International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

Deep Learning-Based Classification Methods for Detection of Diseases in Rice Leaves – A Review

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Submitted: 03/02/2024 **Revised**: 11/03/2024 **Accepted**: 17/03/2024

Abstract: Cultivating rice is crucial in India to meet demands of a growing population. In order to improve crop yield, it's essential to address factors like diseases caused by bacteria, fungi, and viruses. Detecting and managing these diseases is vital, and one effective approach is employing rice plant disease detection methods. Deep learning techniques, known for their ability to analyse data, are used for disease identification in plants. This work explores various deep learning approaches for detecting rice plant disease. Deep learning, particularly in computer vision, has shown significant progress in detecting plant diseases. The study compares the effectiveness deep learning mechanisms, demonstrating superior performance of deep learning models. Utilizing deep learning can help prevent major crop losses by detecting leaf diseases through image analysis.

Keywords: *Rice Leaf Diseases, Deep Learning, Disease Detection, Comparative Analysis, Crop Loss Prevention*

1. Introduction

As a primary source of nutrition for billions, rice cultivation holds a essential role in guaranteeing food security, preserving equilibrium of countless societies [1]. The importance of rice extends beyond mere sustenance; it is deeply interwoven with the cultural fabric and socioeconomic well-being of numerous regions. This cereal grain is more than a dietary component; it is the foundation of livelihoods and cultural traditions in many parts of Asia, Africa, and beyond. Moreover, the economic significance of rice is underscored by its role as a source of income for countless farmers worldwide [2]. In an era marked by population growth and climate variability, the efficient production of rice becomes a paramount concern.

Despite the key role of rice in global agriculture, it faces an ongoing and formidable challenge in the form of diseases that afflict its leaves. These diseases, both fungal and bacterial in nature, have the potential to severely compromise rice crop yield [3]. Beyond the direct impact on agricultural productivity, these diseases contribute to economic losses and threaten the food security of regions heavily dependent on rice.

The early and accurate detection of diseases in rice leaves emerges as a critical component of modern agricultural practices. In this context, the integration of modern technologies, including deep learning, has become instrumental. Deep learning techniques offer the promise of automated and precise disease identification, allowing for timely intervention s and mitigation of crop damage [4]. The objective of this work is to perform an extensive review of deep learning-based classification approaches designed for detection of diseases in leaves of rice. By examining existing literature, categorizing various deep learning approaches, and evaluating their effectiveness, this review aims to give a roadmap for researchers and practitioners in field of crop disease management.

1.1 Addressing Shortcomings in Previous Reviews

Various thorough evaluations have been conducted on the topic of diseases impacting rice leaves. These evaluations have played a crucial role in helping us understand the challenges involved and gaining insights into how to detect and manage diseases in rice crops. Some reviews focus narrowly on specific aspects of disease detection, while others lack a comprehensive analysis of emerging technologies. The reliance on specific datasets generated in controlled laboratory settings may restrict the applicability of the findings to real-world field conditions.

Recognizing these limitations helps us identify gaps in our current understanding, prompting the need for more extensive research. Secondly, understanding these limitations provides insights into the specific challenges that hinder the effectiveness of current methods and

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technologies in addressing diseases in rice leaves. A new review becomes essential to compile the latest findings, introduce new methodologies, and fill existing gaps in knowledge. By doing so, this review aims to contribute to the ongoing discussions about disease management in rice crops and establish a solid foundation to future researchers.

1.2 Addressing Limitations with Proposed Review

Even though we have made progress in spotting rice leaf diseases, there's a issue in the studies done so far that they mostly use data from labs, not real farms. Our review will specifically focus on the challenges we face in real-world situations [5]. Farms are now using computer systems to find plant diseases, and we thoroughly looks at the modern ways of using deep learning for identifying plant diseases [6]. We also discuss about various diseases that can affect rice leaves, making sure we understand all the challenges and solutions in this area [9].

We know that using data from labs, like PlantVillage and IRRI Leaf Image datasets, has its problems. Our review will explore these issues and discuss about ways we can make these high-tech methods work better in real farming situations [7]. Even though using CNN-based methods is successful, we will also explore other ways like using what's already been learned (transfer learning), using ready-made models, changing the images to make them better (data augmentation), using a mix of different models (ensemble models), and finding the best settings (hyperparameter optimization). This wider view will help us understand all the different methods better [12-15].

Numerous studies have employed numerous image-processing mechanisms in conjunction with various deep learning models to address various plant diseases, including those affecting rice plants. Some rice leaf datasets, as illustrated in Figure 1-3, from IRRI (International Rice Research Institute) Leaf Image Dataset have been utilized in these investigations. However, several challenges have been encountered in making use of deep learning models. Approximately 80 % of these studies have relied on laboratory-generated datasets such as PlantVillage and IRRI Leaf Image datasets for training and evaluation purposes, resulting in models that often struggle to perform effectively when confronted with real-field images [5].

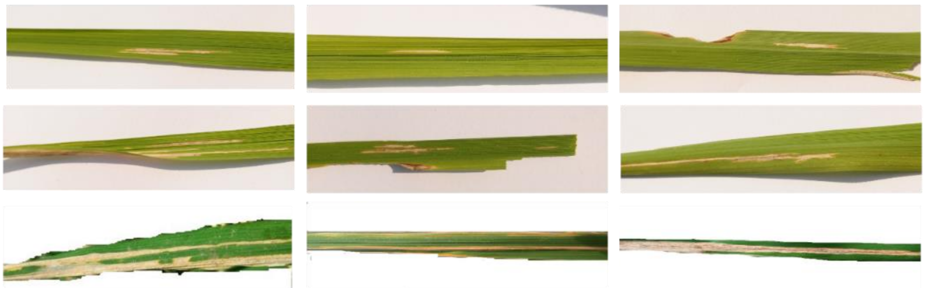

Figure.1 IRRI Bacterial leaf blight samples

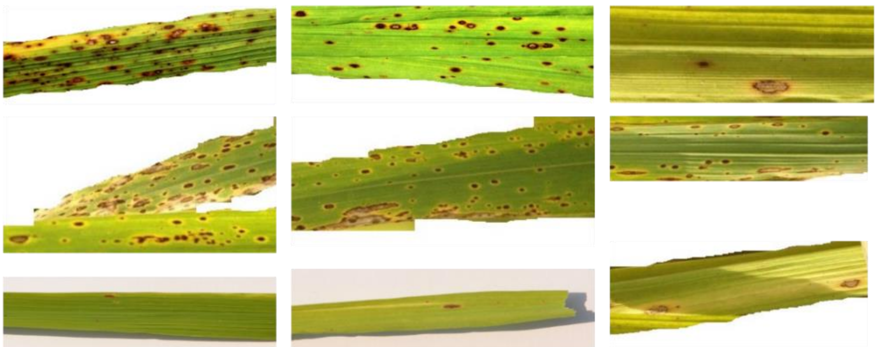

Figure 2 IRRI Brown spot samples

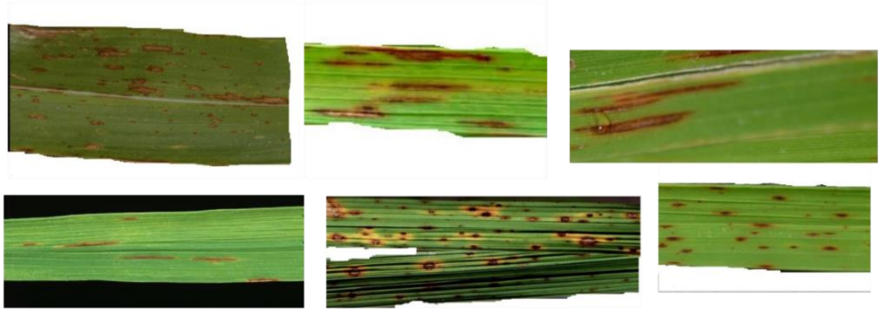

Figure 3 IRRI Leaf smut samples

1.3 Identifying Problems Addressed by the Proposed Review

The proposed work aims to tackle important issues and gaps in what we already know, helping us learn more about finding diseases in rice leaves. We point out specific problems and talk about why they're important, especially for farmers and researchers in agriculture, as given in Table 1. The proposed review identifies and addresses these specific problems and gaps in the literature, recognizing their significance in the context of rice leaf disease detection. By connecting each problem to the objectives of our review, we aim to provide a comprehensive analysis that guides future research works and contributes to the development of robust methodologies for crop disease management.

Table 1 Identifying Problems, Significance and its connection to objectives.

Limited Emphasis on Real-Field Challenges	Issue:	Often overlooks the challenges posed by real-field scenarios, relying heavily on laboratory-generated datasets.
	Significance:	This gap is crucial as real-world conditions differ significantly from controlled environments, impacting the effectiveness of disease detection models in practical agricultural settings.
	Connection to Objectives:	Our work explicitly addresses this problem by searching into the challenges encountered in real-field scenarios, offering insights that are essential for enhancing the applicability of deep learning-based approaches in agricultural practices [5].
Overreliance on Specific Datasets	Issue:	Approximately 80% of studies rely on a limited set of datasets, leading to models that may struggle to perform effectively with diverse, real-world images.
	Significance:	The overreliance on specific datasets limits the generalizability of models, hindering their adaptability to the diverse and dynamic nature of rice crops in different regions.
	Connection to Objectives:	Our work recognizes this problem and explores potential strategies to overcome dataset challenges, ultimately contributing to the optimization of deep learning model efficiency [7].
Narrow Scope of Disease Types	Issue:	Concentrate on specific diseases, potentially neglecting comprehensive insights into the myriad diseases affecting rice leaves.
	Significance:	A limited focus may hinder a holistic understanding of the challenges and solutions associated with different diseases, impacting the development of effective and versatile detection methodologies.
	Connection to Objectives:	Our work broadens its scope to encompass a wide range of diseases, ensuring a comprehensive analysis that is essential for addressing the diverse landscape of rice leaf diseases [9].
Incomplete Evaluation of Deep Learning Approaches	Issue:	Lacks a comprehensive evaluation of various deep learning approaches beyond CNNs.
	Significance:	A narrow focus limits the understanding of the strengths and weaknesses of different methodologies, potentially overlooking innovative solutions.
	Connection to Objectives:	Our work distinguishes itself by providing a thorough evaluation of diverse deep learning approaches, such as transfer learning, pre-trained models, data augmentation techniques, ensemble models, and hyperparameter optimization, offering a broader perspective for future research and implementation [12-15].

1.4 Highlights of Proposed Review

In the proposed work, we share new thoughts, methods, and ways of looking at things that can help us learn more and deal with important challenges, as presented in Table 2. It brings forth innovative elements by getting deep into real-field challenges, offering a diverse evaluation of deep learning approaches, providing a holistic overview of disease types, and proposing strategies for overcoming dataset challenges.

Within the agricultural sector, computer vision systems provide an efficient method for identifying and classifying plant diseases based on specific symptoms associated with each disease. These systems follow a clearly defined series of steps, starting with the acquisition of images and progressing through various image-processing tasks such as scaling, filtering, segmentation, feature extraction, and selection. Ultimately, the detection and classification of diseases are accomplished through the application of Deep Learning(DL)methodologies [6].

Table 2 Review Highlights: Novelty, New Insights and Potential Contributions

In-Depth Exploration of Real-Field Challenges	Novelty:	While existing reviews have made significant contributions, our review pioneers a deeper exploration of real-field challenges associated with rice leaf disease detection.
	New Insights:	By explicitly focusing on challenges encountered in practical agricultural settings, we offer novel insights that bridge the gap between controlled laboratory conditions and the complexities of diverse, real-world environments.
	Potential Contributions:	This approach enhances the applicability of deep learning-based methodologies, providing valuable guidance for researchers and practitioners in optimizing disease detection models for real-world implementation [5].
Diverse Evaluation of Deep Learning Approaches	Novelty:	Our review goes beyond the conventional emphasis on CNNs and presents a comprehensive evaluation of diverse deep learning approaches, including transfer learning[12], pre-trained models[13], data augmentation techniques[14], ensemble models, and hyperparameter optimization[15].
	New Insights:	By exploring a wide array of methodologies, we introduce a new perspective that extends beyond traditional CNN-based methods, enabling researchers to consider innovative approaches for disease detection.
	Potential Contributions:	This diverse evaluation equips the research community with a broader toolkit, facilitating the development of more robust and effective models for rice leaf disease detection [12-15].
Holistic Overview of Disease Types	Novelty:	While some reviews focus on specific diseases, our comprehensive approach encompasses a wide range of diseases affecting rice leaves, including blast, bacterial blight, sheath blight, and brown spot[8][9].
	New Insights:	By offering a holistic overview, our review provides a nuanced understanding of the challenges associated with various diseases, fostering a more inclusive and versatile approach to disease detection.
	Potential Contributions:	Researchers and practitioners benefit from a comprehensive understanding of diverse diseases, enabling them to tailor detection strategies to specific regional or crop-related challenges [9].
Strategies for Overcoming Dataset Challenges	Novelty:	Our review addresses the challenge of overreliance on specific datasets, offering insights into potential strategies for overcoming this limitation.
	New Insights:	By discussing the importance of diverse datasets and proposing solutions, we contribute a new perspective that guides researchers in optimizing model efficiency for real-world applications.
	Potential Contributions:	This aspect of the review offers practical guidance for researchers in selecting and handling datasets, ensuring the development of models that are more adaptable and effective in varying agricultural contexts [7].

While there have been significant advancements in disease detection, challenges encompass a lack of real-field image datasets, the requirement for data annotation, and pre-labeling to support early disease detection, precise identification and extraction of affected regions or symptoms, particularly when faced with similarities among various disease symptoms, the accurate estimation of severity in different stages, and the optimization of deep learning model efficiency [7]. Conventional laboratory techniques, such as PCR and ELISA, are more accurate but time-consuming and may not be well-suited for on-field, real-time disease monitoring [10]. The significance of deep learning lies in its capacity to handle extensive data, grasp intricate features, and offer automated, accurate, and swift disease detection, thereby mitigating the shortcomings of traditional methods. Deep learning models, specifically (CNNs), have been harnessed for analysis of rice leaf images, enabling precise identification of diseases [11]. The literature on DL-driven classification mechanisms for rice leaf disease detection is extensive and multifaceted. Researchers have harnessed the power of deep learning, particularly CNNs, to address the obstacles linked with disease identification in rice plants. The following review provides a glimpse of key studies in the field.

2. Deep Learning-Based Classification Methods

This section provides an in-depth exploration of numerous deep learning mechanisms and algorithms that have been utilized for precise and automated recognition of diseases in rice plants. Five CNN models, specifically Alex Net, Alex Net OWT Bn, VGG, GoogLe Net, and OverFeat, were subjected to evaluation using an open dataset containing around 87,848 images encompassing 25 distinct crops, each with 58 distinct pairs [7][16]. The performance of these models was meticulously assessed, with VGG and Alex Net OWT Bn emerging as the top performers, showcasing the highest success rates. Interestingly, when tested on actual environmental conditions, a noticeable performance drop of 25-35% was observed, suggesting that the models excelled while trained on real images and tested on lab images. Out of all models assessed, VGG achieved highest success rate at 99.53% [7] 16].

In reference to [17], the authors introduced CNN-based models for the diagnosis of plant diseases, which integrated an object detection architecture in conjunction with ResNet50, VGG16, Mobile Net, and ResNet101. The Fast R-CNN and Mask R-CNN were part of the architecture. Fast R-CNN was applied for detection of disease, while Mask R-CNN was used to segment the spaces affected by disease. In [18], authors conducted an examination of DL models employed in plant disease diagnosis. They identified several challenges and factors which impact effectiveness of these models. These factors encompass dataset-related issues, including limitations in annotated datasets, representation of symptoms, covariate shift, image background, and capture conditions, as well as intrinsic aspects associated with plant diseases. In reference to [19], the authors discussed the utilization of a CNN model applied to Plant Village dataset to detect diseases in various kinds of plants, with grape, apple, tomato, and corn. Data augmentation techniques were employed to ensure balance of classes within the dataset.

Paper [20] introduced a method for classifying plant leaf images, which involved detecting edges utilizing a Canny edge detector. Shallow CNNs were used to classify the detected edges into two categories: background edges and plant edges. A region-based segmentation approach was utilized to transform edges into images of leaf, primarily for purpose of leaf counting. This method is particularly effective for binary classification tasks, such as background segmentation.

In paper [21], a compilation of numerous DL models employed for the diagnosis of crop diseases in current studies was provided. The research involved a comparative assessment of strengths and weaknesses of these models. Models were categorized into those with and without visualization techniques, and the study highlighted various visualization techniques for symptom recognition. Furthermore, in [22], authors introduced a deep learning architecture that incorporated a whale optimization algorithm for classification of diverse tomato plant diseases, utilizing Plant Village image dataset.

In [23], authors explored utilization of ResNet50 for classification of tomato plant diseases. They applied data augmentation and transformation techniques to expand the original dataset, thereby improving classification performance and mitigating risk of overfitting. The model followed a two-stage approach, where it initially classified leaves as healthy or unhealthy. If classified as unhealthy, it proceeded to the second stage to identify the specific disease. In [24], three distinct CNN models were employed to assess degree of late blight pathogenicity in tomato plants at various stages. Dataset utilized consisted of diverse tomato leaf images sourced from Plant Village dataset.

In paper [25], novel disease detection approach was introduced, utilizing the ResNet50 architecture, with a focus on greenhouse tomato plants. This method adopted generic features to enhance generalization to unseen instances in the dataset. The approach also incorporated disease severity measurement based on proportion of the leaf area affected by disease. Paper explored various model variations, including a binary categorization system for distinguishing between healthy and diseased leaves, as well as a ten-class model that provided outputs for different disease types.

The study [26] presented a new framework centered on residual CNN learning, combined with an attention mechanism for disease identification in tomato plant leaves, utilizing the Plant Village dataset. This inventive architecture assigns higher importance to contextually relevant features over less significant ones, resulting in a substantial improvement in the model's performance. The investigation utilized a k-way SoftMax classifier for the purpose of image classification.

In an evaluation of effectiveness of four pretrained CNN models for the detection of tomato plant diseases, two datasets were employed—one from a controlled laboratory setting and another from field conditions. The study conducted a total of 8 experiments, consisting of 4 with pretrained parameters and 4 with parameter tuning. Each experiment utilized 10-fold cross-validation for both datasets. Various performance indicators, including accuracy, F1-score, precision, and recall, were calculated and compared. Findings indicated that all four models exhibited improved performance on lab dataset when compared to the field dataset. Out of the models considered, Inception V3 displayed the highest accuracy, achieving 99.6% accuracy on lab dataset and 93.6% accuracy on field dataset [27][28].

Referring to [29], a CNN with hierarchical feature extraction was employed for detecting diseases in tomato plant leaves. To reduce noise in the input images, Gaussian filters were applied before segmentation and feature extraction. Post-preprocessing, a CNN classifier was used to categorize the dataset into two groups: healthy leaves or diseased leaves. Experimental results illustrated that the CNN classifier outperformed both Alex Net and ANN in disease detection.

In the context of [30], Efficient Net DL architecture, comprising a family of eight models labeled as B0 to B7, was introduced for classification and detection of plant diseases using Plant Village dataset with augmentation. Notably, this model utilized Swish, a novel activation function, in place of ReLU. The outcomes of the study revealed that the B5 and B4 models excelled, achieving high accuracy rates of 98.84% on original and 99.39% on augmented datasets.

In [31], a CNN-based model was introduced and applied to Plant Village dataset with data augmentation for the detection and classification of plant diseases. Proposed CNN model demonstrated excellent performance, achieving a 91.2% testing accuracy. In [32], two approaches of segmentation, U-Net and Seg Net, were initially assessed for their performance using a dataset of real-world images to aid in background removal. Following the evaluation, U-Net was chosen, and its encoder phases were adapted to enable the retrieval of multiscale disease features. Authors in [33] presented a model for plant disease detection that combined both segmentation and classification. Study initially employed region-based segmentation for the extraction of disease spots effectively from grape plant leaf images and isolate them from complex backgrounds. Subsequently, the segmented images were fed into a CNN-based model for further categorization. The inclusion of segmentation as a preprocessing step for disease images contributed to enhanced accuracy in disease detection.

Table 3 provides a detailed analysis of deep learning-based investigations, examining parameters individually. This data allowed us to delve deeper into the investigation of various factors, including the kinds of crops utilized, the nature and variations of classifiers, and the characteristics of the datasets as shown in Figure 4. It also emphasizes the top levels of accuracy attained by various classifier classes. A significant proportion of these methods, based on deep learning, utilized CNN or their variants as the foundational models.

Table 3 Comparing Different Methods for Classifying Plant Diseases

Crop type	*Techniques used*	*Datasets*	*Performance metrics*	*Accuracy*
Banana leaves [34]	CNN with fuzzy C-means Segmentation	Real-field Images	Sensitivity, accuracy	93.45
Tomato leaves [35]	Region-based CNN	Real-field Images	Confusion Matrix, Average precision	83.06
Grape leaves [33]	CNN and Enhanced ANN	Plant Village Dataset	F1-score and Accuracy	93.75
Tomato leaves [32]	CNN with Kijani Net	Real conditioned dataset	F1-score , Mean accuracy	98.46
Maize plant leaves [36]	CNN-Alex Net	Plant Village Dataset	Accuracy	99.16
Tomato leaves [31]	CNN	Plant Village Dataset	Accuracy, precision, recall, F1-score	91.2
Multiple types [29]	GoogLe Net, VGG16, Inception V3	Plant Village Dataset	Accuracy	98

Tomato leaves [27]	CNN models	Labo & field datasets	F1-score , Recall, Accuracy, Precision	99.6
Tomato leaves [26]	CNN with attention Technique	Plant Village Dataset	Accuracy	98
Arabidopsis plants [20]	Shallow CNN & Canny edge detector	Aberystwyth leaf evaluation dataset	DIC, FBD, SBD	95
Tomato leaves [25]	Res Net and U-Net	Plant Village Dataset	Accuracy	94
Multicrops [16]	ResNet50	Real-field Images	Accuracy	98
Tomato leaves [22]	DNN, PCA-whale optimization	Plant Village Dataset	Loss rate, Accuracy	86
Multiple plants [19]	CNN	Plant Village Dataset	Accuracy	96.5
Tomato leaves [23]	ResNet50	Plant Village Dataset	Accuracy	97
Different plants [7]	CNN-Alex Net	Open dataset	Success rate	99.53
Tomato leaves [24]	CNN-Alex Net,	Plant Village Dataset	Accuracy, recall, F1-score	93.40,
Mix crop leaves [37]	CNN-Alex Net with PSO optimization	Real-field Images	Accuracy, Sensitivity, Precision, Specificity, F1-score	98.83
Rice Blast Disease [38]	Softmax CNN	Open dataset	Accuracy	95
Rice Diseases Detection [39]	CNN	Open dataset	Accuracy	95

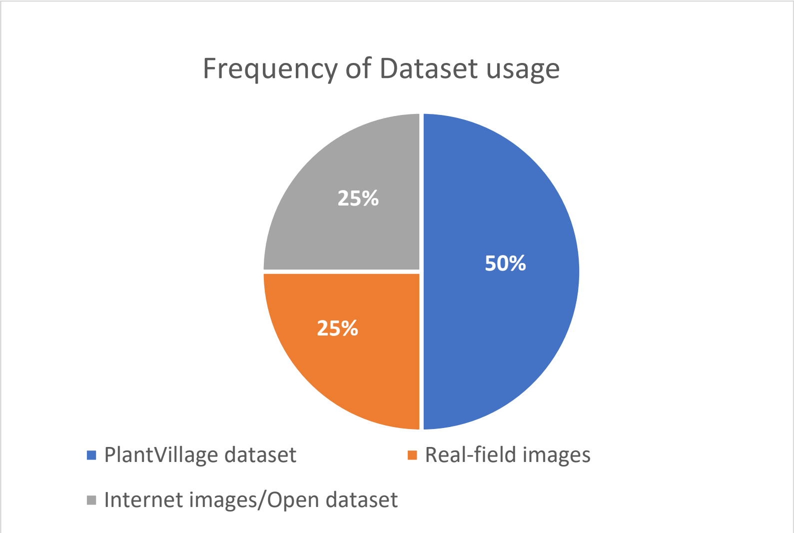

Figure 4 Utilization of Various Datasets' Proportions

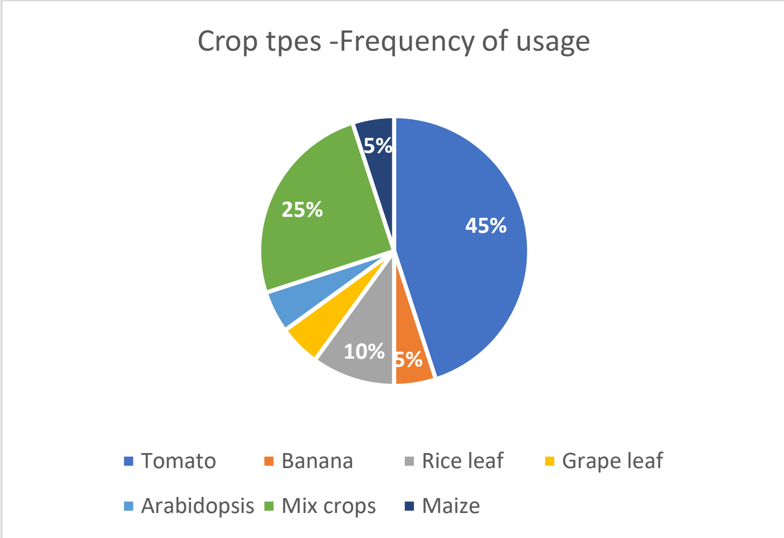

Figure 5 Various crops utilized in deep learning methods

The majority of the studies outlined in Table 3 made use of pretrained deep learning models for tomato leaf image classification as depicted in Figure 5, achieving precision rate of 99.64 percent. Notably, models that employed image preprocessing mechanisms such as segmentation, filtering, integration of contextual data to enhance delineation of lesion areas within images, or used optimization for feature extraction and selection, exhibited superior performance compared to other approaches. It's worth noting that models relying on real-field images tended to achieve comparatively lower performance

Hence, with deep learning models, two critical considerations emerge. Firstly, an ample dataset comprising pertinent plant images is essential for training and generalization done effectively, particularly on images belong to real-field. Secondly, implementation of optimization heuristics for feature extractions and selections is vital for accurately detecting and segmenting lesion areas within input plant leaf images.

3. Rice plant disease detection using Deep learning Techniques

The paper [40] introduced a DL approach to identify diseases in rice plants that may adversely impact crops and agriculture, leading to reduced crop yield. The ongoing advancements in deep learning methods have extended their utility in detecting plant diseases, enhancing the effectiveness of this robust tool with improved accuracy. The existing drawbacks and constraints of the proposed models for plant disease detection are deliberated and outlined.

The paper [41] Proposed an innovative approach for optimizing sub-set function, emphasizing tracking of cultivation based on specific forms for algorithmic items using vector machine assistance in classification. The technology's performance is highlighted, achieving an impressive total accuracy of approximately 89.6%. Work in [42] introduced a concept centered on fuzzy sets, addressing the handling of fluidity and the consideration of brightness levels in-pixel within images for calculated degrees [50].

Work in [43] implemented a neural network algorithm based on rice crops to forecast yield in the Terai district. The author in [44] introduced a knowledge support program tailored for professional use in the domains of rice, coffee, and cocoa production. This program takes into account user input and external factors such as position and environment to provide comprehensive support and information.

The study [45] outlines the creation of an automated device designed to analyze and provide advice to farmers using photos of infected paddy fields. The main goal is to streamline the detection and classification of rice diseases [46] by integrating vector supports and artificial neural networks. Crop forecasting takes into account various parameters, including precipitation quantity, minimum and maximum temperature, soil type, humidity, and soil pH. The data used were sourced from Maharashtra's agriculture website and segmented into nine distinct farming regions. The paper [47] Identified and prioritized key variables influencing sugarcane yield, developing mathematical models for yield prediction using data mining techniques (DMs). The study involved the analysis of databases from several sugarcane mills in Sao Paulo, Brazil, employing three DM techniques: random forest, gradient boosting, and vector assistance. Models generated were assessed using an independent dataset, focusing on the application of the random forest algorithm.

In context of agriculture, utilization of machine learning techniques in studying soil fertility was explored [48]. The research aimed to evaluate, classify, and enhance soil data based on various factors. Agricultural science has witnessed technological advancements such as robotics and data processing, leveraging the benefits of data mining in large-scale applications. Although data mining is relatively new in the agricultural soil dataset domain, it holds immense potential as the vast volumes of data collected can be effectively processed [49]. The challenges posed by factors like atmosphere, temperature, moisture, snow, and others are evaluated, recognizing the need for innovative technological solutions to improve Indian agriculture's economic development.

The research presented in [50] investigated the capabilities of the k-Nearest Neighbor Algorithm for ET0 (potential evapotranspiration) estimation as a data mining tool in semi-arid China, utilizing minimal climate data. Furthermore, the study validated the PM-56 equation against an ET0 prediction model dependent on k-Nearest Neighbor. In a related context, the author in [51] assessed the Multilayer Perceptron (MLP) model by examining activation features and introducing novel activation functions, including adjustments to weights and bias values.

The work [52][53] developed operational laws and weighted aggregation operators relevant to neutral types in membership degrees and probability sums. The study specified new neutral addition and scalar multiplication operational rules and analyzed their implications. In 2020, Surampalli et al. proposed a paper on identification of Tomato plant leaf diseases using DL methodologies [54][56]. The approach focused on recognizing leaf infections in tomato crops through image processing mechanisms, including segmentation, clustering, and open-source methodologies. Author in [55][57][58] presented a deep learning-based scheme representing a breakthrough in computer vision for fine-grained disease classification. This scheme ignores labor-intensive feature extraction and segmentation depending on thresholds.

4. Convolution neural network (CNN)

Primary objective of this methodology is to categorize images based on provided perspective, distinguishing significantly from other neural network approaches. Unlike typical convolutional neural networks (CNNs) that employ minimal pre-processing and contrast calculations in comparison to other image arrangement methods, this methodology involves unique aspects. Specifically, CNNs usually utilize hand-built channels in their standard calculations, whereas this approach implies that the classification process learns channels that were traditionally crafted manually.

In this method, convolutional layer forms core structure of the central square in a CNN. Layer's parameters consist of a set of learnable components with a small receptive field, contrasting with full information volume complexity. Consequently, the system acquires knowledge of channels initiated upon classifying specific highlights at particular spatial positions.

4.1. Inception–V4

Inception V4 stands out as a 48-layered deep CNN network, serving as an extension of the ImageNet model. The model's construction involves both asymmetric and symmetric blocks that execute convolution to generate feature maps by applying filters to images. Additionally, it includes average computation of feature maps for all pixels, a maximum pooling layer, average pooling (8×8), and maximum pixel operations, effectively minimizing computational cost parameters for learning purposes. Maintaining consistent input sizes, dropouts are typically applied after pooling to mitigate overfitting, enhance accuracy, and fully-connected layers establish connections between neurons in each layer. The activation norm incorporates softmax and batch norm for loss computation.

4.2. VGG–16

VGG, developed by the Visual Geometry Group at Oxford University, introduced this deep CNN model for ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2014. Renowned for its optimal performance compared to other deep neural networks, VGG-16 focuses primarily on padding convolution layers, fully connected layers, max pooling, culminating in a softmax layer outcome.

4.3. VGG –19

Similar to VGG-16 and other variants, VGG-19 incorporates an additional three convolution layers, enhancing its ability to effectively identify images. The fundamental concept revolves around employing small-sized and consistent convolutions in designing deep neural networks.

4. Methodology and a comparative review

Figure 6 illustrates culmination of image processing, showcasing the concatenation of lower and upper green and brown masking images using convolutional logic based on the generated model. Feature extraction is carried out on input images to obtain distinctive information crucial for detection. Different types of features, including color, texture, and shape, among others, can be utilized to identify specific diseases in plants. These extracted features serve as input for the classifier, which then categorizes the plant as healthy or unhealthy and/or identifies the presence of disease. The effectiveness and relevance of such systems depend significantly on achieving high classification accuracy.

In plant disease detection, the primary role of feature extraction lies in automatically learning relevant features. Attributes like shape, texture, and color of plant leaf images are predominantly utilized to identify infections. An image feature is a information piece associated with an object, aiding in its unique recognition. While convolutional neural networks were originally designed to address image data-related challenges, they also demonstrate effectiveness when presented with sequential inputs. The convolutional process scrutinizes the color variation range in affected portion with estimated threshold level defined by algorithm models. If variation level surpasses threshold limit of 200, image is labeled as diseased. Conversely, if color variation falls less than 200, the image is considered indicative of a healthy leaf.

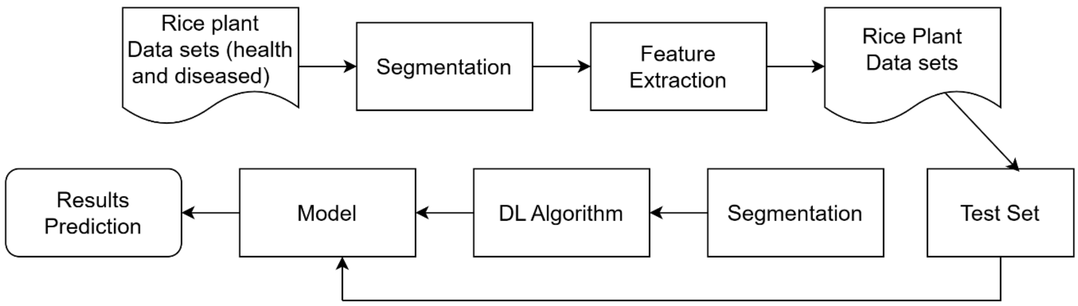

Figure 6 Architectural framework employed for rice plant leaf disease detection.

Figure 7 displays a comparison of machine and deep learning techniques, presenting the results visually. Precision measures the accuracy of positive predictions made by a classifier, calculated as the ratio of true positive predictions to the sum of true positives and false positives. The F1 score is a metric that combines precision and recall into a single value. Classification Accuracy (CA) is the ratio of correctly predicted instances to the total number of instances. Area Under the Receiver Operating Characteristic Curve (AUC-ROC) is a metric used to evaluate the performance of binary classification models, represented graphically by the ROC curve, showcasing the model's ability to distinguish between positive and negative classes at different thresholds. A comprehensive review of numerous research papers utilizing both machine and deep learning techniques has been conducted. The utilization of these techniques is compared and depicted in the bar graph shown in Figure 8.

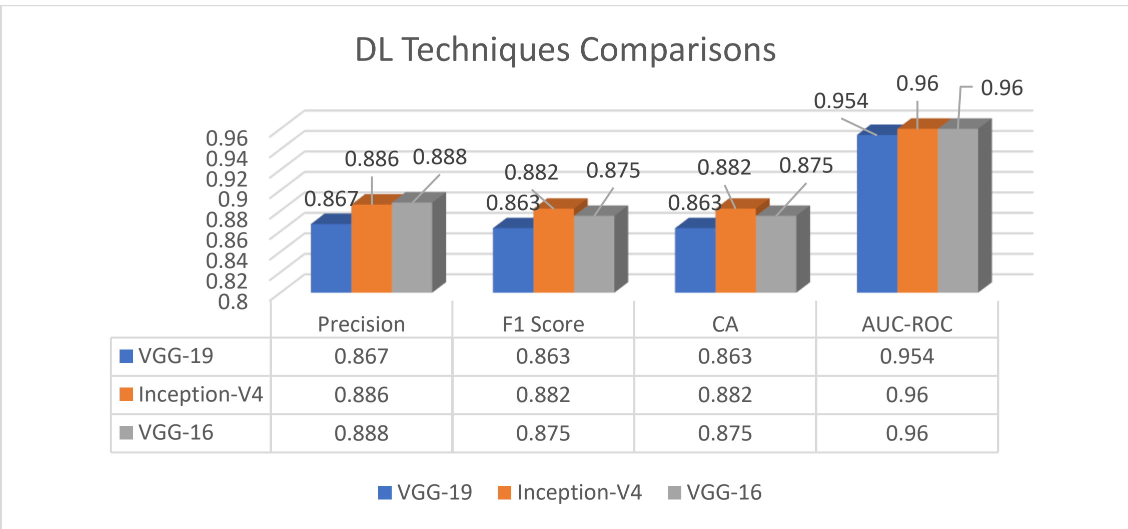

Figure 7 DL Techniques comparisons review

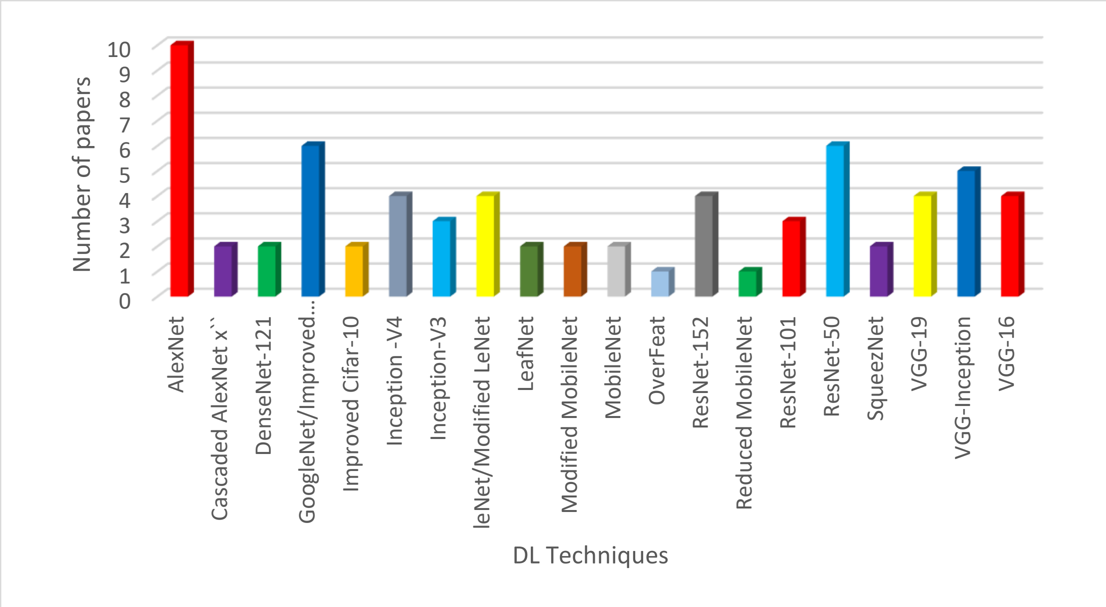

Figure 8 Diverse DL approaches employed in a multitude of research papers.

5. Conclusion

This extensive research explores various DL techniques for recognition and classification of plant diseases, specifically focusing on rice plants. Following this investigation, alternative classification methods within the realm of deep learning may be considered for the detection of diseases in rice plants, aiming to provide automated assistance to farmers. The analysis delves into diverse approaches of deep learning tailored for detecting diseases in rice plants, summarizing various techniques and mappings for identifying disease symptoms. The study highlights the evolution of DL technologies in recent years, specifically in context of identifying plant leaf diseases. The expectation is that this work would serve as a valuable resource for scientists engaged in rice plant disease detection filed. Also, a comparative study among various deep learning techniques is conducted. Despite notable progress in recent years, there remain research gaps that need attention to implement effective techniques for the detection of diseases in rice plants.

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