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Research paper

Contagious disease detection in cereals crops and classification as 'solid' or 'undesirable': an application of pattern recognition, image processing and machine learning algorithms

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Abstract

Illnesses in plants diminish the profitability and economy of a nation. Building up a robotization framework for location and arrangement of illnesses in tainted plants is a thriving exploration territory in the field of exactness farming. Oats crops are generally developed temperate product on the planet. Observing of these yields, particularly amid development, empowers us to lessen the harm at the soonest and exact conclusion of these maladies can diminish the sickness spread which will bring about ecological assurance and better return. By utilizing design acknowledgment and picture preparing calculations, the advancement of choice emotionally supportive network for plant security turns out to be more proficient. This paper shows a way to deal with recognize parasitic maladies in three oats trims in particular Maize, Rice and Wheat, utilizing design acknowledgment, machine-learning and picture handling strategies and arrange them as 'Solid' or 'Unfortunate'. It is finished by separating distinctive highlights like shading, shape and surface from the tainted areas of these plant pictures. 227 parasitic infection pictures of three oat crops i.e. Maize (71), Rice (92) and Wheat (64) were downloaded from different sources and considered in this exploration. Some solid pictures of same harvests were additionally downloaded for characterization reason. According to the calculation took after, after the pre-handling step, K-implies grouping strategy was utilized to section the unhealthy zone from the plant and in view of that three bunches of pictures (K=3) were created. Highlight extraction was performed trailed by include decrease utilizing diverse techniques lastly seven diminished highlights for maize, three highlights for rice and five highlights for wheat were chosen which brought about most extreme grouping precision of 87.60% for maize utilizing Naive Bayes classifier, 92.30% for rice utilizing both Naive Bayes and LibSVM classifiers, and 94.18% for wheat utilizing Multilayer Perceptron. On a huge scale, it can be finished up from the outcomes that Naive Bayes classifier gave best characterization exactness of 90.97% for all the three grain crops consolidated.

Keywords: *GLCM; Gabor; Classification; K-Means Clustering Segmentation; Naive Bayes.*

1. Introduction

Plant illness conclusion is a workmanship and also science. The acknowledgment of signs and side effects in ailing plant has been naturally visual and requires some judgment and utilization of logical strategies. Early data on edit wellbeing and malady recognition can help in controlling the infections through appropriate administration techniques, for example, vector control through pesticide applications, fungicide applications, and illness particular synthetic applications; and in this manner can help enhance the efficiency. Observing of wellbeing and recognition of ailments in plants is fundamental for supportable horticulture. Grain edits particularly Maize, Rice and Wheat are the among the most essential nourishment trims on the planet. They give exceptional returns per section of land when contrasted with most different yields [1]. When all is said in done grains speak to 60% of the calories and proteins devoured by people around the world. Additionally maize, rice and wheat together represented 89% of all oat generation worldwide in 2012, and 43% of all sustenance calories in 2009. For the most part, plant ailments found in farming/cultivation crops are sorted as contagious, bacterial, viral, nematodes and insufficiency, see Fig. 1. This constitutes five classes. Out of these five classes just parasitic infections of three oat crops i.e. maize, rice and wheat have been considered in this examination as these are the most noticeable and genuine sickness influencing the oat crops.

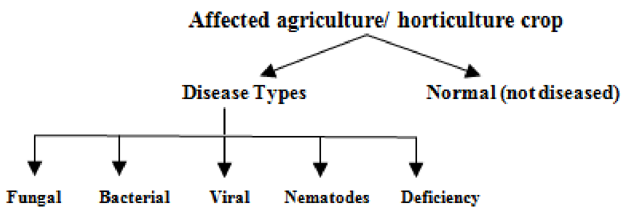

Fig. 1: Classification Tree.

The most widely recognized approach of the calculations which have been proposed so far in this field is nearly the same [2]-[14]. In the first place, unhealthy pictures are acquired utilizing cameras or scanners. Second, sickness spots are isolated or divided from the foundation. Third, the shape, shading or surface highlights are

separated. At last, characterization techniques, for example, neural systems, Bayesian classifier strategy [15], K-closest neighbor [16], Support vector machine [17], are utilized to group plant ailment pictures.
In this investigation, the contagious maladies considered for maize, rice and wheat crops (leaf, stem) are appeared in Table 1.

Table 1: Fungal Diseases of Maize, Rice and Wheat Crops (Leaf, Stem)

Fungal diseases of Maize	Fungal diseases of Rice	Fungal diseases of Wheat
Anthracnose leaf blight	Alternaria leaf spot	Alternaria leaf blight
Common corn rust	Brown spot	Leaf rust
Downy mildew of corn	Leaf scald	Powdery mildew
Eyespot	Narrow brown leaf spot	Stem rust
Gray leaf spot	Rice leaf blast	Stripe rust
Northern corn leaf blight	Sheath blight	Tan spot
Southern corn leaf blight	Sheath rot	-
-	Sheath spot	-
-	Stem rot	-

2. Materials and methods

In this examination, aggregate of 121 pictures of maize (Healthy=50 and Unhealthy=71), 143 pictures of rice (Healthy=51 and Unhealthy=92) and 86 pictures of wheat (Healthy=22 and Unhealthy=64) have been downloaded from different online sources.

2.1. Image dataset

The examination considered 227 contagious pictures (altogether) of maize, rice and wheat crops (test pictures are demonstrated as follows) for acknowledgment and order reason. The sources from where they were acquired are specified underneath:

i). http://www.ipmimages.org/. The determination of these pictures is 768 * 512 with Bit profundity 24 and all in JPEG design.
ii). https://www.google.co.in/. The determination of these pictures isn't settled with Bit profundity 24 and all in JPEG organize.
iii). Some sound pictures of wheat trim were gotten from University of Agricultural Sciences, Dharwad, India.

Every one of the pictures are best of their determination influenced with less commotion. The picture securing, pre-preparing, division calculations and highlight extraction were actualized in MATLAB 2015a. The greater part of information mining related errands like element determination and order were actualized in WEKA 3.9 [18]. Some contagious infection pictures of maize, rice and wheat crops are appeared in Fig. 2.


Anthracnose leaf blight in maize


Gray leaf spot in maize


Alternaria leaf spot in rice


Rice leaf blast


Stripe rust in wheat


Stem rust in wheat

Fig. 2: Sample Images of Some Unhealthy Cereal Crops.

2.2. Proposed methodology

The piece outline of the proposed work is appeared in Fig. 3. The means engaged with the proposed approach comprise of the picture database gathering, pre-preparing of those pictures, division utilizing K-implies bunching based shading division system, include extraction utilizing GLCM [19], Gabor [20],[21] and shading highlight extraction, include diminishment and choice, and after that at last characterization into solid and unfortunate harvest. Right off the bat, a few pictures were utilized for preparing the model and different pictures were utilized as test pictures to check the exactness of the outcomes. 10-overlay cross approval strategy was utilized to prepare the order show. The depiction of each piece is given in the following segment.

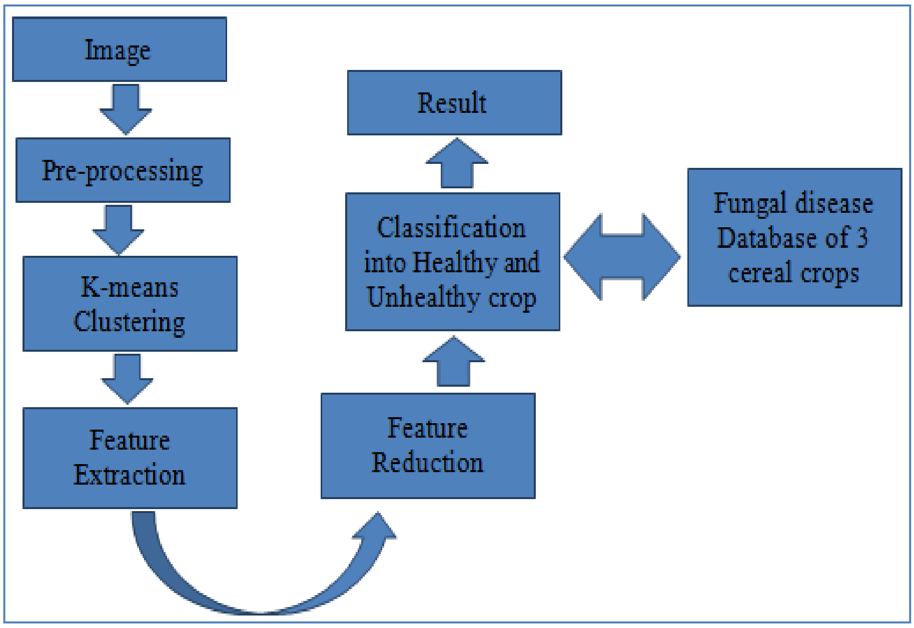

Fig. 3: Block Diagram of the Proposed Approach.

2.3. Algorithm proposed

The calculation in Table 2, which is named (FD2C3) according to its highlights, has been connected to complete this investigation.

Table 2: Fungal Disease Detection and Classification Algorithm for Cereal Crops

FD^2C^3 (Fungal Disease Detection and Classification in Cereal Crops) Algorithm:

1. First the unhealthy segment of the grain edit picture is trimmed to 200*200 size utilizing a trimming rectangle and spared to a particular envelope.
2. Then the edited picture is sifted utilizing a Median channel of size 3*3.
3. Use K-Means Color Image Segmentation:
   i. Convert the picture from RGB to L*a*b* Color Space.
   The L*a*b* space comprises of an iridescence layer 'L*', and chromaticity-layer 'a*' and 'b*'. All the shading data is in the 'a*' and 'b*' layers.
   ii. Classify the hues in a*b* colorspace utilizing K-implies bunching with K=3. Since the picture has 3 hues (Colored Images), make 3 bunches. Name every pixel in the picture from the K-Means comes about.
   iii. Measure the separation utilizing Euclidean Distance Metric.
   iv. Generate pictures that fragment the picture by shading.
   v. Select the fragment which contains the illness.
4. Next, highlights from the divided bunched picture have been separated:
   i. Extract the nine shading highlights in view of two techniques: Color Moments and Color Histograms.
   ii. Convert to grayscale if picture is RGB.
   iii. Generate the Gray Level Co-event Matrices (GLCMs), trailed by extraction of 22 Haralick (Texture) highlights from the ailment influenced locale. These are as per the following with their recipes:-
   a. Autocorrelation
   b. Contrast
   c. Correlation1
   d. Correlation2
   e. Cluster Prominence
   f. Cluster shade
   g. Dissimilarity
   h. Energy
   i. Entropy
   j. Homogeneity1
   k. Homogeneity2
   l. Maximum likelihood
   m. Sum of squares
   n. Sum normal
   o. Sum difference
   p. Sum entropy
   q. Difference difference
   r. Difference entropy
   s. Information measure of correlation1
   t. Information measure of correlation2
   u. Inverse contrast standardized
   v. Inverse contrast minute standardized
   iv. Similarly, six Size and Shape highlights from the infection influenced district are removed. These are:-
   a. Area
   b. Perimeter
   c. Equivdiameter
   d. MajorAxisLength
   e. MinorAxisLength

f. Roundness

v. Next, another surface highlights i.e. Gabor Features are extricated utilizing a 5*5 channel and 0.3, 0.4, 0.5 frequencies at different edges like 0, 45, 90 and 135 degrees bringing about 12 Gabor separated pictures. After that mean and standard deviation of every 12 pictures are ascertained bringing about 24 highlights.

5. Next, all these 61 highlights are put away in an exhibit.
6. Lastly, order utilizing LibSVM, Decision Tree, Adaboost, Simple Cart, Naive Bayes and Multilayer Perceptron has been utilized to choose the best chose and diminished highlights utilizing Weka tool.

The point by point portrayal of each progression connected to all the three sorts of oat crops is clarified underneath:

2.3.1. Image pre-processing

The picture informational index utilized for experimentation in this investigation was pre-handled as the greater part of the part in the picture was unimportant. To enhance the nature of the picture, pre-handling steps were connected over the picture. As a matter of first importance for lessening the computational weight and institutionalizing the picture determination, picture was edited and diminished to 200 x 200 size (containing a large portion of the infected part) utilizing a trimming rectangle. To expel the undesirable clamor from the picture, it was separated utilizing a middle channel of size 3*3.

2.3.2. Segmentation of disease spots

For obtaining the disease spots clearly in the cereal crop we have used K-means clustering segmentation algorithm based on spot color and outline to segment the disease spot area from the cereal crop. Fig. 4 shows the implementation of K-means clustering segmentation on a sample diseased maize crop.

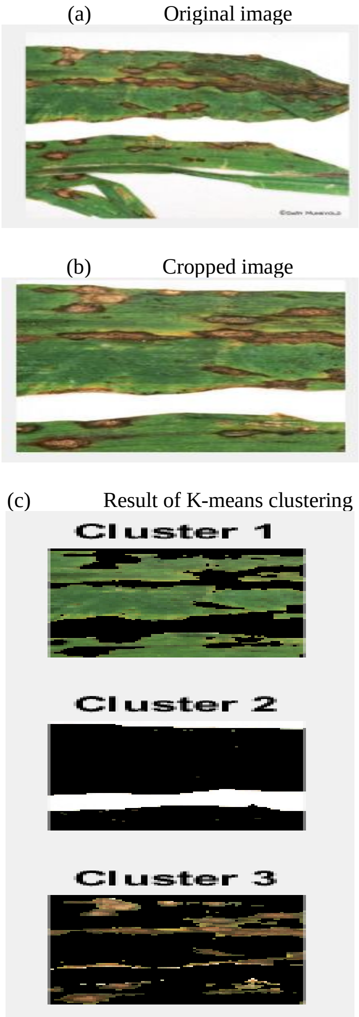

Fig. 4: Output of K-Means Clustering on A Sample Diseased Maize Image.

In this figure, in the wake of applying pre-handling and K-implies grouping calculation, three bunches were framed in which bunch 3 contained the genuine Region of Interest (ROI) i.e. the real territory influenced with parasitic illness in a maize edit.

2.3.3. Feature extraction in cereal crops

As clarified in the calculation FD2C3, add up to 61 highlights (falling in the classification of surface, shading and shape highlights) were separated in this examination. Utilizing them a database of highlights of size 350 x 61 for 350 pictures (121 maize, 143 rice and 86 wheat) was readied. The subtle elements of every one of these highlights are:

a) Texture Features (GLCM and Gabor)

In complete 22 GLCM highlights were removed some of whose conditions are given in Eq. 1-6

1) Autocorrelation (autoc1)

$$=\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}(p_x-\mu_x)(p_y-\mu_y)/\sigma_x\sigma_y \quad \text{(Eq. 1)}$$

2) Contrast(contr2)

$$=\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}p(i,j)\,(i-j)^2 \quad \text{(Eq. 2)}$$

3) Cluster Prominence (cprom5)

$$=\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}p(i,j)\left(i+j-\mu_x-\mu_y\right)^4 \quad \text{(Eq. 3)}$$

4) Cluster Shade (cshad6)

$$=\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}p(i,j)\left(i+j-\mu_x-\mu_y\right)^3 \quad \text{(Eq. 4)}$$

5) Energy (energ8)

$$=\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}p(i,j)^2 \quad \text{(Eq. 5)}$$

6) Entropy (entro9)

$$=-\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}p(i,j)\log(p(i,j)) \quad \text{(Eq. 6)}$$

In the above conditions G is the quantity of dark levels in a picture, p is alluded as GLCM, μ is the mean estimation of p, μ_x and μ_y are the methods for p_x and 〖p〗_y, σ_x and σ_y are standard deviations of p_x and p_y, p_x is the ith passage in the network acquired by summing the lines of p(i,j). Gabor separating is a change based technique that computes the surface data from a picture as a reaction picture. Gabor channel is fundamentally a Gaussian (with changes Sx and Sy along x' hub and y' hub separately) balanced by an intricate sinusoid (with focus frequencies U and V are comparing to x' hub and y' pivot individually) depicted by the accompanying conditions:

$$G(x,y,\theta,f)=e^{\left(\left[-1/2\left\{\left(\frac{x'}{Sx'}\right)^2+\left(\frac{y'}{Sy'}\right)^2\right\}\right]*\cos(2*pi*f*x')\right)} \quad \text{(Eq. 15)}$$

Where

$$x'=x*\cos(\theta)+y*\sin(\theta)\text{ and} \quad \text{(Eq. 16)}$$

$$y'=y*\cos(\theta)-x*\sin(\theta) \quad \text{(Eq. 17)}$$

In Eq. 15-17, x and y are the directions of a picture I, Sx and Sy are the fluctuations along x' hub and y' hub separately, f is the recurrence of the sinusoidal capacity and θ is the introduction of Gabor channel. The span of every Gabor channel is set consistent at 5x5 as indicated by the divided picture of size 200x200. 12 Gabor channels along the four introductions (0°, 45°, 90°, and 135°) utilizing three focus frequencies (1/λ) were convolved. Introduction changed from 0 to 3π/4 (venturing by π/4) and recurrence fluctuated from 0.3 to 0.5 (venturing by 0.1).

b) Shape Features

Size and shape highlights of a picture assume an essential part for ID. Visual highlights of a protest are called its shape attributes. Different size and shape highlights of general materialness incorporate region, edge, sphericity, roundness, circularity, minute invariants and so on. In this examination, six size and shape highlights have been viewed as: Area, Perimeter, Equivdiameter, MajorAxisLength, MinorAxisLength and Roundness.

c) Color Features

Shading is a critical element for portrayal of a picture as it is does not differ as for scaling, interpretation and turn of the picture. In this examination, we have separated shading highlights of HSV pictures in light of the fact that RGB shading space is influenced by light and point of the picture caught, so there is a requirement for change into HSV shading space. Add up to 9 shading highlights have been removed in this work, which are sorted into two primary classes i.e. shading minutes and Color Histograms as appeared in Table 3.

Table 3: Color Features

Color moments	Mean_h Variance_h	Mean_s Variance_s	Mean_v Variance_v
Color Histogram	mhvalues	msvalues	mvvalues

2.4. Feature reduction

Different component lessening techniques were utilized in this examination like CFS (Correlation based Feature Selection) [22] strategy utilizing best to begin with, PCA, data pick up and so on. Out of every one of these, CFS with best first technique gave the most elevated grouping precision to all the three yields (maize, rice and wheat) with lessened best highlights seven if there should arise an occurrence of maize, three for rice harvests and five for wheat trim individually. The best diminished highlights for all the three yields are appeared in Table 4.

Table 4: Best Reduced Features of Maize, Rice and Wheat Crops

Cereal crops	Maize	Rice	Wheat
Reduced Features from 61 extracted features	7 features: i. Cluster Shade ii. Maximum probability iii. Mean_h iv. Variance_h Color moments v. Mean_s vi. mhvalues vii. msvalues Color histogram	3 features: i. Mean_h ii. Mean_s iii. mhvalues	5 features: i. Difference entropy ii. Mean_h iii. Variance_h iv. mhvalues v. mvvalues

2.5. Classification

The last advance i.e. order of the grain trim into two classes-sound and undesirable was performed utilizing information mining apparatus Weka 3.9. We have utilized six classifiers i.e. Choice Tree (J48), Simple Cart, Adaboost, Multilayer Perceptron, Support Vector Machine (LibSVM) and Naive Bayes classifier in this progression. The motivation to pick just these six classifiers is a result of the way that these are the best classifiers in the field of horticulture. The execution of every classifier was contrasted and the other. The outcomes are appeared in the following area.

3. Results

In the wake of removing the right highlights it is required to order the harvests in both of the two classifications i.e. 'Sound' in the event that it has no parasitic infection and 'Unfortunate' on the off chance that it is influenced with any of the contagious illness as specified in Table 1. Table 5 and Fig. 5 demonstrate the similar examination of different classifiers on the decreased highlights separated from maize, rice and wheat.

Table 5: Comparison of Classifiers for Three Cereal Crops

Classifier used	Classification accuracy (in %)			
	Maize	Rice	Wheat	All crops combined
Naive Bayes	87.60	92.30	93.02	90.97
LibSVM	82.64	92.30	88.37	87.77
Multilayer Perceptron	81.81	91.60	94.18	89.19
Adaboost	83.47	90.90	88.37	87.58
J48	77.68	83.91	83.72	81.77
Simple Cart	82.64	90.90	84.88	86.14

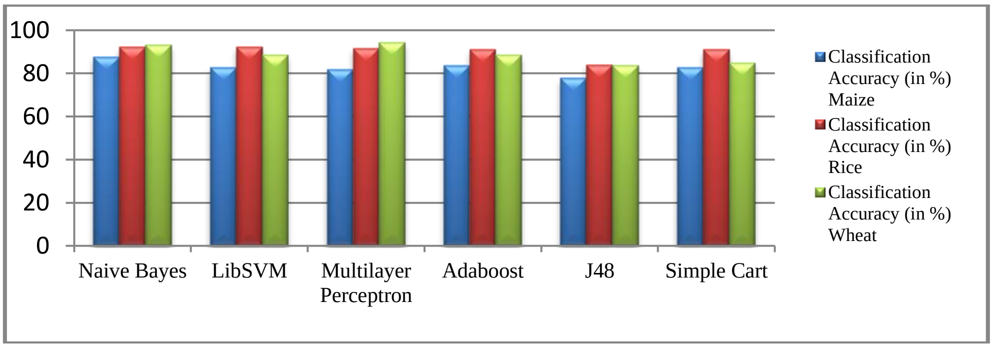

Fig. 5: Comparative Analysis of Various Classifiers Based on Reduced Features.

The outcomes demonstrate that the best order precision for maize is 87.6% utilizing Naive Bayes classifier, for rice is 92.3% utilizing both Naive Bayes and LibSVM and for wheat is 94.18% utilizing Multilayer Perceptron. Be that as it may, for all the three grain crops consolidated, best arrangement exactness is given by Naive Bayes classifier i.e. 90.97%.

4. Conclusion and future scope

Contagious illnesses in grain harvests can bring about gigantic measure of misfortune in farming if required consideration isn't given. With the assistance of PC and correspondence advances, a robotization framework can be constructed which can give early notice of plant infection. Remembering these things, we have endeavored to give commitment utilizing picture preparing and machine learning strategies to identify parasitic illnesses in three grain trims to be specific maize, rice and wheat, at a beginning time of developing and appropriately ranchers and horticultural researchers can take important activities at the opportune time. Through this work we have discovered that extraction of infected locale i.e. the ROI from the leaf, stem picture is the driving advance, for which we utilized the idea of pre-preparing and K-mean grouping division method. The outcomes demonstrate that for all the three oat crops joined, Naive Bayes classifier gave best grouping precision of 90.97%. Future extension in this investigation is to accumulate more example pictures of the contagious maladies in grain trims and arrange them into their specific classification of illness. Additionally more classes of plant maladies separated from parasitic like bacterial and viral infections can be worked upon and additionally tried. This approach can likewise be reached out to different sorts of agrarian harvests like organic product crops, business crops, and so on. A blend of picture handling and machine learning methods can give numerous chances to analysts to take care of the issues in different areas that influence our general public specifically or in a roundabout way and in this way coordinating the picture based calculations with some master framework can make it more effective.

References

[1] Shiferaw, B., Prasanna, B.M., Hellin, J., Bänziger, M., 2011. Products that sustain the world 6. Past triumphs and future difficulties to the pretended by maize in worldwide sustenance security 307– 327. https://doi.org/10.1007/s12571-011-0140-5.

[2] Camargo, A., Smith, J.S., 2009. A picture handling based calculation to naturally recognize plant ailment visual indications. Biosyst. Eng. 102, 9– 21. https://doi.org/10.1016/j.biosystemseng.2008.09.030.

[3] Dandawate, Y., Kokare, R., 2015. A mechanized approach for arrangement of plant sicknesses towards improvement of cutting edge Decision Support System in Indian viewpoint. Int. Conf. Adv. Comput. Commun. Informatics (ICACCI) 794– 799. https://doi.org/10.1109/ICACCI.2015.7275707.

[4] Barbedo, J.G.A., Koenigkan, L.V., Santos, T.T., 2016. Recognizing various plant sicknesses utilizing computerized picture handling. Biosyst. Eng. 147, 104– 116. https://doi.org/10.1016/j.biosystemseng.2016.03.012.

[5] Revathi, P., Hemalatha, M., 2012. Grouping of cotton leaf spot ailments utilizing picture handling edge recognition strategies. Int. Conf. Emerg. Patterns Sci. Eng. Technol. 169– 173. https://doi.org/10.1109/INCOSET.2012.6513900.

[6] Al Hiary, H., Bani Ahmad, S., Reyalat, M., Braik, M., ALRahamneh, Z., 2011. Quick and Accurate Detection and Classification of Plant Diseases. Int. J. Comput. Appl. 17, 31– 38. https://doi.org/10.5120/2183-2754.

[7] Gavhale, K.R., Gawande, U., Hajari, K.O., 2014. Unfortunate district of citrus leaf recognition utilizing picture preparing methods. Int. Conf. Converg. Technol. I2CT 2– 7. https://doi.org/10.1109/I2CT.2014.7092035.

[8] Pujari, J. D., Yakkundimath, R., Byadgi, A. S., 2013. Programmed Fungal Disease Detection in light of Wavelet Feature Extraction and PCA Analysis in Commercial Crops. Worldwide Journal of Image, Graphics and Signal Processing 6, 24. https://doi.org/10.5815/ijigsp.2014.01.04.

[9] Camargo, A., Smith, J.S., 2009. Picture design arrangement for the ID of infection causing operators in plants. Comput. Electron. Agric. 66, 121– 125. https://doi.org/10.1016/j.compag.2009.01.003.

[10] D.Pujari, J., Yakkundimath, R., Byadgi, A.S., 2016. SVM and ANN Based Classification of Plant Diseases Using Feature Reduction Technique. Int. J. Interface. Multimed. Artif. Intell. 3, 6. https://doi.org/10.9781/ijimai.2016.371.

[11] Mokhtar, U., Alit, M.A.S., Hassenian, A.E., Hefny, H., 2015. Tomato leaves ailments identification approach in light of help vector machines. Eleventh Int. Comput. Eng. Conf. 246– 250. https://doi.org/10.1109/ICENCO.2015.7416356.

[12] Pujari, J.D., Yakkundimath, R., 2013. Reviewing and Classification of Anthracnose Fungal Disease of Fruits in light of Statistical Texture Features. Global Journal of Advanced Science and Technology 52, 121– 132.

[13] Bhange, M., Hingoliwala, H.A., 2015. Shrewd Farming: Pomegranate Disease Detection Using Image Processing. Procedia Comput. Sci. 58, 280– 288. https://doi.org/10.1016/j.procs.2015.08.022.

[14] Kurniawati, N.N., Norul, S., Sheik, H., Abdullah, S., Abdullah, S., 2009. Surface Analysis for Diagnosing Paddy Disease. In: International Conference on Electrical Engineering and Informatics 23– 27.

[15] Zhao, Y. X., Wang, K. R., Bai, Z. Y., Li, S. K., Xie, R. Z., &Gao, S. J., 2007. Bayesian classifier strategy on maize leaf infection distinguishing based pictures. Jisuanji Gongcheng yu Yingyong (Computer Engineering and Applications) 43, 193-195.

[16] Islam, M. J., Wu, Q. J., Ahmadi, M., Sid-Ahmed, M. A., 2007. Exploring the execution of innocent bayes classifiers and k-closest neighbor classifiers. In Convergence Information Technology, International Conference on IEEE, 1541-1546.

[17] Löw, F., Schorcht, G., Michel, U., Dech, S., Conrad, C., 2012. Per-field trim order in flooded agrarian locales in center Asia utilizing irregular woods and bolster vector machine group. In SPIE Remote Sensing, International Society for Optics and Photonics, 85380R-85380R.

[18] Witten, I. H., Frank, E., Hall, M. An., and Pal, C. J., 2016. Information Mining: Practical machine learning apparatuses and procedures. Morgan Kaufmann.

[19] Haralick, R. M., Shanmugam, K., 1973. Textural highlights for picture order. IEEE Transactions on frameworks, man, and computer science 3, 610-621.

[20] Barbu, T., 2009. Content-based picture recovery utilizing gabor separating. In: Database and Expert Systems Application, DEXA'09. Twentieth International Workshop IEEE 236-240.

[21] Andrysiak, T., ChoraS, M., 2005. Picture recovery in light of various leveled Gabor channels. Universal Journal of Applied Mathematics and Computer Science 15, 471.

[22] Ting Wang, Sheng-Uei Guan, Fei Liu, 2012. Relationship based Feature Ordering for Classification in light of Neural Incremental Attribute Learning. Universal Journal of Machine Learning and Computing 2, 807-811. https://doi.org/10.7763/IJMLC.2012.V2.242.