Rice Disease Detection Using Deep Learning

V. Vanitha

Abstract--- Rice bacterial leaf blight, Rice sheath bight and rice blast are the commonly occurring pathology in rice. Early identification and accurate diagnosis can help to limit the spread of diseases and ensure the quality of crop. Automatic detection of the commonly occurring plant diseases are desirable to support farmers. This paper proposes an automatic plat disease identification approach using deep convolutional neural network. A dataset of 500 images of healthy and diseased samples were collected and the model is trained to identify the three common diseases on paddy. We have experimented with the convolutional neural networks to improve the accuracy for identification of rice diseases. The results show that we can effectively detect and recognize three classes of rice diseases best accuracy of 99.53% on test set.

Keywords--- Identification of rice diseases, Convolutional neural networks, Deep learning, Image recognition.

I. INTRODUCTION

Rice is the major food crop in India and across the globe. It is the primary staple food in many countries. It is affected by wide variety of diseases. Diseases on plants placed a major constraint on the production and major threat to food security. Hence, early and accurate identification of plant diseases are essential to ensure high quantity and best quality.

In recent years, number of diseases on rice plant and degree of harm caused has increased due to the variation in pathogen varieties, changes in cultivation methods and inadequate plant protection techniques. It is observed that the loss of rice crop due to pathogen varies from 26% to 52%.

There are several leaf diseases having various symptoms. It is difficult to identify the type and intensity of diseases by experienced farmers.

With the expertise and knowledge of experts, it is possible to identify the plant diseases to certain extend in small farms. This traditional method requires availability of specialists and should possess good knowledge. In several places, there is an issue of finding the experts. Secondly, the judgement can be of low accuracy.

Thirdly, it is a time consuming process. Hence, there is a need for an automated system to identify rice diseases.

In order to support the farmers with timely and quick remedy, and to improve the accuracy of plant disease identification, researches have been done on automatic plant disease classification using various machine learning algorithms including Support Vector Machine (SVM)(1-3) , Artificial Neural Networks (ANN) on variety of crops like wheat (4), maize (5), cotton (6). In plant disease identification using machine learning algorithms, the accuracy depends on feature segmentation, feature extraction and classification algorithm used.

Deep learning techniques have shown a great promise in image classification. In recent years, they have been used to analyse diseases of mango [7], apple [8], tomato [9], rice[10], wheat[11]. In most of the cases, they have used leaves or fruits to detect the diseases from the images. In many of these cases, they have used images from homogeneous backgrounds.

Moreover, in most cases, the datasets have been crawled from different internet sources. There are some fundamental differences regarding the pattern of diseases between rice plants and the above mentioned plants. First of all rice leaves are narrow in width and diseases can occur in any part of the leaves.

Second, in addition to leaves, the diseases and pests of rice plant can affect both stem and grain. Third, the healthy area and the affected area of the rice plants do not have any significant contrast in color.

All these factors make it extremely difficult to collect and label the affected rice plants and finally to recognize the correct disease or pest.

In this study, an automated rice disease identification system has been proposed using deep convolutional neural networks.

A summarised review of machine learning techniques employed for anomaly detection in rice plant is presented in Section 2.

The proposed system for detecting three commonly occurring diseases is detailed in Section 3. Section 4 analyses the experimental results. Conclusions are given in Section 5.

II. RELATED WORK

In the last few years, machine learning techniques have been extensively applied for disease detection in plants. Various machine learning algorithm utilized to detect diseases in rice plant has been presented in table 1.

Different classifiers were implemented depending on the morphological feature and data availability. K-Nearest Neighbour (KNN) is commonly used owing to its simplicity and robustness to noisy data.

However, the accuracy depends on the number of training data. Support vector machine with different kernel function have also been used to classify non-linear data as well.

The Support Vector Machine algorithm works well with erroneous data and yields high accuracy.

The other commonly used algorithm is Artificial Neural Network. It predicts with high accuracy if the combination of texture, shape, color and morphological feature are used. The optimization algorithm like Genetic algorithm and Rule based classifier are least

Manuscript received February 01, 2019
V. Vanitha, Vel Tech Rangarajan Dr.Sagunthala R & D Institute of Science and Technology, Avadi, Chennai, Tamil Nadu, India.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

commonly used as their solution depends on the input.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

Table 1: Related work on Rice plant disease detection

Author	images/ class	Types of classifier	Disease	Accuracy
[12]	50	NN	RB, SB, BS	85%
[13]	72	SVM	BLB, SB, RB	97.2%
[14]	50	SVM	BLB, BS & Leaf smut	88.87
[15]	Not specified	SVM	RB	82%
[16]	6	IF-Then Classifier	BS, SR, RB	75%
[17]	500	Bayes Classifier, SVM	RB, BS	68.1%
[4]	20	Back propagation Neural Network	BS	90%
[18]	50	Back propagation Neural network	BLB, BS, RB	100%
[19]	Not specified	Self-organizing map,neural network	BS, RB	92%
[20]	Not specified	Probabilistic neural network	BS, LB, RB	100%

(RB-Rice Blast;BS-Brown Spot; SB-Sheath Blight; LB-Leaf Blight; BS-Brown Spot; BLB-Bacterial Leaf Blight)

III. DESCRIPTION OF RICE DISEASES

The description about three commonly occurring diseases in rice plant has been given.

Leaf Brown Spot

Brown spot, shown in figure 1 is most common and cause most damage to the quality and quantity of productivity. It is a fungal infection that affects leaf, leaf sheath. The foliar lesions may appear as dark brown or black spots measuring 0.5 – 2.0mm in size. It may be in circular or oval in shape and looks like sesame seed. This infection affects the plant at all stages from seedling stage to maturity stage.

Figure 1: Leaf Brown Spot

Sheath Rot

This disease is caused by fungus affecting the leaf sheath enclosing the young panicles. It occurs after the flowering stage. The lesion affecting the leaf sheath show greying brown spots with dark brown edges and irregular in shape. It is shown in figure 2.

Figure 2: Sheath rot

Bacterial Blight

Bacterial blight is caused by bacteria results in wilting of seedling and drying of leaves. It causes water-soaked lesions at leaf margins, a few cm from the tip and spreading towards the leaf base. Length and width of the affected areas increase while colour changes from yellowish to light brown due to drying, shown in figure 3

Figure 3: Bacterial blight

IV. PROPOSED WORK

CNN Architecture

A CNN consists of an input layer and an output layer, as well as multiple hidden layers between them. The hidden layers basically consist of the Convolution layer, Pooling layer, Rectified Linear Unit, Dropout Layer and Normalization layers. The CNN architecture for the proposed method is shown in figure 4.

Convolution Layer

The training data (images of the diseased and healthy rice plant) was sent to input layer of CNN. The convolution operation is then performed on input samples; The input is convolved with filters called kernels, that is, a number of filters slide over the feature map of the previous layer, to produce output feature maps. The output of this layer is represented as

$$x_j^\lambda = \sum_{i \in M_j}^{1} x_i^{\lambda-1} * k_{ij}^\lambda + b_j^\lambda \quad (1)$$

where M_j is a set of input maps, b_j is bias term, k_{ij} represents the convolutional kernel. X_j represents the

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

output feature map and λ represents the layer.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

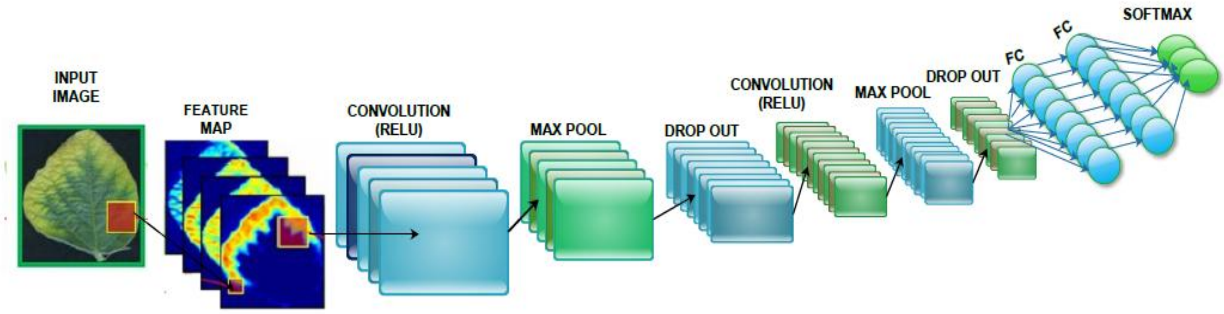

Figure 4: Convolution Neural Network Architecture

Max-Pooling Layer

The max-pooling layer performs nonlinear down-sampling on the input given. This layer reduces the size of the input feature maps but preserves the important feature. The function of the layer is to improve the generalization and to produce faster convergence. When the input feature map passes through this layer, max operation is applied which outputs maximum among the input as shown in equation 2. No learning takes place at this layer.

$$S_j = max_{i \epsilon R_j} a_i \qquad (2)$$

where Rj represents pooling region j, S denotes the output pooled feature maps

Softmax Regression

Softmax regression is employed as this proposed method has four classes. The Softmax function is given in equation (3)

$$h_\theta(x) = \frac{1}{1 + \exp(-\theta^T x)} \quad (3)$$

The model parameters θ are trained to minimize the cost function J(θ). The cost function J(θ) is given in equation (4).

$$J(\theta) = -\frac{1}{m}\left[\sum_{i=1}^{m}\sum_{j=1}^{k} 1\{y^{(i)}\}\log p(y^{(i)} = j|x^{(i)};\theta)\right] \quad (4)$$

The training pair is given as $\{(x^1,y^1),(x^2,y^2),\ldots\ldots.(x^m,y^m)\}$,

$i \in \{1,2\ldots.n\}$.

The input x belonging to the probability of class j is given as

$$p(y^i = j|x^i;\theta) = \frac{e^{\theta_j^T x^i}}{\sum_{l=1}^{k} e^{\theta_l^T x^i}} \quad (5)$$

ReLU Activation Function

The activation function determines the neural network data processing method, and influences the learning ability of the neural network model. This method follows every convolutional layer to introduce non linearity to the output. It changes the negative activation value to zero. The ReLU activation function formula is shown in Equation (6).

$$f(x) = \max(0, x) \qquad (6)$$

Dropout Layer

The basic idea of the dropout layer is that, the input elements with a certain probability are deactivated or dropped out such that the individual neurons are able to learn the features that are less dependent on its surroundings. This process takes place only during the training phase.

Fully Connected Layer

In the fully connected layer all the neurons of this layer are connected to all the neurons in the previous layer, thereby combining all the features learned by the previous layer to facilitate classification. This layer produces an N-dimensional vector at the output, where N is the number of classes.

Architecture of Convolution layer for Rice disease Identification

The complete process for plant disease recognition using deep CNN is described further in detail. The architecture for rice disease classification is shown in figure 5.

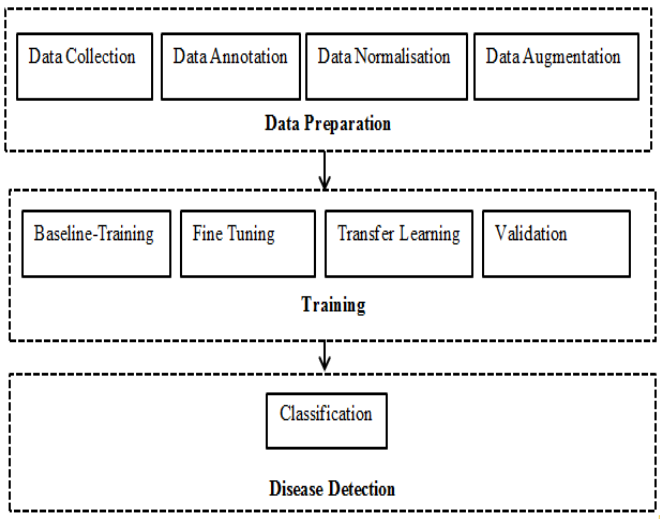

Figure 5: Proposed Method for Rice disease detection

Data Collection and Annotation

A proper dataset compromising images of diseased, healthy and dead leaves are required to improve the accuracy of prediction. A total of 350 images are collected from different sources, such as the Google websites and field. It included dif-ferent periods of occurrence of leaf diseases, which are divided into 3 different categories. There are 3 categories representing infected rice leaves and a category representing healthy leaves.

Rice diseases images database is created, which consists of a total of rice diseases and healthy images.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

Symptoms of different diseases are seen at different parts of the rice plant such as leaf, stem and grain. Bacterial Leaf Blight disease, Brown Spot disease occurs on rice leaf. Sheath Blight disease, Sheath Rot disease, So, we have considered all these parts while capturing images.

To prevent our model from being confused between dead parts and diseased parts of rice plant, we have collected enough images of dead leaf, dead stem and dead grain of rice plants. Images of the dead parts of the plant are considered in the class of healthy plant. We consider a total of three classes. The simultaneous occurrence of diseases has not been considered.

The 3 common rice diseases include rice brown spot (RBS), rice sheath rot (RSR), rice bacterial blight (RBB). The images are captured with digital color camera and images have resolutions of 5760 × 3840 pixels. The images have been captured in the rice field in real life scenario. The images have been captured in different types of backgrounds. In some images, the background is the surroundings of the field, and in some other images, the background is different colored papers. This makes the proposed model robust to any change in background. Weather conditions are also different at different times. Some images have been captured in overcast conditions, some have been captured in sunny weather.

Once captured, the images are assessed by human experts several times and each image is annotated with appropriate acronym. It is very important to label the images with 100% accuracy as they determine the accuracy of testing data. After data annotation, the data is segregated into three datasets. 70% of all the images are randomly chosen of each class and put them into training set. Similarly, another 15% of the images of each class are put into the validation set and the rest of the images are put into the test set. A Python script was created for dividing the data into three datasets, producing uniformly distributed pseudorandom numbers for the random selection of the images, thus the percentages of data augmented images and real images for all datasets (training, validation and testing) were kept similar. The number of images of each class in training set, validation set and test set are shown in Table 2.

Table 2: Number of images for training, validation and testing

Class	No. of images		
	Training set	Validation set	Test set
False Smut	260	3	4
Neck Blast	325	4	5
Brown Spot	491	6	8
Healthy [lant	1089	9	11

Data Augmentation

In order to make the trained model invariant to natural perturbations such as illumination changes, perspective variability and position changes, among others, deep learning based approaches rely on the availability of a very large amount of data presenting high variability, so that robust and unbiased model parameters can be learned. However, the size of the dataset needed to cover such variability precludes its use for common realistic applications. As the number of images are less, with the aim of increasing the training set size and its variability, image augmentation techniques are frequently applied. We have used random rotation of 45 degree,90 degree and 270 degree. We have used rotations of multiple of 90 degree at random. Convolutional neural network classification is not rotation invariant in general. So, these two transformations are of high importance, and they are assigned a high probability. Other transformations such as random distortion, shear transform, vertical flip, horizontal flip and skewing have also been used. The coloured images are transformed to gray scale. By data augmentation techniques the data set is increased which helps to overcome over-fitting issues

Training

After the process of data preparation, proposed CNN models are trained using back gradient-descent algorithm. It comprises two feed forward pass and one back propagation pass.

This algorithm aims to minimize a cost function that measures the total error of the model on the training set. The square error function is calculated using equation (7)

$$E^N = \frac{1}{2}\sum_{n=1}^{N}\sum_{k=1}^{C}(t_k^n - y_k^n)^2 \quad (7)$$

Where y^n_k is the output of layer K and t^n_k is the expected output of layer k for nth input. In the back propagation pass the error is passed from output layer to hidden layer and weights are updated according to equation(8)

$$\frac{\partial E}{\partial w^l} = x^{l-1}(\delta^l)^t \quad \text{and} \quad \Delta w^l = -\eta \frac{\partial E}{\partial w^l} \quad (8)$$

Three variations of training methods for each of the architectures is implemented..

Baseline training: In this method, we train all the network layers from scratch.

We randomly initialize all the layers and train them from scratch. This method of training takes a lot of time to converge but produces fairly good accuracy.

Fine Tuning: In this training method, the pre-trained image net weights of the convolution layers are kept intact. The weights of densely connected layers are initialized. All the layers are then trained until convergence.

Transfer Learning: In this method, we do not train the convolution layers of the CNN architectures at all. Rather we keep the pre-trained image net weights.

We only train the dense layers from their randomly initialized weights.

V. EXPERIMENTAL SETUP

In this process three CNN architectures namelyVGG16, ResNet50, InceptionV3 were used. The three CNN architectures are trained with three different training strategies. They used the same training parameters shown in Table 3.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

Table 3: CNN training Parameters

Parameter	Value
Basic Learning rate	0.01
Momentum	0.9
Batch size	25
Weight Decay	0.004
epoch	5000

VI. RESULTS

We have trained our dataset with three convolutional neural network architectures. They are - VGG16, ResNet50, InceptionV3. The performance of these CNN architectures for fine tuning , transfer learning and training from scratch is shown in Table 4.

Table 4: Performance of VGG16, ResNet50 and InceptionV3

CNN architecture	Train Method	Train Acc	Train Loss	Val Acc	Val Loss	Test Acc
VGG16	Baseline Training	0.943	0.175	0.981	0.081	0.958
	Fine Tuning	0.993	0.035	0.997	0.057	**0.962**
	Transfer Learning	0.991	0.131	0.877	0.638	0.832
ResNet50	Baseline Training	0.9914	0.011	0.9922	0.076	0.9876
	Fine Tuning	0.9956	0.01142	0.995	0.129	**0.9953**
	Transfer Learning	0.992	0.0243	0.9814	0.177	0.956
InceptionV3	Baseline Training	0.9992	0.139	0.989	0.0958	0.991
	Fine Tuning	0.9996	0.0022	0.995	0.082	**0.994**
	Transfer Learning	0.9988	0.004	0.753	1.074	0.745

It is evident that all architectures have given their best accuracy on test set when fine tune them from pre-trained imagenet weights. Moreover, test accuracy of the architectures when trained from scratch is comparable to the test accuracy of corresponding architectures when fine tuning them from imagenet weights. For example, the test accuracy of ResNet50 for fine tuning and training from scratch are 99.53% and 98.7% respectively. The plot for accuracy and loss for training and validation dataset of ResNet50 and InceptionV3 is shown in figure 6 and figure 7 respectively. In fine tuning, we start from imagenet pre-trained weights and then train the whole network on our dataset. So, it is easy to reach the global optimum. On the other hand, we do not train the layers of the original convolutional architecture in transfer learning. So, the model may not capture all the characteristics of the dataset. That is why, accuracy in transfer learning has been found to be lower compared to the other two training methods.

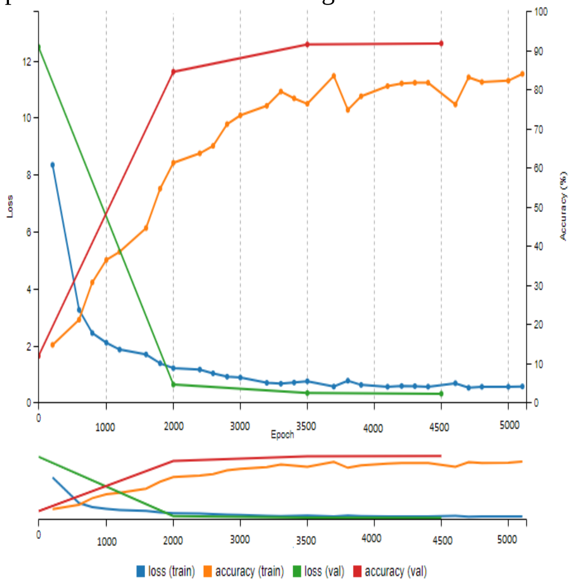

Figure 6: Training and Validation Plot for ResNet50

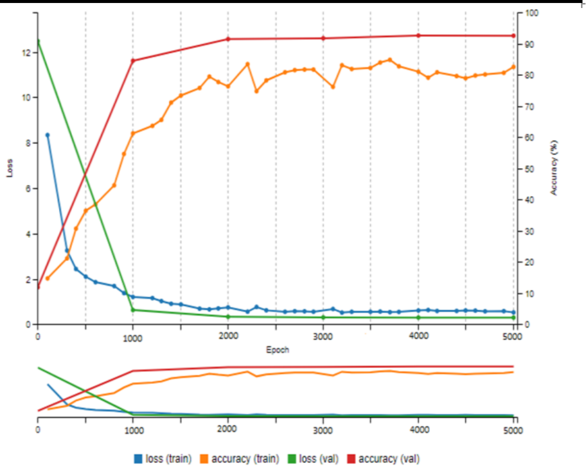

Figure 7: Training and Validation Plot for InceptionV3

From the results of Table, it is observed that the fine tuning is the most successful learning strategy in detecting rice plant diseases for three chosen CNN architectures. Also, it is evident that ResNet50 has a highest accuracy with 99.53% . Furthermore, VGG16, has lowest accuracy with 96.2%. The comparison of accuracy for these three architectures using three different learning strategy is shown in figure 8.

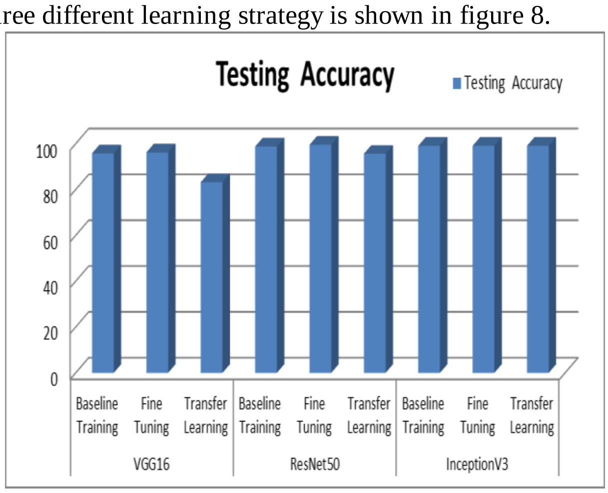

Figure 8: Accuracy plot for Test Dataset

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

VII. CONCLUSION

Though there are several methods in automated plant disease detection, it still lacks in efficiency and accuracy.. In addition, no commercial tools are available for accurate identification of plant diseases.In this paper, deep learning method was explored in order to automatically classify and detect rice plant diseases from leaf images. The developed model was able to detect leaf presence and distinguish between healthy leaves and 3 different diseases. Due to the absence of dataset for rice plant exclusively, a database for rice diseases were created and the images were labelled with the help of experts. Various augment techniques were used to extend the dataset. The dataset was trained with three CNN architectures. ResNet50 has achieved a high accuracy of 99.53% . In the future research, the types of diseases to be detected will be increased. Also we plan to implement other deep network models like deep Boltzmann machine and Faster RCNN (Regions with Convolutional Neural Network) to reduce the time and improve the accuracy.

REFERENCES

1. Gupta, T., 2017, 'Plant leaf disease analysis using image processing technique with modified SVM-CS classifier', *Int. J. Eng. Manag. Technol*, *5*, pp.11-17.
2. Es-saady, Y., El Massi, I., El Yassa, M., Mammass, D. and Benazoun, A., 2016,' Automatic recognition of plant leaves diseases based on serial combination of two SVM classifiers', In *2016 International Conference on Electrical and Information Technologies (ICEIT)* pp. 561-566.
3. P. B. Padol and A. A. Yadav, "SVM classifier based grape leaf disease detection," *2016 Conference on Advances in Signal Processing (CASP)*, Pune, 2016, pp. 175-179.
4. Liu, L. and Zhou, G., 2009, 'Extraction of the rice leaf disease image based on BP neural network', In *2009 International Conference on Computational Intelligence and Software Engineering* (pp. 1-3). IEEE.
5. Dhau, I., Adam, E., Mutanga, O., Ayisi, K., Abdel-Rahman, E.M., Odindi, J. and Masocha, M., 2018,'. Testing the capability of spectral resolution of the new multispectral sensors on detecting the severity of grey leaf spot disease in maize crop', *Geocarto international*, *33*(11), pp.1223-1236.
6. Shicha, Z., Hanping, M., Bo, H. and Yancheng, Z., 2007,' Morphological feature extraction for cotton disease recognition by machine vision', *Microcomputer information*, *23*(4), pp.290-292.
7. Arivazhagan, S. and Ligi, S.V., 2018. Mango Leaf Diseases Identification Using Convolutional Neural Network. *International Journal of Pure and Applied Mathematics*, *120*(6), pp.11067-11079.
8. Liu, B., Zhang, Y., He, D. and Li, Y., 2017,' Identification of apple leaf diseases based on deep convolutional neural networks' *Symmetry*, *10*(1), p.11.
9. Fuentes, A., Yoon, S., Kim, S. and Park, D., 2017, 'A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition', *Sensors*, *17*(9), p.2022.
10. Lu, Y., Yi, S., Zeng, N., Liu, Y. and Zhang, Y., 2017,' Identification of rice diseases using deep convolutional neural networks', *Neurocomputing*, *267*, pp.378-384.
11. Jin, X., Jie, L., Wang, S., Qi, H. and Li, S., 2018,' Classifying wheat hyperspectral pixels of healthy heads and Fusarium head blight disease using a deep neural network in the wild field', *Remote Sensing*, *10*(3), p.395.
12. Anthonys, G. and Wickramarachchi, N., 2009, ' An image recognition system for crop disease identification of paddy fields in Sri Lanka', In *2009 International Conference on Industrial and Information Systems (ICIIS)* (pp. 403-407). IEEE.
13. Yao, Q., Guan, Z., Zhou, Y., Tang, J., Hu, Y. and Yang, B., 2009, ' Application of support vector machine for detecting rice diseases using shape and color texture features', In *2009 international conference on engineering computation* pp. 79-83.
14. Maharjan, G., Takahashi, T. and Zhang, S.H., 2011,' Classification methods based on pattern discrimination models for web-based diagnosis of rice diseases', *Journal of Agricultural Science and Technology*, *1*(1), pp.48-56.
15. N. N Kurniawati, and S.Abdullah. "Texture analysis for diagnosing paddy disease." In International Conference on Electrical Engineering and Informatics, 2009. ICEEI'09., vol. 1, pp. 23-27. IEEE, 2009.
16. Singh, A.K., Rubiya, A. and Raja, B.S., 2015,' Classification of rice disease using digital image processing and svm classifier', *International Journal of Electrical and Electronics Engineers*, *7*(1), pp.294-299.
17. Phadikar, S., Sil, J. and Das, A.K., 2012,' Classification of rice leaf diseases based on morphological changes', *International Journal of Information and Electronics Engineering*, *2*(3), pp.460-463.
18. Orillo, J.W., Cruz, J.D., Agapito, L., Satimbre, P.J. and Valenzuela, I., 2014, 'Identification of diseases in rice plant (oryza sativa) using back propagation Artificial Neural Network', In *2014 International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM)* (pp. 1-6). IEEE.
19. Phadikar, S. and Sil, J., 2008, ' Rice disease identification using pattern recognition techniques', In *2008 11th International Conference on Computer and Information Technology* (pp. 420-423). IEEE.
20. Majid, K., Herdiyeni, Y. and Rauf, A., 2013, ' I-PEDIA: Mobile application for paddy disease identification using fuzzy entropy and probabilistic neural network', In *2013 International Conference on Advanced Computer Science and Information Systems (ICACSIS)* (pp. 403-406). IEEE.