

## Computer Vision For Predicting Unhealthy Region Of Rice Leaves - A Review

K. S. Archana and Arun Sahayadhas

*Vels Institute of Science, Technology and Advanced Studies, Department of Computer Science and Engineering, Chennai*

Rice (*Oryza sativa*) is a very important food crop of Indian overall agricultural economy. Moreover, it is the staple food of southern and eastern India. Since the consumption is more the rice plant has to be analyzed well with its diseases and proper disease control measures should be taken with rice otherwise it gives major economic loss and reduce grain quality. This paper reviews the importance of rice plant infection due to plant pathogen. In the last two decades the scientist draws the attention on automatic plant disease identification from visible symptoms due to the quick development of computer technology, it makes researchers to automatically identify the diseases in plant from early symptoms. This review summarizes completely different survey with numerous ways supported on colour conversion, segmenting the pigment, extracting the features and classifying the disease. Though advancement has taken place some of the challenges were still lacking. To overcome the problem, it concludes with intensive studies on the prediction and classification of rice plant diseases for each methodology.

### KEYWORDS

Crop disease, Computer vision, Segmentation, Feature extraction and classification

### 1. INTRODUCTION

Agricultural sector plays a strategic role in the process of Indian economic development. Today, India ranks second worldwide in agricultural production. Additionally, it contributes a major share within the gross domestic product (GDP) of the country and, therefore, the employees around 65% of the population. India's agriculture is composed of many crops; an accounting India is one in every of the world's largest producers of rice and is the most staple food of the people [1]. Therefore, to extend the productivity there should be good attention towards the crops. Several significant diseases are caused to the plant which made a dropout in cultivation of crops. Plant disease causes major economic loss in agriculture.

The rice crop is ravaged by 70 different diseases caused by various fungi, bacteria, viruses or nematodes. Numerous researchers have reported some common diseases, such as brown spot: bacterial leaf blight, blast, tungro and in rice leaves that hamper the growth of the plants [2,3]. Earlier research has shown that the strain in plants strictly depends on common characteristics of every illness, for instance in plants [4].

### 1.1 Characteristics of different symptom in infected rice plant

The diseases caused due to attack by fungi, virus, bacteria, bad weather condition, vitamin deficiency and improper observation. For example figure 1 shows a paddy leaves infected with numerous diseases, like brown spot is caused by plant pathogens, such as fungi and tungro by a combination of two viruses. Understanding the contrast between a sign and a symptom is key in identifying a rice disease.

Table 1 summarizes that few studies on rice plant in different characteristic of pathogens. Control of diseases is important for the study of various plant pathogens it could be a key in distinctive a plant disease [7]. When the plant gets the disease, the visual symptoms of the pathogen frequently amendment their colour, texture and shape. There are some diseases that don't have visible symptoms and furthermore the farmers to spot the disease from the early symptoms [8]. Earlier, the main approach of the expert used to predict the rice plant disease was naked eye observation of from the symptoms. Therefore, the disease will be known mechanically once the symptoms occur in leaves. A common approach, in this case, is the use of image processing techniques to predict the disease on time before it extends to the whole field. This study can explore computer vision technology to spot the disease from early symptoms with high accuracy as well as reduction of cost comparing with eye observation.

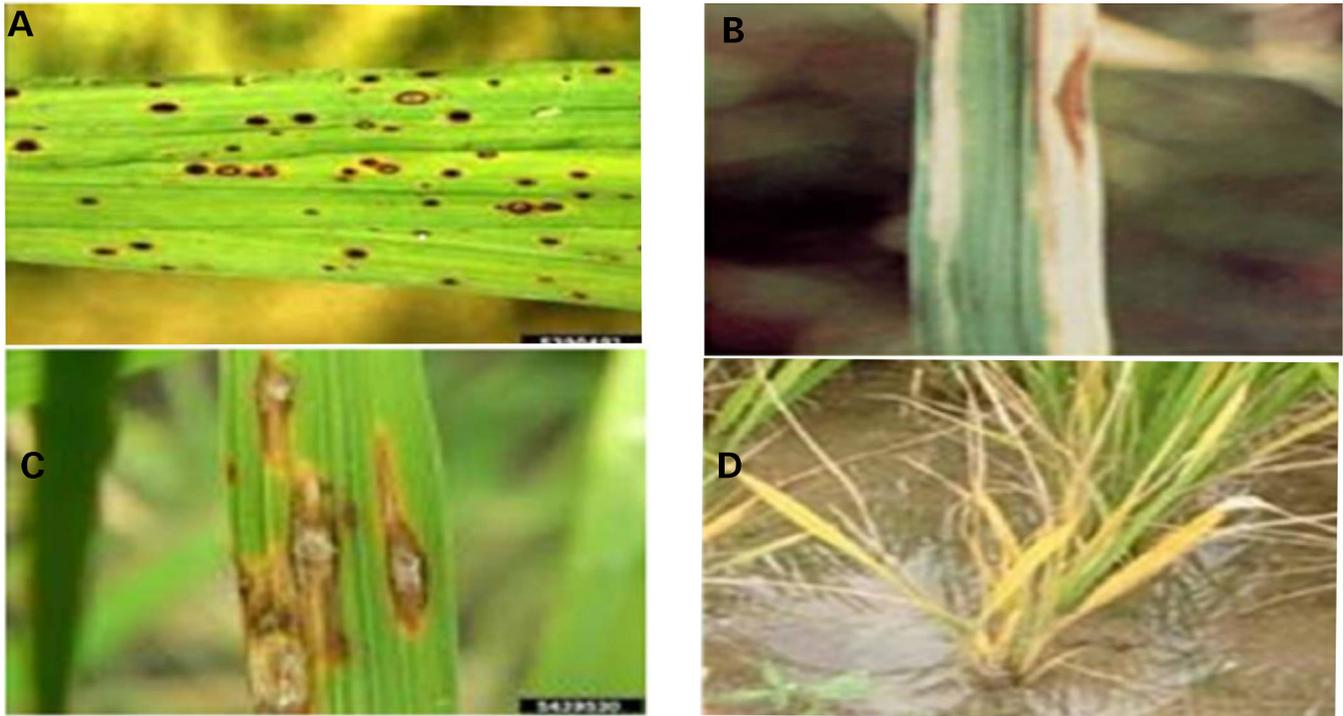


Figure 1. Example of diseased leaf image in rice plant: (A) leaf infected by brown spot, (B) bacteria leaf blight disease, (C) rice blast disease and (D) tungro

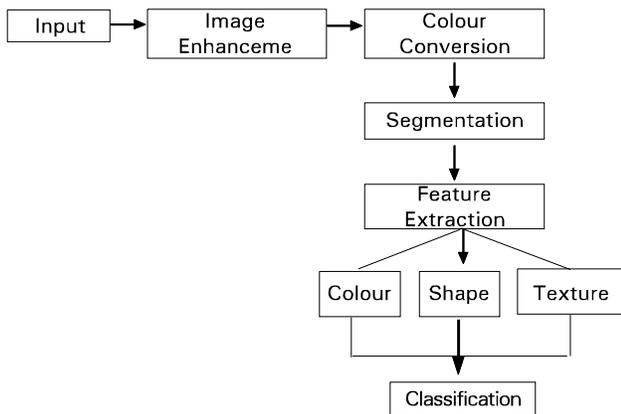


Figure 2. Methodologies for predicting disease in rice plant

### 1.2 The role of imaging techniques in plant pathology

The machine vision develops the tools to perform automatic image acquisition and analyze the image to classify the aspect [9]. It fundamentally includes the following three steps:

1. First, the image can be importing via image acquisition tools listed in figure 2.
2. Evaluate and manipulating the image for feature extraction.
3. The parameter reported by the previous method was used to differentiate the disease.

## 2. IMAGE BASED METHODOLOGIES FOR PREDICTING DISEASE IN RICE LEAVES

### 2.1 Image capturing device

Zhang presented a bacterial disease detection in citrus tree leaves [10]. The images were captured at different phases under various environments using Sony DSCP92 and Canon EOS350D. The size of the image was between 1280x960 and 3456x2304, the lesions' length is from 60x100 pixels. About 500 samples are collected from citrus phytopathologist to extract the disease. Two different types of data sets are used to predict the disease in *Alternaria alternata* and *Sclerotium rolfsii*. In the first one, scanned images are used to predict the disease and the images were captured by a mobile camera with high resolution of 1600x1200 with different megapixel with controlled lighting. Using a controlled light about 200 images were taken to identify the plant leaf disease. In both cases, the segmentation techniques were applied to diagnosis the disease and the result sent back to the user via SMS [11].

The method proposed by Li aims to identify the disease in grape leaves [12]. First, the images were captured by using a digital camera at a perpendicular angle. Reflectance characteristics between 2592x1944 with JPG format, 24 bitmap, were

**Table 1. Common diseases of rice plants with symptoms**

Reference	Types of diseases and their pathogens	Favourable conditions for pathogens	Disease cycles	Key diagnostic signs	Extent of yield loss
[5]	Bacterial leaf blight (bacteria <i>Xanthomonas oryzae</i> )	Tropical and temperate environments, strong winds and continuous heavy rains	During maturity, affecting all plant parts (leaf, neck and node)	Water-soaked and yellowish stripes in wavy margins. Severely infested leaves tend to dry quickly	Serious diseases yield a loss of upto 70%
[6]	Brown spot (fungus helminthosporiose)	Humidity (86'100%) and temperature at 16 and 36°C Nutrient-deficient soil	Nurseries and open fields	Dots as circles and oval spots. The seeds are sometimes shriveled and discolored	50% yield reduction in severe cases
[6]	Leaf blast (fungal <i>Pyricularia grisea</i> )	Temperature and soil problems	Seedling to maturity	Grayish dots, pinhead-sized with brown margins, increased drying of leaves and death	In case of a severe infection, the entire crop blasts, hence the name blast
[5]	Tungro (fungal <i>Pyricularia grisea</i> )	Leafhoppers transfer pathogens from one plant to another	During the vegetative phase and tillering stage	Yellow or orange-yellow, coloured spots on leaf begins from the leaf tip and extends to the lower leaf portion	For a severe infection, the yield loss is upto 100%

analyzed using taking photos. Then the image was compressed to 2592 × 1944 to 800 × 600 without changing the image. About 50 images were taken for future analysis to predict the disease under controlled lighting conditions. Therefore, to focus the image a macro mode used to cover the distance of the object and for illumination 3 mm LEDs and the 330 ohm resistor are used to capture the rice leaf for analyzing the image [13]. The device used to capture in this method was a digital camera with a high resolution of 3648 × 2736 and the focal length upto 16 mm. The area covered by the camera of the image was 30 m<sup>2</sup>. So, the pixel calculation is about 0.03 cm<sup>2</sup> and the camera is located 5 m above the ground for identification of maize plant growth Li megni.

## 2.2 Colour image analysis and segmentation

To enhance the image pre-processing techniques are applied to remove undesired distortion to enhance some features from image to focus the region of interest. Because the quality of image is very important to predict the diseases. According to the author presented a methodology to detect the plant disease with two main steps are as follows: first, conversion of the RGB images into HIS colour space to extract unique feature from the image symptoms using colour co-correlation method. After that, the extracted feature values are compared to feature library to identify and quantify the disease severity in various plants. Garcia presented a method to automatically identify the disease in plant leaves [8].

The algorithm begins with two stages of segmentation. First one, it separates the region of interest from the background to extract the features. Those features are submitted for final classification. Finally, the author concluded that the algorithm is capable of detecting the disease from a variety of symptom, being fast and more accurate.

The method proposed by Clément aims to identify the pathogens or pests from automated tool based on colour image analysis. The research divided their algorithm into two main steps: colour image analysis and segmentation. In the first step, the quantification of injury was identified with the help of the key parameters, leaf colour and leaf area. In a second step, the Otsu method was used to separate the pigment from the background. The authors concluded, the high reliability was drawn from the comparison of expert segmentation and the image analysis tool. Sena proposed a method to identify the fall armyworm damage based on segmentation techniques [14]. The tests were performed using the maize plant. In the following, the method starts with searching foreground and background pixel values using image histogram. Next, those values are used for median filter to reduce the noise due to segmentation errors. Finally, those values are submitted to differentiate diseased region and healthy tissue under special lighting conditions.

## 2.3 Feature extraction

Feature extraction plays an important role to transfer

**Table 2. Comparison study of feature extraction in rice plant**

Reference	Plant species	Type of Infection	Classes	Method	Main features
[18]	Cotton crops	Bacteria fungal	Southern green stink bug, bacterial angular ascochyta blight	I3a, I3b and channels	Texture and Shape
[14]	Maize plant	Insect	Fall armyworm	Binary filter	To differentiate the disease-damaged or non-damaged. The information are subdivided into number of blocks according to the features
[19]	Citrus leaves	Fungal	Melanose, greasy spot	CCM	Texture
[20]	Sugar beet	Fungal	Cercospora beticola Uromyces betae	GMM	Shape
[21]	Banana, beans lemon, rose	Bacteria fungal	5 types of disease	K mean	Colour, shape and texture
[22]	Brinjal leaves	Bacteria fungal viru	Cercospora leaf spot tobacco mosaic virus collar rot	K-means clustering	Mainly focusing on texture

**Table 3. A comparison of feature selection and feature extraction merits and demerits**

Method	Advantage	Disadvantage
Selection	Preserving data characteristics for interpretability	Take longer timing to measure
Extraction	Measuring more meaning information to classify the result	Loss of data

the input data into set of features. Those features were carefully chosen to increase the classifier efficiently and gives higher classification accuracy [15]. Table 2 summarize few studies on different methods using feature extraction. VijayaLakshmi proposed a method to automatically identify the leaf disease using texture, shape and colour on multiple plants [16]. The device used to capture the image was done by digital camera. According to the authors, the algorithm starts to extract colour, texture and shape features are extracted and analyzed using the six different features, such as mean, median, standard deviations, minimum and the maximum functions for selecting the parameter using kernel-based PSO. At last, those features were submitted for final classification. Barbedo tackled the problem of detecting and quantifying the leaf symptoms using conventional colour digital image in coffee leaves [23]. According to the author, the proposed method was analysed by mathematical operations and the colour channel, like  $L^*a^*b^*$  used to differentiate the shade and hue characteristics. Next, thresholding applied to mask the background pixel from foreground. The colour of the leaves was divided into different colour categories. Next, based

on the proposed methodology it automatically classifies the error report. Hence, the author stated that the method was very simple but reduction of errors due to pixel misclassification. According to authors, advantages and disadvantages between feature selection and feature extractions were differentiate in table 3.

## 2.4 Classification

Classification is a challenging task in image processing. Classification is identified via texture, shape and colour feature analysis. Based on database that contains predefined data that compared with the object to classify the appropriate category. The following methods were used to predict the type of disease from classification (Table 4).

## 2.5 Support vector machines

The system proposed by Reza aims to classify five different types of diseases from jute plants [24]. Image thresholding used to split the infected region from an image. In the following, some shape, texture and colour features were extracted. Next, those features are feed to support vector machine (SVM) for final classification. The accuracy level measured from the test images was 86%. Singh aims to detect and classify the disease in different plant leaves [21]. The algorithm starts by converting the image from RGB to HIS colour space to remove the undesired distortion from the image. Next, the infected region is segmented with the help of genetic algorithm. In the following, some colour, shape and texture features are extracted. The final classification was

**Table 4. Comparative study of classification techniques**

Reference	Culture	No. of image	Pathogen	Method	Accuracy
[18]	Banana and plantain crops	20	Yellow sigatoka disease (mycosphaerella)	SVM	90%
[14]	Maize plant	720	Fall armyworm	Damaged or non-damaged block classification	94.72%
[19]	Citrus leaves	40	Melanose, greasy spot	SAS discriminant analysis	95%
[20]	Sugar beet	30	Cercospora beticola Uromyces betae	KNN	91% 86%
[25]	Apple grapevine	2589	15 types of disease	CNN	96.3%
[21]	Banana, beans lemon, rose	90	5 types of disease	SVM	95.71%
[26]	Tobacco leaves	30	Tobacco mosaic virus	SPA-PLS-DA ELM and BPNN	98.33% and 96.67%, respectively
[27]	Maize	1,796	Northern leaf blight	CNN	96.7%

SVM - Support vector machine, KNN - K-nearest neighbours, BPNN - Back propagation neural networks, CNN - Convolution neural networks

performed by SVM. Compared to other approached SVM reported better result to 95.71%. Camargo proposed a method to identify three different types of disease in cotton plants. First, the diseased region was extracted using feature matching [17]. Next, following features are submitted to SVM for final classification. At last, the accuracy of 90% is achieved for 117 images. After classification, the types of diseases were identified.

### 2.6 Convolution neural networks

Sladojevi presents a methodology for deep neural networks based recognition of plant diseases using convolution neural networks (CNN) [25]. The proposed algorithm is based on CNN to differentiate the types of diseases and augmentation layer for mapping to differentiate the diseased leaves from healthy region. Those samples were submitted for final classification. At last, the overall accuracy of the trained model was 96.3%.

### 2.7 Probabilistic neural networks

A new approach was proposed by Shi to detect the disease in cucumber leaves using probabilistic neural networks (PNNs) classifier [28]. The proposed method tries to detect diseases through image feature extraction, such as 24 colour features, 4 shape features, 5 texture features and 5 meteorological data features. At last, those features were submitted to PNN for final classification. Finally, three types of cucumber leaves were classified with accuracy of 91.08%.

### 2.8 Artificial neural networks

Espinoza have presented a novel algorithm for early detection of two different diseases on sticky traps in plant leaves using artificial neural networks (ANN) [29]. The feature of the image was extracted according to shape, texture and colour. After extraction, those features submitted for final classification. The final classification was performed using ANN to differentiate *Bemisia tabaci* and *Frankliniella*.

## 3. RESULT AND DISCUSSION

It is more challenging to differentiate between the sign and symptom of the disease. Because illumination is very important to identify the characteristics of the symptom. Therefore, capturing the image of leaf should be very perfect to analyze environmental factors, such as overcast condition, time and the position of the sun. Another most difficult issue is the capturing angle that can also cause problems. In future, universal app should be build to detect the disease very easily and on an other hand it assists farmers improper identification and increase productivity. In future, the researchers can follow a selection of image preprocessing methods, that is unique histogram equalization can be used to speed up the preprocessing by using colour conversion methods. In some cases, the accuracy level was still lacking. Thus to increase more accuracy the database extension is improved and add more training samples were required to

predict the disease accurately. The performance of the algorithm can be improved to gain in better accuracy.

#### 4. CONCLUSION

The characteristics of the pathogens are basically responsible for the rice plant disease which destroys the leaf and reduce production. Hence, this present paper reviews and summarizes the survey of different image processing techniques for rice plant. The benefit of using image processing method is that the leaf diseases can be predicted at its early stage. Some of the common challenges are still lacking: standard dataset, exploring new features, optimizing classifier and user friendly app. Due to a large number of references, this paper provides a quick overview to underlying each of the solutions. Hence, a fast and accurate system is required to detect diseases on rice plant.

#### REFERENCES

1. Zhang, N. M. Wang and N. Wang. 2002. Precision agriculture – A worldwide overview. *Computer and Electronics in Agriculture*. 36(2-3):113-132. [http://doi.org/10.1016/S0168-1699\(02\)00096-0](http://doi.org/10.1016/S0168-1699(02)00096-0).
2. Keshavarz, K., et al. 2011. Genetic diversity of xanthomonas oryzae pv. oryzae strains from rice fields in Malaysia. *J. Plant Pathology*. 93:719-724.
3. Sastry, K.S. 2013. Plant virus and viroid disease in the tropics: Volume 1: Introduction of plant viruses and sub-viral agents, classification, assessment of loss, transmission and diagnosis. <http://doi.org/10.1007/978-84-007-6524-5>.
4. Barbedo, J.G.A. 2016. A new automatic method for disease symptom segmentation in digital photographs of plants leaves. *European J. Plant Pathology*. 1-16. <http://doi.org/10.1007/s10658-016-1007-6>.
5. Phadikar, S., J. Sil and A.K. Das. 2013. Rice diseases classification using feature selection and rule generation techniques. *Computers and Electronics in Agriculture*. 90:76-85. <https://doi.org/10.1016/j.compag.2012.11.001>.
6. Asfarian, A., et al. 2013. Paddy diseases identification with texture analysis using fractal descriptors based on fourier spectrum. International Conference on computer, control, informatics and its application: Recent challenges in computer, control and informatics (ICZINA). Proceedings, pp 77-81. <http://doi.org/10.1109/ICZINA.2013.6819152>.
7. Phadikar, S. and J. Sil. 2008. Rice disease identification using pattern recognition techniques. *ICCIT*. 25-27.
8. Garcia, J., A. Barbedo and L.V. Koenigkan. 2016. Science direct identification multiple plant diseases using digital image processing. *Biosystems Eng.*, 147:104-116. <https://doi.org/10.1016/j.biosystemseng.2016.03.012>.
9. Ravikumar, S., K.I. Ramachandran and V. Sugumaran. 2011. Machine learning approach for automated visual inspection components. *Expert Systems with Application*. <https://doi.org/10.1016/j.eswa.2010.09.013>.
10. Zhang, M. and Q. Meng. 2011. Automatic citrus canker detection from leaf images capture in field. *Pattern Recognition Letters*. <https://doi.org/10.1016/j.patrec.2011.08.003>.
11. Prasad, S., S.K. Peddoju and D. Ghosh. 2013. Unsupervised resolution independent based natural plant leaf disease segmentation approach for mobile devices. 5th IBM Collaboration Academia Research Exchange Workshop. <https://doi.org/10.1145/2528228.2528240>.
12. Li, G., Z. Ma and H. Wang. 2012. Computer and computing technologies in agriculture. V International Conference on Computer and computing technologies in agriculture. Proceedings, 370:151-162. <https://doi.org/10.1007/978-3-642-27275-2>.
13. Orillo, J.W., et al. 2014. Identification of diseases in rice plant (*Oryza sativa*) using back propagation artificial neural network. International Conference on Humanoid, nanotechnology, information technology, communication and control, environment and management (HNICEM) joint with 6th International Symposium on Computational intelligence and intelligent. <https://doi.org/10.1109/HNICEM.2014.7016248>.
14. Sena, D.G., et al. 2003. Fall armyworm damaged maize plant identification using digital images. *Biosystems Eng.*, 85(4): 449-454. [https://doi.org/10.1016/S1537-5110\(03\)0098-9](https://doi.org/10.1016/S1537-5110(03)0098-9).
15. Khalid, S., T. Khalil and S. Nasreen. 2014. A survey of feature selection and feature extraction techniques in machine learning. Science and information Conference. Proceedings, pp 372-378. <https://doi.org/10.1109/SAI.2014.6918213>.
16. Vijayalakshmi, B. and V. Mohan. 2016. Kernel-based PSO and FRVM: An automatic plant leaf type detection using texture, shape and colour features. *Computers and Electronics in*

- Agriculture*. <https://doi.org/10.1016/j.compag.2016.04.033>.
17. Camargo, A. and J.S. Smith. 2009a. An image-processing based algorithm to automatically identify plant disease visual symptoms. *Biosystems Eng.*, 102(1): 9-21. <https://doi.org/10.1016/j.biosystemseng.2008.09.030>.
  18. Camargo, A. and J.S. Smith. 2009b. Image pattern classification for the identification of disease causing agents in plants. *Computers and Electronics in Agriculture*. 66(2): 121-125. <https://doi.org/10.1016/j.compag.2009.01.003>.
  19. Pydipati, R., T.F. Burks and W.S. Lee, 2006. Identification of citrus disease using colour texture features and discriminant analysis. *Computers and Electronics in Agriculture*. 52(1-2): 49-59. <https://doi.org/10.1016/j.compag.2006.01.004>.
  20. Bauer, S.D., F. Korc and W. Forstner. 2011. The potential of automatic methods of classification to identify leaf diseases from multispectral images. *Precision Agriculture*. 12(3):361:377. <http://doi.org/10.1007/s.11119-c.9217-6>.
  21. Singh, V. and A.K. Misra. 2017. Detection of plant leaf diseases using image segmentation and soft computing techniques. *Information Processing in Agriculture*. <https://doi.org/10.1016/j.inpa.2016.10.005>.
  22. Anand, R., S. Veni and J. Aravinth. 2016. An application of image processing techniques for detection of diseases on brinjal leaves using k-means clustering method. International Conference on Recent trends in information technology (ICRTIT). <https://doi.org/10.1109/ICRTIT.2016.7569531>.
  23. Barbedo, J.G.A. 2014. An automatic method to detect and measure leaf disease symptoms using digital image processing. *Plant Disease*. 98(12):1709-1716. <https://doi.org/10.1094/PDIS-03-14-0290-RE>.
  24. Reza, Z.N., *et al.* 2016. Detecting jute plant disease using image processing and machine learning.
  25. Sladojevic, S., *et al.* 2016. Deep neural networks based recognition of plant diseases by leaf image classification. *Computational Intelligence and Neurosci.*, <https://doi.org/10.1155/20163289801>.
  26. Zhu, H., *et al.* 2016. Early detection and classification of tobacco leaves inoculated with tobacco mosaic virus based on hyperspectral imaging technique. pp 1. <https://doi.org/10.13031/AIM.20162460422>.
  27. DeChant, C., *et al.* 2017. Automated identification of northern leaf blight infected maize plants from field imagery using deep learning. *Phytopathology* PHYTO-11-16-041. <https://doi.org/10.1094/PHYTO-11-16-0417-R>.
  28. Shi, Y., *et al.* 2015. PNN based crop disease recognition with leaf image features and meteorological data. *Int. J. Agri. and Biological Eng.*, 8(4):60-68.
  29. Espinoza, K., *et al.* 2016. Combination of image processing and artificial neural networks as a novel approach for the identification of Bemisia tabaci and Frankliniella occidentalis on sticky traps in greenhouse agriculture. *Computers and Electronics in Agriculture*. 127:495-505. <https://doi.org/10.1016/j.compag.2016.07.008>.
  30. Rastogi, A., R. Arora and S. Sharma. 2015. Leaf disease detection and grading using computer vision technology and fuzzy logic. 2nd International Conference on Signal processing and integrated networks (SPIN 2015). <https://doi.org/10.1109/SPIN.2015.7095350>.