REVIEW ON DETECTION OF RICE PLANT LEAVES DISEASES USING DATA AUGMENTATION AND TRANSFER LEARNING TECHNIQUES

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Abstract **- The most important cereal crop in the world is rice (Oryza sativa). Over half of the world's population uses it as a staple food and energy source. Abiotic and biotic factors such as precipitation, soil fertility, temperature, pests, bacteria, and viruses, among others, impact the yield production and quality of rice grain. Farmers spend a lot of time and money managing diseases, and they do so using a bankrupt "eye" method that leads to unsanitary farming practices. The development of agricultural technology is greatly conducive to the automatic detection of pathogenic organisms in the leaves of rice plants. Several deep learning algorithms are discussed, and processors for computer vision problems such as image classification, object segmentation, and image analysis are discussed. The paper showed many methods for detecting, characterizing, estimating, and using diseases in a range of crops. The methods of increasing the number of images in the data set were shown. Two methods were presented, the first is traditional reinforcement methods, and the second is generative adversarial networks. And many of the advantages have been demonstrated in the research paper for the work that has been done in the field of deep learning .**

Index Terms - Convolutional Neural Network; Computer Vision ; Deep Learning.

I. INTRODUCTION

Rice is intentionally consumed by a considerable portion of the world's rural population, as well as being the second most widely farmed cereal crop overall in the world. The Japonica and the Indica subspecies of rice both belong to the family known as Poaceae. The Japonica subspecies is the more frequent of the two. Rice is the dish that most accurately exemplifies Asian cuisine due to its widespread consumption, ease of preparation, and high nutrient content. Oceania, America, Africa, and Europe are the five distinct regions on Earth where the cultivation of rice is possible. Most of it is produced in Asia because of its favourable growing conditions. According to an overview provided by the Food and Agricultural Organization of the United Nations (FAOSTAT), Asian countries are responsible for delivering and consuming 91.05 per cent of the world's rice [1] . The remaining rice production is divided among other regions of the world, with 2.95 per cent going to Africa, 5.19 per cent to America, 0.67 per cent to Europe, and 0.15 per cent to Oceania. By 2025, the World Bank predicts that the demand for rice would rise by 51%, which is significantly faster than the pace of population growth.

In most nations, it is anticipated that rice demand will increase more quickly than supply. Damage to the rice crop in this situation, regardless of the reason, is unacceptable [2]. It has always been difficult to diagnose rice plant illness and determine how severe it is. Earlier, the sole method for diagnosing rice illness was naked-eye observation (visual analysis). This method calls for ongoing crop field monitoring for the accurate diagnosis of illness by subject-matter experts. For huge regions of plants, the visual analysis procedure can be exceedingly expensive, labour-intensive, and time-consuming because it necessitates continuous human observation. The population is growing exponentially, which quickly alters the reality of food production demand and availability. One of the most effective and economical methods for assessing the parameters associated with various plant diseases is data augmentation and transfer learning.

The limitations of the traditional method serve as inspiration for the researchers as they develop their ideas for technological solutions to the problem of disease prediction in plants. Models for the automated diagnosis of diseases are developed with tools such as (ANN), (SVM), Bayes classifier, Random Forests, K-Nearest Neighbor (KNN)[3][4][5][6][7][8][9] Acquiring plant leaf photographs, undergoing picture preprocessing, segmentation, extraction of features, and disease classification are the five stages through which a disease detection model works to complete its task. Effective disease identification can be achieved by employing already established models. On the other hand, the accuracy of disease classification is dependent on human skill in the collection of leaf pictures. As a consequence of this, these models are capable of being improved based on the kind of datasets that are easily accessible and the experimental conditions[10-15].

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II. RELATED WORK

In recent years, many researchers have created various architectures for diagnosing plant leaf diseases using machine learning and deep learning techniques.

Manoj Kumar et al. (2020) [16] In their methodology, the authors referred to the Inception V3 architecture. This study uses two distinct kinds of datasets: the initial leaf images and chosen symptoms from the leaf photos. These kinds of datasets were taken from the same set of photographs. There are five different categories of leaf pictures included in each of the datasets. A result of 97.61 per cent was achieved, which can be considered to be satisfactory for the IncepionV3 model.

Coleman Coulibaly et al. (2019) [17] employed a VGG16 model with a transferred learning technique in order to identify the disease that was present in millet crops. This study collected 124 images of leaves and organized them into categories based on whether the leaves had mildew infections or were healthy. A 95 % confidence accuracy rate was achieved by the VGG16 model.

S.Santhana Hari et al. (2019) [18] recommended using CNN as a viable way for identifying illnesses in so many species of plants, like apple, tomato, maize, and grape. This method was proposed as a helpful way to identify illnesses in many plant species. The dataset, which was used for either the training or the testing of the model, has a total of 15 210 photos of leaves, which are categorized into 10 different categories. 86% of correct predictions were made by the convolutional neural network that was suggested.

Ding Jiang et al. (2020) [19] The tomato leaf images were analyzed with a ResNet50 model in order to identify the diseases that were present. The dataset includes 3000 pictures that are categorized according to one of three categories. This model is correct approximately 98.0 per cent of the time.

N. Nandhini et al. (2020) [20] Several different machine learning techniques, such as support vector machines, K-nearest neighbours, and decision trees, have been introduced with the aim of diagnosing plant diseases by examining plant leaves. Using a method known as feature extraction, they were able to isolate the diseased area from the rest of the leaf image. The support vector machine (SVM) performed much better with the other two methods than with the other two.

Poojan Panchal et al. (2019) [21] In order to determine if plant leaves were affected by bacterial spot, early blight, or late blight, a random forest classifier was utilized. During the image segmentation process, the HSVHerpes Simplex Virus methodology was utilized to differentiate between the diseased and healthy parts of the leaf, and a grey-level co-occurrence matrix was used to extract the features. This model achieved an accuracy level of 98%.

The issue of data scarcity has been addressed in several ways. The researchers used a variety of techniques to extend the dataset's image production. Changing the image is a typical way to achieve this. The image may be cropped, resized, grayscale, or inverted, for example [23]. Yet, these modifications cannot do enough to enhance results. Artificial images can be produced to help if standard operations do not yield good results. A number of other GAN models have been proposed as a possible solution to the problem of lack of images in collections currently accessible to the public by a number of different authors. CNN was used in a smartphone application in [24] for classification. Tests on Inception V3 and MobileNet yielded accuracy results of 88.3% and 92%, respectively. To deal with the limited number of images available, DCGAN was used to enlarge the image after pre-processing to reduce sample size and remove noise. Other work [25] has shown that GAN may produce accurate images for a given data set.

The automatic selection of SVM parameters using genetic algorithms (GA) is another method for detecting plant diseases. The proposed approach for plant disease recognition was accurate to 98.14 per cent, according to the authors [22]. DL was used to detect plant diseases using a variety of picture attributes. These features can be extracted using particle swarm optimization (PSO). For the purpose of identifying cotton illnesses, Revathi et al. employed PSO [23].

A description of the many DL approaches for classifying plant diseases can be seen in Table 1, and a list of their drawbacks can be found in Table 2.

Table 1. Comparison of Deep Learning for plant disease detection.

Paper	Dataset			Preprocessing and Augmentation Techniques	Network		Acc [%]	
	Name (Species/Classes)	Number of Images	Number of Images After Preprocessing		(Best) CNN Architecture	Transfer Learning	Overall	Separate Classes
[24]	PlantVillage (1/3)	3700	3700	Re	Modified LeNet	No	92.88	N/A
[25]	Collected (1/9)	5000	43398	AB, AC, Cr, Fl, NR Re, Ro	R-FCN and ResNet-50	No	85.98	75–95
[26]	Collected (1/3)	299	N/A	NR, Re, Sg, AB, AC, AS,	Modified LeNet	Yes	98.60	N/A
[27]	Collected (1/4)	1053	13689	AT, NR, MS, PCA jittering	Modified AlexNet	No	97.62	91–100
[28]	Collected (14/56)	1567	46409	BR, Re, Sg	GoogLeNet	Yes	95	75–100
[29]	Collected (6/15)	4483	33469	AT, Cr, PT, Re, Ro	Modified CaffeNet	Yes	96.30	91–98
[30]	PlantVillage (1/4)	2086	N/A	Re, No, Ro, Fl, Zo	VGG16	Yes	90.40	83–100

Augmentation Techniques	
Geometrical transformations: • AT—Affine Transformation (translations and rotations) • Cr—Cropping • Fl—Flipping • MS—Mirror Symmetry • PT—Perspective Transformation • Re—Resizing • Ro—Rotation	Intensity transformations: • AB—Adjusting Brightness • AC—Adjusting Contrast • AS—Adjusting Sharpness • Additional: • BR—Background Removal • NR—Noise Removal • Sg—Segmentation • Zo—Zooming

Table 2. Limitations of DL methods for plant disease detection.

Paper	Limitation							
	Small Number of Examples in Dataset	Small Number of Plant Species/Disease	Low Accuracy When Testing in Real Conditions	Complex Background	Multiple Diseases in the Same Sample	Location	Infection Status	Train and Test Data are From the Same Database
[24]	-	-	-	*	-	-	-	-
[25]	-	-	*	+	+	+	+	-
[26]	-	-	+	-	-	-	-	-
[27]	-	-	-	-	-	-	-	-
[28]	-	+	*	-	+	-	-	-
[29]	-	*	-	+	-	-	-	-
[30]	-	-	-	-	-	-	+	-

Legend: + Resolved – Unresolved * Partially Resolved.

In Table 1, several techniques and algorithms were used to detect plant diseases, and it was observed that the highest accuracy achieved was 98.60% since the data was pre-processed. Table 2 shows the limitations of DL methods for detecting plant diseases. The table shows the solutions made at different levels, such as the small number of samples in the database or the imprecision and complexity of the background images. Icons have been developed to show this. Although the authors have somewhat overcome the above problems, there is still potential for improvement. The primary focus of the vast majority of these investigations has been to improve classification reliability. The models achieved mostly high accuracy. It is important to remember that the percentage dropped significantly when the models were tested on a dataset not part of the same database. This is something to keep in mind at all times..

III. Methodology and Experiments

This section discusses some studies that attempt to address the difficulties in plant disease detection tasks. The purpose of this section is to present the problems and methods that have been adopted to overcome the troubleshooting methods. Analysis of a variety of image recognition and classification algorithms.

Table 3. Details of datasets

I. Datasets

A significant decline in classification performance [31] Plant diseases were collected from field sites and were collected in an image data set, and sampling is one of the limitations in the work of disease detection. This is due to the fact that there are not many public datasets of significant size pertaining to plant diseases, and the vast majority of recent achievements are founded on the PlantVillage dataset [32]. Kaggle, an online platform for crowdsourcing, makes available PlantVillage, a set of 54,323 photographs based on 14 distinct different crops and 38 different sorts of healthy and ailing plants [33].

The rice leaf image dataset can be obtained from Google Images via the Internet and the Kaggle platform. The dataset was compiled using 5200 photographs, and it consists of three categories of diseases. Each and every image only contains a single illness. The training set and the test set both have 1000 photographs for every class label, but the test set only has 300 photos. The sample has been split into a training dataset and a test dataset with a ratio of seventy to thirty. InceptionResNetV2 was utilized so that the classification function could be implemented [34]. Three open-source datasets of rice leaf photos are listed in Table 3.

Paper	Dataset	Number of Samples	Train: Test Split	Classes
[35]	Rice Leaf Diseases	120	80:20	Bacterial leaf blight, Brown spot, Leaf smut
[36]	Rice Diseases Image Dataset	2092	75:25	Brown Spot, Hispa, Leaf Blast, Healthy
[37]	Leaf Diseases Dataset	8293, 12496 (after balance)	80:20	Bacterial Leaf Streak, Brown Spot, False Smut, Sheath Blight

In this method, the dataset is composed of photos that depict real-world situations in which the model could be put to use. These pictures represent the scenarios. Agricultural experts painstakingly labelled and checked each and every one of the images included in the dataset. The picture classifications and the number of objects for each class are shown in Table 4.

Table 4. PlantDisease Dataset.

Class Number	Class Name Images	Name Images PlantDisease	Images (PlantVillage)	Objects
1	Venturia inequality (Apple)	1736	630	3423
2	Gymnosporangium juniperi-virginianae (Apple)	2538	276	4296
3	Podosphaera leucotricha (Apple)	1302		2478
4	Botryosphaeria obtuse (Apple)	705	621	1207
5	Alternaria pomi (Apple	3084		5436
6	Malus domestica (Apple-healthy)	2058	1645	3552
7	Xanthomonas euvesicatoria (Bell Pepper)	2402		4044
8	Xanthomonas campestris (Bell Pepper)	1344	997	2445
9	Capsicum (Bell Pepper-healthy)	2414	1478	4443
10	Blumeriella jaapii (Cherry	1914		3480
11	Podosphaera spp. (Cherry)	1064	1052	1851
12	Prunus cerasus (Cherry-healthy)	1022	854	1863
13	Uncinula necator (Grape)	1708		2811
14	Plasmopara viticola (Grape)	2038		3372
15	Botrytis cinerea (Grape)	2254		4560
16	Botryosphaeria obtuse (Grape)	1790		3549
17	Pseudocercospor a vitis (Grape)	1704	1076	3087
18	Guignardia bidwellii (Grape)	1584	1180	2613
19	Phaeomoniella spp. (Grape)	1692	1284	2739
20	Vitis vinifera (Grape-healthy)	1898		3657
21	Peronospora destructor (Onion)	2984		5199
22	Allium cepa (Onion-healthy)	1361		2448
23	Claserosporium carpophilum (Peach)	804		1401
24	Prunus persica (Peach-healthy)	901	360	1831
25	Alternaria solani (Potato)	2310	1000	3948
26	Solanum tuberosum (Potato-healthy)	1718	152	3345
27	Polystigma rubrum (Plum)	2482		4182
28	Plum Plox (Plum)	1806		3474
29	Tranzschelia pruni-spinosae (Plum)	1746		3228
30	Stigmina carpofilia (Plum)	2192		4149
31	(Plum-healthy)	2653		3423
32	Mycosphaerella fragariae (Strawberry)	1242		2181
33	Fragaria (Strawberry-healthy)	1686	456	2700
34	Cercospora beticola (Sugar beets)	2748		4629
35	Beta vulgaris (Sugar beets healthy)	2953		4387

36	Phytophthora infestans (Tomato)	2792	1910	4755
37	Septoria lycopersici (Tomato)	2214	1771	3837
38	Solanum lycopersicum (Tomato-healthy)	2826	1592	4683
39	Erysiphe graminis (Wheat)	1566		2940
40	Puccinia spp. (Wheat)	2036		3690
41	Septoria spp. (Wheat)	1204		2028
42	Triticum sp. (Wheat-healthy)	790		1647
	Total	79,265	18,334	139,011

II. Image Pre-Processing

Image processing consists of turning an input image into a digital frame and then running that digital frame through a variety of processes in an attempt to either generate an additional image or extract some useful information from the one that was processed. It is a type of signal distribution in which an image, such as a video edge or photo, is used as the input, and the result could be an image or attributes associated with that image [38]. Filtering, colour conversion, and picture detail improvement are all included in the pre-processing of images [39]. The associated image pre-processing methods used for diagnosing paddy diseases are listed in Table 5 in accordance with recent research studies.

Table 5. Comparison of the various techniques used in the pre-processing stage.

Reference	Year	Objective	Methodology	Parametric Measure	Result
[40]	2018	Noise Reduction	Gaussian Filtering	Accuracy	98.63%
[41]	2017	Detection of plant disease over cotton plant	Machine Learning Regression-Median Filtering	Accuracy	83.26%
[42]	2017	Detection of infected and healthy leaf	Image processing-Weiner Filtering	Accuracy	80%
[43]	2017	Automated crop disease identification	HSV colour extraction	Accuracy	Precision= 99.04%
[44]	2017	Diagnosing plant disease	Gaussian smooth approach	Accuracy	90.96%

Using a quicker method, T. Islam et al. (2018) [40] reported on a rice illness. The Naive Bayes classifier combined with green pixel masking has an accuracy of 98.63% when used to detect bacterial blight, rice brown spot, and rice blast, respectively. Sarangdhar et al. (2017) presented evidence that supported the use of a support vector machine (SVM) regression framework for the detection and characterization of many cotton leaf diseases [41]. Research conducted by Rewar et al. in 2017 [42] . above agricultural engineering in terms of priority given to the earlier detection and classification of plant diseases. For recognizing the edges of damaged and healthy leaf sections, Canny offers an accuracy of 80 per cent using a range of edge detection approaches. Hamuda et al. (2017) developed a technique that is dependent on the characteristics of colour space as well as morphological disintegration and growth [43]. Evaluation of the calculation's performance is performed by comparing the produced results to the techniques that correspond to them. Individually, we were able to attain an accuracy of 99.04 per cent and a sensitivity of 98.91 per cent. Nti et al. published in 2017 an article that highlighted their research on the extensive monitoring of plant disease validation and prospective prevention strategies that are currently being implemented [44].

III. Feature Extraction

In picture classification, the feature extraction method is crucial. The primary variable used for classifying an image is its characteristics.

Texture Extraction: The process of extracting information from a structure using a random interval is known as texture extraction. Size, shape, thickness, characterisation, and extent of an object's fundamental features are thereby represented by its texture attributes and appearance. Texture component extraction is the first step in the process of using texture extraction to collect these features [45].

Extraction of colours: Extraction of colours is crucial for creating unique classes. The colour estimations that are generated by digital image processing are highly beneficial while conducting a study on the sore in the hopes of obtaining an early diagnosis [46]. A pixel in a picture is often addressed using the colour space RGB, for each pixel's colour space is just a combination of the three primary colours. These processes also state and study the benefits and drawbacks of utilizing these other colour spaces. It is good knowledge that the difference in the human vision impression throughout the CIE Lab colour space can be traced back to the Euclidean division of the various hues [47].

Shape Extraction: In order to describe the shape of an image, general descriptors like item count, shape region, image dimension, and picture zone are important. The ache and degree of the injury are two things that are used to get rid of them. [48].

Edge detection: sections in an image that have solid borders and an element by one pixel then onto the next can generate an actual variance in the image's quality. Edges can be found through the use of edge detection software. Edge detection is a method for processing images that locates the boundaries inside the associated image. The way it works is by detecting different levels of brightness. Edge recognition is a technique that is utilized in a variety of domains, like photo editing, computer vision, and machine vision, for the purposes of segmentation and information extraction [49]. As a result, the precise edges are employed in the picture for limit estimate and extraction. The present feature extraction methods used by numerous researchers to diagnose plant diseases are shown in Table 6.

Table 6. Comparative Evaluation of Various Feature Extraction Methods for the Identification of Plant Diseases .

Reference	Year	Objective	Methodology	Result
[45]	2007	Texture Extraction	Image Processing	Accuracy= 88.56%
[46]	2013	Detecting unhealthy leaf portion	Texture feature	Accuracy= 94%
[47]	2018	Evaluation of soybean leaf Defoliation	Colour Extraction	Accuracy= 96%
[48]	2017	Identification of infected leaf	Image extraction- leaf color	Higher accuracy
[49]	2018	Detection of Leaf Disease	Feature extraction-Edge detection	Accuracy= 82%

Typical classification systems involve processing images taken by cameras. The most crucial preparation in supervised classification involved known pixel collecting. The trained classifier was utilized to group various images. The Unsupervised order uses the characteristics of the pixels to group them, and this clustering process is known as grouping [50]. cluster sizes determined by users. Unsupervised categorization is utilized when trained pixels are not accessible.

The robust discriminative parallel classifier that goes under the name Support Vector Machine models the selection between two classes (SVM). This divides into two classes, the first of which is comprised of the target preparation vector and the second of which is comprised of the preparation vectors from a population that is imitating the foundation [51].

Probabilistic Neural Network (PNN) is an artificial intelligence technique that uses Bayesian classifiers, a statistical procedure. Input, cover-up, and yield layers are utilized by a feed-forward system that is referred to as a PNN., a layer that is hidden from view, also called the example layer. To be more specific, the Bayesian classifier is included as a component of the design layer. By generating multivariate probability and density functions with the assistance of a non-parametric estimator, PNN was shown to be successful. Finding rice leaves that will eventually be infected by rice leaf rollers is still easiest with a PNN, which continues to be the optimal neural architecture. PNN design applied to ghostly and identifiable groups in the shortwave infrared spectrum (SWIR). PNN was able to anticipate both an annoying disease and an illness. The mixture of PCA and PNN data is the best indicator of whether or not a rice plant is affected by a disease [52].

CNNs, which stand for convolutional neural networks, are significant unsupervised profound learning designs that permit the learning of "filters performing convolution" in the domain. This is one of the fundamental variances between the two. The brain architecture and natural vision are brought into synchronization in a specific order by CNN. The complicated architecture of CNN allows the neurons a discernibly increased amount of time to become ready. In spite of this, the accuracy of the orders is astonishingly high [53][54].

The numerous studies that were conducted are shown in Table 7, along with potential classifiers that may be used to categorize the disease affecting rice plants. The comparison investigation shows that the adopted methodology outperforms some relevant parametric metrics.

Table 7. Comparison of various classification techniques for the diagnosis of plant diseases.

Reference	Year	Objective	Methodology	Parametric Measure	Result
[43]	2012	Leaf disease detection	Colour extraction	Accuracy	Disease spot accurately

					detected.
[44]	2017	Detect the classification of leaf disease	K-Mean Clustering	Accuracy	FCM=95% K-Mean=85.05%
[45]	2009	Detection of rice seed disease	Support Vector Machine	Accuracy	97.2%
[46]	2015	Identification of rice panicle	Principal Component Analysis and Support Vector Machine	Accuracy • Raw Reflectance Spectra • Second Reflectance Spectra	96.55% 96.55%
[47]	2018	Rice disease determination	Principal Component Analysis and Neural network	Accuracy of BP neural network	95.83%

3.4 Augmentation

Big datasets are frequently used by DL algorithms in order to overcome problems like overfitting. When developing algorithms for more widespread practical applications, this provides a general challenge. Data collection can be a time-consuming procedure, and labelling activities may call for the assistance of subject-matter specialists. A popular strategy is to use augmentation techniques to increase the size of the current datasets. Two augmentation procedures were applied in this work. The first included conventional augmentation techniques that were frequently used in research to identify plant diseases [28],[55],[25],[26] .

The second method involved training GANs [56] that would produce syntactic data depending on the dataset already available. The discriminator seeks to determine whether the data is true or false. The generator seeks to structure the information to trick the discriminator into believing the data is real. GAN is designed from two neural networks. The discriminator sought to determine whether the data was real or fake, and the generator sought to produce the data with all necessary features to deceive the discriminator into believing that the data were real. A specialized GAN can generate brand-new images with the assistance of this approach, which can then be used to train a plant disease classifier.

DCGAN [57], because of its straightforward architecture, was used as a proof of concept to show that the syntactic data could have qualities like colour, shape, and texture similar to the actual plant leaves. This was done to demonstrate that the syntactic data could have qualities like these.

3.5. Convolution Neural Network Approaches

This method involves choosing the training dataset in order to identify and categorize diseases. Datasets can be found online, such as work [37] which employs a public dataset consisting of 87,848 photographs of leaves from 25 distinct plant species, with and without 58 different types of disease. [29] To create a dataset, you can gather images at random from the internet, but using datasets that have been verified by an expert is better for model accuracy. For example, works [58]and [59] are the most effective for the development of real-time disease classification systems since they make use of confirmed photos of cucumbers and cassava.

The optimal structure is chosen based on criteria including error rate, accuracy, and training duration. Researchers frequently train the image in more than one architecture. Similar to the work [60] and the work [37], in which accuracy of 99.35 per cent and 99.53 per cent were reached, respectively, using GoogLeNet and VGG. The identification of tomato disease was accomplished by using meta deep structure in the paper [25]. A speedier region-based convolutional neural network, a single-shot multi-box detector, and a complete region-based convolutional network with extractors like VGG-16, ZF Net, ResNet-50, ResNet-101, and so on make up the Meta architecture. It is possible to determine the type of disease affecting the area as well as the location of leaves affected by the disease using this sophisticated superstructure.

The development of graphics processing units (GPU) in recent years has made the building of convolutional neural networks (CNN) much less complicated. CNNs are an effective tool for simulating sophisticated processes such as this one, which involves the detection of illness on the leaves of plants. Because it has the ability to automatically learn new elements of an image, this method may be applied to the task of diagnosing several diseases based on photographs of leaves from different types of plants. It performs well and has an accuracy rate of more than 95%. The review of products that use Convolutional Neural Networks is summarized in Table 8 below.

MatConvNet architecture from MATLAB	Training from Scratch	93.4% and 92.2% on balance and unbalance dataset	This type of training reduces the accuracy of the model [25]

Table 8. Summary of review, which use the CNNs approach

Architectures used	Training mechanism	The accuracy of the model	Demerits
-AlexNet -ALexNetOWTBn -GoogLeNet -Overfeat -VGG	Training from scratch	99.53 % on VGG architecture	Take time during the training process. [37]
- Inception v3	Transfer Learning	93% accuracy	Drop in the performance of the model [58]
-AlexNet -GoogLeNet	-Transfer Learning -Training from Scratch	99.35% accuracy on GoogLeNet using Transfer Learning	Take time to experiment [59]
- The CafeNet - Image processing	Transfer Learning	Over 96.3% accuracy	stage takes time. [60]
- Deep meta architectures	Transfer Learning	Over 99.96% accuracy	Complex architecture, which is difficult to implement. [29]

3.6. Transfer learning

Transfer learning is a method of machine learning in which CNNs that were trained for one job are used as the foundation for a model on some other [61]. This allows the CNNs to be used more than once. We don't need to start the train from scratch and randomly initialize the weights because we may leverage a network that has already been trained on large labelled datasets, such as public photo datasets, etc., to build the weights instead of doing so. Using the models that were trained using the typical massive dataset ImageNet to the specific job that was trained using the objective sample is an example. The following is an explanation of the primary stages involved in the approach known as transfer learning :

1. Determine the base networks

Determine the transfer learning base networks by using the CNN model that has already been trained, and assign the network weights (W 1, W 2,..., W n). A qualified CNN (https://ker-as.io/applications/) will be able to provide you with a download link for the weights of the lower levels.

2. Establish a new neural network
3. The structure of the network can be altered according to the bottom layers by, for instance, exchanging layers, adding layers, or deleting layers from networks. This allows for the formation of an entirely new network architecture.
4. Fine-tuning the neural network.

The newly constructed networks can be fine-tuned to reduce the loss function E by employing our own data X and the labels that correspond to it, as shown in the equation (1).

$$E(W) = -\frac{1}{N}\sum_{Xi=1}^{N}\sum_{K=1}^{K}[Y_{ik}\ \log P(X_i = K) + (1+Y_{ik})\log(1-P(X_i=K))] \quad (1)$$

where n is the total number of training samples, I represents the index of training samples, k represents the index of classes, and W represents the weighting matrices used by the convolutional and fully-connected layers. The probability that the given input xi is a member of the expected k-th class is denoted by the symbol P(xi = k).

Specifically, the random gradient descent (SGD) algorithm [62] is mostly used to calculate the optimal W by minimizing the loss function E in the target data set, as defined in Eq. (2).

$$W_k = W_{k-1} - a(\partial E(W)/\partial W) \quad (2)$$

where k is the class index, and an is the learning rate

The same domains were used to train a pre-trained model. There are many pre-trained architectures available. The following list includes the justifications for doing so. First, it takes more processing resources to train the massive models on vast datasets. Second, It takes too long to train the network—weeks, in fact. The learning process can be sped up by training the new network with trained weights. Table 9 lists the top five CNN's architectural error rates.

Table-9: top-5 network architecture error rates

CNN Architectures Top-5	error rate (%)
LeNet[4]	28.2
AlexNet[5]	16.4
VGG[6]	7.30
GoogleNet[7][8]	6.70
ResNet[9]	3.57

LeNet :The first convolutional design is LeNet [63], which consists of two convolutional layers with ReLu and average pooling layers, another convolutional layer for flattening, two fully connected layers, and finally one softmax layer.

AlexNet :Compared to LeNet, AlexNet [64] is a considerably deeper neural network. Rectified Linear Units (ReLUs) are employed in this network to introduce nonlinearity, which speeds up the network. Five convolutional layers, three fully connected layers, an output layer, and 62.3 million parameters make up this network.

VGG :Visual Geometry Group is known by its full name, VGG [65]. VGG16 and VGG19 are typically found in the VGG network. We are able to extract complicated features at a low cost in this network because numerous 3x3 filters are used in place of the huge-size kernels.

GoogleNet :Although this GoogleNet [66] produces good accuracy, the amount of computation required was considerable due to the calculations' high order. In order to reduce the amount of parameters, GoogleNet's last convolutional layer was replaced with average pooling rather than fully-connected layers.

ResNet :Up until now, accuracy has increased automatically as network depth has increased. However, as ResNet's network depth increases, some issues do as well [67]. The prediction gets smaller at the bottom of the network as a result of increased depth that requires altering the weights. Another is the considerable amount of parameter space required. Residual modules were introduced to solve these issues. Examples of ResNet networks include ResNet50 and ResNet152.

IV. . Conclusion

This article discusses most of the methods used in deep learning, transfer learning, data augmentation, and processing and the algorithms used and provides a review of the information to gain a greater understanding of pre-processing, segmentation, feature extraction, feature selection, and classification procedures. Issues related to the diagnosis of various plant diseases, including various rice leaf diseases, were examined. These imaging systems were directly affected by the image quality, quantity of practice images, and set of sample features. If the capture system is set up incorrectly, it will directly affect how it works. Again, adapting to different AI algorithms requires a complex architecture with large memory and processing power. One potential solution is to cleverly combine the idea of an expert system with machine learning and computer vision techniques. Researchers in this field would be very interested in trying to create such a system.

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