A Comprehensive Review: Advancements in Pretrained and Deep Learning Methods in the Disease Detection of Rice Plants

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Abstract

Rice cultivation is essential to the global economy, particularly in India, where it holds the distinction of being the largest rice exporter and the second-largest rice producer. However, the agricultural sector faces significant challenges due to diseases and pests that negatively impact the crops, by hindering the plant growth, reducing the yield, and, in extreme cases, leading to famine. The use of pesticides, intended to increase production, often results in a decline in crop quality. Prompt as well as precise disease identification in plants is requisite for prevention and control of disease, enabling timely implementation of pesticide control measures. This has spurred research at the intersection of computer science and agriculture, specifically focused on identifying diseases in rice through collected and real-time images. Deep learning (DL) has emerged as a key area of study within this domain, addressing various aspects of agricultural plant protection, including disease detection and pest control. Pretrained models have proven to be invaluable tools in the realm of rice plant disease identification and monitoring. These models leverage transfer learning, enhance feature extraction, reduce training time and resource requirements, improve generalization and resilience, and facilitate knowledge sharing and collaboration. This article examines rice plant diseases, explores deep learning and pre-trained models for diagnosis, reviews relevant publications, and presents a comparative analysis of research studies to assess advancements in rice plant disease detection.

Keywords: Deep learning, Rice disease detection, CNN models, Transfer learning

1.   Introduction

Rice, scientifically known as Oryza sativa, holds immense importance as a staple food crop, sustaining more than half of the global population. Notably, India has emerged as a formidable player in rice production since 2015, securing the second-highest position on the global scale. Moreover, India's dominance extends to rice exports, making it the leading contributor to the international rice market. For a visual representation, refer to Figure 1, which showcases the top ten countries in terms of rice production on a global scale in the year 2022.
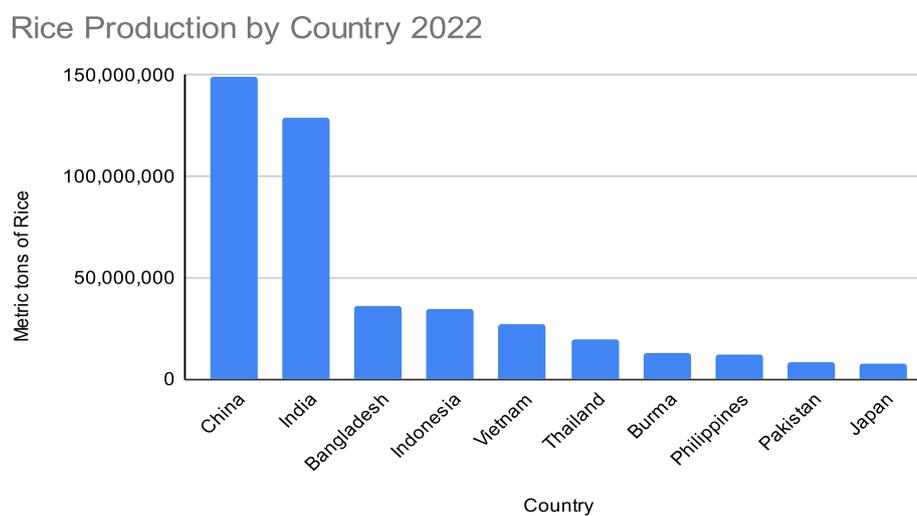
Rice Production by Country 2022

Figure 1. The countries that Emerged as the Leading Producers of Rice in 2022, based on Metric Tons (**Rice Production by Country 2022**).

The quality as well as the quantity of the rice production are greatly influenced by the disease caused in the rice plants. Additionally, the repercussions extend to other sectors indirectly reliant on rice, thereby jeopardizing the overall food production safety [1]. Consequently, there is a pressing need for automated detection and identification of diseases that affect rice plants within the agricultural domain. Every year, numerous diseases plague crops, leading to substantial production losses for farmers. The timely recognition of infections becomes a challenge, resulting in delayed recovery and reduced productivity [2]. Afflicted plants often display conspicuous markings or lesions on their leaves, stems, and grains. Leaves, being a primary indicator of plant health, commonly exhibit initial signs of diseases [3]. Swift identification, detection, and appropriate remedial measures play a pivotal role in mitigating

the detrimental effects of diseases. Traditionally, farmers relied on manuals or personal experience to diagnose the plant disease, but the process was time consuming and hindered the selection of suitable pesticides at the right time. Recent developments in deep learning and image processing have made it possible to create autonomous systems that can classify rice diseases using transfer learning and pretrained models. Previous research efforts have focused on image recognition, employing specific classifiers to distinguish between healthy and unhealthy images. The disease identification procedure involves capturing periodic images of different parts of the rice plant, followed by image collection, preprocessing, and classification stages [4]. Researchers have explored various machine learning techniques, including Support Vector Machine (SVM), Random Forest (RF), Stochastic Gradient Descent (SGD), deep learning techniques, and pre-trained models such as CNN, Inception-v3, ResNet-50, ResNet-152, DenseNet, VGG-16, VGG-19, MobileNet, MobileNetV2, EfficientNet, and YoLoV3, among others. These approaches have yielded promising results in disease identification. Particularly, CNN and Transfer Learning approaches have emerged as frontrunners in disease classification due to their exceptional performance [5]. This survey study delves into the diagnosis of twelve major rice plant diseases, employing a range of deep learning and transfer learning methods. The paper provides a brief overview of each disease category and subsequently explores CNN and Transfer Learning techniques, along with an explanation of the image classification process. Additionally, the publication offers a comparative analysis of the latest deep-learning methods proposed by researchers in this field along with future possibilities for the advancements in rice plant disease identification.

1.1 Rice Plant Disease

Twelve diseases make up the majority of the several forms of rice plant diseases [6]; The Bacterial blight kills seedlings and causes the leaves to yellow and dry. As the disease worsens, the leaves wilt and turn straw-colored, which causes the entire seedling to dry out and die. Small, water-soaked, linear lesions between leaf veins are the first signs of Bacterial Leaf streak. Dark green at first, these streaks ultimately become light brown to grayish-yellow. False Smut: Rice grains are used to make velvety spores by the diseased plant. Membrane breaks as a result of spore growth. Initially, orange in color, mature spores eventually become yellowish-green or greenish-black. Blast (Leaf, Collar): The first signs of the disease are diseased leaves with green-gray patches and deep green margins. The spots or lesions take on an oval or spindle

form as they mature and have reddish-brown edges. Rice ragged stunt: Infected plant leaves have a ragged look. Check for leaves that are darker than usual in color, partly exerted panicles, and unfilled grains on the plant to identify the rice-ragged stunt virus. Brown Spot: Early-stage lesions take the form of small, circular growths that are dark brown. The borders of mature lesions are reddish-brown, with a grey center. Tungro Disease: The color of a leaf affected by the tungro disease changes from orange-yellow to yellow. On the diseased leaf, rust-colored spots and striped patterns may be seen. Leaf Scald: Leaves start to seem scorched as a result. When mature leaves are examined, zonate lesions with light brown haloes that alternate between light tan and dark brown are visible. Blast (Node, Neck): Lesions in the node are grayish-brown in tone. The panicle collapses due to grayish-brown blemishes near the throat. At the boring site, stem borers can fracture the stem. Stem Rot: The infected culms contain a large number of microscopic white and black mycelium and sclerotia. Infected culms lodge, resulting in empty panicles and grain that is chalky. Yellow Mottle Virus: Yellow-green linear to rectangular dots at the base of the youngest leaves are the first indication of the disease, leaves frequently develop in a twisted, mottled fashion. Rice Hispa: Hispa often generates irregular transparent white spots that run parallel to the leaf veins. Diseases may occur in rice plants due to various factors and microorganisms such as viruses, bacteria, and fungus. It is important to understand which disease is affected by which microorganism to timely diagnose the plant. In Table 1, a concise summary of the primary symptom features of rice diseases, complemented by sample images for visual reference is presented. Additionally, Table 2 classifies the rice leaf diseases into distinct categories, namely Bacterial diseases, Fungal diseases, and Virus diseases, providing a structured organization of the disease types for better understanding and analysis.

Table 1. Different Categories of Rice Plant Diseases with Key Symptoms.

S.No.	Disease Name	Key Symptoms	Sample Image
1	Bacterial blight	Leaves exhibit yellowing, drying, and wilting.	

2	Bacterial leaf streak	Browning and drying of leaves.	
3	False Smut	Grains display yellow spores, leading to membrane damage.	
4	Leaf and Sheath—Blast	Infected leaves with green-gray spots surrounded by deep green borders.	
5	Rice ragged stunt	Infected plants exhibit a jagged appearance, with green leaves appearing darker than usual.	
6	Brown Spot	During the early stage, lesions develop and manifest as small, circular patches with a dark brown hue.	
7	Tungro Disease	The leaf transitions into shades of orange-yellow or yellow, displaying noticeable rust-colored spots on the infected area.	

8	Leaf Scald	the scalded appearance of leaves, light brown halos in mature leaves.	
9	Neck Blast	Grayish-brown lesions are noticed at the neck.	
10	Stem Rot	Inside the infected culms, one can observe the presence of small white and black sclerotia, along with mycelium.	
11	Yellow Mottle Virus	On the base of the youngest leaves, there are oblong to linear spots that exhibit a yellow-green coloration.	
12	Rice Hispa	white patches that are parallel to the leaf veins.	

Table 2. Different Categories of Rice Diseases.

Bacterial diseases	Fungal diseases	Viruses diseases
Bacterial blight	Blast (leaf, neck [rotten neck], nodal, and collar)	Rice black-streaked dwarf virus
Bacterial leaf streak	Brown spot	Rice dwarf virus
Foot rot	False smut	Rice yellow mottle virus
Grain rot	Leaf smut	Rice tungro bacilliform virus
Sheath brown rot	Leaf scald	Rice tungro spherical virus
Pecky rice (kernel spotting)	Sheath rot	Rice ragged stunt virus

1.2 Convolutional Neural Network (CNN)

Object recognition was very challenging before CNN was created [7]. Since an image is made up of a sequence of pixels that range from 0 to 255, it is challenging to convert these pixels to a "yes" or "no" response using only one technique. In order to focus on certain more specialized and distinct characteristics that are more relevant to the object, the underlying image is narrowed down using the convolution method [8][9]. The image classifier technique finds the significant characteristics (such as edges and shapes) that are necessary to decide the output and may be used to construct a deeper neural network more readily when the filter parameters are learned from data. The result of a convolution is referred to as a feature map or activation map, and the convolution procedure itself is usually referred to as filtering. The cross-correlation operation served as the inspiration for the convolution operation's development, and the following equation provides an example of a 2D convolutional operation:

$$S\,(i, j) = I\,(i, j) * K\,(i, j) = \sum m \sum n I\,(i + m, j + n)\,K\,(m, n)$$

where (i, j) specifies the entry point in a 2-D matrix, I stand for input, K stands for kernel or filter, S is referred to as feature map, and m and n stand for the kernel's length and breadth, respectively [10].

1.3 Transfer Learning

It, is a prominent deep learning (DL) technique, that involves leveraging a pretrained convolutional neural network (CNN), trained using a large labelled dataset, such as ImageNet, as a foundational model for a different task [11]. Acquiring a large labelled dataset for training a model can be challenging, as DL architectures demand significant time and computational resources due to their vast parameter space. By utilizing transfer learning, the final classification layer parameters are alone trained from scratch using the target dataset, making it a preferred approach in practical applications. The transfer learning process used in the classification of images is illustrated in Figure 2, showcasing its workflow and impact.
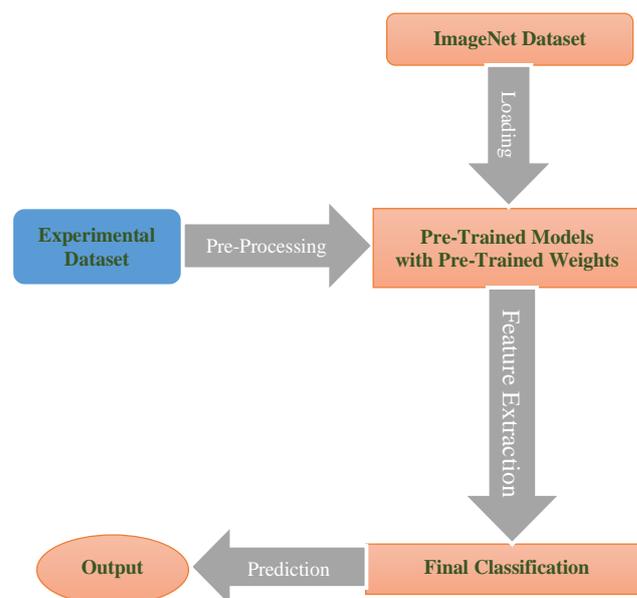

Figure 2. Transfer Learning Process for Image Classification.

1.4 Pre-Trained Models

Transfer learning includes pre-trained models. Deep learning models that have been trained and loaded with pre-learned weights are referred to as pre-trained models. These models may be applied for feature extraction, prediction, and fine-tuning. They are always trained on

a very big dataset and are typically used to address deep learning-based challenges. Some popular pre-trained models are shown in Table 3.

Table 3. Frequently used Pre-Trained Models.

S.no.	Reference No.	Year	Model Name	Size (MB)	Top-5 Accuracy	Parameters (In Millions)
1	[16]	2014	VGG16	528	90.1%	138.4M
2	[16]	2014	VGG19	549	90.0%	143.7M
3	[17]	2015	ResNet50	98	92.1%	25.6M
4	[17]	2015	ResNet152	232	93.1%	60.4M
5	[18]	2015	InceptionV3	92	93.7%	23.9M
6	[19]	2016	InceptionResNetV2	215	95.3%	55.9M
7	[20]	2017	MobileNet	16	89.5%	4.3M
8	[21]	2018	DenseNet121	33	92.3%	8.1M
9	[22]	2019	EfficientNetB0	29	93.3%	5.3M
10	[22]	2019	EfficientNetB7	31	94.4%	7.9M

1.5 Rice Disease Classification Process

The process of classifying rice diseases typically involves the following steps:

A) Data Collection and Labeling: Images of rice diseases are collected using digital cameras, scanners, or drones. These images are then labeled based on the expertise of subject-matter specialists who identify and categorize the diseases present in the images.

B) Image Processing: The collected images undergo various image-processing techniques, such as resizing, noise reduction, sharpening, and edge filling. These procedures enhance the quality and clarity of the images, making them suitable for further analysis.

C) Data Augmentation: To expand the dataset and improve its diversity, data augmentation techniques are applied. These techniques involve generating new sample images by introducing variations such as rotation, zooming, flipping, adjusting brightness, and translation. Augmenting the dataset helps in training a more robust and generalized model.

D) Model Training: The augmented dataset is then used to train a pre-trained model or a custom-designed convolutional neural network (CNN). The model learns to identify patterns and features related to the color, shape, and texture of the diseased parts of the rice plant.

E) Prediction and Categorization: Once the model is trained, it can analyze and predict the class of new images of rice diseases based on its learned knowledge. The model considers the color, shape, and texture characteristics of the diseased parts and assigns them to the appropriate disease category.

F) Categorization Results: The final outcomes of the classification process are determined, providing insights into the specific rice diseases present in the analyzed images.

2. Analysis of Recent Studies

Various studies have proposed different approaches in recognizing and classifying disease in rice using DL and pre-trained models. For example, Yang Lu et al. (2017) introduced a Deep-CNN method with a high accuracy of 95.48% using 10-fold cross-validation [12]. Liang et al. (2019) developed a new CNN-based method for rice blast identification, achieving improved accuracy using LBPH, Haar-WT, SVM, and Sofmax techniques [13]. Zhou et al.

(2019) addressed challenges in rice disease images by using FCM-KM and Faster R-CNN, obtaining accurate and fast detection of disease in rice plants [14]. Other studies combined support vector machines (SVM) with deep CNNs. Hasan et al. (2019) proposed an advanced AI system by combining SVM and DCNN, achieving an evaluation accuracy of approximately 97.5% [15]. Chen et al. (2020) utilized transfer learning and deep CNNs, such as VGGNet and the Inception module, to identify rice diseases with high accuracy [23]. Chen et al. (2020) studied transfer learning of deep convolutional neural networks by using a pre-trained model (VGGNet) on ImageNet and the Inception module. They achieved 92.00% average accuracy in classifying rice plant images. Their future goal is to extend this approach to automatic monitoring and identification of diverse plant diseases on portable devices [24]. Sethy et al. (2020) compared 13 CNN models using SVM and deep features, where resnet50 + SVM achieved the best classification performance [25]. Rahman et al. (2020) introduced the "two-stage training" technique, improving accuracy while reducing model size [26]. Other approaches focused on specific architectures and methods. Ghosal et al. (2020) proposed a CNN architecture based on VGG-16 for rice leaf disease classification [27]. Jiang et al. (2020) used CNNs and SVM for rice leaf disease identification with a high accuracy rate of 96.8% [28]. Krishnamoorthy N et al. (2021) employed InceptionResNetV2 with transfer learning, achieving an optimized accuracy of 95.67% [29]. Wang et al. (2021) suggested an attention-based depth-wise separable neural network with Bayesian optimization, achieving a test accuracy of 94.6% [30]. The technique for automatically detecting rice diseases from images of rice paddies was presented by Temniranrat et al. in 2021. The built LINE Bot system in this article will leverage the YOLOv3 deep learning model architecture. A well-liked upgrade to YOLO is YOLOv3 [31]. Bari et al. (2021) utilized a Faster R-CNN framework for real-time diagnosis of rice leaf diseases [32].

Studies also emphasized the use of large datasets and specific architectures. Deng et al. (2021) trained models on a sizable dataset using ResNet, ResNeXt, DenseNet, ResNeSt, and SE-ResNet, achieving high accuracy and F1 scores [33]. Chen et al. (2021) integrated the attention mechanism with MobileNet-V2 for lightweight disease identification [34]. Shivam et al. (2021) utilized various CNN models such as VGG-19, LeNet5, and MobileNet-V2 for rice plant disease identification [35]. Latif et al. (2022) proposed a DCNN transfer learning method based on VGG19, achieving an average accuracy of 96.08% [36]. Narmadha et al. (2022)

suggested DenseNet169-MLP for classifying rice diseases, achieving a maximum accuracy of 97.68% [37]. Patel and Sharaff (2023) developed a model using a gated recurrent network and ResNet/VGGNet-based CNN for automatic disease diagnosis in rice plants [38].

These studies demonstrate the diverse range of approaches, architectures, and techniques employed to accurately detect and classify rice diseases, contributing to the development of effective disease management strategies in agriculture. Table 4 presents a comparative analysis of several research studies conducted by different researchers.

Table 4. Comparing Previous Studies.

Author and Application name	Technologies used	Disease	Remarks
Yang Lu et al. A method for identifying rice diseases.	CNNs-based model	"Rice blight, rice false smut, rice brown spot, rice bakanae disease, rice sheath blight, rice sheath rot, rice bacterial leaf blight, rice bacterial sheath rot, rice seeding blight, and rice bacterial wilt"	An accuracy of 95.48% was achieved.
Liang et al. Rice blast identification method.	LBPH and Haar-WT and SVM	Rice blast	SVM achieves 95.82% accuracy
Zhou et al. A technique for identifying quick rice illness.	FCM-KM and Faster R-CNN	"Rice Blast, Bacterial Blight, and Sheath Blight"	It achieves 96.71% accuracy.
Hasan et al. Disease detection model for rice plant.	SVM and DCNN	"Bacterial Leaf Blight, Rice Blast, Brown spot, False Smut, Leaf Smut, Red Stripe, Leaf	It achieves an accuracy of 97.5%

		Scald, Sheath Blight, and Tungro"	
Chen et al. Disease detection model for rice plant	DenseNet and Inception modules	"Rice stack burn, rice leaf scald, rice leaf smut, rice white tip, and rice bacterial leaf streak"	It achieves an accuracy of 94.07%
Chen et al. Rice plant leaf disease identification method	VGGNet and Inception module	"Bacterial Leaf Streak, Rice Stackburn, Rice Leaf Scald, Rice Leaf Smut, and Rice White Tip"	It achieves an average accuracy of 92.00%
Sethy et al. Rice leaf disease identification model	Resnet50 and SVM	"Bacterial blight, blast, brown spot, and tungro"	It achieves an F1 score of 0.9838
Rahman et al. Method to identify rice diseases and pests	VGG16 and InceptionV3	"Bacterial Leaf Blight disease, Brown Spot disease, Hispa, Sheath Blight, Neck Blast"	It achieves an accuracy of 93.3%
Ghosal et al. Rice leaf disease classification method	VGG-16	"Leaf Blast, Leaf Blight, Brown Spot, and healthy plant images"	The suggested model has a 92.46% accuracy rate
Jiang et al. Image identification approach for detecting	Support Vector Machine	"Rice sheath blight, Rice blast, Rice bacterial spot, and healthy rice"	It achieves an accuracy of 96.8%

disease in rice leaves			
Krishnamoorthy N et al. Rice leaf disease identification method	InceptionResNetV2 CNN model	"Leaf blast, Brown spot, and Bacterial blight"	It achieves an optimized accuracy of 95.67%
Wang et al. Identification method for rice plant disease	MobileNet	"Brown spot, Hispa, and rice leaf blast"	It achieves a test accuracy of 94.6 percent
Temniranrat et al. A technique for automatically detecting rice diseases	YOLOv3	"Blast, Blight, Brown spot (BSP), Narrow Brown spot (NBS), Bacterial leaf streak (streak), and Rice ragged stunt virus disease (RRSV)"	Average true positive point of 78.86%
Bari et al. Method of diagnosing rice leaf disease	Faster R-CNN	Rice blast, Brown spot, and Hispa	It achieves an accuracy of 98.09%, 98.85%, and 99.17%
Deng et al. Rice leaf disease identification method	DenseNet-121, SE-ResNet-50, and ResNeSt-50	Brown spot, False smut, Sheath blight, Neck blast, and Leaf blast	Algorithms achieve over 98% accuracy and above 0.95 F1 score
Chen et al. Identification technique for rice plant diseases	MobileNet-V2	"Rice stack burn, Rice leaf smut, Rice leaf scald, Rice fake smut, Rice blast, Rice stem rot, Rice white tip, Rice sheath rot, Rice stripe blight, Rice sheath blight, Bacterial leaf blight,	It gets an average identification accuracy of 99.67%

		and Rice brown spot"	
Shivam et al. Rice leaf disease identification method	VGG-19, LeNet5, and MobileNet-V2	"Bacterial leaf, Brown spot, and Leaf smut"	Accuracies observed to be 77.09%, 76.63%, and 76.92%
Latif et al. Method for detection and classification of rice leaf disease	VGG19	"Healthy, Narrow brown spot, Leaf scald, Leaf blast, Brown spot, and Bacterial leaf blight"	It achieves an average accuracy of 96.08%
Narmadha et al. Detection method for rice plant disease	DenseNet with Multilayer Perceptron (MLP)	"Bacterial Leaf Blight, Brown Spot, and Leaf Smut"	Maximum accuracy of 97.68% was achieved
Patel and Sharaff Model for automatically diagnosing diseases in rice plants	ResNet and VGGNet	"False Smut, Grassy Stunt, Ragged Stunt, Sheath Blight, Tungro, Leaf Scald, Narrow Brown Spot, Narrow Brown Spot, Sheath Rot, Neck Blast, Stem Rot, Bacterial sheath brown rot, Rice Stripe, Yellow Mottle Virus, Bacterial leaf blight, Bacterial leaf streak, Blast Leaf, and Brown Spot"	An accuracy of 99% was achieved

3. Discussion

- The review section highlights various models, such as convolutional neural networks (CNNs), support vector machines (SVM), and transfer learning techniques, that have been explored for accurate rice disease identification. Researchers have achieved impressive accuracy rates, ranging from 92.00% to approximately 99%, showcasing the effectiveness of these models.

- Some studies have focused on specific architectures like VGG-16, VGG19, InceptionResNetV2, and attention-based depth-wise separable neural networks, which have demonstrated enhanced efficiency in recognizing and categorizing the rice diseases with optimized accuracy levels.

- The use of large datasets is emphasized in several studies, leading to improved accuracy and F1 scores. This suggests that data availability takes an important role in enhancing the performance of the model.

- Researchers have successfully utilized diverse algorithms and methodologies to address the complexities and challenges associated with rice disease identification, aiming to optimize accuracy and minimize model size for real-world applications.

- The emergence of real-time diagnosis frameworks, like Faster R-CNN and YOLOv3 showcase the potential for deploying practical and timely solutions for rice leaf disease identification.

4. Possibility and Future Scope for Improving Disease Detection in Rice Plants

The latest pretrained models, like InceptionV3, VGG19, MobileNetV2, DenseNet201, EfficientNet, InceptionResNetV2, Faster R-CNN, and YOLOv3 have significantly advanced the plant disease identification process using diseased leaves. These models excel in feature extraction and classification tasks, enabling accurate identification of diseases based on leaf symptoms. They leverage deep learning techniques and large-scale datasets to learn intricate patterns and relationships between leaf images and corresponding diseases. The future scope of pre-trained models in plant disease identification lies in live real-time monitoring.

To facilitate real-time monitoring, lightweight pre-trained models can be employed, specifically designed to be resource-efficient and suitable for IoT devices. These models

consume less computational power and memory, making them ideal for deployment on edge devices such as sensors, drones, and other IoT devices. With the integration of lightweight models, real-time disease monitoring becomes feasible, enabling timely intervention and minimizing crop losses. To extract more advanced features of leaves like spots, wilting, deformities, and other disease-related symptoms, advanced pre-trained models can be fine-tuned or combined with other computer vision techniques. Techniques such as image segmentation and object detection can be employed to identify and localize specific leaf abnormalities. This approach enables the extraction of detailed information from leaf images, improving disease diagnosis and monitoring. Furthermore, advanced pre-trained models can incorporate environmental factors and surrounding conditions like temperature, humidity, sunlight, etc. By incorporating these variables, the models can account for the influence of environmental conditions on disease development and progression. This holistic approach enhances the accuracy of disease identification and provides valuable insights into the relationship between environmental factors and plant health. Some studies focus on specific diseases like rice blast and bacterial blight, leaving room for investigating multi-class classification systems that can handle a wider range of rice plant diseases.

Expanding the scope of plant disease identification models beyond leaves to include diseased stems, roots, flowers, or fruits is a possibility. With appropriate datasets and training, pre-trained models can be adapted to analyze various plant parts for disease symptoms. This comprehensive approach enables comprehensive monitoring and diagnosis of plant health throughout different stages of growth and development. To address the mentioned problems, researchers can focus on developing integrated systems that combine advanced pre-trained models, environmental sensing technologies, and multi-modal data fusion techniques. Applying the DL techniques and incorporating diverse sources of information, these systems can offer comprehensive and accurate solutions for plant disease identification, monitoring, and management.

5. Conclusion

The research work carried out is a comprehensive review of deep learning and pre-trained methods for rice plant disease prediction and identification i. After examining various CNN algorithms and their features, it was found that combining CNN with pre-trained models

is the most effective approach for predicting rice leaf diseases from image data. Notably, SVM, InceptionV3, MobileNet-V2, and DenseNet models achieved high accuracies in training and testing. Other models like ResNet, VGG-16, VGG-19, Faster R-CNN, InceptionResNetV2, YOLOv3, and ResNeSt-50 were also utilized by researchers. Additionally, hybrid models such as CNN with the Inception module, InceptionV3 with ResNet-50, VGG16 with the InceptionV3 module, and DenseNet with the InceptionV3 module performed well. Furthermore, the deployment and practical implementation of these models in real agricultural scenarios could be explored further, considering factors like computational efficiency and ease of use for farmers. Future research may also focus on developing rice disease detection approaches with a refined CNN model and expanding the range of diseases considered. Furthermore, integrating deep learning techniques into IoT sensors, drones, and other high-tech devices can enable real-time monitoring and identification of rice diseases, thereby enhancing performance.

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