Diagnosis of Sugarcane Diseases Using Image processing and Machine Learning Techniques

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Abstract

In India, high-yielding sugar cane is the main crop. The earliest identification of the disease can regulate the disease and can be cured. This enables to achieve high output. Sugarcane diseases are recognized through the use of image processing and soft computing methods in this research work. Based on the picture recorded, the diseases are analyzed. There are two phases in this research, one is image processing and the other is image analysis. The following methods are included in the image analysis phase: Case-Based Reasoning (CBR), Fuzzy logic and ANFIS (Adaptive Neuro Fuzzy Inference system); in the image processing phase: pre-processing and feature extraction methods. Using the two techniques above, it is possible to diagnose sugarcane diseases at the earliest stage, which is very helpful to farmers. The proposed system's accuracy is 97 percent; ANFIS provides greater accuracy than the CBR technique.

Key words: pre-processing, feature extraction, fuzzy logic, CBR, ANFIS.

1. Introduction:

In India, two-thirds of the total sugar cane in the world is produced [4]. Sugarcane is grown roughly 4 million hectares and sugarcane yield is roughly 66 tons/hectare and information is gathered from the Coimbatore sugarcane research institute. The output of sugarcane in Tamil Nadu is 11 percent. Area under cultivation of sugarcane in India is 6 percent and the largest yield is 1067.8 quintals per hectare[6]. Overall 80 percent of manufacturing in Tamil Nadu comes from the districts of Salem, Tiruchirapalli and Coimbatore. Over 20 percentage points come from the districts of Dharmapuri, Thanjavur, Madurai and Ramanathapuram.

Arifa Khan (2016) suggested sugarcane leave disease detection scheme The following diseases are red rot, mosaic and leaf scald. It is possible to collect images of Sugarcane using a digital camera. The pre-processing method was used to extract undesirable data from the picture of the sugarcane. The technique of image segmentation was used to identify the diseases of the sugarcane leaf and also to classify the pixel value of the diseased and the pixel values of the diseased. The suggested scheme was 82% accurate.

Tisentiuang (2017) has created a sugarcane borer disease detection scheme for cutting sugarcane. Using the picture acquisition scheme, the input picture was collected. Adaptive threshold segmentation technique was used to obtain the diseased region from the input picture, representing a pixel value of 1 and a non-diseased zone pixel value of 0. The three pictures of sugarcane were processed by the filling and corrosion operator and the interval was 120 degree. The SVM classifier was used to classify the region of disease and the region of disease based on the parameters of regularization of C and the function parameter of the kernel. To detect the diseased region, the cross validation technique was used. The accuracy of the suggested disease-affected sugarcane picture was 96% and the disease-free picture of sugarcane was 95.83%.

Srdjan Sladojevic (2017) suggested a fresh strategy to plant disease recognition using a profound standard network based on the classification of the leaf picture. Thirteen distinct diseases of plants have been identified. Thirteen distinct diseased pictures and healthy leaf pictures were developed to create an image database. Caffe was the work of the deep learning frame used for the standard neural network (CNN). Using CNN, the input pictures were classified into distinct classes. The suggested system's accuracy value was 96.3 percent

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In this study, Sakina Kachwala (2018) created a fresh strategy to red rot and leaf scald infection detection. The technique of things on the Internet was used to interact with the Arduino UNO model with the MQ3 sensor and colour sensor. MQ3 detector was used to identify sugarcane red rot disease. The sugarcane leaf scald disease was detected using a colour sensor. The suggested system's precision was higher than 85 percent than other standard techniques.

Moises Alencastre-Miranda (2018) used computer vision techniques for sugarcane cultivation to analyze billet quality. This study work was carried out at the Research Farm in Houma, LA, USA. The correlation between sugarcane germination and damage type was plotted. In each class, 120 samples were used in plots. Billet input pictures were gathered using both indoor and outdoor light stereovision sensors and charging coupled devices. The technique of extraction and classification is used to identify the sugarcane billet harm using pre-processing. The suggested scheme was 90% accurate.

2. FIELD SURVEY

A study was conducted between 1000 farmers in different districts in Tamilnadu on June 2017-May 2018. The primary aim of this field survey was to define sugarcane farmers ' issues. The primary issues faced by farmers were fresh disease owing to climate change, unconscious of fresh signs of disease and strategies for managing the disease. As shown in table (1), we had gathered the study from the sugarcane farmers of the following districts and listed the types of sugarcane.

Table 1 Sugarcane Varieties

District	Sugarcane Varieties
Sivagangai	Co V 94102, CoC 24 TNAU SC Si7,Co 86032, Co 85019, Co Si(Sc)6, Co G (Sc)5, Co C (Sc)22, TNAU SC Si 8
Virudhunagar& Tirunelveli	Co G (Sc)5, Co C (Sc)22,Co 86032, Co 85019, Co Si(Sc)6, CoC 24 TNAU SC Si7, TNAU SC Si 8
Trichy	Co C (Sc)22, CoC 24 TNAU SC Si7, Co Si 95071, CoC Co Si(Sc)6, Co G (Sc)5, TNAU SC Si 8
Thanjavur, Nagapattinam& Tiruvarur	Co G (Sc)5, Co C (Sc)22, CoC 24 TNAU SC Si7, Co V 92102, CoG93076,CoG94077, Co Si(Sc)6, TNAU SC Si 8
Coimbatore	Co 97009, Co Si(Sc)6, Co G (Sc)5, Co C (Sc)22,Co 86032, CoV 92102, Co 86027, CoC 90063, CoC 24 TNAU SC Si7, TNAU SC Si 8
Theni,Madurai &Dindigul	Co Si(Sc)6, Co G (Sc)5, Co C (Sc)22, Co 92012, Co 92008, Co 93001, Co 86032, CoC 24 TNAU SC Si7, TNAU SC Si 8
Namakkal& Salem	Co Si(Sc)6, Co G (Sc)5, Co C (Sc)22,CoV 92102, CoC 24 TNAU SC Si7, TNAU SC Si 8

As shown in table (1), we had gathered the survey from the sugarcane farmers of the following districts and listed the types of sugarcane diseases.

- Leaf scald
- Sugarcane yellow leaf disease
- Pokkahboeng
- Mosaic disease

Table 2 Field survey sample images of sugarcane

Leaf scald

Leaf scald disease induced by Pathogen, can only be recognized in the final phase, symptoms cannot be seen first appear after some time sugarcane plant has been severely infected the only one we can see. Leaf scald disease's first symptoms are the growth of white pencil lines with yellow boundaries following the veins on the sugarcane leaf that lead to plant tissue dying. The scald significance was disease from specific regions of the leaf that lost their colour and changed a pale green colour as they were unable to generate chloroplasts. The pathogen survives on grasses and elephant grass; it can be transferred from grass to sugar cane through water and air medium. Favourable conditions were water logging, thirsty and low temperature to boost the seriousness of Leaf scald disease.

Table 3 Sugarcane leaf scald disease images

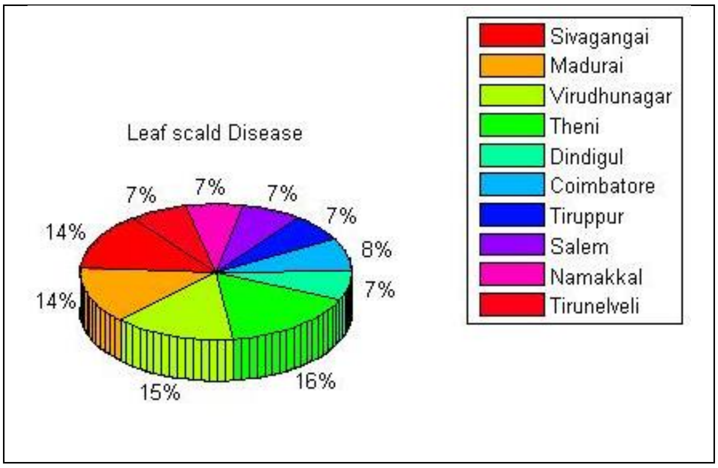


Figure 1 Data collection graph for sugarcane leaf scald disease

From this graph, scald disease affects the four districts in the sugarcane leaf. 1.Sivangangai, 2.Madurai and 3.Virudunagar 4.Theni may be faced with this disease by about 15 percent of farmers. During the rainy season, the following remarks can be produced on the sugarcane leaf scald disease and its spread very quickly in air and water.

Sugarcane yellow leaf disease

Yellow leaf disease in sugarcane was triggered by viruses transmitted by aphids, melanaphissacchari, and rhopalosiphummaidis. The symptoms of yellow leaf disease in the sugar cane plant midrib were the leaf underside yellowing. The yellowing appears on the spindle leaf at the top. The initial symptoms of Sugarcane yellow leaf disease were a yellow leaf in leaf midrib the lower surface of leaves 3 to 6 counting from the top expanding spindle leaf. The yellowing of the sugar cane leaf midrib is most noticeable in mature sugar cane from October to March. The yellowing of the sugar cane leaf midrib expands into the leaf blade depending on the severity of the disease. Dry weather was the favourite environment between the end of October and the end of March.

Table 4 Sugarcane yellow leaf disease images

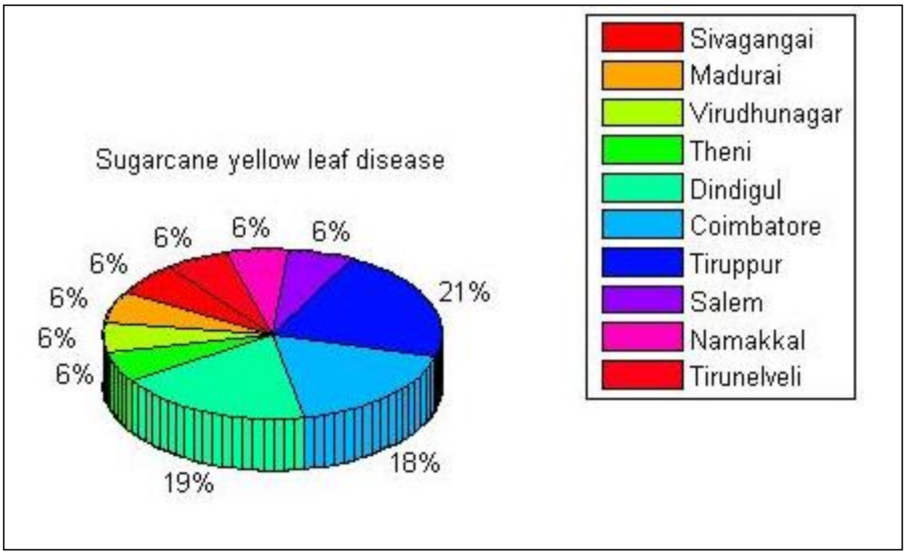


Figure 2 Data collection graph for sugarcane yellow leaf disease

From this chart, the three districts have a major impact on the sugarcane yellow leaf disease 1. Dindigul, 2.Coimbatore, and 3.Tiruppur may experience this disease by about 19 percent of farmers. The following remarks on the sugarcane yellow leaf disease can happen between October and March and spread very quickly through air and rain.

Pokkahboeng

The disease of Pokkahboeng was an airborne disease. There were three kinds of Pokkahboeng disease symptoms: 1.Chlorotic Phase, 2.Top-Rot Phase, 3.Knife-cut Phase. The Chlorotic Phase: Pokkahboeng's original symptom was the basis of the youthful leaves in chlorotic situation, and sometimes the leaf blades were also in chlorotic condition. The young leaves distortion caused the sugar cane to twist, shorten and flash. The base of the leaves impacted by the Pokkahboeng disease was seen to be much smaller than ordinary leaves of sugarcane. The Top-Rot Phase was a very severe phase of Pokkahboeng's disease, at the top of the sugarcane young spindles were murdered. Sometimes the infection of Leaf has continued downwards and has penetrated a growing point of sugarcane, stripes and Red specks. Next stage of the top rot stage was the Knife-cut stage. The symptoms of knife-cut stage were noted in conjunction with the Pokkahboeng disease's top rot stage characterized by transverse stem / stalk rind reductions in a standardized way and ladder lesion on young sugarcane leaves. Pokkahboeng disease transferred through air, irrigation water, soil, infected setting and splashed rain. The temperature at favourable conditions was 20-30 ° C and humidity at cloudy weather was higher than 70-80%.

Table 5 sugarcane Pokkahboeng disease images

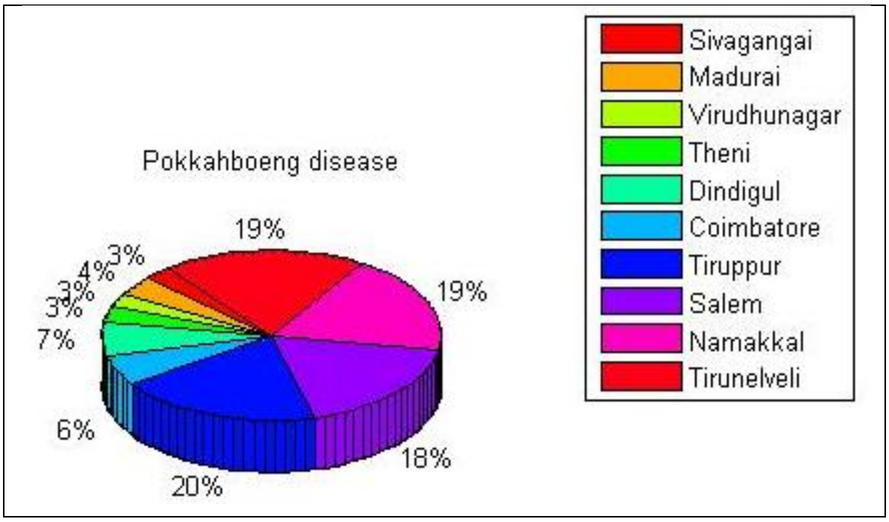


Figure 3 Data collection graph for sugarcane Pokkahboeng disease

From this graph, Pokkahboeng disease in the sugarcane has a major impact on the four districts 1. Tripur, 2.Salem and 3.Namakkal 4.Tirunelveli can cope with this disease by about 19 percent of farmers. During the winter season, the following remarks can be produced about the sugarcane Pokkahboeng disease and its spread very quickly in water and air media.

Mosaic disease

The mosaic disease of Sugarcane was triggered by mosaic virus. The symptoms of mosaic disease were Young sugarcane leaves against light source display chlorotic and normal sugarcane green zone leaves conveying mosaic pattern. The colour of the chlorotic region altered to reddening. This symptom is also comparable to the Leaf-sheath disease of sugarcane. The mosaic virus can be transferred and perpetuated by rationing through the Mosaic diseased sugarcane seed material. Sugarcane mosaic disease is also manually transferred by the cutting knife for sugarcane.

Table 6 Sugarcane mosaic virus disease images

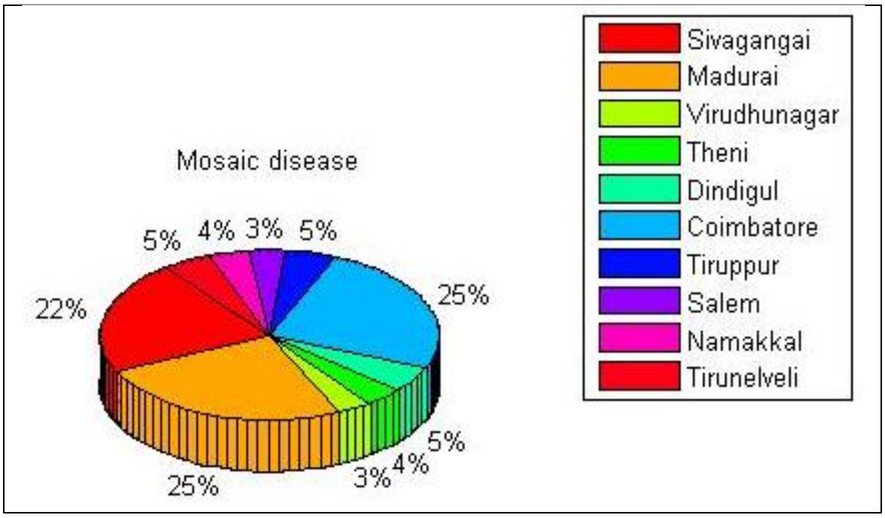


Figure 4 Data collection graph for sugarcane mosaic virus disease

From this graph, the three districts are largely affected by the sugarcane mosaic virus illness 1. Sivagangai, 2.Madurai, 3.Coimbatore can experience this disease for about 24 percent of farmers. The following remarks can be produced on the disease of the sugarcane mosaic virus occurring during the rainy season and spreading it very quickly in water.

3. METHODOLOGY

In this research work, sugarcane diseases are diagnosed using image processing and the Adaptive Neuro Fuzzy Inference System (ANFIS). Due to environmental conditions, input pictures from the agricultural field were gathered; pre-processing technique was used to remove noise. The feature extraction was used to acquire information from the diseased region from the pre-processed output image. Artificial Neural Network Fuzzy Inference System has been used to diagnose diseases of sugarcane. The Operating Characteristic Receiver (ROC) curve was used to evaluate the proposed scheme's effectiveness.

The following modules are used in this research work as shown in figure 5.

1. Input image
2. Preprocessing
3. Feature extraction
4. CBR, ANFIS
5. ROC curve
6. Result Analysis

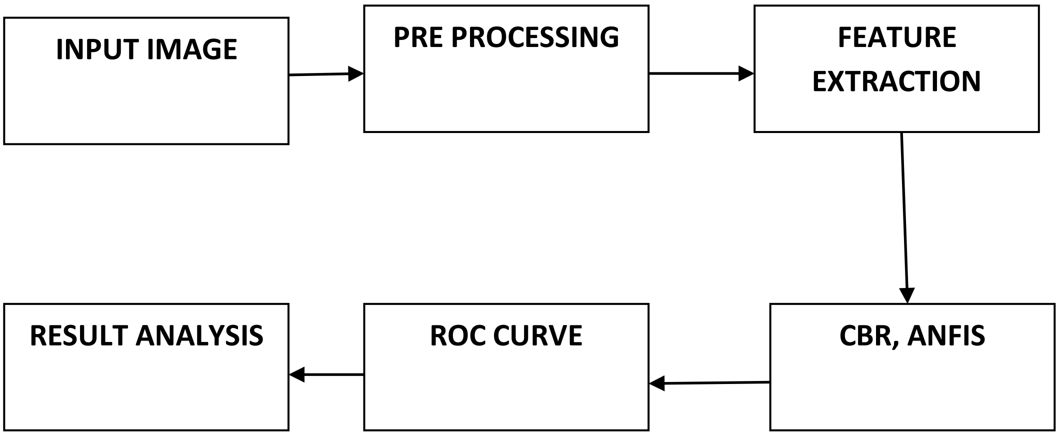


Figure 5 Block diagram for Computer Aided Diagnosis of agricultural diseases

INPUT IMAGE

The image is usually stored in matrix format ; it is called as a pixel each matrix element. Using a digital camera, it is classified into two types to capture the input image.

1. Testing image
2. Training image

Training images are collected from the University of Agriculture Coimbatore, Madurai in Tamilnadu and several rice research institutes in India. Testing images are collected from rice-growing agricultural fields. In this research work, we use 1000 images for input images. 700 images are used for training data collection and 300 images are used for testing information. Blast, Brown spot, Bacterial Blight, Sheath Rot, Leaf Scald and Stem Root input picture as shown in the following table (7)

 **EYESPOT**	 **LEAF SCALD**
 **YELLOW LEAF**	 **POKKAH BOENG**

Table 7 Input images of sugarcane diseases

PREPROCESSING

Pre-processing is used to remove the noise from the input image. In this research, the method of standardization and soft coring filtering are used. Use the equation (1) below to transform the RGB image to a gray image.

$$I(x, y, z) = \frac{(Gx+Gy+Gz)}{3} \qquad (1)$$

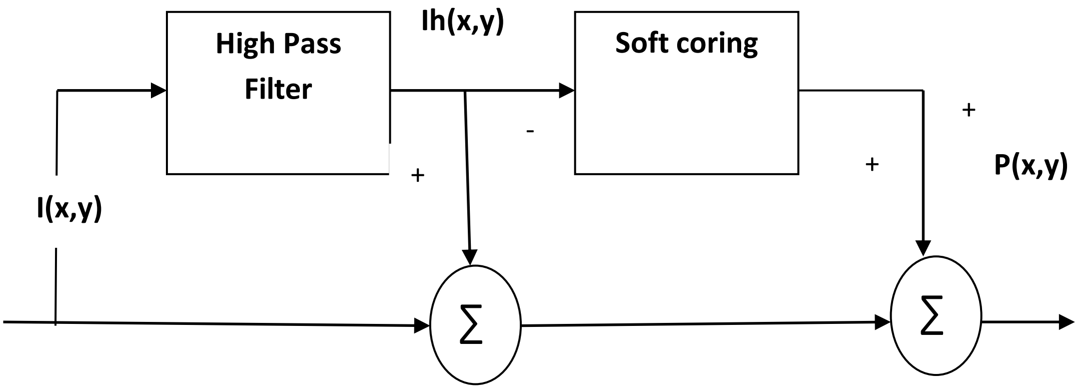


Figure 6 Soft coring filter

Soft coring filtering method is a nonlinear filtering method. It is used to obtain the information from the standardized image. The visually representative is acquired using the Gaussian high-pass filter based on the high-pass filter kernel function that can be done in the frequency domain. Using sliding windowing technique, Gaussian high-pass filter converts Fourier rapidly into two-dimensional convolutions. The standardized output image is passed to the high-pass filter and the output of the high-pass filter is added with the α.) (smooth coring function as shown in figure(6). Table demonstrates the performance (8)

$$P(x,y) = Ih(x,y) + \alpha\big(I(x,y)\big) \qquad (2)$$

Where$P(x,y) - \ Preprocessedoutputimage$

$Ih(x,y) - \ Highpassfiteroutputimage$

$$Ih(x,y) = I(x,y) - Z(e^{jwx}, e^{jwy}) \qquad (3)$$

$Z(e^{jwx}, e^{jwy})$- High pass filter co-efficient

$\alpha(I(x,y))$- Soft coring function

$$\alpha\big(I(x,y)\big) = m\,.\,I(x,y)(1 - e^{\left|\frac{I(x,y)}{\tau}\right|}(4)$$

m, τ – Random variables ranges between 0 to 1.

The Gaussian high-pass filter is used to extract the noise from the input image. The smooth coring kernel function is used for the image line and edge information input. For two-dimensional images, the soft coring filtering method is used and information loss is much smaller compared to the median filtering technique. The two-step pre-processing method contributes to improving image quality, reducing processing time, component illumination, reducing shaded background and retaining image contrast and brightness.

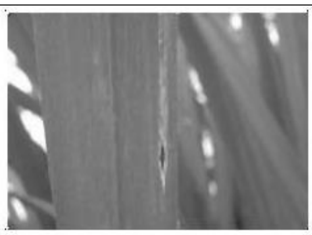
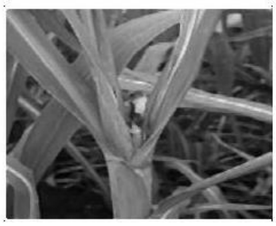
 **EYESPOT**	 **LEAF SCALD**
 **YELLOW LEAF**	 **POKKAH BOENG**

Table 8 Pre processing output of sugarcane disease

FEATURE EXTRACTION

Image stores pixel values, in each pixel value some features are displayed. Colour, texture and shape are some of the picture's overall features.

COLOUR FEATURE EXTRACTION

The feature is acquired using the colour, shape and texture features of the pre-processed image. To acquire the colour characteristic, Segment by threshold method is used. Table 9 indicates each disease's threshold value.

Table 9 Threshold value for sugarcane diseases

S.No	Name of the disease	Lower Threshold value	Upper Threshold value
1	Leaf Scald	140	175
2	yellow leaf disease	90	150
3	Pokkahboeng	50	80
4	Eye spot	130	160

Colour feature is extracted by using the following equation (5)

$$E(x,y) = \begin{cases} o \; if \; P(x,y) < T1 \\ 1 \; if \; T1 \le P(x,y) \le T2 \\ 0 \; if \; P(x,y) > T2 \end{cases} \quad (5)$$

Where T1 –Lower threshold value, T2- Upper threshold value

Colour feature extraction output image is shown table 10

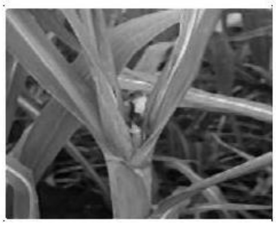
 **EYESPOT**	 **LEAF SCALD**
 **YELLOW LEAF**	 **POKKAH BOENG**

Table 8 Pre processing output of sugarcane disease

Shape Features Extraction

Using the shape function extraction, the single object is obtained from more objects in the image. This method is used to get the particular shape of the object from the picture drawing.

- Noise resistance
- Statistically independent
- Identifiability
- Occultation , invariance
- Translation, Rotation and Scale invariance
- Affine invariance

- Reliability

We used the method of conducting edge detection to extract shape characteristics in this research work. Using this method, a wide range of object edges are detected in a picture.

1. Smoothing
2. Finding gradients
3. Non maximum suppression
4. Double thresholding
5. Edge tracking by hysteresis

STEP 1: SMOOTHING

Drawn from a digital camera, the input image involves some noise due to sunlight leading to a blurring of the image. The Gaussian filter can be used in a smoothing method to remove the noise and remove the noise.

$$Is = I * Gf \quad (6)$$

To find out the smoothed image using the equation (6) where

Is =>smoothed filter output

I =>input image

Gf=>kernel function of Gaussian filter

The kernel function of the Gaussian filter is calculated using equation (7) with standard deviationσ=1.4

$$Gf = \frac{1}{59}\begin{bmatrix} 2 & 4 & 5 & 4 & 2 \\ 4 & 9 & 12 & 9 & 4 \\ 5 & 12 & 15 & 12 & 5 \\ 4 & 9 & 12 & 9 & 4 \\ 2 & 4 & 5 & 4 & 2 \end{bmatrix} \quad (7)$$

STEP 2: FINDING GRADIENTS

If the smoothed image gradients have a large magnitude, the edges of the image objects should be marked. In this method, we mostly find corners of objects based on the intensity of the grayscale, then the gradients of the image are determined. The gradient value of each pixel is determined using the sobel operator. To find the approximate gradient in X and Y direction as shown in equation (8) and (9)

$$FGX = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \quad (8)$$

$$FGY = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \quad (9)$$

The gradient magnitude value can be calculated using Euclidean distance measurement as shown in equation (10).

$$|G| = \sqrt{GX^2 + GY^2} \quad (10)$$

The gradient magnitude can be determined using Manhattan distance measurement as shown in equation (11)

$$|G| = |GX| + |GY| \quad (11)$$

Where,

GX = gradients in X-direction

GY = gradients in Y-direction

The direction of the edges of object can be determined using the equation (12)

$$\theta_g = arctan\left(\frac{|GY|}{|GX|}\right) \quad (12)$$

STEP 3: NON MAXIMUM SUPPRESSION

It is possible to use local maximum picture values to build the edge of an object. This step is used to transform the blurred edges of the object into the sharp edges of the object. It will be considered as the local maximum in the gradient and will detect the remaining gradient values.

1. Round the gradient direction to the nearest 45°, using the neighborhood's 8- connection..

2. Compare edge strength using current pixel gradient magnitude with positive and negative gradient direction gradient magnitude values. If the direction of the gradient is improved, compare the direction of boosting and decreasing with current pixels.

3. If the gradient magnitude value of the current pixel value is large, keep the value of the edge resistance and otherwise delete (remove) the value of the pixel.

STEP 4:DOUBLE THRESHOLDING

Thresholding method may determine the item's remaining potential edges. For instance, due to rough surfaces, some object edges may be missed due to noise or colour variation. The method of canny edge detection is learning, dual thresholding. It has two restriction values, one larger and the other lower. If the value of the edge pixel exceeds the limit value specified as a strong value of the edge pixel. If the value of the edge pixel is lower than (weaker than) the decreased threshold value is removed (deleted) if the value of the edge pixel between the two threshold values is labelled as a soft edge in an image object. White colour depicts the powerful edges of the image and the fragile edges of the image are represented by gray colour.

STEP 5: EDGE TRACKING BY HYSTERESIS

By removing all the edges not linked to the powerful edges, the final edges are calculated. All the strong edges are considered the final edges of an object, and the weak edges are those connected to the strong edges, the final edges of an object can be considered, the remaining weak edges can be suppressed. Edge training can be implemented using BLOB – analysis (Binary Large OBject).

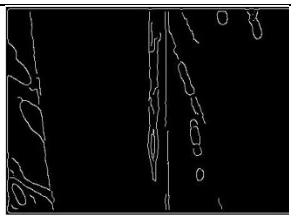
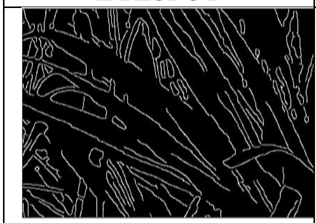
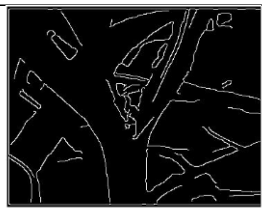
 **EYESPOT**	 **LEAF SCALD**
 **YELLOW LEAF**	 **POKKAH BOENG**

Table 11 Shape Feature Extraction output of sugarcane diseases

TEXTURE FEATURE EXTRACTION

Texture is defined as the image description based on pixel scale, regularity and directionality-texture is represented by the intensities of the adjacent pixel values to ignore the current pixel value type. The extraction of texture characteristics is used to classify image application and image application segmentation, ground inspection, surface and shape orientation. The following four techniques are used to obtain the texture characteristic,

1. Statistical methods
2. Structural methods
3. Model based methods
4. Transform based methods

CO-OCCURRENCES MATRIX BASED FEATURES

The probability distribution of a picture in the second order gray level can be evaluated in pairs at a time using the pixel gray level values. The following features of the occurrence matrix can be assessed.

1. Contrast
2. Energy
3. Entropy

CONTRAST

A comparison is called the element difference moment of order 2. If peak values appear in the co-occurrence matrix's primary diagonal, they have relatively minimum values.

$$Contrast = \sum_{g1} \sum_{g2} (g1 - g2)^2 \ C_{g1\,g2} \quad (13)$$

Where, g 1 = grey level value of pixel location at(x,y)
g 2=grey level value of pixel location at(x,Dx,y,Dy)
Dx,Dy=displacement vector of x and y
C=co-occurrence matrix

ENERGY

The energy value calculated using the following equation (14)

$$ENERGY = \sum_{g1} \sum_{g2} {C_{g1\,g2}}^2 \quad (14)$$

If all co-occurrence matrix values are equal then the maximum energy value.

ENTROPY

Entropy is used to calculate the image information at the gray level. The following equation (15) is used for the entropy value calculation,

$$ENTROPY = -\sum_{g1} \sum_{g2} C_{g1g2} log_2 C_{g1g2} \quad (15)$$

Table 12 shows the impact of the texture extraction technique

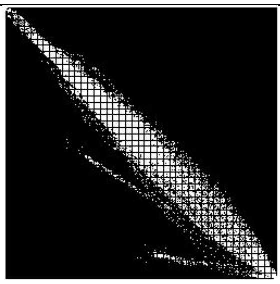
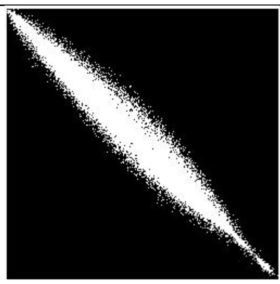
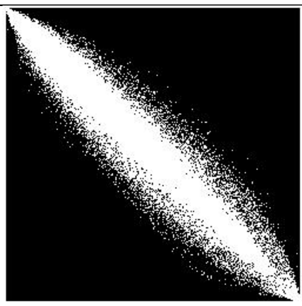
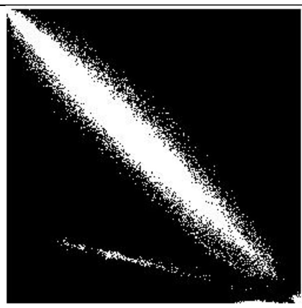
 **EYESPOT**	 **LEAF SCALD**
 **YELLOW LEAF**	 **POKKAH BOENG**

Table 12 Texture Feature Extraction output of sugarcane diseases

CASE BASED REASONING

Case Based Reasoning (CBR) is a predictive technique used for the diagnosis of disease. CBR is separate from the Perceptron algorithm; the present database data will be used. The data from the past year's databases is used as the input data for the prediction procedure. Case-based reasoning is a teaching technique that is not controlled. The case-based reasoning in two groups is classified as normal and abnormal. In addition, the abnormal class is classified as initial, very small, small, medium, high, very high, six classes. Because each class ' threshold values are taken from the present input database as shown in table 13, the output data is expected to be very precise.

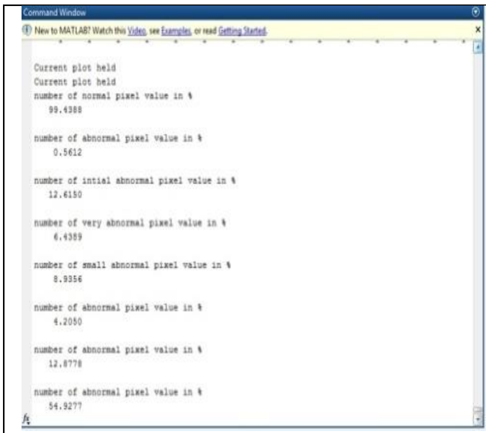
Classification	Eyespot	Leaf Scald	Yellow Leaf	PokkahBoeng
Normal	<130&>160	<140 &>175	<90 &>150	<50 &>80
Abnormal	130-160	140-175	90-150	50-80
Initial	130-135	140-145	90-100	50-55
very small	136-140	146-150	101-110	56-60
Small	141-145	151-159	111-120	61-65
Medium	146-150	160-165	121-130	66-70
High	150-155	166-170	131-140	71-75
very high	156-160	171-175	141-150	75-80

Table 13Threshold value for sugarcane diseases

Fuzzy logic is one of the many-valued classification-based logic methods where the outputs of classification are delivered in degrees of reality. The value of reality varies from 0 to 1. In crisp logic, the results are either binary values 1 or 0.fuzzy logic offers results based on 0, 0.25, 0.5 and 1. truth values. If an abnormal class uses the rule.

- If the abnormal Class > 60 then removing the agricultural plant from the farming sector is suggested.
- If the abnormal class > 20-40 then suggested using natural fertilizers to treat the agricultural plant.

Table 14 shows the output of CBR for different diseases



EYESPOT

LEAF SCALD

YELLOW LEAF

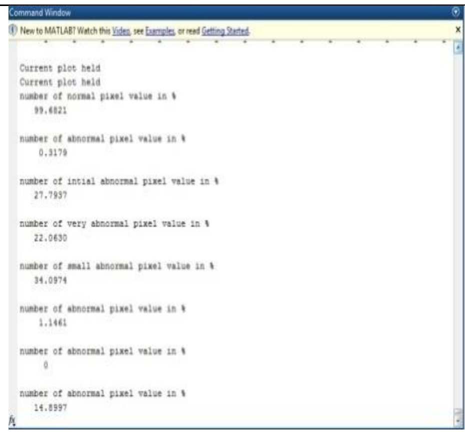


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Table 14 CBR output for sugarcane diseases

ANFIS (ADAPTIVE NEURO FUZZY INFERENCE SYSTEM):

ANFIS is a learning technique that is monitored. It's a mix of neural network method and fuzzy logic. We use the neural network feed forward in this research work as a neural network technique and the fuzzy takagi-sugeno fuzzy model logic process. Figure (7) demonstrates ANFIS's architecture. The fuzzy model of takagisugeno uses six guidelines. ANFIS is used to resolve problems related to disease detection. A combination of the least square method and the gradient method of back propagation with a hybrid learning rule is used to identify the disease. ANFIS network is made up of nodes with the demands of each layer. ANFIS IF / THEN's laws may create a network realization. In each layer of neurons, ANFIS network neurons conduct the same function. Table 15 demonstrates the ANFIS output

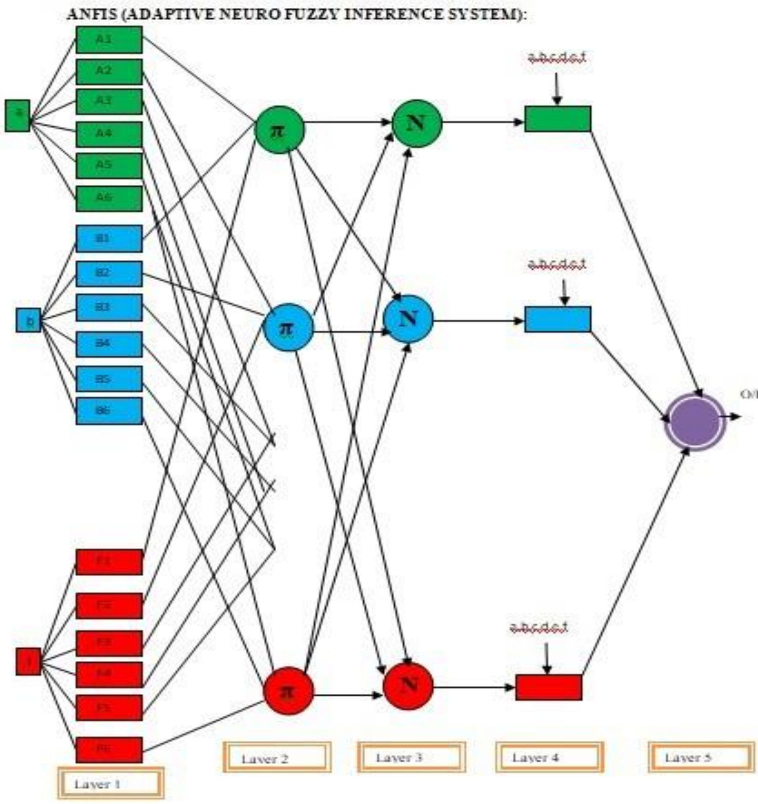


Figure 7 ANFIS Architecture

Rule 1= If a is A1, b is B1, c is C1, d is D1, e is E1 and f is F1 then

O/P1= p1a+q1a+r1a+s1a+t1a+u1a+v1 (16)

Rule 2= If a is A2, b is B2, c is C2, d is D2, e is E2 and f is F2 then

O/P2= p2b+q2b+r2b+s2b+t2b+u2b+v2 (17)

Rule 3= If a is A3, b is B3, c is C3, d is D3, e is E3 and f is F3 then

O/P3= p3c+q3c+r3c+s3c+t3c+u3c+v3 (18)

Rule 4= If a is A4, b is B4, c is C4, d is D4, e is E4 and f is F4 then

O/P4= p4d+q4d+r4d+s4d+t4d+u4d+v4 (19)

Rule 5= If a is A5, b is B5, c is C5, d is D5, e is E5 and f is F5 then

O/P5= p5e+q5e+r5e+s5e+t5e+u5e+v5 (20)

Rule 6= If a is A6, b is B6, c is C6, d is D6, e is E6 and f is F6 then

O/P6= p6f+q6f+r6f+s6f+t6f+u6f+v6 (21)

Where

A1,A2,A3,A4,A5,A6,B1,B2,B3,B4,B5,B6,C1,C2,C3,C4,C5,C6,D1,D2,D3,D4,D5,D6,E1,E2,E3,E4,E5,E6,F1,F2,F3,F4,F5,F6 – membership function.

p1,q1,r1,s1,t1,u1,v1,p2,q2,r2,s2,t2,u2,v2,p3,q3,r3,s3,t3,u3,v3,p4,q4,r4,s4,t4,u4,v4,p5,q5,r5,s5,t5,u5,v5, p6,q6,r6,s6,t6,u6,v6 –linear parameters.

Layer 1

In this research work, we use the Gaussian membership function equation (22) with a generalized bell-shaped membership function equation (23).

$$\mu Ai(a) = exp\left[\frac{-(a-zi)^2}{(2ai)^2}\right] \text{ (22)}$$

$$\mu Bi(b) = exp\left[\frac{-(b-zi)^2}{(2bi)^2}\right] \text{ (23)}$$

$$\mu Ci(c) = exp\left[\frac{-(c-zi)^2}{(2ci)^2}\right] \text{ (24)}$$

$$\mu Di(d) = exp\left[\frac{-(d-zi)^2}{(2di)^2}\right] \text{ (25)}$$

$$\mu Ei(e) = exp\left[\frac{-(e-zi)^2}{(2ei)^2}\right] \text{ (26)}$$

$$\mu Fi(f) = exp\left[\frac{-(f-zi)^2}{(2fi)^2}\right] \text{ (27)}$$

$$layer1\ ouput\ (i) = \ \mu Ai(a), \quad i = 1,2,3,4,5,6 \text{ (28)}$$

$$layer1\ ouput\ (i) = \ \mu Bi(b), \quad i = 1,2,3,4,5,6 \text{ (29)}$$

$$layer1\ ouput\ (i) = \ \mu Ci(c), \quad i = 1,2,3,4,5,6 \text{ (30)}$$

$$layer1\ ouput\ (i) = \ \mu Di(d), \quad i = 1,2,3,4,5,6 \text{ (31)}$$

$$layer1\ ouput\ (i) = \ \mu Ei(e), \quad i = 1,2,3,4,5,6 \text{ (32)}$$

$$layer1\ ouput\ (i) = \ \mu Fi(f), \quad i = 1,2,3,4,5,6 \text{ (33)}$$

$\mu Ai(a)$- degree of fuzzy set membership function

Ai- Bi – fuzzy set

Layer 2

In this layer, each node is adaptive, it is labelled as π. The production of this layer is the multiplying result of the first layer as shown in the ANFIS architecture figure (9). In this research, the target value is calculated using OR logic.

$$layer2output\ (i) = FS(i) = \ \mu Ai(a) * \mu Bi(b) * \ \mu Ci(c) * \mu Di(d) * \mu Ei(e) * \mu Fi\ (f) \ \ i = 1,2,3,4,5,6 \text{(34)}$$

Where FS (i) – firing strength of the each node.

Layer 3

In this layer, each node is adaptive, it is labelled as N. The output of this layer is the ratio of the firing power of each node to the total of all the nodes ' firing power.

$$layer3\ output(i) = \overline{FS(\imath)} = \frac{FS(i)}{\sum FS(i)} \text{ (35)}$$

Layer 4

Each node in this layer is adaptive. The output of this layer is calculated using the following equation (36)

$$layer4\ ouput\ (i) = \ \overline{FS(\imath)}\, K(i) \text{ (36)}$$

$$= \ \overline{FS(\imath)}\, (pia + qib + ric + sid + tie + uif + vi)$$

Where $\overline{FS(\imath)} - \ Output\ of\ layer\ 3$

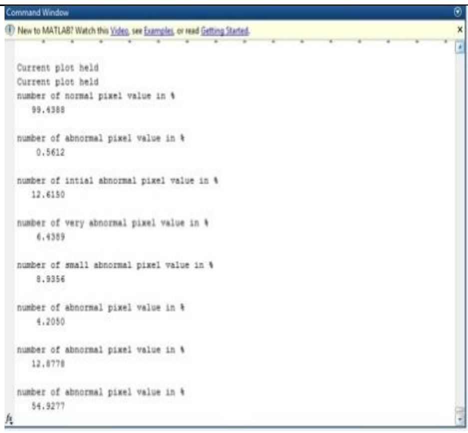
$$K(i) = pia + qib + ric + sid + tie + uif + vi - \ parameter\ of\ the\ node.$$

Layer 5

This layer contains a single node, it is non-adaptive, and it is shown as a single node. This layer's yield is the summation of the values of the previous output layer, calculated using the following equation (37)

$$layer5\ output\ (i) = \ \textstyle\sum_i \overline{FS(\imath)}\ \ K(i) \text{ (37)}$$

$$= \frac{\sum_i FS(i)K(i)}{\sum_i Fs(i)}$$



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Command Window
New to MATLAB? Watch this Video, see Examples, or read Getting Started.

Current plot held
Current plot held
number of normal pixel value in %
   99.4388

number of abnormal pixel value in %
    0.5612

number of intial abnormal pixel value in %
   12.6150

number of very abnormal pixel value in %
    6.4389

number of small abnormal pixel value in %
    8.9356

number of abnormal pixel value in %
    4.2050

number of abnormal pixel value in %
   12.8778

number of abnormal pixel value in %
   54.9277
```

EYESPOT

```
Command Window
New to MATLAB? Watch this Video, see Examples, or read Getting Started.

Current plot released
Current plot held
number of normal pixel value in %
   98.3225

number of abnormal pixel value in %
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number of intial abnormal pixel value in %
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number of very abnormal pixel value in %
   21.6344

number of small abnormal pixel value in %
   40.2151

number of abnormal pixel value in %
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number of abnormal pixel value in %
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number of abnormal pixel value in %
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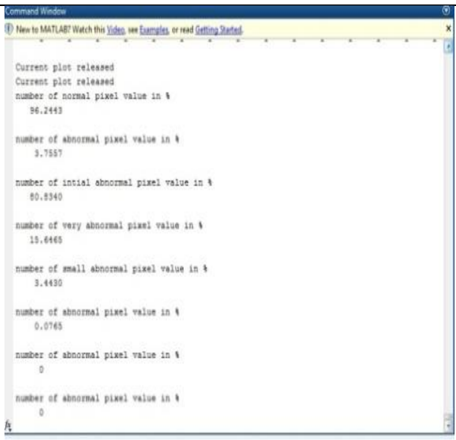
LEAF SCALD



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Command Window
New to MATLAB? Watch this Video, see Examples, or read Getting Started.

Current plot released
Current plot released
number of normal pixel value in %
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number of abnormal pixel value in %
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number of intial abnormal pixel value in %
   80.8340

number of very abnormal pixel value in %
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number of small abnormal pixel value in %
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number of abnormal pixel value in %
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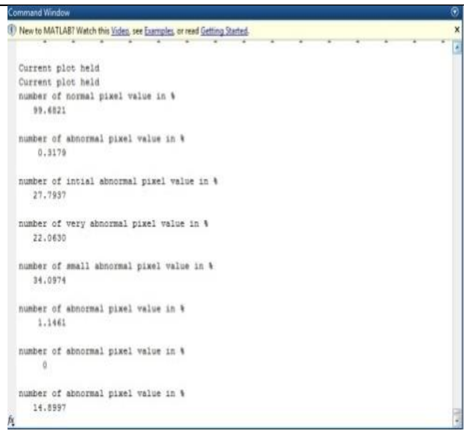
number of abnormal pixel value in %
     0

number of abnormal pixel value in %
     0
```

YELLOW LEAF



```
Command Window
New to MATLAB? Watch this Video, see Examples, or read Getting Started.

Current plot held
Current plot held
number of normal pixel value in %
   99.6821

number of abnormal pixel value in %
    0.3179

number of intial abnormal pixel value in %
   27.7937

number of very abnormal pixel value in %
   22.0630

number of small abnormal pixel value in %
   34.0974

number of abnormal pixel value in %
    1.1461

number of abnormal pixel value in %
     0

number of abnormal pixel value in %
   14.8997
```

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Table15 ANFIS output for sugarcane diseases

ROC CURVE

ROC (Receiver Operating Characteristics) curve is a graph representing the classifier's system output for a separate threshold value to plot the graph between sensitivity and specificity. Sensitivity is also called a true positive rate (tpr), probability detection and recall. Also referred to as specificity as false positive rate (fpr), probability of false alarm and dropping out.

ROC (Receiver Operating Characteristics) curve is a model for diagnosing a grouping of examples between different classes. The diagnostic output is the continuing (real) output. The classifier can be classified by threshold value with separate boundaries between different classes. There are two classes in the binary classification scheme, one is labeled as Positive (P) and the other as an abnormal class of cells and is labeled as Negative (N). There are four possible outcomes for True Positive (TP) binary classification

1. False Positive (FP)
2. True Negative (TN)
3. False Negative (FN)

The ROC curve is created by plotting the cumulative distribution sensitivity function in the y-axis and the cumulative distribution specificity function in the x-axis. Using equation (38) & (39) to assess sensitivity and specificity values based on actual positive and negative values. Calculate the real positive and negative values based on the following criteria as shown in table(16)

Table 16 True positive and negative values

		Training Image	
		P	N
Testing Image	P	TP	FN
	N	FP	TN

$$Senstivity = \frac{TP}{(TP+FN)} \quad (38)$$

$$Specificity = \frac{TN}{TN+FP} \quad (39)$$

Where, TP- True Positive
TN- True Negative
FN- False Negative
FP- False Positive

ROC curve analysis is a better tool for optimization model selection, class distribution, diagnosis of disease, and decision making. ROC curve is used in a multitude of applications such as biometrics, machine learning, natural hazard prediction, radiology, assessment of performance model and medicine. ROC curve evaluation is used to diagnose banana diseases based on diagonal divisions in the ROC region. The ROC curve above the diagonal shows the disease-affected image and the ROC curve below the diagonal shows the disease-free image. The performance of the ROC curve depends mainly on the threshold value; to improve the effectiveness of the ROC curve assessment, we need to select the appropriate threshold value. The ROC curve is shown in Table 17. If the curve in the plot is above the 45 degree slope line, this means that the output of the scheme is good and exceptional or the output of the scheme is bad or worse.

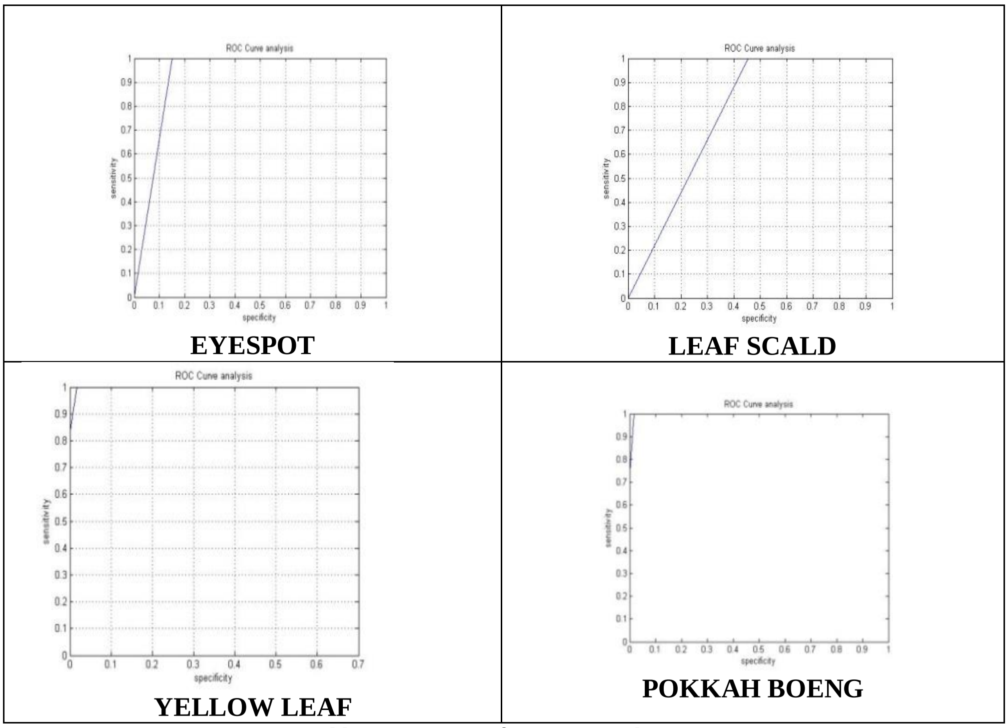

Table 17 ROC curve for sugarcane diseases

RESULT ANALYSIS

The accuracy value for the proposed system is calculated using the following equation (40).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (40)$$

Where,

TP- True Positive

TN- True Negative

FN- False Negative

FP- False Positive

The precision value of the proposed system is compared with the precision rate of other present schemes. Table 18 – 21 indicates the table of comparison and the graph is shown in Figure 8 – 11.

Table 18 Result Comparison for sugarcane Leaf scald disease diagnosis

S.NO	Parameters (%)	MDC	KNN	SVM	CBR	ANFIS
1	Accuracy	70.7	81.5	87.6	95.4	96.8
2	Sensitivity	88.2	89.4	91.7	93.1	95.4
3	Specificity	89.5	94.2	95.1	96.2	96.8
4	Precision	95.7	96.8	96.1	96.5	97.7

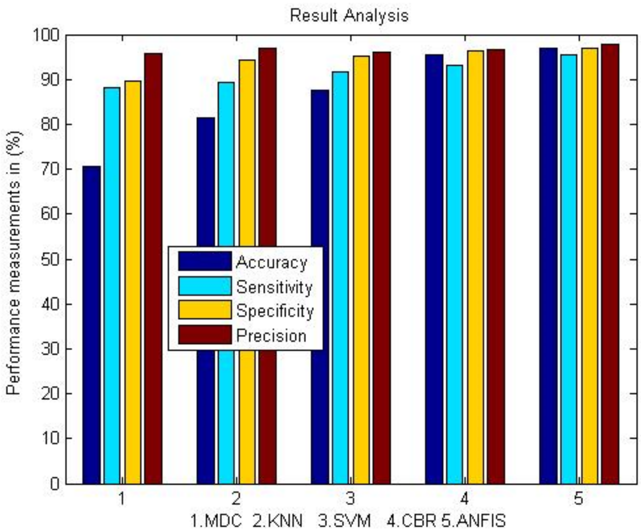

Figure 8 Result Comparison for sugarcane Leaf scald disease diagnosis

Table 19 Result Comparison for sugarcane Yellow leaf disease diagnosis

S.NO	Parameters (%)	MDC	KNN	SVM	CBR	ANFIS
1	Accuracy	77.4	80.2	85.1	96.1	97.3
2	Sensitivity	85.7	86.8	93.2	94.6	97.5
3	Specificity	81.6	91.1	92.4	95.7	97.3
4	Precision	93.8	94.9	95.6	96.6	96.9

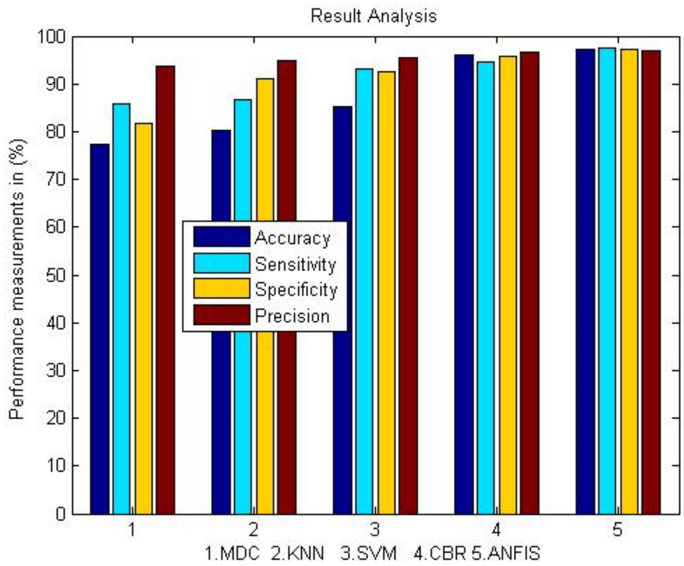

Figure 9 Result Comparison for sugarcane Yellow leaf disease diagnosis

Table 20 Result Comparison for sugarcane Pokkah Boeng disease diagnosis

S.NO	Parameters (%)	MDC	KNN	SVM	CBR	ANFIS
1	Accuracy	78.5	85.5	89.7	95.8	96.8
2	Sensitivity	86.8	87.1	91.3	93.5	96.4
3	Specificity	84.7	92.6	93.5	94.4	96.6
4	Precision	92.1	93.2	96.7	96.2	97.1

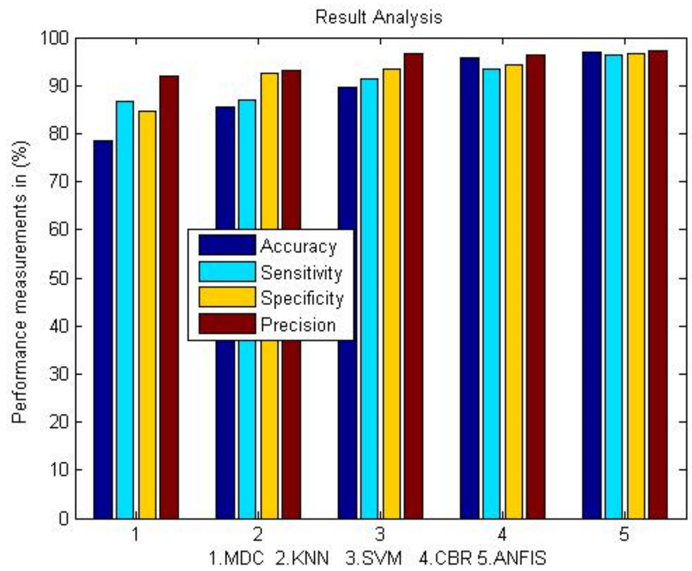

Figure 10 Result Comparison for sugarcane Pokkah Boeng disease diagnosis

Table 21 Result Comparison for sugarcane Eyespot disease diagnosis

S.NO	**Parameters** (%)	**MDC**	**KNN**	**SVM**	**CBR**	**ANFIS**
1	Accuracy	81.7	83.8	87.9	96.1	97.2
2	Sensitivity	83.5	85.6	93.5	96.2	96.3
3	Specificity	87.2	95.5	96.7	96.8	96.9
4	Precision	91.7	95.4	96.6	96.7	97.2

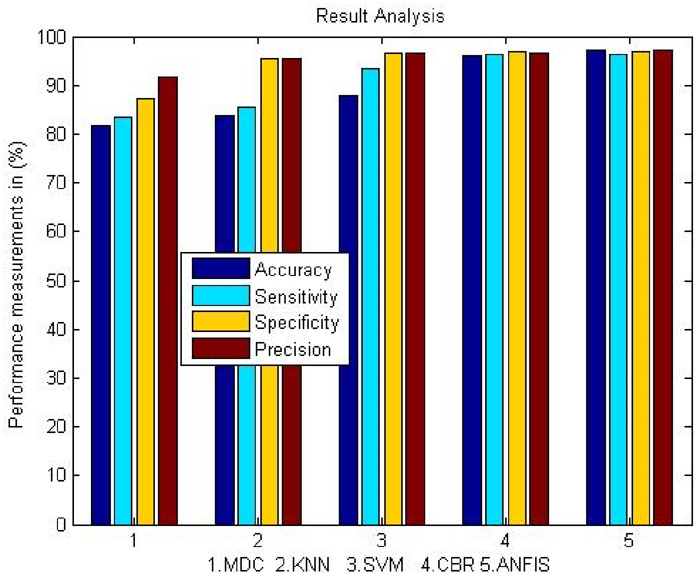

Figure 11 Result Comparison for sugarcane Eyespot disease diagnosis

4. CONCLUSION

Using image processing and soft computing technique to detect and diagnose sugarcane diseases and provide farmers with instant solutions. The effectiveness of the technique suggested relies on the threshold value used in the choice of features and the logic of fuzzy. Machine learning is supervised by ANN and the output is more reliable. The ANFIS technique provides better results in precision than CBR. The suggested assessment or execution time is very small compared to the manual techniques, so the disease can be readily recognized at the earliest point and helps enhance sugarcane output and productivity. The output of the suggested scheme or recommendation will be sent by mobile phone to the farmer in the message format. This can be created into an android application in the future to identify and diagnose the different illnesses of sugarcane. This data about android applications will be in their own language so that farmers can comprehend the data readily.

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