cucumber moving insects.

Fungal diseases - A fungus, like downy mildew, anthracnose, and powdery mildew, causes diseases that show up on the leaves. It first shows up on old lower leaves that are spotty with gray-green color or are wet. The spots get darker as the bug grows up because fungus grows on them.

Bacterial - Pathogens make veggies sick in very bad ways. They don't get into the plants directly; instead, they get in through holes or damage in the crop. Plants get hurt by different pathogens, insects, and tools used for farming jobs like pruning and picking.

Background required for automated plant disease detection

At present, automatic tools that can detect plant diseases are essential. These tools help prevent the occurrence of crop diseases and the subsequent losses. The AI-based automated approach to disease detection follows a specific sequence of steps. The process begins with the installation of various sensors in agricultural fields to capture images of plants, which are then stored. Once the images are collected, they undergo a cleaning and separation process to prepare them for input into machine learning algorithms. The ML models then analyze the images to determine whether a leaf is healthy or diseased. This approach includes a set of defined steps for identifying the specific plant disease (Figure 1). Capturing clear and detailed images of the plants is a crucial first step in the process. These images are stored for subsequent automated classification. Since images are composed of binary code, they can be processed by computers for analysis. High-resolution cameras are typically used to capture these images, and they can be taken using smartphones in formats such as jpg, png, tif, and others [17]. Once the necessary images are collected, they are sent for processing to ensure they meet the quality requirements. If the initial images don't meet processing standards, image-enhancement techniques are applied. This image collection step is critical to accurately classifying plant diseases, as the quality of the images plays a significant role in the overall system's performance. The images gathered are used to train machine learning models. Numerous well-known image datasets containing images of various plant species are available in agricultural research literature. These datasets include both healthy and diseased leaves, allowing researchers to study how different diseases impact plant health. Platforms such as PlantVillage, among others, offer online collections focused on plant infections in vegetables [18].

Image preprocessing

It is an important part of the first step of getting a picture. The pictures that were taken have many things in them, like noise, blur, uneven lighting, unwanted backgrounds, and so on. Because of this, it is very important to handle this raw data and make it useful for automatically classifying the disease. The raw data is changed into a certain file and then any noise or distortion is taken out. Later, the pictures are sent to the step where the work of segmenting and extracting features is done. By preprocessing their photos, researchers can get the most out of their computers and make sure that the resolutions of their pictures stay near the standard. Common preparation steps include standardization, regularizing the picture size, color scaling, getting rid of distortions, and getting rid of noise. All of these help in this step get the picture to the right size. For better analysis and understanding, the picture is also changed to fit the set color scale. Images with a white background have been shown to be easier to understand in the past[19]. The type, capacity, and value (HSV) method is a normal way to do preprocessing in agricultural research. It closely matches what human observers can do. Masking and background removal methods are often used by agricultural researchers to make processing faster and more accurate [20] People use the well-known HSI (Hue, Saturation, Intensity) color space model to change colored images because it looks a lot like how humans see colors. The H part of the Hyperspectral Imaging (HSI) system is most often used for further study, according to research that has already been published .High-frequency noise can be cut down with low-pass filters. The negative weighting factors of the high-pass filter make those areas with a big difference in strength stand out more at the same time. The process pulls out the most important parts [22]In the study of agriculture, the Laplacian filter is often used to improve the clarity of picture outline structures. The Fourier transform (FT) filter changes the pictures into the spatial frequency domain using the Fast Fourier Transform method [23] For the sigma chance of the Gaussian distribution, a channel for cleaning out noise is used. This method is easy to use and works well. Histograms, a method for changing how pictures are powered, can be used to make images of plant diseases better [24] To get a very accurate diagnosis of illness, it is important to separate the image of the infected leaf into its parts.

Image segmentation

According to agricultural science, segmentation is a basic method for carefully separating a picture into its parts. The main goal is to look at each item more closely and pull out useful details that could help us understand and learn more. Based on the returned features, it is possible to tell the difference between areas that are not affected and areas that are affected. To get different traits that might be useful, it's important to divide the preprocessed images into groups that show diseased leaves. To divide pictures into groups, traditional methods like thresholding, edge detection, region-based, and clustering need people who know a lot about math and image processing. Using thresholding to divide pictures into groups based on pixel intensity values is one of the best ways to do it. It is used for many things, like sorting, finding things, and getting information from far away. There are three different kinds of thresholding segmentation: global, variable, and adaptable. There are different ways to divide images into groups. For example, mean, median, and Otsu thresholding are all Global Thresholding methods[25] When employing edge detection, you divide an image into parts based on its edges, which are also called the picture's boundaries. Three well-known methods for discovering edges are the Sobel operator, the Canny edge detector, and the Laplacian of Gaussian (LoG) filter. If two pixels are similar in color, shape, and intensity value, region-based segmentation divides the image into several parts. Area Growing and Area Splitting are two well-known ways to separate data into groups based on areas [26] .The two ways of splitting the picture both work the other way around. One method makes the area bigger by adding seed pixels of close pixels. They can also split pixels in a picture by clustering them based on how similar they are in terms of texture, color, or anything else that is needed. This is a list of well-known picture segmentation and clustering methods. They are K-means [17]

Feature extraction

In the agricultural sector, the process of deriving meaningful features from raw data is known as feature extraction. This involves incorporating visual descriptors such as the shape, color, and texture of the elements. The process of putting things into categories is an essential component of occupations that require this. According to Basavaiah and Anthony's research from 2020, feature engineering is an essential component of machine learning (ML) that functions to transform raw data into a collection of relevant features. The information is used as input in this step, which makes a determination regarding the health of the plants. What are the most fundamental aspects of an image? Color, texture, shape, and other comparable characteristics. Some morphological characteristics are more effective than others when it comes to locating the broken area on a leaf. The use of color attributes such as color moments and Gabor texture is common among people. Obtaining these properties can be accomplished by a variety of methods, such as the color histogram. The color correlogram [29], the color R moment and other associated methods. Contrast, homogeneity, variance, and entropy are all elements that can be employed to enhance the texture. Research has shown that the utilization of textural features as a means of resolving issues related to the detection of plant diseases was more effective. To determine the energy, entropy, contrast, homogeneity, moment of inertia, and other textural aspects of a region, the grey-level co-occurrence matrix (GLCM) approach can be utilized [31]This method was developed by [32] order to isolate the characteristics of a texture, FT and wavelet packet decomposition can be utilized. Kaur et al. (2019) have shown through their research that additional features, including the Speed-up strong feature, Histogram of Oriented Gradients, and Pyramid Histogram of Visual Words (PHOW), function as anticipated.

ARTIFICIAL INTELLIGENCE

When it comes to agricultural research, artificial intelligence is becoming increasingly crucial, particularly for identifying and categorizing plant diseases. The first step in this process is classification, which divides data into groups. In this case, it's especially interested in finding and classifying plant leaves, especially ones that are healthy and ones that are sick. They need to know about the ML and DL methods for classification and detection in order to do.

Machine learning algorithms

To understand how AI is used in this area, it's important to know that machine learning is a type of AI. ML aims to help computers to learn from experience. There are many kinds in the field of machine learning right now, and each one works best in a different learning situation. When you use supervised learning, it give the system raw data and goal values that they think it will reach based on that data. The clear objective is to learn and build a connection that lets the system guess what will happen based on what goes in .Labeled leaves are used to teach computers how to put leaves into groups based on plant diseases. On the other hand, independent learning uses a different method. In this particular instance, the system is provided with facts without input-output rules that are crystal obvious. for the purpose of discovering hidden patterns or connections within the data .As described by [33] semi-supervised learning is a type of learning in which some of the data is labeled, similar to supervised learning, while some data is not labeled, similar to unsupervised learning. Because classification and regression tasks produce distinct kinds of data, it is essential to be able to differentiate between the two when it comes to machine learning techniques. Tasks that involve classification try to get good results and arrange data into groups called classes. Plant leaf diseases can be put into different groups using the classification. On the other hand, regression jobs try to guess values based on input data and deal with numbers. There are many different supervised machine learning methods, and Table 3 shows them all. Each has its own pros and cons. A lot of different methods are used, like decision trees, random forests, k-nearest neighbors, support vector machines, artificial neural networks, naive Bayes, linear regression, and linear discriminant analysis

Application of Machine Learning and Image Processing in Disease Identification

pictures of the leaves are a great way to learn about plant diseases and how their shapes and sizes affect them, so these pictures need to be carefully collected and analyzed. It is very important to use image processing [28] to find and study leaf diseases. In this leaf disease identification process, the steps were shown in Figure 2. This gives you an idea of the different image processing and artificial intelligence methods the authors used to find the disease.

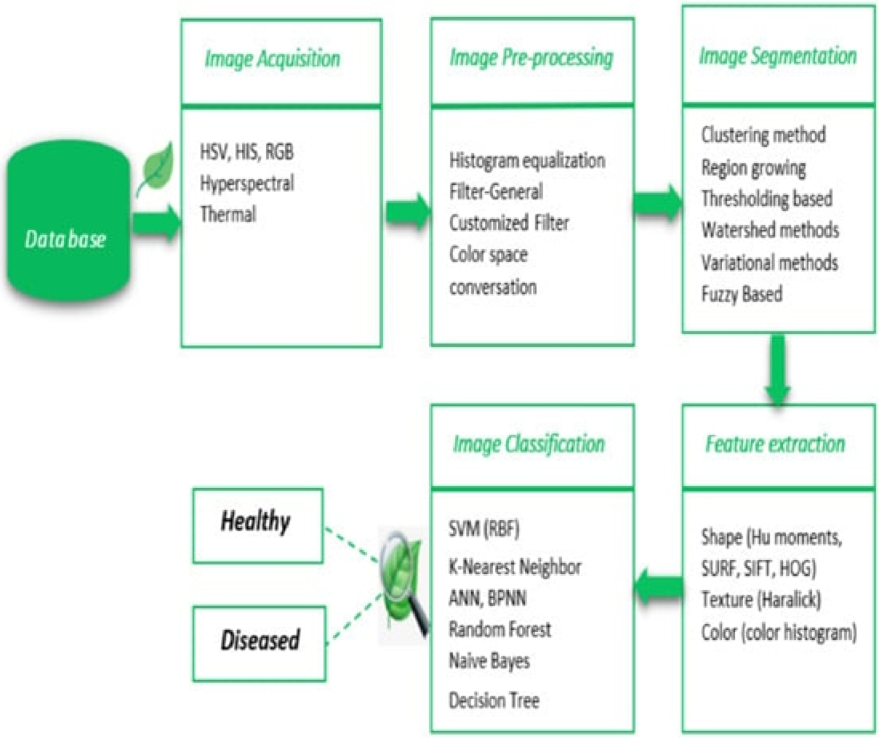


Figure 2. Different approaches for the identification of leaf diseases.

As the first step [29] in the process of disease diagnosis, it is essential to acquire images with the patient. In the present day, digital cameras and image systems are both capable of making images. Both of these devices are capable of producing photographs. The removal of noise from raw photos is essential due to the fact that it is a characteristic that is rather widespread in these photographs. Therefore, the second phase is known as "image pre-processing," and it is comprised of correcting any distortions that are not intended and increasing the contrast in order to make the qualities of the image more evident. This is done in order to make the image more appealing to the viewer. The usage of a Gaussian function that produces a soft blur is a common method that is utilized to reduce the amount of noise present in an image. Image segmentation [30] is the third phase, by which the picture is separated from its background and the area of interest (ROI) is divided in order to highlight the sections that are most essential. A picture's information and details are brought to light in the fourth stage, which is referred to as "feature extraction" (31). It is common practice to determine the type of plant by analyzing the shape, texture, and color of the leaves. This is a side note. The input feature vector is then supplied to the classifier after these features have been combined to form the input feature vector. With the help of this vector, you will be able to differentiate between two different groups of things. Classifying [32] is the final step in the process. It is essential to keep in mind that the classification method that is most appropriate for the task at hand will be subject to the circumstances. The classifier's duty is to recognize the photographs by placing them into a number of predefined categories, and it does this by using the feature vector that it obtained in the fourth phase. For this reason, the categorization assignment is divided into two parts: the teaching portion and the testing portion. The classifier is educated using a dataset that is used for training. Keeping in mind that the objective, which is to get the crop to the healthy or sick state defined by the species name as quickly as possible, there is a correlation between the number of training sets and the accuracy of the results.

Deep learning models

Deep learning (DL), a branch of artificial intelligence and machine learning, has significantly influenced various fields, including object recognition, image classification, and natural language processing. One of the key advantages of deep learning is that it reduces the need for manual feature engineering, as neural networks can autonomously extract features. By working with raw data, deep learning models can create high-level abstract features, thereby enhancing the accuracy and efficiency of tasks like image recognition and object detection. The evolution of deep learning can be divided into two distinct phases: the first phase, spanning from 1943 to 1998, laid the groundwork with concepts such as backpropagation, the chain rule, the Neocognitron, and systems like LeNet for handwritten text recognition. In the second phase, starting from 2006 to the present, new algorithms and architectures were introduced, such as deep belief networks (DBNs), autoencoders, convolutional neural networks (CNNs), and various extensions of these models. These advancements have enabled breakthroughs in applications like text recognition, image recognition, and autonomous driving, as well as in healthcare, marketing, banking, and even earthquake prediction. Within the realm of deep learning, several neural network architectures are used to address specific types of problems. Notable networks include deep neural networks (DNNs), backpropagation (BP), and multi-layer perceptrons (MLPs). The original MLP demonstrated strong performance on linear classification tasks, while the BP method in the second iteration proved more effective for nonlinear classification and learning challenges. The release of the second phase of deep learning in 2006 was a response to the gradient vanishing problem. The breakthrough came in 2012 when Hinton's team triumphed in the ImageNet competition using the deep learning model, AlexNet, which sparked the rapid growth of deep learning.

LITERATURE REVIEW

Rice diseases

Many different types of pathogens, like fungus, bacteria, viruses, and others, can make rice sick. This makes it very hard to grow rice around the world. One common and destructive rice disease is Blast Disease, which affects all parts of the plant that are above ground and damages leaves, stems, and grains, leading to big output losses. A fungus called Sheath Blight damages the leaves and sheaths, causing sores and rot that lower the quality and output of the grainSores and blighting that are wet with water are caused by bacterial leaf blight, which results in significant losses in crop growth during the growing season. Rice plants can be affected by fungus illnesses known as Brown Spot and Rice Blast. These diseases harm the leaves, panicles, and nodes of rice plants, which ultimately prevents the growth of grains. Other diseases include the Rice Water Weevil, the Rice Grassy Stunt, the Rice Ragged Stunt, and the Rice Yellow Mottle Virus. All of these diseases could affect rice. Utilizing crop kinds that are resistant to illnesses, cultural traditions, and emerging technology such as artificial intelligence are all examples of strategies that can be utilized for disease management. These strategies aim to detect diseases at an early stage and take control of them before they spread. This multifaceted strategy is very important for protecting rice production around the world from the dangers of different pathogens and pests.Some rice diseases don't affect all rice plants; they depend on where the rice is grown. Some rice diseases affect all rice. For example, sheath rot is a disease that affects rice fields all over the world [33]. Rice blast disease, which is caused by

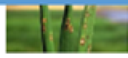
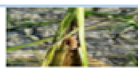
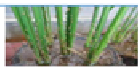
Magnaporthe oryzae, is a big problem all over the world .Fusarium fujikuroi causes the Bakanae disease, which is seen in most places where rice is grown.There are different diseases in different places. For example, Fusarium moniliforme causes Bakanae disease in western Uttar Pradesh, India. So, rice diseases like sheath rot and blast disease are common around the world, but the types of diseases and how common they are change from place to place depending on things like climate, soil, and farming methods. The active ingredients are very important for both protecting and improving crops. As an example, a study on pesticide levels in organic rice farming in Vietnam found that azoxystrobin, propiconazole, and tebuconazole were among the active ingredients [35]. A study that looked at how to stop rice sheath blight used a special pesticide nanocapsule delivery method with validamycin and thifluzamide as active ingredients.

Because they contain bioactive molecules like vitamins, minerals, fiber, and phenolic substances, rice byproducts have been shown to be good for your health .This means that they could be used to make foods and supplements healthier. Active ingredients are used for more than just protecting crops. They are also used in diet and medicine. For example, colored rice types have more antioxidants and physiologically active ingredients than white rice, which makes them useful for health reasons .As a by-product of processing rice, rice bran has bioactive substances such as magnesium, potassium, phosphorus, and B vitamins that help keep body processes in check.Monacolin K (lovastatin) and GABA, which are found in red yeast rice, are known to be good for your health because they lower your risk of heart disease [36]. Active ingredients are easy for rice farmers in many countries to get. These include a wide range of compounds that are used to protect crops, improve nutrients, and treat illnesses.

Magnaporthe oryzae, which causes blast disease, is the main pathogen that threatens the rice crop. Different parts of rice plants can get this invading fungus, which can cause leaf blast, stem blast, panicle blast, and grain blast. The fact that this pathogen destroys rice crops shows how much money is lost every year because of how damaging it is [37]. Breeding rice plants that are resistant to diseases has become an important way for major rice-producing countries to control rice illnesses and make their crops more resilient. A significant amount of effort has been put forth in China, for instance, in order to investigate and produce crops that are resistant to bacterial blight, blast, and sheath blight attacks. The addition of resistance genes such as Xa21, Pi9, and qSB-9 (TQ) brings about this result .When it comes to adding disease-resistant genes to well-known high-yielding varieties, India has achieved significant success through the utilization of marker-assisted selection (MAS).Through collaboration with local organizations, the International Rice Research Institute (IRRI) in Bangladesh has developed a variety of disease-resistant rice varieties, such as the BRRI dhan varieties, that are better able to deal with the specific biotic stressors that are present in the region. Similarly, study in the Philippines has led to the creation of disease-resistant, high-yielding varieties. This has been done using both traditional breeding methods and biotechnological methods, such as gene editing tools like CRISPR/Cas9.In these countries, making rice types that are resistant to diseases not only lessens the effects of diseases but also cuts down on the use of chemical pesticides, which helps to make farming more sustainable [38]. This focus on resistance breeding shows how important genetic study and new ideas are for making sure there is enough food and that farming can continue in places where rice is grown a lot. In terms of accepted error percentages, it is important to aim for as few mistakes as possible to make sure that diseases are reliably found and treated. Even though the acceptable error rate might be different depending on the product and the stakeholders' level of tolerance.

Normal error rates should be less than 5% if there aren't too many output factors. The mistake rate could be 10% to 15% if there are too many output factors that cover a lot of diseases. However, this threshold could be changed depending on how bad the sickness is, how much it will cost, and how easily it can be done.

Table 1: Common Rice Diseases

Disease	Pathogen	Symptoms	Sample Image
Rice Blast	Fungi	It was discovered that certain portions of the plant had lesions.	
Rice bacterial Blight	Bacteria	Marginal necrosis with yellowish-undulated lesions Cascading and drying out of the leaves	
Brown spots	Fungi	Yellow-brown lesions that are small and round in shape	
False Smut	Fungi	The manifestation of velvet or golden spores might be observed. Loss of grain weight and decreased seed germination, respectively	
Node Blast orNeck blast	Fungi	Those lesions on the nodes that are brownish or blackish Gramme of grain of poor quality.	
Paddy stemborer	-	The presence of an egg mass, which is brown in color, close to the leading edge of a leaf. Within the core region of the stalk, there is evidence of a caterpillar bore.	
Rice Tungro virus (RTSV, RTBV)	-	Grains that are only partially loaded The leaves turn yellow or orange-yellow in color.	
BLB	Bacteria	A borderline necrosis that is yellowish and undulating The process of drying and curling the leaves	
BPH	-	After the plant has reached maturity, it will exhibit circular regions of drying and lodging. "Hopper burn" is the name given to the condition in which the damaged plant dries out and appears completely burnt.	
Hispa	-	The leaves will be visible as a result of the grubs' mining on them. The young stage of the plants is typically the one that is affected.	
Leaf Blast	-	Wide bands that are narrow and reddish-brown in color are the symptoms. There are situations when the lesions are located on the margins.	
Sheath Blight	Fungus	This panicle is identical to the bottom panicle in that it is filled with empty grain.	

Wheat Disease Detection

[39] the performance of seven Convolutional Neural Networks (CNNs) was evaluated for their ability to diagnose wheat leaf diseases by using field photos. In order to enhance the PlantVillage dataset, which is comprised of photos taken under controlled conditions, they produced the Field-based Wheat Diseases photos (FWDI) collection. According to the findings of their research, the most accurate results were obtained using transfer learning with full parameter retuning, with Inception-v3 obtaining an accuracy rate of 22.5%. Additionally, they made the observation that lightweight CNN models such as ShuffleNet-v2 and MobileNetV3 delivered faster processing but had worse accuracy. The study highlighted that environmental factors and symptom similarities contributed to misclassification in field images.

[40] investigated how the host plant genotype influences spectral reflectance in wheat infected by pathogens. Their study spanned three growing seasons (2021–2023) and examined three winter wheat

varieties (Grom, Svarog, and Bezostaya 100) with different susceptibilities to diseases. They observed that spectral characteristics varied based on disease intensity and host plant genotype, particularly in the near-infrared range at 720 nm. A distinct spectral separation of wheat varieties was only evident when pathogen development exceeded 5%, indicating a significant interaction between varietal resistance and spectral responses.

[41] analyzed the pathogenicity of Bipolaris sorokiniana strains from wheat leaves (W-B. sorokiniana) and Pogostemon cablin (P-B. sorokiniana). The comparisons that they made between transcriptomics and metabolomics showed that W-B. sorokiniana had a greater level of pathogenicity. This was driven by genes that were associated with pathogenicity, toxicity, and cell wall breakdown among other things. The researchers discovered that the loss-of-pathogenicity B (LopB) protein, glycosyl hydrolase-related genes, and Ptr necrosis toxin-producing genes all played significant roles in the infection of wheat. Their study also identified key defensive responses in wheat, including the upregulation of hydrolase inhibitors, NAC transcription factors, and peroxidases.

[42] developed remote sensing techniques for monitoring wheat diseases using spectral equipment. Their experimental field included infected and fungicide-treated plots, where they synchronized high-precision ground spectrometry with satellite and UAV-based surveys. Their findings indicated that healthy plants had lower reflectance in the visible spectrum but higher near-infrared reflectance throughout the growing season. They emphasized that frequent spectral measurements were more critical than high-density data collection in accurately assessing disease progression.

[43] explored the effectiveness of chitosan nanoparticles and salicylic acid (SA) in controlling wheat leaf rust. They tested three application methods—pre-inoculation, post-inoculation, and combined pre/post-inoculation—finding significant reductions in urediniospore germination. Chitosan nanoparticles altered urediniospore structure, increased peroxidase and catalase activity, and enhanced anatomical features such as mesophyll thickness and epidermal layer integrity. They also observed increased expression of PR genes, indicating an improved immune response in treated wheat plants.

[44] developed a machine learning-based framework for wheat disease recognition and classification. They collected a dataset from Pakistani wheat fields, accounting for variations in lighting and camera orientation. Their method involved segmentation and resizing techniques to differentiate healthy and diseased regions before training ML models. The proposed system achieved a 99.8% accuracy rate, outperforming existing methods in precision, recall, and F1-score.

[45] evaluated the resistance of 50 Egyptian wheat varieties to leaf rust over two consecutive seasons. They conducted field assessments and identified the presence or absence of 28 leaf rust resistance (Lr) genes within the varieties. Their results showed that most tested varieties exhibited moderate to high resistance, but some varieties displayed fast rusting behavior. They detected 21 Lr genes, including five key genes (Lr13, Lr22a, Lr34, Lr37, and Lr67) associated with slow rusting behavior. Their study provided insights into breeding strategies for enhanced resistance against wheat leaf rust.

Table 2 wheat diseases, including their pathogens, symptoms, and a placeholder for sample images.

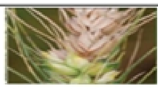
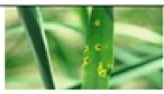
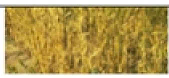
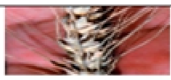
Disease	Pathogen	Symptoms	Sample Image
Leaf Rust	Puccinia triticina	Orange-brown pustules on leaves, leading to defoliation	
Stem Rust	Puccinia graminis f. sp. tritici	Reddish-brown pustules on stems, leaves, and spikes	
Stripe Rust	Puccinia striiformis	Yellow-orange pustules forming stripes on leaves	
Powdery Mildew	Blumeria graminis f. sp. tritici	White powdery patches on leaves and stems	
Septoria Leaf Blotch	Zymoseptoria tritici	Brown lesions with yellow halos, black fruiting bodies	
Fusarium Head Blight	Fusarium spp.	Bleached spikelets, pinkish mold, shriveled grains	
Tan Spot	Pyrenophora tritici-repentis	Brown, oval spots with yellow halos on leaves	
Take-All	Gaeumannomyces graminis	Blackened roots, stunted growth, premature death	
Common Bunt	Tilletia spp.	Fishy-smelling, darkened kernels filled with spores	
Loose Smut	Ustilago tritici	Black powdery mass replacing wheat kernels	

Table 3: Publicly available datasets of wheat diseases

Dataset Name	**Source / Link**	**Description**
Wheat Disease Database	Kaggle	Contains labeled images of wheat diseases such as rust, mildew, and blight
PlantVillage Dataset	PlantVillage	Collection of various plant disease images, including wheat diseases
Global Wheat Disease Dataset	Zenodo	Large dataset of wheat diseases with annotated images
AI Challenger: Crop Disease Dataset	AI Challenger	Includes images of wheat and other crop diseases for deep learning applications
ICAR-NBPGR Wheat Disease Dataset	ICAR-NBPGR	Indian Council of Agricultural Research's dataset on wheat diseases

Table 4: publicly available rice disease datasets

Dataset Name	Source / Link	Description
Rice Leaf Disease Dataset	Kaggle	Contains images of diseased and healthy rice leaves with labels
Rice Disease Image Dataset (UCI)	UCI Machine Learning Repository	Dataset with annotated rice leaf disease images
Rice Disease Detection Dataset	Zenodo	High-quality images of different rice diseases for classification tasks
Rice Leaf Diseases (PlantVillage Extension)	PlantVillage	Part of PlantVillage dataset, includes rice leaf disease images
AI Challenger: Rice Disease Dataset	AI Challenger	AI-focused dataset with rice disease images for deep learning applications

Limitation

Agricultural disease detection faces several limitations, including variability in environmental conditions such as lighting, humidity, and seasonal changes that affect accuracy. Many plant diseases exhibit similar symptoms like leaf yellowing and wilting, making differentiation difficult and increasing the chances of misclassification. The availability of high-quality, labeled datasets is often limited, leading to class imbalance and reducing the effectiveness of AI-based models. Early-stage detection is also challenging, as some diseases do not show visible symptoms until they have already spread. Additionally, models trained on specific datasets may struggle to generalize across different geographical regions and crop varieties, further limiting their effectiveness in real-world applications.

CONCLUSION

Detecting and classifying diseases in rice and wheat leaves are crucial for maintaining farm productivity and ensuring food security. Traditional disease detection methods, such as manual inspections by farmers or agricultural experts, are often time-consuming, prone to errors, and inefficient. To overcome these challenges, this study investigates the use of deep learning and image processing technologies to automate the disease detection process. The proposed system employs advanced computer vision techniques, including Convolutional Neural Networks (CNNs), to analyze leaf images and accurately identify common diseases affecting rice and wheat crops. By utilizing a comprehensive dataset, the system can detect diseases like bacterial blight, brown spot, and blast in rice, as well as rust, powdery mildew, and leaf blight in wheat. Experimental results show that deep learning models outperform traditional machine learning methods and manual inspections, achieving high levels of accuracy in disease classification. Despite these promising outcomes, there are some challenges associated with automated disease detection. Factors such as dataset quality, environmental variations, and the similarity of symptoms across diseases can impact the model's ability to generalize. Furthermore, deploying these models in real-world settings requires addressing issues like model interpretability, hardware specifications, and ensuring accessibility for farmers, particularly in rural areas. Future research should focus on improving the diversity of datasets by including images from a range of sources and different environmental conditions to boost the model's robustness. Additionally, combining different approaches, such as hyperspectral imaging and IoT-based sensors, can further enhance detection accuracy. The development of mobile applications and cloud-based platforms will also help make disease detection more accessible, allowing farmers to receive real-time diagnoses and tailored recommendations for disease management. The use of deep learning for agricultural disease detection represents a significant step forward in precision farming. This technology provides an automated, accurate, and scalable solution, with the potential to reduce crop losses, enhance farming efficiency, and contribute to global food security. With ongoing research and technological advancements, deep learning-based plant disease detection systems could become a key element in modern farming practices.

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