Review Paper

Rice plant disease diagnosing using machine learning techniques: a comprehensive review

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Received: 8 March 2022 / Accepted: 3 October 2022
Published online: 20 October 2022

Abstract

The impact of rice plant diseases has led to a 37% annual drop in rice production. It may happen basically due to the lack of knowledge in identifying and controlling rice plant diseases, but still there isn't any proper application has been developed which is capable enough to identify these rice plant diseases accurately and control those diseases. In order to identify rice plant disease by an application itself, Convolutional Neural Networks (CNN) can be used. Many of researchers have used CNNs for plant disease identification because of their accuracy in image identification and classification. But, there's still a handful researches have been conducted regarding the identification of rice plant diseases. This study provides a comprehensive understanding of current rice plant illnesses as well as the Deep Learning approaches used to detect such diseases. It also analyzes several kinds of techniques that have been employed in the literature by analyzing all of them with their benefits and drawbacks. It has discovered the most accurate ways in all levels of the image identification procedure as a consequence of this research, that will be valuable in recognizing rice plant illnesses.

Article Highlights

- When identifying rice plant diseases through machine learningmodels, many of the studies have focused only on fewer numberof diseases due to the lack of datasets available in the literature.There are some diseases that cannot be identified by just observingor scanning the external surface of the rice leaf. Those kindsof diseases may occur due to pests who are attacking the riceplant internally. In these kind of situations, it is impossible toidentify these diseases in the initial stages of spreading.
- According to the literature review which was conducted by theauthors, they were able to identify some common and popularCNN models which have been used to identify rice plant diseaseswhich are known as VGG 16, VGG 19, MobileNet, LeNet5 andResNet 50. According to the studies, researchers have highlightedthat they was able to reach 77.09%, 76.63%, and 76.92% trainingaccuracies for VGG-19, LeNet5, and MobileNet-V2 respectively.
- When comparing the machine learning models which has beenused for the identification process of rice plant diseases in the paststudies, it has been identified that ResNet 50 is the best suitedmodel which has given the highest accuracy for Rice plant diseasedetection.

Keywords Deep learning approaches · Hybrid systems · Convolutional neural networks · Plant disease diagnosis · Machine learning

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1 Introduction

The Rice plant has grown to be an enormously important food crop for society, particularly for those living in Asia, where rice is a staple food for Sri Lankans. As per polls, approximately there are 3 billion people depend on rice on a daily basis. Paddy farming has a long-rooted history within eastern civilizations. As an Asian country, Sri Lanka has its own ancient rice varieties including Ma wee, Pachcha perumal, Suwadal, Kurulu thuda, Masuran, Kahawanu, Kalu heenati [1]. In Sri Lanka, Paddy Cultivating process is done without considering the locations as well as it continues rice production under various weather conditions from the wettest areas to the driest areas in a tropical country like Sri Lanka. Due to the current state of disease-related concerns, several diseases do exist that have a direct impact on the nation's rice production. According to past studies fungi's, viruses and bacteria related diseases has primarily caused to this reduction in annual rice production. Around 37% of annual rice production tend to become decreased due these rice plant diseases [1]. Still, there are a considerable amount of people involving rice cultivation as a life strategy same as in the past, thus the majority of those people have a proper understanding of paddy cultivation and may not have needed to be taught how to identify these diseases. However, the current scenario is a little different; individuals from younger generations are less aware of such disorders, thus the government is providing agricultural instructors with technical expertise about those problems. It can be a challenging chore at times since, because there are so many diseases, even the instructors cannot determine the particular disease without visiting the fields. When considering all these things you may understand why should we need to find some efficient method to control this issue.

Farmers may use advancements in technology to diagnose rice diseases, which would be a highly effective solution to these problems. Many studies are now being undertaken on the use of Deep Learning technologies to diagnose such disorders. Several studies employed deep learning concepts and approaches, while others built their own techniques to handle this issue. This research discusses how deep learning models may be employed as pre-plant disease detection techniques. The aim of conducting this study is to examine various methodologies by evaluating the merits and weaknesses of those studies and analyzing them. There have been numerous studies on detecting illnesses in other plants such as tomatoes and peach, but there have been few studies on disease diagnosis in rice plants. However, it can be shown that the technique employed to diagnose illnesses in those all-important plants is the same. According to the author's best of knowledge, they have identified various rice leaf diseases, among those diseases some already widespread in some other countries. But some of those diseases are unique to Sri Lanka "Pecky rice", "Grain spotting", "Brown spot", "Leaf scald", "Root-knot", "Narrow Brown Leaf spot", "Bacterial blight", "False smut", "Sheath rot", "Bacterial leaf streak", "Rice blast", "Rice sheath blight" [1] are some common types of rice plant diseases (see Table 1).

Authors have already secured a publication titled "Plant Disease Diagnosis and Controlling using Convolutional Neural Networks" [2] and in that study was mainly focused to review related studies in the literature which were conducted about common plant disease detection and control. Through the extended study, authors have observed that even though there were ample of studies that have been conducted regarding disease diagnosis of common plants such as tomato, pepper, potato, etc. there is very few studies has conducted regarding rice plant disease diagnosing and controlling. From this study, authors have reviewed a number of studies that were conducted regarding rice plant disease diagnosing and controlling to identify existing better-performing technologies and models in rice plant disease diagnosing with the intent of implementing a better model for detecting rice plant diseases as the further work. A summary of the findings have been included in Table 2 and they are further been described in the discussion section. Table 3 will reflex the merits and demerits of those reviewed papers in detailed.

When it comes to the structure of the manuscript, this section provides a brief introduction to the study conducted by the authors. The next section discussed the deep learning technologies that have been used in the studies conducted in the literature. The third and fourth sections briefly describe and compare the co-findings of the study that has been conducted. Under the discussion section, it further analyzes and discusses the findings. Under the final section, it is concluded with the best suited technologies and models which will be suitable to build a better and more accurate rice plant disease diagnosing model.

2 Deep learning for rice plant disease detection

Deep Learning was created as the assistance of neurons to act or think like a person. DL was created utilizing a multi-neural network design with numerous convolution layers to forecast the needed outcomes. DL includes several network architectures ranging from simplest to more complex structures. Deep Learning originated as a subclass of

Table 1 Types of rice diseases. *Source*: [1]

Disease name	Bacteria/fungi	Infected part of the plant	Symptoms	Solutions
Rice blast	Xanthomonas oryzae pv. oryzae	Leaf collar, Panicle, panicle neck, culm nodes. culm	The leaf spots are spindly and have reddish or brownish margins. It has pointy ends. Fully developed lesions are 0.3–0.5 cm wide and 1.0–1.5 cm long	As a treatment for this condition, balanced doses of plant nutrients might be used. and unclean fields can serve as hosts for germs, thus it is critical to keep the field's surroundings clean
Sheath blight	Rhizoctonia solani	Panicles,upper leaf sheaths, leaf blades	On the leaf scabbard, there are ellipsoidal or oral dots. The center is greenish, while the borders are brownish. Panicked exertion suffers in the final stage	In addition, resistant versions are being used. These illnesses can be controlled by using balanced plant nutrition
Brown Spot	Pseudomonas syringae pv. syringae	Cleoptile, leaves, leaf sheath	Leaf spots can clearly identify on young rice plants. becomes spreading when its getting mature and the leaves begin to senesce	Improving soil fertility. This disease also can control in the initial stages by treat seeds with hot water before planting
False smut	Ustilaginoidea virens	Panicle grains	Large fruiting structures in orange, green, and brown	To avoid this disease, remove diseased plants and use resistant varieties
Grain Spotting and Pecky Rice	Sphaerulina oryzina	Coleoptile, leaves, leaf sheath, panicle branches, glumes,	Usually found on maturing leaves. Lesions form at the tips of the leaves. sores with chevron shapes and reddish and brownish regions	Can use resistant variants
Narrow Brown Leaf Spot	Sphaerulina oryzina	Leaves, sheaths, panicles	As rice plants mature, the disease becomes more severe	Can control by applying sufficient amount of potassium to the soil
Sheath Rot	Sarocladium oryzae	Panicles, grains	Severe symptoms in uppermost leaf. Lesions contains abnormal rounded brown spots. contains irregular target patterns When an infection is severe turning the florets red brown to dark brown	Can reduce spreading by using optimal spacing among plants other than that you can add potash at the initial stage and can apply calcium sulfate and zinc sulfate foliar sprays

Machine Learning (ML) in the early 1940s, parallel with the invention of "threshold logic". It has been used to create computer simulations which have been closely resembled human biological pathways. Figure 1 demonstrates the general flow of image processing techniques used in rice plant disease detection by state of the art researches.

2.1 CNN for image processing

Convolutional neural networks are widely recognized as a unique and necessary core of deep learning due to their excellent feature extraction capabilities. Convolutional autoencoders and CNNs are two of the main Deep learning methodologies that have been employed in a variety of Computer Science applications due to their success in image data processing. Convolution operations are used by these two primary technologies to extract spatial and temporal information from picture data. As presented in Fig. 2, in CNNs, there are common Layers which are known as input layer, convolutional layer, pooling layer etc. The input layer can be considered as the input of the entire CNN in the image recognition process, and it commonly reflects the picture's pixel matrix. In contrast, the Convolutional layer is utilized to extract picture characteristics. Normally, layer which is known as pooling is used to minimize the size of the feature maps. As a result, it decreases the number of parameters to learn as well as the amount of processing power done in the network. Whereas, all inputs from one phase are linked to every activation unit in the layer below by Fully linked layers. The activation function is included in the Softmax layer of NN models that predict a multinomial probability distribution. It may contain multiple pooling and activation layers inside hidden layers of Convolutional Neural Networks and there are numerous activation and pooling layers. Fully Connected Levels are the network's ultimate layers.

2.2 Feed forward neural network (FFNN)

Feed forward neural network process information sequentially from input to output and there is no feedback between layers as demonstrated in Fig. 3. If the user of a Neural Network is primarily concerned with the input or the output layers, then these Feed Forward Neural Networks are extremely important, and they are frequently employed in non parametric data analysis. R, N, and S are the inputs, neurons in the buried layer and generates numbers accordingly. Networks input vector is denoted by x. The input and hidden values matrices are denoted by iw and hw, accordingly. ho is the hidden layer's output vector and y is the network's output vector. The bias vectors of the output neuron are denoted by hb and ob, accordingly.

2.3 Single layer perception (SLP)

Single Layer Perceptron, as shown in Fig. 4, is kind of a model which transforms a linear into a nonlinear function with the help of activation function. According to the Single Layer Perception, vectors can be allocated to one of two classes.

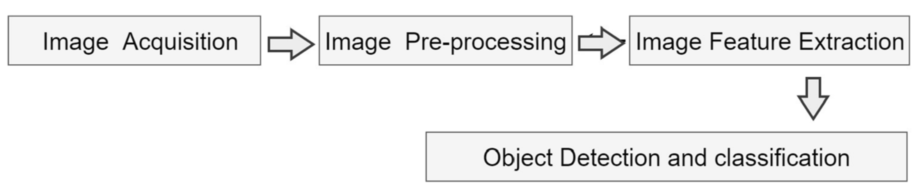


Fig. 1 Image processing pipeline. *Source*: [3]

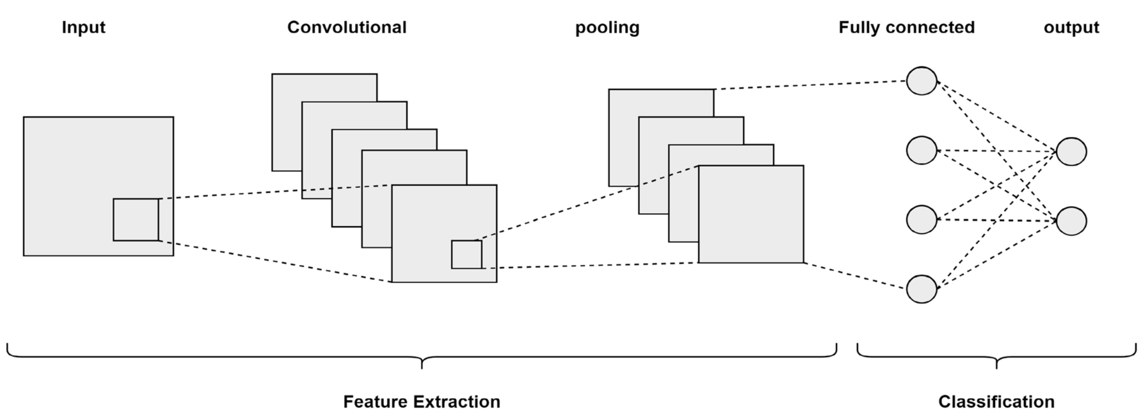


Fig. 2 Basic diagram for CNN. *Source*: [4]

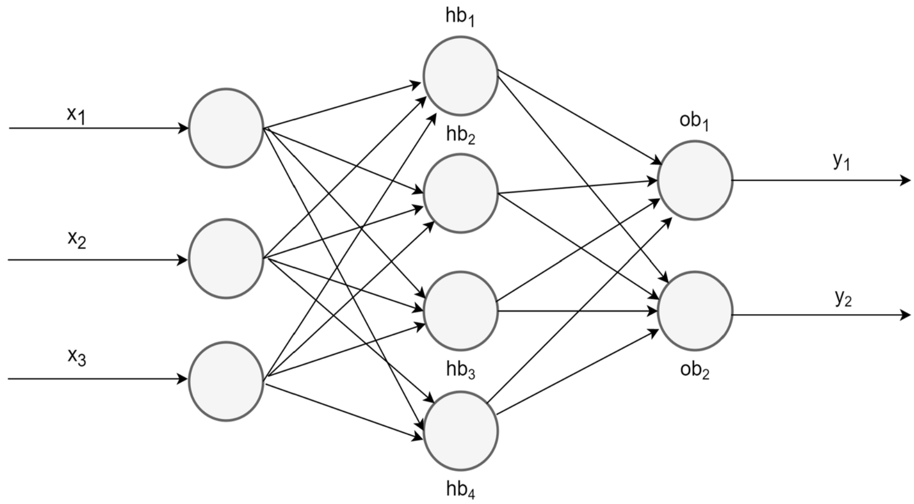


Fig. 3 Feed forward network. *Source*: [5]

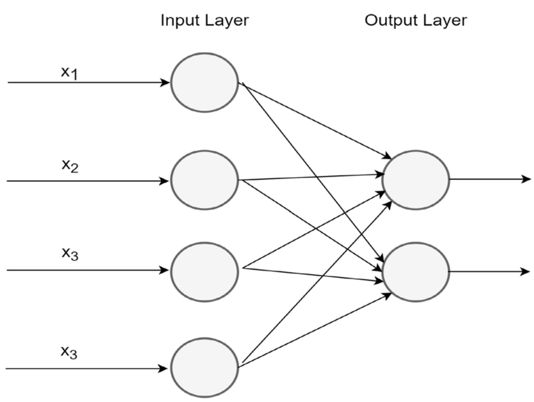


Fig. 4 Single layer perception. *Source*: [6]

2.4 Multi layer perception (MLP)

This is a kind of perception in a conventional network that comprises only one hidden layer, as seen in Fig. 5. Multi Layer Perception is a kind of perception with several layers that comprise of output, hidden and input layers. Input layer of the ANN is also called as the initial passive layer of an ANN, acts as a data intake conduit. The hidden layer in the second layer of this MLP increases the network's capabilities and enables for the modeling of more challenging issues. The last layer is referred to as the output layer, and it is responsible for generating network output signals.

2.5 Honen's self organizing map (SOM)

SOM, which is illustrated as in Fig. 6, can be defined as unsupervised learning network which has a design essentially based on the Feed Forward network, which, it has two levels, those are known as the Kohonen layer and the

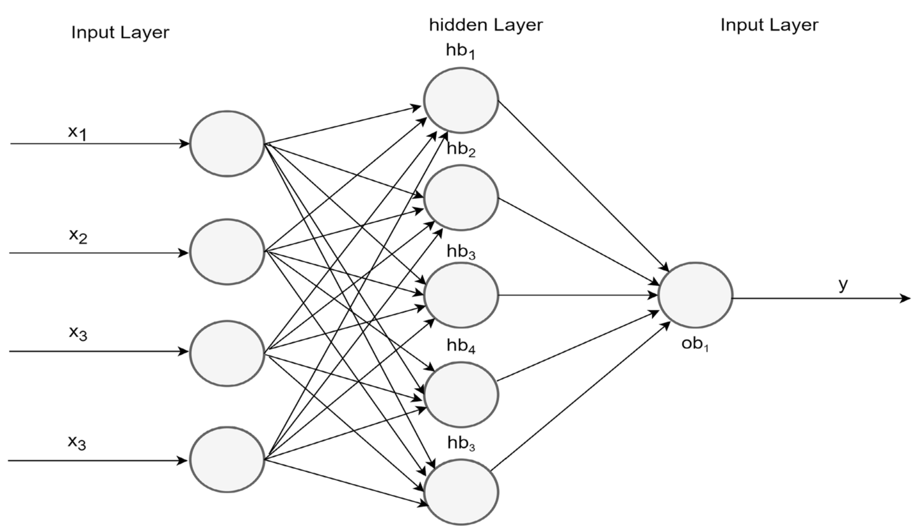


Fig. 5 Multi layer perception. *Source*: [7]

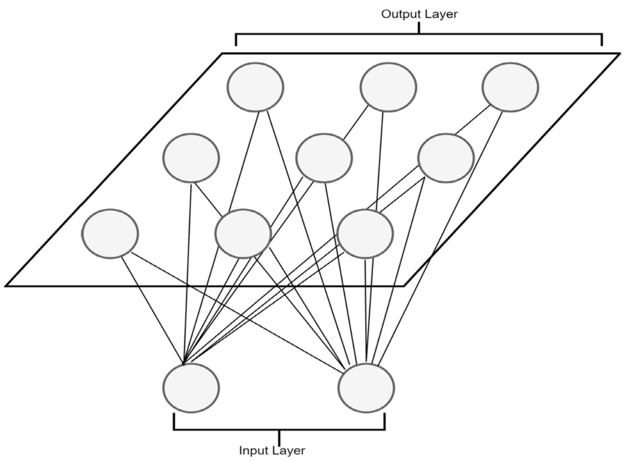


Fig. 6 SOM. *Source*: [8]

input layer. A Self-Organizing Map network's neurons are organized as a grid, it can be either rectangularly or hexagonally. The input layer is connected to the Kohonen layer. Maps are usually created in the input space of the network.

2.6 Radial-basis function network (RBFN)

The RBF network seen in Fig. 7 is composed of three layers which are known as input and output layers, hidden layer of RBF neurons. In data modeling, hidden layer of this network can be introduced as crucial. When observing the Fig. 7 x, y(x), ci, and M signify input, output, center, width, and number of basis functions centered at ci, respectively, while wi specifies weights.

2.7 Probabilistic neural network (PNN)

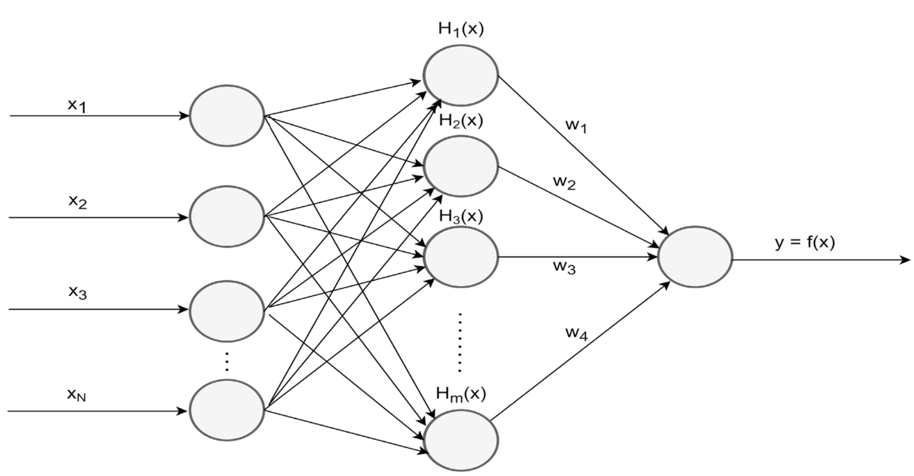
A general feed forward network is a CNN that contains input, output and hidden layers is referred to as a Probabilistic Neural Network. The hidden layer also known as pattern layer. A sample network diagram can be visualized as in Fig. 8. A Bayesian classifier uses in this PNN. The PNN incorporates a non parametric estimation method to obtain multi-variate possibility and density estimation. PNN is currently the finest neural network for dealing with classification problems. According to the diagram, the output layer has M classes, and each class m includes N m hidden pattern neurons in the pattern layer and In the summation layer there is only one G m summation neuron. Training patterns are imported into the pattern layer and separated into M groups as it get one for each class.

3 Research findings

This section compares and contrasts the previous studies that were reviewed. A comprehensive analysis under selected parameters are evaluated in Table 2, while the merits and demerits of these analyzed studies and techniques have been discussed in Table 3.

When observing past researches on this technical arena, it was able to realize that the three primary procedures in plant disease detection which are known as feature extraction, classification and segmentation. Among these procedures k mean segmentation approach is commonly used for image segmentation. The GLCM method is utilized for extracting features, and a categorization strategy is used to forecast illness names, which are both classic machine learning methodologies. When it comes to rice plant disease detection there were some advanced machine learning approaches has found such as RasNet, DensNet, MobileNet, VGG16 etc. This section focuses on discussing about technologies that were used in the literature by contrasting each of them, following Table 2 will give brief idea about these advanced machine learning technologies used in each study.

Fig. 7 RBF network. *Source*: [8]



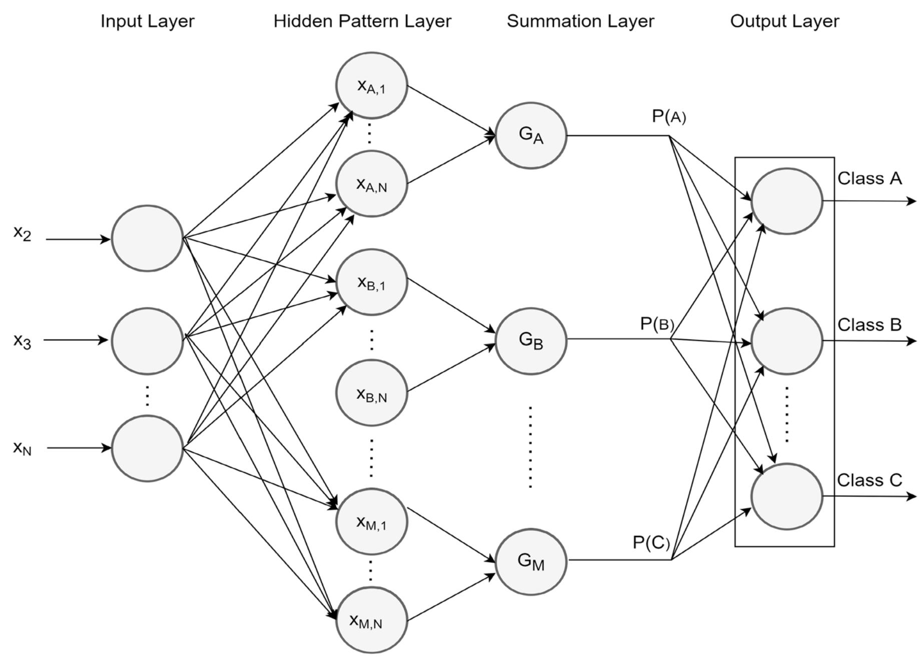


Fig. 8 Probabilistic neural network diagram. *Source*: [9]

4 Comparison of datasets used

ML is heavily dependent on datasets. This is the most significant feature that allows algorithmic training and explains why ML has grown in popularity in recent years. According to many researches, size of the dataset will directly be affecting to the accuracy of the developing models. Although data can take various forms, machine learning models rely on basic data kinds; Categorical data, Numerical data, Text data and Time-series data. When you are searching datasets of rice plant diseases you may realize that there are lack of datasets available in the literature, therefore researches has spent more time to gather required datasets to build their models. Some of them has used existing datasets while some of them use their own datasets.

4.1 Newly collected datasets

Researches who have used their own datasets to train and test their models have used devices like mobile phones, cameras to collect those images. In studies [9, 10] they have used these kind of methods to collect their datasets (refer Table 2). In the study which has been conducted by Ruoling et al. [10], he has used a dataset which contains images taken by mobile phone with high resolution. According to the study using this mobile device he could able to collect about 33,026 images which are related to six types of rice diseases during two year period of time [10]. In the study [12] which was conducted by Anandhan et al. they have use a dataset of 1500 paddy leaf Images collected through a Sony camera and using a Mobile device called Vivo V9 [12]. Through collecting the images for the dataset by their own, researches can increase the accuracy of their implementation, but the problem is according to the above reviewed studies collecting data to the dataset and create their own dataset is not that much easy process it takes lot of time. But they don't want to limit their development only for available dataset, they can expand the model if they have the ability to collect more verities or more classes of data.

4.2 Existing datasets

Some researchers have used existing datasets in order to train and test their models. In studies [12–15] they have used these kind of methods to collect their datasets (refer Table 2). In some studies they have used modified datasets which are created by merging two or more existing datasets. As an example, in study [14] which was conducted by Surya Pratap et al. they have used a combination of two different datasets which are having 2092 and 120 images of rice plant diseases [14]. Kaggle is a very important web resource which contains thousands of datasets which can be used to train deep learning models. Kaggle allows users to search for and upload data sets, analyze and build models in an internet-based data science environment, cooperate with other data scientists, including machine learning specialists, and compete to solve data science issues. It is a community network for attracting, nurturing, training, and challenging computer scientists from everywhere in the world to tackle data science, deep learning, and advanced analytic challenges. It has around 536,000 active users from 194 countries and receives over

Table 2 Comparing previous studies

No.	Paper title	Technologies used	Parameters	Species	Disease	Data set	Remark
1	"Automatic Diagnosis of Rice Diseases Using Deep Learning" [10]	DenseNet-121 model, SE-ResNet-50 model, ResNeSt-50 model	Model size, speed	Rice leaves	Bacterial stripe disease, neck blast, false smut, rice leaf blast, brown spot sheath blight	Rice disease dataset	Overall accuracy of 91% was achieved
2	"Rice Diseases Detection and Classification Using Attention Based Neural Network and Bayesian Optimization" [11]	ADSNN-BO model, Mobile Net model	Height X, Width X	Rice leaves	Brown spot, Rice hispa damage, Leaf blast	Public rice disease dataset	ADSNN-BO model achieves a test accuracy of 94.65%
3	"Detection of Paddy Crops Diseases and Early Diagnosis Using Faster Regional Convolutional Neural Networks" [12]	Faster R-CNN, Mask R-CNN	Height X, Width X, Depth tensors	Rice leaves	Brown spot, Sheath blight, Blast, Leaf streak	1500 images captured by Sony camera and a Mobile phone	Accuracy-Faster Mask R-CNN—87.45%, R-CNN—85.4% R-CNN is ideal for detecting many rice illnesses.
4	"Rice leaf diseases prediction using deep neural networks with transfer learning." [13]	InceptionResNetV2, CNN	Width X and Height X	Rice leaves	Leaf blast, brown spot, and bacterial blight	Google images	By running 15 epochs, a basic CNN model was fine-tuned utilizing multiple hyper parameters and obtained an accuracy of 84.75%.
5	"Rice Plant Infection Recognition using Deep Neural Network Systems" [14]	VG 19,LeNet5,MobileNet-V2	Size of each filter, Activation	Rice leaves	Brown Spot, Hispa,Leaf Blast,Bacterial Leaf, Leaf Smut	Combination of two different datasets having 120 and 2092 samples	Mobile Net and VGG19 perform almost similar on the same dataset as the accuracy and validation loss are almost the same
6	"Smartphone Application for Deep Learning-Based Rice Plant Disease Detection" [15]	CNN VGG16	Input image size	Rice leaves	Hispa, leaf blast, brown spot	Kaggle dataset with 1600 images	VGG16 with a train accuracy value of 100% and a test accuracy value of 60%
7	"Rice Leaves Disease Diagnose Empowered with Transfer Learning" [16]	Alex net Model	False negative, False positive,True positive, True negative	Rice leaves	Bacterial leaf blight, Brown spot, Leaf smut	120 pictures, where each disease category contain 40 images.	Using Alex Net—99.0 % accuracy rate for diagnosing rice leaves disease
8	"Rice plant disease classification using transfer learning of deep convolution neural network" [17]	Pre-trained deep convolutional neural network, Support Vector Machine	Not mention	Rice leaves	Rice Blast, Bacterial Leaf Blight, Sheat Blight	Total of 619 rice plant diseased images from the real field condition belong to four classes	Classification accuracy of 91.37%
9	"A real-time approach of diagnosing rice leaf disease using deep learning-based faster R-CNN framework" [18]	Faster region-based convolutional neural network (Faster R-CNN)	Dimension, balancing	Rice leaves	Rice blast, Brown spot, Hispa	Real-field rice leaf datasets	Rice blast—98.09%, brown spot-98.85%, hispa—99.17%

Table 2 (continued)

No.	Paper title	Technologies used	Parameters	Species	Disease	Data set	Remark
10	"Detection of Rice Plant Diseases using Convolutional Neural Network." [19]	Convolutional Neural Network (CNN), multilayer perception (MLP)	Loss, optimizer	Rice leaves	Leaf Blast, Brown spot, Bacterial Leaf Blight, Tungro	Four types of leaf diseases in rice plants with each type of disease consisting of 2239 training image data	This research has succeeded in detecting diseases in leaf images automatically with the best training accuracy obtained at 91%

150,000 contributions every month. Yibin et al. and Andrianto et al. has used Kaggle datasets which contains 5200 images [13] and 1600 images [15] respectively for the studies [12, 14] even though these datasets makes researches dataset finding process easy as using the same datasets in many studies sometimes on the same models may not produce innovate outcome to the research world some of the researches like Yibin et al. [11] used some other public datasets which are available on the internet for training and testing purposes of their studies in that study they have used about 2370 rice leaf samples in total, even though the data collecting process is easy. Accuracy of collected data may be low as they were taken from untrustworthy resources. So, the accuracy of collected data sets may directly affected to the accuracy of the model.

5 Discussion

Many ML techniques have been implemented with the intent of recognizing and classifying various diseases of plants. Moreover, as Machine Learning and Deep Learning technologies progress, this area of study seems to consist significant capacity for enhanced accuracy. To recognize and characterize the symptoms of Rice plant ailments, many original and customized deep learning structures, as well as many visualization methodologies, have been explored. The deep learning models used to diagnose rice plant illnesses are described in depth in this research. The research examines updated and well known deep learning architectures, along with visualization mapping methodologies for detecting plant diseases. It makes suggestions for future improvements in detection and visualization.

Observing past studies, several researchers employed hybrid models to meet their study goals. In the study of "Automatic Diagnosis of Rice Diseases Using Deep Learning" [10] which was conducted by R. Deng et al. has used a hybrid model which contains three sub models, they are ResNeSt 50, DenseNet 121 and SE ResNet-50. Here they created an Android application. It was created with the use of deep learning methods and for the application, they employed a huge dataset including around 33,026 photos of rice illnesses known as sheath. The Ensemble Model was tested using a multiple collection of photos, proving the model's efficiency. The author employed a set of characteristics for the validation procedure, such as recall accuracy, learning rate, illness recognition accuracy, and precision accuracy. They attained 91 percent accuracy with this model. According to this implementation, ResNeSt 50 is very accurate model which has reached better accuracies, modified version of this model has used by Krishnamoorthy et al. In the study of "Rice leaf diseases prediction using deep neural networks with transfer learning " [13], they

Table 3 Comparison of the drawbacks of the previous studies

No.	Merits	Demerits
1 [10]	This study was able to collect a dataset of 33,026 photos of six different types of rice diseases, and it obtained over 98 percent accuracy and an F1 score of 0.95. According to the confusion matrixes study, the Ensemble Model delivered reliable assessment of confusable diseases, with F1 values exceeding 0.99 for each of the six categories of disease and achieving 91 percent accuracy. This has sufficient generalization ability to be used in a rice disease detection app for field applications. This smartphone app offers a high-accuracy, simple-to-use, and low-cost method for detecting rice diseases	The Ensemble Model features a large number of factors that might impact the speed of identification. As a result, network pruning should be performed to reduce the number of parameters
2 [11]	This study provides an overview of deep learning models and applications in rice illnesses. ADSNN-OB, a novel model, has been suggested, tested, and discussed. This suggested ADSNN-OB model outperformed other deep learning models in many situations and all evaluated state-of-the-art models, and it also fits well with the developed mobile device environment	The performance and the procedure of the proposed model is less effective. Therefore, this ADSNN-OB model should be evaluated using various optimization strategies as well as hyperparameter tuning for improvement. Furthermore, the dataset utilized differs from those previously published. As a result, this model should be tested by running it on several public datasets. It would be desirable to investigate a more comprehensive and automated rice disease detection and classification approach that combines location, weather, and soil data with the provided rice disease image
3 [12]	For identifying diseases in rice leaf pictures, the InceptionResNetV2 CNN model was combined with a transfer learning technique. The suggested model's parameters were optimized for the classification task, yielding an accuracy level of 95.67 percent	Lack of datasets has used it my be improved the accuracies by training the model with more datasets
4 [15]	A smartphone-based rice plant disease detection application was created, and it has proven to be effective.It was able to detect several types of rice plant diseases based on image processing of rice plant leaves using VGG16 with a train accuracy of 100% and a test accuracy of 60%. When compared to other classes, the Hispa class is the most accurate	The test accuracy value is poor, and it might be improved by utilizing more datasets and removing noise out of the datasets. This application does not offer advice on how to treat the reported plant diseases. Therefore, in addition, further functions could be added to the program
5 [14]	Advanced CNN models were utilized in this work, and they were all run on the same dataset. In terms of accuracy and validation loss, this study revealed that MobileNet and VGG19 perform almost equally on the same dataset, whereas LeNet performs slightly differently than both CNN models. Though the epoch for each model was the same, and therefore less variance was found, it was revealed that LeNet performed better than MobileNetV2 and VGG19 when a lower number of epochs were utilized. It was revealed that LeNet outperforms the other models for a smaller number of epochs	This has a poor degree of accuracy. It might be improved by using picture preprocessing techniques prior to training the model
6 [12]	To identify different leaf diseases, a fresh image collection from village rice plants was proposed.When employing faster R-CNN and mask R-CNN, The deep learning models proposed offer the greatest outcomes. Mask R-CNN was shown to be most suitable for recognizing and diagnosing numerous rice blast infections, including Blast-96%, Brown spot-95%, and Sheath blight-94.5%	The limit in dataset used, It may be improved by recording video from agricultural property in order to expand the input dataset
7 [16]	Farmers would be able to obtain more exact and faster results with this technology, allowing them to administer the most appropriate treatment available	This architecture tackles the issue of overfitting by adding a Dropout layer after each FC layer
8 [17]	This approach of detecting rice infections early might be used as a preventive strategy as well as an early warning system. It might possibly be developed into a real-world rice plant disease detection system	The suggested model's performance can be enhanced further with a big datasets of rice sick photos

Table 3 (continued)

No.	Merits	Demerits
9 [18]	To create candidate areas, the faster R-CNN algorithm employs enhanced RPN architecture that addresses the object position extremely accurately. Because illness spot diagnosis is regarded the foundation of rice leaf pathogen detection, the efficiency of spot diagnosis has a direct influence on the results of rice leaf disease diagnosis	Misclassified difficulties might occur as a consequence of the illnesses' topological feature similarity. To counter this issue, more samples with equivalent geometrical properties should be essential to train the system. It also suggested developing a more efficient deep learning algorithm capable of classifying illnesses with minor differences in features. Network examines the entire image, not all at once, but gradually focusing on different parts of the image. As a result, the technique requires numerous runs to extract all objects from a single image, which takes time
10 [19]	As per the researchers, this study was successful in automatically recognizing illnesses in leaf photos with the highest accuracy rate	When compared to the accuracy rates of other research in the literature, training accuracy is 91 percent. The outcome of this experiment might be improved by testing several types of CNN design

have developed deep learning model InceptionResNetV2. This is a CNN model that uses a transfer learning strategy to detect illnesses in rice leaf pictures. The suggested model's parameters have been tuned for the classification job, and it has an excellent accuracy of 95.67 percent. To diagnosis plant diseases, several research employ regional convolution NNs and quicker regional convolution neural networks. This sort of research was carried out by Assistant Professor of Galgotias University whose name was Anandhan. When analyzing the research [10], DL models were employed to identify the early stages of a rice blast illness such as blast disease, leaf streak, sheath blight, and brown spot. According to the findings of the experiments, R-CNN model is the most appropriate model for detecting or recognizing several rice blast illnesses such as Sheath blight-94.5%, Brown spot-95%, and Blast-96%, with the intent of identifying various leaf diseases, they developed a unique picture dataset collected from local village rice plants. The suggested deep learning models offer the best results when using mask R-CNN and R-CNN. This strategy will aid farmers in the healthy and safe prevention of rice plant illnesses.

According to the previous studies, which has been conducted by researchers, VGG16 and VGG19 models has performed very well with better accuracies in training, testing and validating the data. Simonyan and Zesserman suggested VGG19, is an architecture with two distinct layer variants, 16 layers one is known as VGG16 and 19 layers one is known as VGG19. VGG had taken first and second place in the localization and classification tracks, respectively. VGG19's structure is completed by three fully linked layers and five blocks of convolutional layers. Surya et al. has conducted a research on detecting rice plant diseases using mobile application in the study of "Rice Plant Infection Recognition using Deep Neural Network Systems" [14], after the trial was successfully finished, it was discovered that the accuracy of the LeNet5, VGG-19, and MobileNet-V2 was 76.63 percent, 77.09 percent and 76.92 percent, respectively. According to these details developer has chosen VGG19 model for the development. VGG16 model has used by another Indonesian researcher whose name is Andrianto has conducted his study on implementing a "Smartphone Application for Deep Learning Based Rice Plant Disease Detection " [15], according to this paper, they describe that they have already developed a deep learning-based rice disease detection system, which consists of a machine learning model on a distant server and a mobile application. The train accuracy of the rice leaf disease detection system utilizing the VGG16 model is 100%, while the test accuracy is 60%. The author of this study claims that the "Hispa" class is the most accurate when compared to other classes since it has the most data from the test results. That proves us using large number of data for the training purposes will also increase the accuracy of the model.

When referring to previous review papers, it can be understood that different types of technologies have been used by them which are varying from simplest to complex. Some researchers have utilized existing machine learning algorithms, whilst some have gone through their own methods and algorithms in order to recognize images. And, some of the algorithms they have used has been mentioned in the above Table 2. According to the paper "Rice leaf diseases prediction using deep neural networks with transfer learning." [13], which has written by Krishnamoorthy et al., CNN is also an algorithm of deep learning techniques that has been successfully invoked for handling computer vision issues such as picture classification, object segmentation, and image analysis. According to the author, CNN is efficient in detecting visual representations. It is kind of a feed forward ANN composed of three separate layers as input, output and hidden. Transfer learning is a technique for repurposing a previously trained CNN for a new issue and in this paper author has discussed about the potent algorithm. According to the study it is a powerful deep learning algorithm that has been introduced into the world of agriculture to address many challenges such as weed and seed identification, plant disease categorization, root segmentation and fruit counting.

When observing the previous studies, some researchers have utilized existing deep learning models, whilst some have gone through developing their own deep learning models. "Attention based Depth wise Separable Neural Network with Bayesian Optimization" or in short term ADSNN-BO is that kind of innovative model which has introduced by Yibin through his study on "Rice Diseases Detection and Classification Using Attention Based Neural Network and Bayesian Optimization " [11], where they have suggested to identify and diagnose rice illness using photographs of rice leaves. The author presented the ADSNN-BO model, which is based on the MobileNet structure and an enhanced augmented attention mechanism, to accomplish AI-assisted speedy and accurate illness diagnosis. As the name contains the term mobile, MobileNet is indeed a CNN architecture which specializes in categorizing Mobile Versions and pictures. In depth convolutions, which filter the inputs without creating new features, and point to point convolutions. The Bayesian optimization approach is used to optimize the model's hyperparameters. On the basis of a public rice illness dataset with 4 groups, cross verified classification studies are carried out. The experimental findings show that this mobile compatible ADSNN-BO model surpasses all of the previous models examined, with a test accuracy of 94.65 percent. Author has stated that the findings of this study will encourage the use of artificial intelligence in the agricultural area for rapid plant disease detection and control. To improve the performance of all CNN designs, pretrained ImageNet weights are employed. As a further step, they intend to investigate their suggested ADSNN-OB model further using various optimization approaches and hyperparameter optimization to improve the efficiency and make the procedure more successful. Hence, In summary, this study examined standard and customized Deep Learning structures, as well as regular mapping approaches, that are employed in rice plants disease detection. There are very few number of studies has been conducted regarding rice plant disease detection. Through this study it encourage to build software which are capable of effectively identifying rice plant diseases. And it focuses on identifying best machine learning technologies used in the past studies for Rice plant disease detection. When discussing about the limitations of this study it mainly focuses on rice plant related diseases not about the all plant diseases. It could be further expand to discuss about more plant diseases in the future. When it comes to the future scope this study has conducted with the aim of identifying best Machine learning technologies used in the previous studies in order to develop an new ensemble model which is more accurate than the existing models in rice plant disease identification. It would be very beneficial for increase annual rice production by effectively identifying rice plant diseases.

6 Conclusion

CNN are widely regarded as the most successful technique for any prediction problem involving input image data. It is critical since it needs very little pre-processing. This work examines how DL aids in the diagnosis and categorization of rice plant diseases based on past research. Because image detection comprises numerous phases such as classification, recognition, segmentation and detection each with its own set of accuracies and efficiencies. The ultimate accuracy of picture identification must be determined by taking into account all of these stages. Researchers have used multiple efficient models to train their datasets according to their findings VGG16 and VGG19 models has performed very well with better accuracies in training and they have also use models like mobileNet, LeNet5 and ResNet. According to the past research papers conducted MobileNet-V2, LeNet5, and VGG-19 has given 76.92%,76.63% and 77.09% accuracies respectively. And when it comes to the hybrid model identified through the review process, it could able to find that it as it needs less parameters for training, it is also more accurate than the other identified models. When comparing with the all other previous studies regarding to rice plant disease detection, R-CNN model has been identified as the most appropriate model for identifying and detecting various rice plant diseases. as it shows 96% accuracy for blast diseases, 95% accuracy for Brown Spot disease, and 94.5% for Sheath blight disease. Hence, in summary, this review study examined standard and updated Deep Learning structures, as well as regular mapping approaches, employed for disease detection in rice plants.

Funding The authors have not disclosed any funding.

Declarations

Conflict of interest The authors declare that there are no conflicts of interest regarding the publication of this article.

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