JOURNAL OF CRITICAL REVIEWS

ISSN- 2394-5125 VOL 7, ISSUE 11, 2020

RICE PLANT DISEASES DETECTION & CLASSIFICATION USING DEEP LEARNING MODELS: A SYSTEMATIC REVIEW

Mr. MANOJ AGRAWAL[1], Dr. SHWETA AGRAWAL[2]

[1] Research Scholar, Department of Computer Science & Engineering, Sage University, Indore, India
[2] Professor, Department of Computer Science & Engineering, Sage University, Indore, India
[1]manoj2179@gmail.com, [2]shweta.cse@sageuniversity.in

ABSTRACT:

As the structure of rice plant diseases and insects is complex and the appearance of these diseases and different species is very similar, it is a difficult task to classify them. These diseases and various insects in crops need to be identified and classified as early as possible, especially to prevent the spread of diseases and insects. At present, it is generally considered that the deep intricate neural network (CNN) is the latest image recognition solution. This article aims to explore various machine learning and deep neural network technologies used to identify rice plant diseases based on images of infected rice plants. We conducted a detailed study of the number of papers covering different rice plant diseases and other different plants and fruits, and examined these papers according to important criteria. These conditions include the size of the image data set, No. class (disease), pretreatment, segmentation technique, classification type, classification accuracy, etc. We use research and research to propose and design work on detection and classification of rice diseases. This article deals with the research findings published in the international review articles over the last five years, comparing and analyzing various types of intricate neural networks and models of deep learning used to detect and classify rice plant diseases. This article also mentioned detailed information about different types of data sources. Following this study, we found that most researchers achieved higher accuracy by implementing deep learning, incorporating neural network models to detect rice diseases. The purpose of this study is to review various models of deep learning and find the most appropriate model to achieve higher accuracy and precision.

KEY WORDS: Deep learning, Rice Disease, CNN, Feature Extraction, Segmentation

I. INTRODUCTION

The timely discovery of plant diseases and pests is one of the major challenges of the agricultural sector. In India, rice amounts to approx. 70% of the total crop and 93% of the total grain production, which is why timely detection of rice diseases is very important to ensure the sustainable production of rice [1]. Identifying and classifying plant diseases and pests is one of biggest difficulties in the agricultural sector. Insects cause crop damage, mainly affecting crop productivity. Due to the complex formation and high connection in emergence between different species, the classification of insects is a difficult task. It is essential to recognize and categorize insects in crops as early as possible, particularly by choosing effectual pesticide and biological organize method to prevent increase of insects causing crop diseases [2]. At present, if there is an epidemic of rice in one place, rice pest experts from different research institutions will advise farmers. Rice damage is a complex disease, usually caused by some microorganisms caused by spikelets or both. In microorganisms, fungi are the pathogen of the disease. Other than fungi, several bacteria are also reported with their involvement in development of this disease. Besides the involvement of microorganisms, some biotic conditions may also cause similar effects leading to abnormal color changes in rice grain [3][4]. Some of these factors are abnormal fertilization unfavorable, weather conditions viz., temperature and/or moisture stress and imbalanced soil nutrients. Besides these, if seeds are harvested prematurely and kept in heaps or injury occurs by strong wind or cyclone due to collision of panicle or attack of insect pest during grain formation stage, may also lead in formation of discolored grains. Deep learning technology shows great hope in image classification. This is a technique based on feature learning from labeled training data sets. This technique used by diseases of tea [5] apple [6] tomato [7] grapes, peaches and pears. Mostly they use leaves to identify diseases from pictures. Mostly reasons, they use picture from a homogeneous background. Furthermore, in most cases, the data is available from various sources on the Internet. There is a fundamental difference in the risk of infection between varieties and above plants rice pests and diseases can be detected both on the stem and on the stem. Second, there is no obvious contrast in color between the healthy rice area and the affected area. All of these factors make it extremely difficult to collect and label the affected rice plants and identify the right pests and diseases.

Different Types of Rice Plant Diseases: There are different types of rice plant diseases. This division clarifies the dissimilar kind of infection that infested on rice plants. The reason behind putting this section is that one can appreciate curved whatever kinds of picture discussing processes would be wanted or what kind of structures want to be measured to articulate such viruses cognition structure, figure 1 shows images of six common diseases. We briefly define each disease. For more detailed information on all kind of rice plant diseases, see [8].

1. **Leaf Blast (LB)**: The indication of the disease is black dots to oval dots, with reddish brown and gray or white points [8].
2. **Brown Spot (BS):** The disease infected on the leaves of rice. The indication of disease is round to oval, with dark brown lesions [8].
3. **Sheath Blight (SB):** This infection suggests itself on both leaves and stems. The indication is oval, white or straw colored show in center with reddish brown spots [8].
4. **Leaf scald (LS):** The symptoms are narrow reddish-brown wide bands. Sometimes the lesion is on the edge of the leaf, the border is yellow or gold [8].
5. **Bacterial Leaf Blight (BLB):**The indication have elongated lesions at the tip of the leaf, which are several centimeters long, and change from white to yellow due to the action of the bacterium [8].
6. **Rice Blast (RB):** It is because of the fungus Magnaporthe Oryza. The white to gray-green lesions or blemishes have a dark green border on the first time. The more obvious lesions on the leaves are oval or spindle-shaped, whitish to gray center, red to brown or necrotic edge. Usually the spots are elongated and point at both ends [9].
7. **Sheath Rot (SR):** It was created by two fungal species, Sarocladium Oryza and sacroladium tensum. Typical casing root begins with the upper sheath of the spikelet. It looks like an oblong or asymmetrical stain with dark red, Brown edges, gray midpoint or brownish gray generally, more spots are experiential, these spots will expand, and rise can cover most of the leaf sheath. The panics remain in the cloak or may appear partially. The diseased leaflets showed a large amount of white, powdery fungal increase (mycelia) on outer surface. The panicles did not rot or small flowers changed from reddish brown to dark brown [9].The picture in Figure 1 shows the symptoms of various rice plant diseases and insect pests. In some pictures, the area around the environment, in the other image is the color of our hand or paper. Weather conditions vary from time to time. Some pictures were taken in cloudy conditions; others were taken in clear weather. Symptoms of pseudo snail, dry borer, healthy plants, wild and / or rot. The proposal covers all symptoms in these categories. In addition, the early symptoms of Hispa and Brown Plant Hopper are different from the later symptoms.

Following figure shows different types of rice diseases:

(a) Bacterial Leaf Blight (Disease) (b) Brown Plant Hopper (Pest) (c) Brown Spot (Disease)

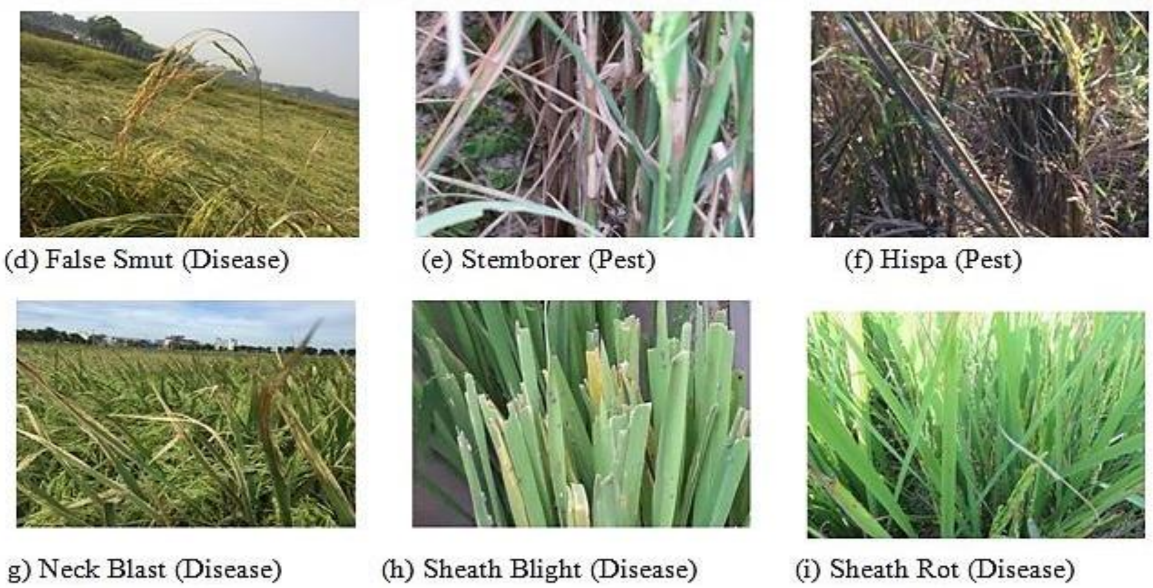

Figure 1: Different types of rice disease

II. METHODOLOGY

The present methodical review plan to provide a survey of different machine-learning& deep neural network procedure used in recognition of rice plant diseases based on images of tainted rice plants. The methodology of review consists following steps:

1. Data Collection
2. Searched databases

Five databases were used for analysis of this literature: Science Direct, Scopus, Springer, ACM (Association for Computing Machinery) and IEEE (Institute of Electrical and Electronic Engineers) (IEEE Explore Digital Library). The time interval used in this survey was defined from 2015 to 2020.

Searched Terms: For the survey of papers, the following search expression was defined: (“Convolutional Neural Network” OR “Machine Learning” OR “Artificial Neural Network” OR “Deep Learning”) AND (“Rice Plant Diseases” OR “Crop Diseases Detection & Classification” OR “Crop Pest Classification”“Grape/Tea/Apple/Tomato/Grapevine/Peach/Pear Diseases Detection”).

Inclusion criteria: To find the paper meeting desired criteria Titles and Abstract represented the first selection step, and then duplicate papers were removed.

Exclusion criteria: Papers that are not specifically dealing with Rice or other plant diseases detection and classification using deep learning/CNN were excluded from the study.

Data Analysis: After selecting around 50 papers found to be suitable for the review data analysis has been done by keeping following points into consideration:

- **Year of Publication:** The studied topic CNN/Deep learning for rice diseases detection has gained attention from researchers in the last decades. Hence, knowing its year of publication is important to analyze when this interest has risen.
- **Purpose of the study:** Different types of task performed for various rice diseases in the study with the different purposes like discoloration & lesion detection, classification, segmentation etc.
- **Deep Learning Architecture:** Deep learning architectures such as Deep Neural Network, Convolution Neural Network, and Recurrent Neural Network have been used for various crop diseases detection & pest prediction.

ISSN- 2394-5125 VOL 7, ISSUE 11, 2020

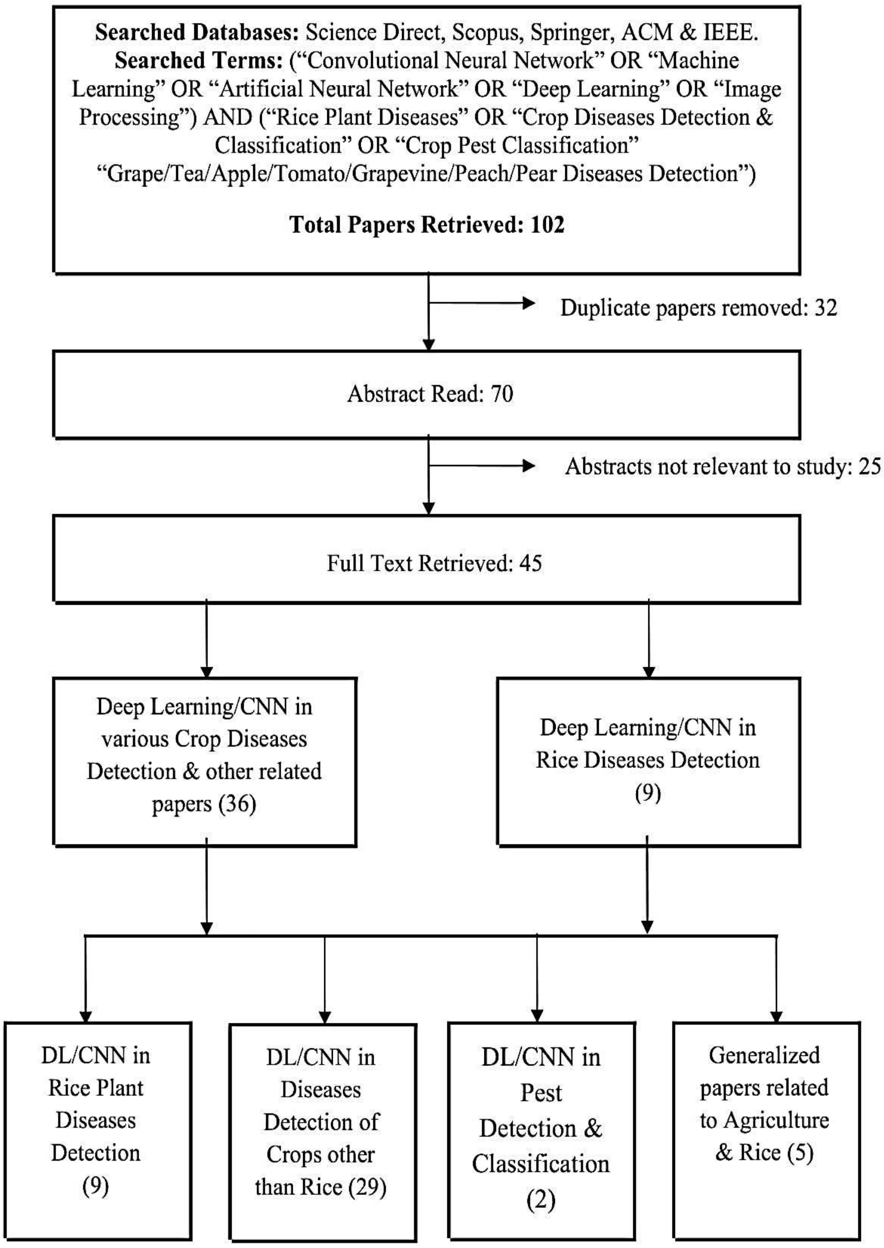

Figure 2: Research Methodology Flow

III. LITERATURE SURVEY

Many methods are applied to accurately determine the pathology of images. Most of them use general image processing technology, SVM classifiers, K-means clustering, clustering algorithms, etc., but they cannot get much more attention. In recent years, some researchers have used a field-based approach to this field. Deep neural networks are far superior to traditional image recognition techniques for image recognition.

Yang Lu et.al. Committed to automatic documentation or analysis of rice diseases. Deep learning is a hot investigation matter in present pattern recognition and machine learning. You can effectively solve these problems in plant pathology; we suggest a different technique for vascular disease based on Convolution

Neural network technology. With over 500 images taken from the leaves of the pink field and extracts were taken from the field, CNN was trained to recognize 10 common diseases. Under the single-track correction strategy, the proposed CNN model achieves 95.48% accuracy. This view is far superior to the traditional learning model. Outcome of rice price index analysis show probability or usefulness of this procedure [10].

Hu Genshengaet.al. Low speed learning methods are proposed to identify the disorders in the tea to prevent and manage the disorders in the tea on time. By removing the color and texture, the provision course engine is used to distribute the defects in the image of the tea disease. Tentative outcome show that mishmash of traditional learning techniques or deep knowledge technique can efficiently classify tea illnesses by multiple mechanisms. It achieved 90% approval rating for red tea sc, erythematic tea and 90% tea, which is more than 30% more than the supported vector machine. The next step is to find a better data generation method with strong generalization performance and a low-speed learning method, to improve the robustness and accuracy of tea disease identification with fewer training samples [11].

Jayme Garcia et.al Deep learning has become an art of drawing technology. The main problem that is encountered when using this diagnostic tool is the lack of visual information that can reflect the nature of the various conditions and symptoms present in the application. The ion-augmentation technology minimizes the impact of this problem, but these technologies are unable to reproduce much of the real distinction. This article examines the use of single-stranded lesions in this work, rather than examining the whole leaf later all area has its own unique features, it does not require additional images to increase data conversion. It too lets for detection of many diseases distress same leaf. On other hand, the distribution of potential symptoms still needs to be done in a way that prevents complete automation. The accuracy of using this procedure is on average 12% higher than accuracy used in the original image. The solutions presented in this paper not only enhance size of the existing images, but enhance complexity of data, as natural variation in each image is not in use into account. They are better understood when they are divided into smaller parts. This method also has some disadvantages, but in the light of limited data it obviously leads to reliable results [12].

Artzai Picona It has been approved by 3 diverse CNN sites that join non-image metadata into a convolution neural network based on images. It combines the benefits of the study with multiple data combinations at the same time, while decreasing difficulty of disease classification task. Genetic network of plant diseases attains a 0.98 warning by providing segmentation alerts and status information at the created vector level, improving all existing methods. first, and eliminates 71% of previously unrecorded methods Using the CNN architecture of the proposed culture condition, we obtained richer and more robust shared visual characteristics, with an average BAC of 0.98, which is higher than other methods and eliminates 71% of the classification errors. This shows that other metadata can be added to the deep learning model to achieve a coherent analysis of categorical data that is beyond the reach of other methods. The method is presented in conjunction with the image information and the entire database change without affecting the same symptoms as the whole [13].

Parul Sharma Most of the profound knowledge copies offered for the control of plant infections have deadly wounds. When tested with these data, their performance will not diminish. This work examines how this difficulty may be work out using CNN modeling using image-sharing techniques. Compared to F-CNN model trained with complete image, the S-CNN model with the combined image doubled its efficiency when testing independent data that did not fit the models or categories 10 even. 98.6% accurate. Not only that, by taking tomato plants and other types of occupational diseases for example, we show that self-confidence in the S-CNN model is greatly enhanced in comparison to 'of the F-CNN model. This research work has led to the application of automated approaches to the non-experts to detect disease over time [14].

Karthik R. et.al. The traditional disease detection method used is based on the extraction of manual characteristics from acquired images to identify the type of infection. In addition, the recital of these tasks depends entirely on the nature of the manual work selected. It can be visualized through an automated study with CNN. This study proposes two dissimilar systems for finding tomato leaf virus infections. The first architecture uses a dozen courses to learn important work. The second architecture applies the pull mechanism to the top of the remaining deep network. The experiment was carried out using Botanical Village data, which included three diseases, namely, original blight, fire measurements and butterflies. The proposed work uses extraction mechanics, a feature learned by CNN at various processing levels, and achieves complete precision of 98% of proof in 5-point cross-validation [15].

S. Ramesh et.al. In agriculture, one of most novel study subjects is recognition or classification of diseases from plant leaflets. Identifying agricultural diseases through the use of image processing technologies will reduce farmers' lives to protect their agricultural products. A neural network based on the Jaya algorithm has been proposed to notice or order the leaf diseases of rice. For the purpose of photography, images of the amount of light, bacteria, wool and blasts of rice were taken directly from the farm. In preprocessing, in order to remove their origin, RGB images are converted to HSV images, and binary images are taken based on hue and saturation portions to divide patients and non-infections [16].

Wanjie Liang1 In order to study distribution of the affected areas, their proportions and their origins were developed. Through the use of profound neural networks with Jaya optimization algorithm for deep diarrhea and

ISSN- 2394-5125 VOL 7, ISSUE 11, 2020

disease control to classify disease, potential management and monitoring of proposed fields insects can lead to the rise of wheat. According to the Institute's data, farmers are losing up to 37% of their crop due to pests and diseases each year [17].

Pranali et.al. In this article, we propose a system for preparing image capture plant village dataset The second is a convolutional neural network, which is used to classify Tensor Flow disease and technology to prescribe pesticides. The two steps we use in the system are Android applications with Java Web Services and deep learning. We used convolutional neural networks in the fifth, fourth, and third layers to train our Android models and applications to become user-friendly with JWS [18].

S. Arivazhagan et.al. Identifying diseases from plants plays an important role in providing disease control measures to improve the quality and quantity of their products. Lung diseases are very useful as they reduce the control of large farms. Leaves are a great source of nutrients for plants, so it is important to identify leaf infections in a fast and accurate manner. This work includes a method based on in-depth studies, which can identify the leaf pathogens of different types of blue plants. Five different types of diseases, e.g.Anthracnose, Alternaria leaf spots, Leaf Gall, Leaf webber, Leaf burn of Mango. The identification was made from a database of 1200 images of beneficial and diseased mangoes. The proposed CNN model achieves 96.67% response to the diagnosis of leaf diseases in blue plants, proving their ability to apply in real time [19].

The work in [20] studied image dispensation or machine learning systems for fruit research schemes. Fruit massage refers to fruit massage based on size, shape, color, shape, body, or calyx. Color is greatest imperative feature of an image. This article presents changed colors. This article also discourses comparative investigation on machine learning methods, such as rules-based systems, vector machines, close neighbors, or artificial neural networks.

The work in [21] presents research on image processing and machine learning techniques that use leaf blades to identify plant diseases. First create a color conversion system, and set up an independent conversion method for the device in the color conversion system. Predictive techniques such as image reduction, image stabilization, image enhancement and histogram matching are proposed. It also briefly introduces distributed techniques such as boundary control and point detection, K-means modeling and Otsu single-phase distribution. Basic factors such as color, texture, morphology and edge are also discussed. Discussing classification based on the principles of neural networks.

The first two plants, the first grapes and the wheat, were used to identify plant diseases. A total of 185 images were analyzed, including 85 grape leaves and 100 large leaves. If the image resolution was not modified, the nearest neighbor method was used. Set up a median filter to replace the image. The K-means distribution is used [22].

Ensure monitoring and classification of plant diseases. All five diseases are treated as duck coke, silkworm, hair dye, latex coke and white. The RGB image is converted to CIE L * a * b * color conversion form. K-medium coating is used to remove large areas of the leaves. The green screen is detected and then wrapped in the original image. The affected areas (groups) are then converted to HSI colors to capture features. Matrix from the height and saturation of the HSI model is generated by means of centimeters of spatial resolution. Finally, neural networks are used for classification [23].

This section introduces image processing techniques to detect a variety of genetic disorders. In this section, 13 articles on surveillance of genetic disorders are reviewed, including standards such as image data. For the disease, as mentioned above, after oppression, a step is needed. Researchers used media censors to remove or reduce the noise in the images [24].

The median filter uses a 3X3 mask, which covers the entire image and replaces all the pixels with the median on the adjacent pixel. In some cases, applying a median filter removes or deletes the spreadsheet [25].

In [26], the authors used various techniques for image enhancement, such as an aging [27] histogram matching and Laplace filter.

In [28], the authors developed the green plane. They tried to improve the affected part of the leaf by removing the green part of the image, because when an infection occurs in the leaf it will damage the green.

In [29], to eliminate unnecessary processing, median filters and morphological operators are used.

This section [30] describes the machine learning techniques that classify cardiovascular disease. The following principles were used for the analysis: class type, format, input, and accuracy.

In this article, an effective way to describe diseases called Anthracnose and other symptoms. In recent years, with the increasing use of methods and techniques, computer vision and deep learning have gained popularity in the

ISSN- 2394-5125 VOL 7, ISSUE 11, 2020

classification of various diseases. Therefore, the Neural Convolutional Network (MCNN) has been proposed to classify blue leaves infected with cervical disease. This article was corrected by real data from Shri Mata Vaishno Devi University, J&K Katra, India, with a photo of a blue tree. Her list includes photos of healthy leaves and photos of infected leaves. The results show that, compared to the latter method, the proposed MCNN model has higher accuracy and higher classification capabilities [31].

This paper presented a model for the standard image-based image processing. Experimental results show that the model based on the principle has 129 leaflets, collected from the mango area under the control of the product and standard of Maeda University, and responds to 3 types of anesthesia (Anthracnose, Algae Staining, and Normal) with 89.92%. Experimental results show that the rule-based model can be applied to business diagnostic applications [32].

In this paper, MRKT-based strategies are used to calculate trajectories and histograms of plants such as leaves and fruit trees. These histograms and a series of indicators used by artificial neural networks led to improved Anthracnose recognition techniques, which appear as black areas in blue fruits and leaves. The results obtained using the MRKT test set showed a better response with up to 98% sensitivity [33].

In this paper we study healthy leaf litter and inoculated powdery mildew. Every 3 to 14 days after inoculation, leaflets were collected daily using a hyper spectral microscope which provides two ways to evaluate predefined sets of contexts [34].

The study of plants refers to the study of the visual features of specific plants. Plants, leaves, roots and discovering viruses or diseases or percentages are very effective in cultivation. Visual is a method used by many farmers to identify and diagnose plant diseases. It requires constant supervision and is found to be less useful on farms and giants. In addition, farmers do not receive localized disease [35].

In [36], the focus was on optimizing and evaluating the Deep Convolutional Neural Network for classification of image disorders with comparative comparisons of deep learning systems. The updated values include VGG 16, Inseption V4, ResNet with 50, 101, 152 and DenseNet with 121 layers.

For these two reasons, it is difficult to use the data compiled to train CNN (Convolutional Neural Network) for greater accuracy: small data size and inadequate CMD (cassava mosaic) Disease) CBB (infected with raw beans). Class disadvantages are a problem in machine learning and exist in many fields [37].

In this paper, the effects of four different transfer models based on deep neural networks in plant classification are analyzed in four datasets. Our findings suggest that transfer control can provide significant benefits for the identification of mature plants and can improve the low-cost fertilizer model [38].

This document presents a faster, better-performing ReCNN model for the Field-Based Field (FRP) model, which is designed to create an image that automatically and automatically and straight corn to varying degrees. Get ready for a sharp room in the complex work environment [39].

It is necessary to detect disease severity through a photo-based expert system, and to use 155 images for training and testing. As a result of the test, the overall classification rate was 95.48%. In addition, the proposed method shows that changing the size of the CNN depending on the image and the area to be seen can improve the success rate of R-CNN markers faster. Compared to the modern methods described in the previous literature, this method produces better results in terms of related groups [40].

Based on related tasks, this study compares and contrasts the application of different transfer mechanisms: (1) related tasks: corporate and public domain and 2) Network architecture: VGG16 (16) Layer), GoogLeNetBN (34 pages) and InceptionV3 (48 pages). Through experimentation, we show that pre-service training in firms can reduce the impact of their deep learning on more firm-based models, whereas pre-service training models ImageNet VGG16 demonstrates better performance in customizing new data [41].

Recently, mechanism knowledge has been used to analyze or diagnose plant poisons, and has shown imperative manners to homily this problem. Deep knowledge is one of auspicious new services in machine learning, or can make prodigious treads in the classification of plant pictures. In this certificate, CNN is used as one of central search tools for organization of plant images using the big data used in this document. On other hand, CNN has a hyper parameter difficult. So, the OLPOS algorithm is used to decrease CNN difficulties [42].

The act of defining stress and categorization of normal prices depends on human experts using visual symptoms as a classification method. Admittedly, this process is interrelated and vulnerable, which can lead to misunderstandings in decisions about pressure management [43].

ISSN- 2394-5125 VOL 7, ISSUE 11, 2020

In this work, based on the structure of a special Convolutional Communication Network, a comprehensive in-depth study designed to identify plant diseases through simple leaf imaging of healthy plants or ill. The model was trained using publicly available visual data of 87,848 images taken in cultivated land under laboratory conditions and actual conditions. It contains 25 plants in 58 different classes of plants, diseases, including healthy plants [44].

This article presents the most recent partitioning process for the detection and distribution of silver. By extending the R-CNN Mask to include HSV access data, there is an in-depth approach. Implementation of the development system was justified by the use of images obtained in the shade of gray under light conditions. The results show that combined with HSV data in RGB images can reduce the error rate (that is, increase the true number) and improve the performance of the mask distribution, which is consistent with harvesting of robot robots [45].

This article briefly introduces a variety of medical articles and images, and discusses existing models and applications of natural language processing, machine learning, computer vision and deep learning. In the field of medicine, as well as the issues and applications of natural medicine. Difficulties. Language publishing, machine learning and in-depth study of medical data [46].

Table 1 presents the summary of analysis of preprocessing and feature extraction applied in rice disease identification:

S. No.	Disease	Preprocessing	Segmentation	Edge Detection	Feature Extraction
1	RB,SB,BS	Digitization, Quantization	Thresholding	YES	Differences of two colour space, area, roundness Shape complexity,
2	RB	Weiner filter, Contrast enhancement using histogram equalization	K-mean	NO	Mean, standard deviation
3	BLB,SB,RB	Resolution reduction, remove noise using median filter	Otsu's method	NO	Area, perimeter, contrast, uniformity, entropy, inverse difference, linearity correlation, rectangularity
4	BS,SR,RB	NO	Otsu's method	YES	R,G,B mean and standard deviation of infected and background pixels
5	RB,BS	Mean Filter For Image Enhancement	Otsu's method	NO	Radial distribution of hue from centre to boundary of spot
6	BS,NBS, BLB,RB	Green plane HSV extraction, median filtering, linearization	Otsu's method	NO	Radial distribution of hue from centre to boundary of spot
7	BLB,RB,BS	Crop area of CIE LAB interest, resize image(50*50), Smoothing	K-mean	NO	Radial distribution of hue from centre to boundary of spot
8	Mango Leaf Diseases	Mean Filter For Image Enhancement	8-connected component Labelling	NO	Mean of H,S,V

Table 1: Summary of Analysis of Preprocessing and Feature Extraction

Table 2 summarizes the summary of research papers for detection of various diseases using deep learning models:

Reference	Public-ation Year	Purpose	Image Acquisition Technique	Deep Learning Architecture	Training Method	Dataset	No. of Images	Accuracy

Yang Lu, et.al.	2017	Rice Diseases Detection	RGB	CNN	Learning Algorithm	http://bcch.ahnw.gov.cn/Right.aspx	*500* images	95%
Hu Gensheng aet.al.	2019	Tea Leaf's Disease	RGB	SVM	Deep Learning	Plant VillageDataset	1500 Images	90%
Jayme Garcia, et.al.	2019	Plant Disease Detection	RGB	CNN	Transfer Learning	https://www.digipathosrep.cnptia.embrapa.br	*1567* images	85%
Artzai Picona, et.al.	2019	Multi Crop Plant Disease	RGB	CNN	Learning Algorithm	Plant Village Dataset	*1000* images	93%
Parul Sharma, et.al.	2019	Plant Disease Detection	RGB	CNN	Deep Learning Model	Plant Village Dataset	*600* images	95%
Karthik R., et.al.	2019	Tomato	CT images	CNN	Deep Learning	Plant Village Dataset	*1000* images	98%
S. Ramesh, et.al.	2019	Paddy Leaf Diseases	Color features	Optimized Deep Neural Network	Transfer Learning	Plant Village Dataset	*400* images	86.42%
Wan-jie Liang, et.al	2018	Rice Blast Disease	Color features	Softmax CNN	Back-Propagation Algorithm.	http://www.51agritech.com/zdataset.data.zip	*1000* images	95%
Pranali, et.al	2018	Leaf Disease Detection	RGB	CNN,ANN	Learning Algorithm	Plant Village Dataset	*2539* images	84%
S. Arivazhagan, et.al.	2018	Mango Leaf Diseases	RGB	CNN	Deep Learning	Plant Village Dataset	*1500* images	96.67%
Edna ChebetToa, et.al.	2018	Plant Disease Detection	RGB	CNN	Deep Learning algorithm	Plant Village Dataset	*1000* Images	99.75%
G. Sambasivam, et.al.	2019	Cassava Plant Diseases	RGB	CNN	Deep learning	Kaggle	10000 Images	93%
Aydin Kayaa, et.al.	2019	Plant Species classification	RGB	CNN	Transfer learning/Fine-tuning	Flavia, Swedish Leaf, UCI Leaf&Plant Village	57781 Images	90.17%
Mehmet Metin Ozguven, et.al.	2019	Sugar Beet Leaf Spot Disease	RGB	CNN/ Faster R-CNN deep learning model	Faster R-CNN	Plant Village Dataset	155 Images	95.48%
Longzhe Quan, et.al.	2019	Maize Seedling Detection	RGB	CNN/ Faster R-CNN	Deep Learning Model	Plant Village Dataset	20000 Images	97.71%
Ashraf Darwish, et.al.	2019	Plant Diseases Diagnosis	RGB	CNN	Deep Learning	Plant Village Dataset	*10000* Images	96.6
Basavaraj S. Anami, et.al.	2019	Paddy Crop Stresses classificatio	RGB	CNN	Deep Learning	Kaggel dataset	30000 Images	92.89%

		n						
Konstantinos P. Ferentinos	2018	Plant Disease Detection	RGB	CNN	CNN	Plant Village Dataset	87848 Images	99.53%
P. Ganesh,et .al.	2019	Orange Disease Detection	RGB, HSV	CNN	Deep Learning	Plant Village Dataset	*1500* Images	97.53%
Uday Pratap Singh, et.al.	2019	Mango Leaves Anthracnose Disease Detection	RGB	Multilayer CNN	RBFNN /MCNN	Shri Mata Vaishno Devi University, Katra, J&K Dataset	1070 images	88.39%

Table 2: Summary of the Research papers for different plant disease detection using Deep Learning models

Following graph shows the summary of various Deep Learning models used to detect different types of rice plant diseases & other crops:

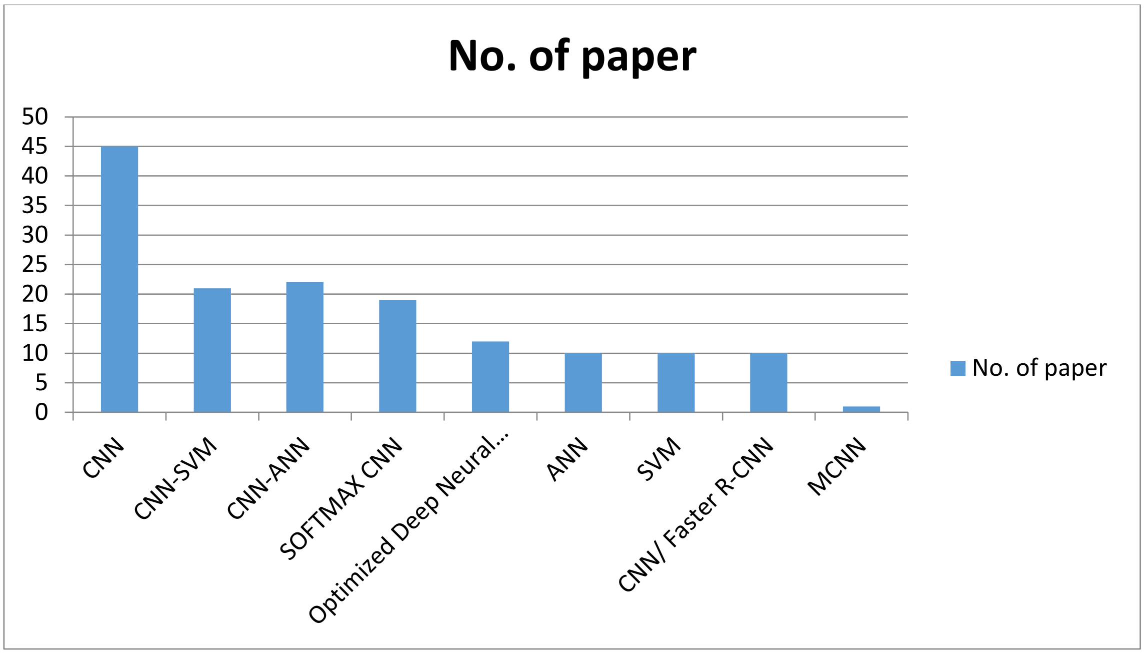

Figure 3: Summary of the DL models used to detect Different types of Rice disease

Following graph shows the summary of the papers for different types of diseases detection using Deep Learning models:

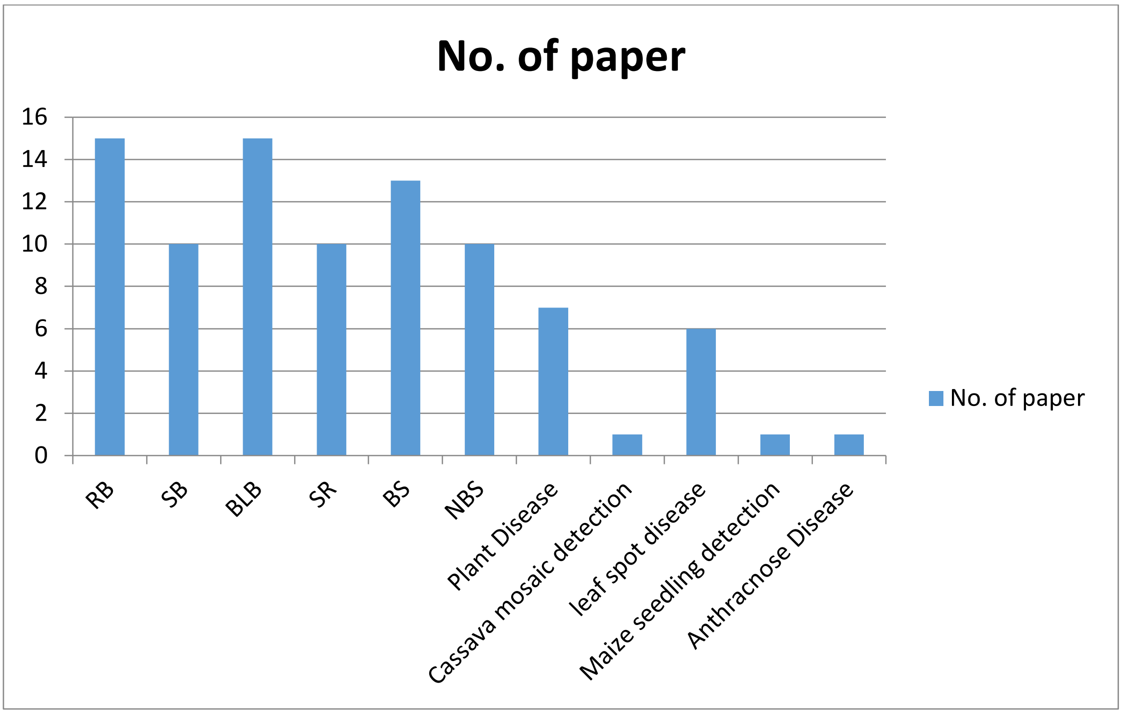

Figure 4: Summary of the papers for Different types of diseases detection using DL

IV. CHALLENGES & FUTURE DIRECTION

Given rice diseases, there are several techniques for detecting rice diseases such as edge detection, water separation, cluster, sale, active contour, threshold, etc. In all methods, the finding process remains more or less the same. The image must four main steps, counting processing, segmentation, feature extraction, or classification. The pre-treatment stage can be used for the following purposes in agricultural sciences (1) Identify diseases of leaves, fruits and stems of rice plants (2) Detect sick areas of rice plants (3) Find out the shape and color of rice plants and infected areas (4) Find a solution on rice diseases. The segmentation method includes dividing the image into regions of special importance, which is the most important technique for extracting image functions. The characteristic image properties represent texture, shape, color and motion-related properties. Classification is a classification result that depends on the selected features recently. Some research articles related to automatic detection of leaf disease have been proposed and various segmentation and feature extraction methods have been discussed, such as threshold stand, edge foundation, region based, wavelet transformation, Gabor's procedure. Main component filters and analysis (PCA). Segmentation and background removal techniques will be suggested for background removal. They use green pixel masks for color segmentation and then apply Otsu thresholding techniques to infected images. Another study briefly discussed image-based plant segmentation methods and discussed ten plant diseases, such as burning late, bacterial spots, fungal spots, sunburn, soot morning and evening, and late blight. Characteristics are the similarities, contradictions, energy and clusters that CNN uses to define shadows and their branches to determine the forms of illness. In light of the lack of existing research, we provide details on rice diseases, including preparation, distribution, exploitation, feature selection, Classification and its problems, benefits and disadvantages In addition, differences in the methods involved in improving detection and accuracy are included. Detailed comparisons are made with existing research.

In some literature reviews, we found that data availability is still limited. The proposed solution not only significantly increases the size of the image dataset, but also increases the diversity of the data, because the natural variation in each image is indirectly considered when dividing into smaller regions. This method also has some drawbacks, but in case of limited data availability it will naturally lead to more reliable results. Pre-processing the image before performing model training through machine learning will prove to be a valuable method of achieving high performance. To improve the recognition and the classification of rice plant diseases, any improved method can be used to achieve the best performance by reducing the false classification. Expand the dataset of rice disease, and establish a comprehensive tool for rice disease diagnosis system when the number of samples is not sufficient, data improvement methods are used to build good classifiers. By providing more images in the dataset and adjusting the parameters of the machine learning model, the classification accuracy can be further improved. However, obtaining optimal parameters for machine learning models remains a research challenge.

The attack of various pests can affect the growth of the main field crops, such as rice, wheat, corn, soya beans and sugarcane, and because of the different insect types the crops are reduced. There are several diseases that affect plants that can cause great damage to different economies and communities. It can even cause major ecological losses. Proper classification and identification of crop diseases and pests is a intricate task for farmers because they look early stages of crop growth. Therefore, it is best to diagnose plant diseases and insect pests accurately and in time to avoid causing such losses. If not given enough attention, rice diseases will cause heavy losses in agriculture. An automatic system that can provide early announcement of the disease can be established.

V. DISCUSSION

In this survey paper we have explored recent studies on detection of different types of rice plant diseases & various other plants/fruits diseases. 20 surveyed papers are related to Brown Spot disease detection, 10 studies are related to sheath blight disease classification, 15 are related to BLB detection, 13 are related to BS detection, 20 papers are related to NBS detection, 06 papers are related to various other types of plant diseases detection, 01 paper is related to Cassava mosaic detection, 01 paper is related to leaf spot disease detection & one of the paper is related to Maize seedling detection. 30 surveyed papers of different diseases detection, 16 studies are about the plant leaf diseases detection, 15 papers studies are about the segmentation to identify the shape of spot on plant leaf, 10 paper studies about the clustering techniques to find uniformity and shape measure of plant leaf. 05 surveyed papers of plant disease detection, 04 papers are related to the leaf segmentation method to classify the lesion of plant leaf, 05 papers studies are about to use the different segmentation method to discriminate the shape and intensity of lesion on plant, 10 studies are related to rice diseases detection using DL. 20 surveyed papers of Convolution Neural Network, 08 studies are about the transfer learning techniques of CNN, 20 studies are about the classification using learning algorithm. 15 surveyed papers of machine leaning, 15 papers studies are about the classification of disease using SVM classifier and 11 studies are about the classification of plant disease using Artificial Neural Network.

VI. CONCLUSION

In this survey paper we have explored recent studies on diseases detection & classification of various plants & fruits including rice, tea, mango, paddy leaves, cassava, sugar beet, maize seedling, orange etc. We have conducted detailed studies of a large number of papers covering the research results of various rice plant diseases and other different plants and fruits, and examined these articles according to important standards. These conditions include the size of the image data set, No. class (disease), processing, segmentation technique, classification type, classification accuracy etc.

In this survey paper we explored recent studies on detection of different types of rice & other plants diseases including Leaf Blast(LB), Brown Spot(BS), Sheath Blight(SB), Leaf scald(LS), Bacterial Leaf Blight(BLB), Leaf Spot Disease, Mango Leaf Diseases, Cassava Mosaic Detection using DL models. After examining these articles, we have concluded that many researchers have done excellent work in deep learning to detect rice diseases in the agricultural field. We also found that most researchers achieved greater accuracy by implementing deep learning, intricate neural network models to detect rice and other plant / fruit diseases. In some literature reviews, we found that data availability is still limited. This solution not only proposes to significantly increase the size of the image dataset, but also to increase the diversity of the data, because the natural variation in each image is indirectly considered when dividing into smaller regions. This method also has some drawbacks, but in case of limited data availability it will naturally lead to more reliable results. Pre-processing the image before performing model training through machine learning will prove to be a valuable method of achieving high performance. To improve the identification and classification of rice plant diseases, any improved method can be used to obtain the best performance by reducing misclassification. Expanding rice disease data sets and establishing comprehensive tools for rice disease diagnostic systems is still a good research challenge. When the number of samples is not sufficient, data improvement methods are used to build a good classifier. We can study other deep neural network architectures and make full use of deep learning algorithms to improve classification accuracy and improve the reliability and robustness of rice disease diagnostic systems. By providing more images in the dataset and adjusting the parameters of the deep learning model, classification accuracy can be further improved. However, obtaining the best parameters for deep learning models remains a research challenge.

REFERENCES

1. Wang H., Li G., Ma Z., & Li X,"Image Recognition of Plant Diseases based on Back-Propagation Networks". Proceedings of the 5th IEEE International Congress on Image and Signal Processing". 2012; p. 894-900.
2. M. Martineau, D. Conte, R. Raveaux, I. Arnault, D. Munier, et al, "A survey on image-based insect classification", *Pattern Recognition, Elsevier*, vol. 65, pp.273 – 284, 2017.

3. S. Phadikar, J. Sil, and A. K. Das, "Classification of Rice Leaf Disease Based on Morphological Changes," *International Journal of Information and Electronics Engineering(IJIEE)*, vol. 2, pp. 460-463, May 2012.
4. D. Groth and L. S. U. Agcenter, “Rice Disease Identification Photo Link.” “IRRI - Rice Science for a better world.” Nov-2015.
5. S. D. Khirade and A. B. Patil, “Plant Disease Detection Using Image Processing”, in International Conference on Computing Communication Control and Automation (ICCUBEA), IEEE, Pune, India, 2015, pp. 768- 771.
6. Suman T. and Dhruvakumar T., “Classification of paddy leaf diseases using shape and color features”, *International Journal of Electrical and Electronics Engineers* (IJEEE) vol. 07, Issue 01, pp. 239–250, Jan-June 2015.
7. P. L. Sahu, A. Singh and K. L. Sinha, "A Survey on Data Mining Techniques for Classification of Images", in International Conference on Mechanical, Electronics and Computer Engineering (ICMECE-2014), Raipur, India, vol. 2, Issue 1, pp. 65-70, 2015.
8. A. K. Singh, Rubiya A.&B. Senthil R., "Classification of Rice Disease Using Digital Image Processing and SVM Classifier" *International Journal of Electrical and Electronics Engineers (IJEEE)*, vol. 07, issue 01, Jan-June 2015.
9. J. Amara, B. Bouaziz, & A. Algergawy, “A Deep Learning Based Approach for Banana Leaf Diseases Classification”in International Conference on Database System for Business, Technology & Web (BTW), Stuttgart, Germany, published in Lecture notes in informatics (LNI) pp.79-88,March 2017, Bonn, Germany GesellschaftInformatik.
10. Yang Lu,Shujuan Yi,Nianyin Zeng, Yurong Liu,&Yong Zhang,“*Identification of Rice Diseases using Deep Convolutional Neural Networks*”, Neuro-Computing, 267, Elsevier, pp. 378-384, July 2017.
11. Genshenga Hu, HaoyuaWu, Yan Zhang &Mingzhu Wan“A Low Shot Learning Method for Tea Leaf’s Disease Identification”,“*Journal of Computers & Electronics in Agriculture, published by Elsevier”,* vol. 163, issue 7, extent 104852, 2019.
12. Jayme Garcia,ArnalBarbedo“Plant Disease Identification from Individual Lesions and Spots using Deep Learning”,“*Journal of Biosystems Engineering, published by Elsevier”,* vol. 180, pp. 96-107, April 2019.
13. ArtzaiPicon, MaximiliamSeitz,Aitor Alvarez-Gila, Patrick Mohnke, Amaia Ortiz-Barredo&JoneEchazarra, “Crop Conditional Convolutional Neural Networks for Massive Multi-Crop Plant Disease Classification over Cell Phone Acquired Images Taken on Real Field Conditions”, in “*Journal of Computers & Electronics in Agriculture, published by Elsevier”*, vol. 167, pp. 105093, Dec. 2019.
14. Parul Sharma, Yash Paul Singh Berwal&WiqasGhai“Performance Analysis of Deep Learning CNN Models for Disease Detection in Plants using Image Segmentations” in “*Journal of Information Processing in Agriculture, published by Elsevier”,*vol. 6, issue 4, Dec 2019.
15. Karthik R., Hariharan M. Sundar Anand, Priyanka Mathikshara, Annie Johnson, Menaka R. “Attention Embedded Residual CNN for Disease Detection In Tomato Leaves” in “*Journal of Applied Soft Computing published by Elsevier”,* vol. 86, Article 105933, 2019.
16. S. Ramesh, D. Vydeki “Recognition And Classification of Paddy Leaf Diseases using Optimized Deep Neural Network with Jaya Algorithm” in “*Journal of Information Processing in Agriculture, published by Elsevier”, vol. 6, issue 3,* Sep. 2019.
17. Wan-jie Liang, Hong Zhang, Gu-feng Zhang & Hong-xin Cao“Rice Blast Disease Recognition Using a Deep Convolutional Neural Network”, “*Scientific Reports - a Nature Research Journal”,* Article no. 2869, doi: 10.1038/s41598-019-38966-0,Feb. 2019.
18. Pranali K., Kosamkar K. Thenmozhi, Dr.V.Y.Kulkarni,KrushnaMantri“Leaf Disease Detection and Recommendation of Pesticides Using Convolution Neural Network”in Fourth International Conference on Computing Communication, Control & Automation (ICCUBEA), August 2018, Pune, India, 18617820, IEEE.
19. S. Arivazhagan, S. Vineth“Mango Leaf Diseases Identification Using Convolutional Neural Network”, in “*International Journal of Pure and Applied Mathematics, published by Elsevier”*, Vol. 120, issue 6,pp. 11067-11079, Aug. 4, 2018.
20. Md. Khalid Imam R., Naina Pal and Kamiya Arora “Clustering of Image Data Using K-Means and Fuzzy K-Means”in “*International Journal of Advance Computer Science and Applications*” volume 5, issue 7,pp. 160-163, 2014.
21. LeonardGianessi “Importance of Pesticides for Growing Rice in South and South East Asia”, International Pesticide Benefit Case Study for Crop Life Foundation, pp. 30–33, 2014, IEEE.
22. J.W.Orillo, J.D. Cruz, L. Agapito, P. J.Satimbre and I. Valenzuela, “Identification of Diseases in Rice Plant (Oryza Sativa) Using Back Propagation Artificial Neural Network",in 7th IEEE International

Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM), Palawan, Philippines, pp. 1-6, 2014.

23. Jayme Garcia and ArnalBarbedo, "Digital Image Processing Techniques for Detecting, Quantifying and Classifying Plant Diseases","*Springer Plus – a Springer Open Journal"*, vol. 2, pp. 1-12, 2013.
24. K. Majid, Y. Herdiyeni, and A. M. Rauf,"I-PEDIA: Mobile Application for Paddy Disease Identification Using Fuzzy Entropy and Probabilistic Neural Network",in International Conference on Advanced Computer Science and Information Systems (ICACSIS), Bali, Indonesia, pp. 403-406. IEEE, 2013.
25. R. Pandey, S. Naik, and R. Marfatia "Image Processing and Machine Learning for Automated Fruit Grading System: A Technical Review", in "*International Journal of Computer Applications"* vol. 81, issue 16, Nov. 2013.
26. A.Fakhri, A. Nasir, M.Nordin, A. Rahman and A. R.Mamat, "A Study of Image Processing in Agriculture Application under High Performance Computing Environment", in "*International Journal of Computer Science and Telecommunications"*, vol. 3, issue 8, pp. 16-24, Aug. 2012.
27. G. Maharjan, T. Takahashi, and S. H. Zhang "Classification Methods Based on Pattern Discrimination Models for Web-Based Diagnosis of Rice Diseases" in "*Journal of Agricultural Science and Technology"* vol. 13, issue 1, pp. 48-56, Nov. 2011.
28. H. Al-Hiary, S. Bani-Ahmad, M. Reyalat, M. Braik and Z. Alrahamneh "Fast and Accurate Detection and Classification of Plant Diseases using Machine Learning", in "*International Journal of Computer Applications"* Volume 17, issue1, pp. 31-38, March 2011.
29. Q. Yao, Z. Guan, and Y. Zhou, "Application of Support Vector Machine for Detecting Rice Diseases Using Shape and Color Texture Features" in International Conference on Engineering Computation, published by IEEE, pp. 79-83, 978-0-7695-3655-2, Hong Kong, China, May 2009.
30. Y. L. Nene, "Basmati Rice: A Distant Variety (Cultivar) of the Indian Sub-Continent" *Asian Agri-History, India*, vol. 2, issue 3, 1999.
31. Uday Pratap Singh, Siddharth Singh Chouhan, et.al., "Multilayer Convolution Neural Network for the Classification of Mango Leaves Infected by Anthracnose Disease", in "*International Journal of IEEE Access published by IEEE",* vol. 7, pp. 43721-43729, 2019.
32. Chutinan Trongtorkid Part Pramokchon "Expert System for Diagnosis Mango Diseases using Leaf Symptoms Analysis" in International Conference on Digital Arts, Media and Technology (ICDAMT) published by IEEE Xplore,**DOI:** 10.1109/ICDAMT.2018.8376496, 25-28 Feb. 2018, Phayao, Thailand.
33. S. B. Ullagaddi & S. Viswanadha Raju, "Disease Recognition in Mango Crop using Modified Rotational Kernel Transform Features" in 4th International Conference on Advanced Computing and Communication Systems (ICACCS), published by IEEE, ISBN: 978-1-5090-4559-4, DOI: 10.1109, 6-7 January 2017, Coimbatore, India
34. Alina Förster, Jens Behley, Jan Behmann, Ribana Roscher, "Hyper Spectral Plant Disease Forecasting using Generative Adversarial Networks" in IEEE International Geosciences and Remote Sensing Symposium DOI: 10.1109/IGARSS.2019.8898749, 2019.
35. Jobin Francis, Anto Sahaya Dhas D. & Anoop B. K. "Identification of Leaf Diseases in Pepper Plants using Soft Computing Techniques" in International Conference on Emerging Devices and Smart Systems (ICEDSS), published by IEEE Xplore, **DOI:** 10.1109/ICEDSS.2016.7587787, 4-5 March 2016, Namakkal, India.
36. Edna ChebetTooa , Li Yujian, Sam Njukia &Liu Yingchun,"Comparative Study of Fine-tuning Deep Learning Models for Plant DiseaseIdentification", in "*International Journal of Computers & Electronics in Agriculture, published by Elsevier"*,vol. 161, issue 1, pp. 272-279, 2019.
37. G. Sambasivam& Geoffrey Duncan Opiyo,"A Predictive Machine Learning Application in Agriculture: Cassava DiseaseDetection and Classification with Imbalanced Dataset using ConvolutionalNeural Networks", in "*Egyptian Informatics Journal published by Elsevier"*, March, 2020.
38. Aydin Kayaa, Ali SeydiKecelia, et.al. "Analysis of Transfer Learning for Deep Neural Network Based PlantClassification Models" in "*International Journal of Computers & Electronics in Agriculture, published by Elsevier"*,vol. 158, issue 3, pp. 20-29, 2019.
39. Mehmet MetinOzguven, Kemal Adem, "Automatic Detection and Classification of Leaf Spot Disease in Sugar Beet using Deep Learning Algorithms", in "*Physica A: Journal of Statistical Mechanics and its Applicationspublished by Elsevier"*, Vol. 535, article id. 122537, 2019.
40. LongzheQuan , Huaiqu Feng a, YingjieLv, Qi Wang,Chuanbin Zhang, Jingguo Liu&Zongyang Yuan "Maize Seedling Detection under Different GrowthStages and Complex Field Environments Based onan Improved Faster R-CNN", in "*International Journal of Biosystems Engineering, published by Elsevier"*,vol. 184, issue 8, pp. 1-23, 2019.

41. Sue Han Lee, HerveGoeau, Pierre Bonnet& Alexis Joly,"New Perspectives on PlantDisease Characterization Based on Deep Learning", in "*International Journal of Computers & Electronics in Agriculture, published by Elsevier"*,vol. 170, issue 3, 2020.
42. A. Darwish, D. Ezzat, A.E. Hassanien, "An Optimized Model Based on Convolutional Neural Networks and Orthogonal Learning Particle Swarm Optimization Algorithm forPlant Diseases Diagnosis", in "*International Journal of Swarm and Evolutionary Computationpublished by Elsevier",* vol. 52, issue 1, 2020.
43. B.S. Anami, N.N. Malvade and S. Palaiah, "Deep Learning Approach for Recognition and Classification of Yield Affecting Paddy Crop Stresses using Field Images", in "*International Journal of Artificial Intelligence in Agriculturepublished by Elsevier",* vol. 4, issue 1, pp. 12-20,2020.
44. Konstantinos P. Ferentinos"Deep Learning Models for Plant Disease Detection and Diagnosis", in "*International Journal of Computers & Electronics in Agriculture, published by Elsevier"*,vol. 145, issue 2, pp. 311-318, 2020.
45. P. Ganesh, K. Volle, T. F. Burks& S. S. Mehta,"Deep Orange: Mask R-CNN Based Orange Detection and Segmentation"in 6th IFAC Conference on Sensing, Control and Automation Technologies for Agriculture AGRICONTROL, published by Elsevier,vol. 52, issue 30, pp. 70-75, 4-6 December 2019, Sydney, Australia.
46. Agrawal, Shweta & Jain, Sanjiv, Medical Text and Image Processing: Applications, Issues and Challenges. 10.1007/978-3-030-40850-3_11, 2020.