IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

RECOGNITION AND CLASSIFICATION OF CASSAVA LEAF DISEASES USING MACHINE LEARNING TECHNIQUES

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Abstract: Recently, one of the active research areas in agriculture is the productivity and quality of a crop. Image processing and deep learning techniques are being used to recognize plant diseases, which is a hot research topic right now. The majority of research has focused on identifying illnesses using images of complete leaves. Plants are considered essential because they supply mankind with a source of energy. Between seeding and harvesting, plants can be affected at any time. The plant is affected by several infections like viruses, bacteria, and fungal. If pre-preparing is not followed, it will have serious consequences for the plants, as well as a reduction in product quality, quantity, and productivity. Image processing is an early stage of plant disease detection role-playing the well. The goal of this research work is to develop an image recognition system that can recognize plant diseases. Nowadays we need automatic plant disease detection for increasing the food crops and, easily diagnosis the disease. The cassava plant is a worldwide food crop, and it is the third-largest source of food carbohydrates. The early stage of cassava leaf disease detection is very important in the agriculture field. The cassava leaf images are used for the disease identification process. The hybrid algorithm includes the pre-processing steps and the segmentation process is done using the CLAHE. Then the K-means cluster and GLCM are used for the feature affected area identification. The diseased image is classified by the SVM classifiers. Finally, the disease grade is measured by fuzzy logic. The result, we have achieved are more useful and they prove to the helpful for farmers during the cultivation of cassava, which is a major food crop in the world.

***Keywords* – CLAHE, SVM, Plant disease, FUZZY logic**

1 INTRODUCTION

The image processing technique is used for the early stage of plant disease and pests. The complex background of whole leaf images is used for the early research work [1]. The plant leaf disease decreases agriculture product quality and quantity as proven by recent surveys. The early stage of plant disease identification and detection is very difficult for farmers. The beginning stage of disease detection is to set aside the entire crops from disease. Agriculture is also one of the backbones of the Indian economy. Most people are involved directly or indirectly in farming activities. Farmers have quite a tedious task to recognize and identification of plant diseases with open view eyes [2]. The proposed method for plant disease detection is seeing a naked eye by an expert in disease identification in plants. A larger number of experts is required for continuous plant monitoring, if we have a large farm then the cost goes high. At the same time, some countries don't have a proper expert and are not well cost to spend the large farms [3]. Recently, computational automatic plant disease diagnosis based on images is playing an important role in agriculture. Computer vision and image processing are already used in a variety of diagnosis applications in agriculture, like plant classification, plant disease identification, and leaf disease recognition [4].

Cassava is one of the most common food crops grown worldwide. The cassava is commonly most eaten by humans because it contains a valuable source of energy and it can be eaten raw, boiled, roasted, or processed in different ways. Environment and climate conditions are contributing to agricultural crops of cassava growing size [5]. The early stage of cassava plant disease is only analyzed by an expert farmer person, visual monitoring is carried out time-consuming, and laboratory analysis is a long process. So the internet and mobile technology are developed various applications for farmer assistance. Here we use an automated plant disease identification and diagnosis based on image processing and machine learning process [6]. Support vector machine (SVM) is a supervised learning method, and it is applied successfully for the classification of the corps [4, 6]. This research is not only used for cassava plants we use other crops also, like cotton, citrus, tomato, etc. The diseased agriculture images segmentation process is not an easy task. Traditional machine learning techniques are faced many difficulties in the classification of diseased images with acceptable results [6].

1.1 Comparatively analysis of the literature work

Authors/references	Plant	Techniques	Results
Lawrence C. Ngugi et al., [1]	bean, cashew nut, citrus, and passion fruit categories	GoogLeNet CNN	recognition accuracy 79.64% lesion images 94.99%
G. Yashodha et al., [2]	Tea crop	IOT	A disease detection system that detects diseases automatically is more efficient and detects diseases earlier than a traditional detection technique.
Vijai Singh et al., [3]	Banana Beans Lomen Rose	K-mean cluster SVM	k-means accuracy of 86.54% SVM accuracy of 95.71%
Qiaokang Liang et al., [4]	Apple Grape Cherry Peach Pepper	convolutional neural networks SVM KNN	For disease severity estimation, plant species recognition, and plant disease categorization, overall accuracies of 0.91, 0.99, and 0.98 were found, respectively.
G. Sambasivam et al., [5]	Cassava plant leaf	CNN	When class-imbalanced rectification techniques were used with data augmentation and high input image dimensions, we achieved an increase in accuracy of over 5% and a log loss of 0.06 percent, up from over 20%.
Prabira Kumar Sethy et al., [6]	Different types of rice leaf	Per trained CNN SVM	This research will be continued with more rice disease kinds and a fine-tuned CNN model in the hopes of improving performance.
Preeti et al., [7]	Plant diesase	GLCM SVM KNN	In comparison to existing outcomes, the accuracy and false positive rate have been reduced to 10%.
Patike Kiran Rao et al., [9]	Cassava leaf	Separable Convolutions UNet Fully Convolution Networks	accuracies of 83.9% and 61.6% respectively
Jaskaran Singh et al., [10]	Potato leaves	KNN GLCM	For classification, around 97 percent accuracy was achieved.
Anjna et al., [11]	Capsicum and capsicum leaf	GLCM Tree Linear discriminant SVM KNN	Healthy and diseased capsicum can be distinguished with a precision of nearly 100 percent using the SVM classifier.
RUPALI KALE et al., [12]	Apple leaf	Support Vector Machine (SVM), K-Nearest Neighbors (KNN)	In comparison to other classifiers, the Multivariate Support Vector Machine (SVM) Classifier delivers the best results for testing datasets.
Archana Jadhav et al., [13]	Cotton plant	OpenCV SVM	It is possible to diagnose sickness as well as recommend treatments for curing it.
Gautam Kaushal et al., [14]	Plant leaf	GLCM K-means SVM KNN	In the proposed study, To classify data into numerous classes, the SVM classifier is replaced by the KNN classifier.. When compared to existing techniques, the proposed algorithm's performance is evaluated in terms of accuracy and false-positive rate, with an increase of up to 10%.
Seksan Mathulaprangsan et al., [15]	Cassava leaf	CNN VGGs ResNet DenseNet	The highest classification score was achieved by DenseNet121, which was 80.52 percent. With the addition of brightness modification, the classification accuracy has increased to 94.32 percent.
H R Ayu et al., [16]	Cassava leaf	MobileNetV2 Graphical User Interface (GUI)	The overall accuracy of test data is 65.6%
Ozichi Emuoyibofarhe et al., [17]	Cassava plant	Cubic support vector machine (CSVM)	an 83.9 percent accurate cubic support vector machine model, and a 61.6 percent

		Coarse Gaussian support vector machine (CGSVM)	accurate coarse Gaussian support vector machine

The earlier stage of plant disease detection is done by farmers through eye observation, but it takes a long time and also gives less accuracy. The farmers are having some time intervals for plant growth monitoring and them having difficulty with plant disease detection and identification in the early stage without any expert guidance. If they found any symptoms of disease, they use their own prescription or either prescribed by the local shop, sometimes it goes wrong and reduces the overall plants. Without any expert knowledge person, manual plant disease identification is not an easy task for farmers, they suffer a lot in the economy and also personally. As a result, an automated system is required that can give the necessary plant disease information as well as detect and identify plant infections as soon as possible to make. The accurate disease diagnosis gained by a complete understanding of plants, their infections, and preventive measures as indicated by specialists is the most important factor for the identification and detection of various plant diseases. The proposed scheme in this paper uses image processing techniques for accurate plant disease diagnosis with the help of expert knowledge, which will help farmers identify plant diseases, make the right decision, and choose the right treatment for the disease on time, resulting in better crop production.

2 MATERIALS

2.1 Dataset

The cassava leaf disease images are collected for input images. The image dataset is collected from the Kaggle plant dataset and cassava leaf gallery format of the jpeg image. The dataset contains cassava leaf disease images which include Cassava Bacterial Blight (CBB), Cassava Mosaic Disease (CMD), Cassava Green Mite (CGM), Cassava Brown Streak Disease (CBSD), and Healthy.

(a)Healthy (b)CBB (c)CMD (d)CBSD (e)CGM

Fig 1 cassava diseased leaf and healthy leaf

Table 1 Detail of cassava leaf dataset

Diseased leaf	Number of samples		
	Original images	Training images	Testing images
Cassava Bacterial Blight	2519	1764	755
Cassava Mosaic Disease	2684	1889	795
Cassava Green Mite	2270	1592	678
Cassava Brown Streak Disease	2620	1820	800
Healthy	2502	1767	735
Total	12595	8832	3763

2.2 Cassava Bacterial Blight (CBB)

The bacterial blight symptoms are infection begins small area, spots are turned brown and yellow shades then the tissues have died. The dark spots are surrounded by yellowish-green. Moisture is one of the important sources of plant infection. So, the cassava plants are in a moisture area the cassava plant is easily affected by bacteria [5].

2.3 Cassava Mosaic Disease (CMD)

The cassava mosaic disease variety of foliar symptoms are mosaic, mottling, and the leaves are instructed, twisted, then the overall plants and leaf size are reduced. The leaves are getting green patches with different shades of the yellow and white color [8].

2.4 Cassava Green Mite (CGM)

The CGM symptoms are the leaf getting white spots on the top side. The white spots are entered in a small portion of the leaf and then will cover the whole leaf, which also causes mottling symptoms so we are easily confused with cassava mosaic disease [5]. The leaves are falling down.

2.5 Cassava Brown Streak Disease (CBSD)

The cassava brown streak symptoms are yellow patches mixed with the normal leaf green color. Sometimes the yellow patches cover too large an area of the leaf. The dark brown necrotic area on the tuber root and also root size is reduced.

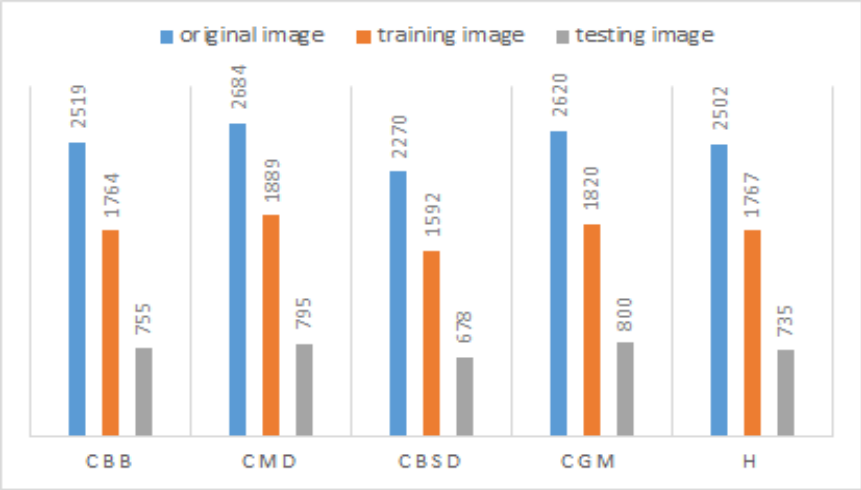

Fig 2 Cassava leaf dataset

3 RESEARCH METHODOLOGY

A digital camera or data set of different types of diseased cassava leaf images is used for identifying the affected area of the leaf. The different types of image processing algorithms are applied to the diseased leaf images for analysis.

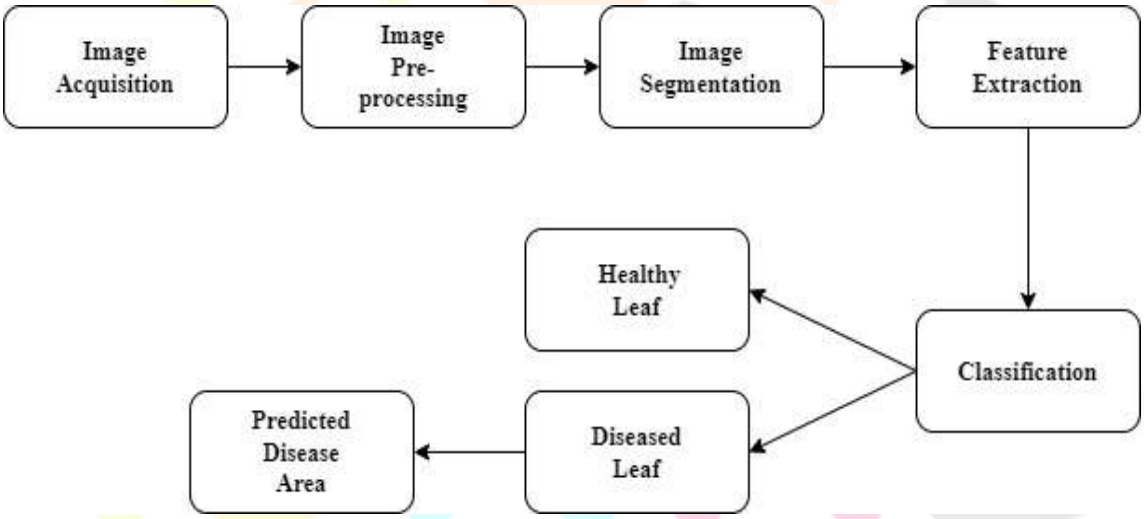

Fig 3 Block Diagram of Proposed Method

3.1 Image Pre-Processing Techniques

The pre-processing is used in leaf disease images for the better visual quality of the input image. It removes the many problems in diseased leaf images like noises, illumination, the brightness of images, and poor contrast. Image resizing [9], RGB channel extraction, noise reduction, Enhancement of contrast, and HSI conversion works are used in pre-processing.

The foreground is split from the background in green channel extraction. The accurate segmentation of the foreground is done by green channel extraction, it is the crucial one of the segmentation process.

The mean filter gives more accurate results and a very high noise ratio. The smoothing process of the median filter is very well. When compared to the Gaussian function, it produces better results. Also, rather having a mean filter, provide more particular information about the edge pixels.

$$I_{Median}(x,y) = Median\{I(m,y),(x,y)??\} \quad (1)$$

$$I_{Mean}(x,y) = \frac{1}{mn}?I(m,n) \quad (2)$$

The contrast enhancement is increased or adjusted in the intensity values. So the visibility and brightness of the image are improved. A variant of Adaptive Histogram equalization (CLAHE) is an image enhancement technique for boosting an image's local contrast, which is focused on small parts of the image rather than the full image.

The mathematical expression for changed grey levels in the standard CLAHE Approach with Uniform Distribution can be given as in this method.

$$G = [gmax - gmin]*P(f) + g(min) \quad (3)$$

Where gmax = Maximum pixel value

gmin = Minimum pixel value

g = Computed pixel value

P (f) = CPD (Cumulative Probability Distribution)

3.2 Thresholding

Otsu's method is used for the identification of patterns, Binarization of documents, and computer vision.

$$\text{Otsu Global Thresholding} = g(x, y) = \begin{Bmatrix} 1\ if\ f(x,y) > T \\ 0, if\ f(x,y) = T \end{Bmatrix} \quad (4)$$

- Decide on a starting point for T.
- Using T, segment each image. Two kinds of pixels will be created as a result of this. C0 is made up of all pixels with Gray level values greater than T, while C1 is made up of pixels with values equal to T.
- For pixels in areas C0 and C1, compute the average Gray level values M1 and M2.
- Thresholding converts by putting all pixels below a given threshold to zero, grayscale images can be converted to binary images, and all pixels above that threshold to one.

3.3 HSI Equalized Conversion

Hue (H) is a measurement of color spectrum combination. With a range of values, the angle around the vertical axis is measured from 0 to 360 degrees, starting with red at 0°.

The relativistic purity or even the quantity of white light combined with a hue is referred to as saturation (S). It's a ratio that starts at 0 and extends radially outwards to a maximum value of 1 on the cylinder's surface.

Intensity is used to assess the relative brightness ranges between 0 and 1. (I). The saturation component is 0 when R=G=B is true. The hue is indeterminate at any position along with the intensity (I) axis.

The RGB image is transformed to HSI (Hue, Saturation, and Intensity) format, then the histogram is equalized. And the updated HSI image's RGB conversion.

$$\theta = \left\{ \frac{\frac{1}{2}[(R-G)(R-B)]}{\sqrt{[(R-G)2(R-B)(G-B)]}} \right\} \quad (5)$$

$$\text{Hue (H)} = \begin{Bmatrix} \theta, & if\ B \le G \\ 360 - \theta, & if\ B > G \end{Bmatrix} \quad (6)$$

$$\text{Saturation (S)} = 1 - \frac{3}{(R+G+B)}[\min(R, G, B)] \quad (7)$$

$$\text{Intensity (I)} = \frac{1}{3}(R + G + B) \quad (8)$$

HueEq = histeq (H) ---------- (i)

SatEq = histeq (S) ---------- (ii)

IntEq = histeq (I) ---------- (iii)

Concatenate a HueEq, SatEq, and IntEq (i), (ii) and (iii)

HSIEq=cat (3, HueEq, SatEq, IntEq) (9)

3.4 Feature extraction of GLCM

The difference between the spatial relationship of pixels and its type of co-occurrence matrix are determined with help of GLCM. The Graycomatrix function is used to make GLCM by calculating pixels with intensities in i that occur a pixel with the value j in a spatial connection The total output of the GLCM is the number of times a pixel in i appeared in the input image in the defined A pixel with the value j has a spatial link to it. The size of the output image is determined by the number of grey levels in the original image of GLCM. GLCM determines the spatial distribution of grey levels in texture picture attributes. The horizontal neighboring pixel and the pixel of interest determine the spatial relationship [10].

Table 2 Feature Extraction Mathematical Formulas

Feature	Formula
Mean	$\mu = \frac{1}{AB}\sum_{i=1}^{A}\sum_{j=1}^{B} P(i,j)$
Standard Deviation	$\text{S.D} = \frac{1}{AB} = \sum_{i=1}^{A}\sum_{j=1}^{B}(P(i,j) - \mu)^2$
Entropy	$E = ?\,(P.* \log^2(P))$

RMS	$RMS = \sqrt{\frac{?_{I=1}^{A} \lvert mij \rvert^2}{A}}$
Variance	$V = \sqrt{S.D}$
Smoothness	$Smoothness = 1 - \left(\frac{1}{(1+a)}\right)$
Kurtosis	$K = \left\{\frac{1}{AB}\sum_{i=1}^{A}\sum_{j=1}^{B}\left[\frac{P(i,j)-\mu^4}{\sigma}\right]\right\} - 3$
Skewness	$Ske = \frac{1}{AB}\sum_{i=1}^{A}\sum_{j=1}^{B}\left[\frac{P(i,j)-\mu^3}{\sigma}\right]$
IDM	$IDM = \frac{P(i,j)}{1+\lvert i-j \rvert}$
Contrast	$c =?_{i,j} \lvert i-j \rvert^2 P(i,j)$
Correlation	$correlation = \sum_{i,j} \frac{(i-\mu i)(j-\mu j)P(i,j)}{\sigma_i \sigma_j}$
Energy	$Energy =?_{i,j} P(i,j)^2$
Homogeneity	$Homo =?_{i,j} \frac{P(i,j)}{1+\lvert i-j \rvert}$

3.5 Support Vector Machine Classification

In the field of pattern recognition, SVM is a supervised learning technique. SVM determines a hyperplane for dividing the data into two classes based on the given training dataset, and it is used to classify the testing data [11].

Let us consider training data set D to be given as $x_{i,}y_i$ = 1,2, …, m where $X_i \epsilon R^d$ and $Y_i \epsilon \{-1, +1\}$ are feature vectors and associated class label respectively.

The separating hyperplane is expressed as W^TX + b = 0, where w is the normal vector and b denotes the bias. If one has the maximum distance to their closet training data and either class is built using the equation below, the goal of this relation is to identify the largest marginal hyperplane:

$$y_i\ (W^T\mathrm{X} + \mathrm{b}) \geq 1 - \xi_{i,} \forall \mathrm{i} \qquad (10)$$

Where, parameter $\xi_{i,}$ defines the stock variable which relaxes the ith constraint.

The primal problem of SVM is defined in below equation:

$$\min p(W, b, \xi) = \frac{1}{2} x \|W\|^2 + C \sum_{i=1}^{m} \xi_i \qquad (11)$$

$$\text{Subject to} \quad y_i\ (W^T\mathrm{X} + \mathrm{b}) \geq 1 - \xi_{i,} \forall \mathrm{I} \qquad (12)$$

$$\xi_i \geq 0, \forall \mathrm{I} \qquad (13)$$

Where C is a penalty for violations of the constraints. Lagrange multiplier α_i is introduced and converting into dual forms is given in below optimization problem.

$$\max \mathrm{D}(\alpha) = \sum_{i=1}^{m} \alpha_i - \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m} \alpha_i \alpha_j Y_i Y_j X_i X_j \qquad (14)$$

$$\text{Subject to } 0 \leq \alpha_i \leq C, \forall_i \qquad (15)$$

$$\sum_{j=1}^{m} \alpha_i Y_j = 0 \qquad (16)$$

Kernel function maps the data into high dimensional and it has a possibility to handle the case when it is a non-linear separable condition. In this work, Gaussian RBF is used and it is defined in the below equation:

$$K(X_i X_j) = exp\ \frac{-\|X_i - X_j\|^2}{2\gamma^2} \qquad (17)$$

In the above equation, γ defines the Gaussian RBF kernel scaling factor.

3.6 Fuzzy Logic

Fuzzy Logic, which was developed by Lotfi Zadeh in 1965, is dealing with how a system handles Risk, uncertainty, and vagueness are all factors to consider. The image displaying the cluster of illness spots is considered and converted to binary after segmentation with K-Means. Calculating the total diseased area is a standard procedure (DA). The total amount of pixels in an image is referred to as the region of a binary representation in image processing specifications. As a result, the primary scaled image is converted to a binary representation, with the pixels corresponding to the cassava leaf on White. The complete cassava leaf area (CA) of this leaf is obtained from here. After identifying CA, including DA, the percentage of infection (percent of I) can be calculated using the following equation.

$$\%I = \left(\frac{Diseased\ Area}{Complete\ Area}\right) * 100 \qquad (18)$$

3.7 Accuracy Calculation

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (19)$$

Where:

- True Positive (TP) is the no. of defected images and is classified as defected.
- False Positive (FP) is the no. of defect-free images and is classified as defect-free.
- True Negative (TN) is the no. of defective images and is classified as defect-free.
- False Negative (FN) is the no. of defect-free images and is classified as defective

3.8 Flow chat

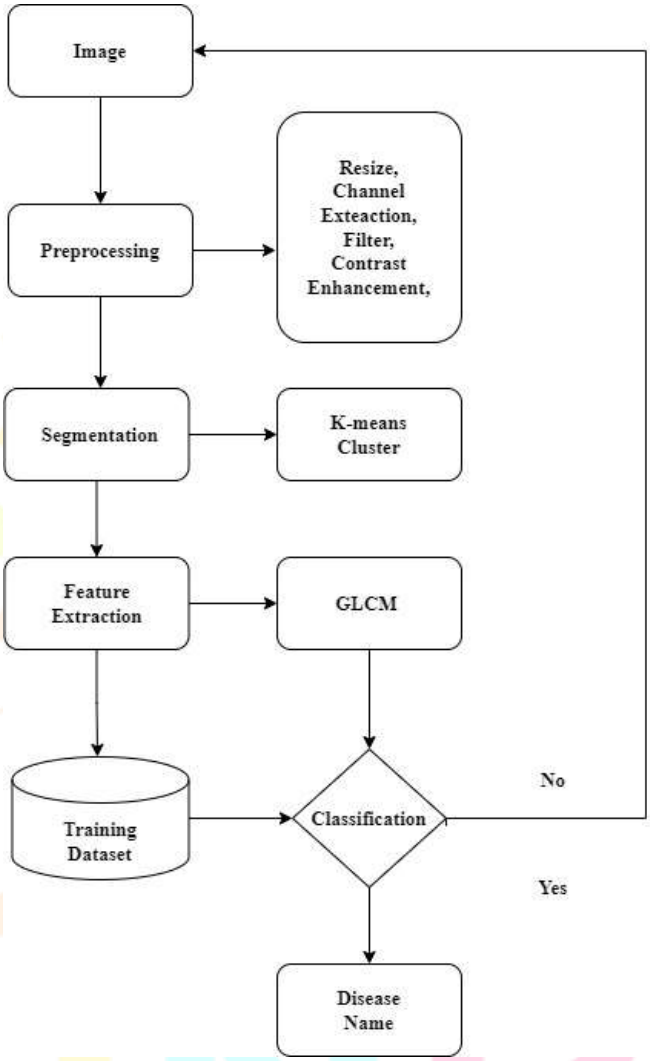

Fig 4 Flow Chart of Proposed Method

4 RESULTS AND DISCUSSION

All the image processing algorithms are performed, for an input set of cassava plant leaves diseased images like cassava bacterial blight, cassava mosaic disease, cassava brown streak disease, cassava green mite, and a healthy leaf of cassava. In this work, cassava leaf disease datasets are collected from the Kaggle plant dataset and cassava leaf gallery. The dataset is divided into two sets training dataset and the testing dataset on the 70:30 rule.

4.1 Pre-processing and segmentation results

The pre-processing image fig 3 (ii) shows the enhancement image of cassava leaf using histogram equalization, it is used to enhance the image for better visual quality. Fig 3 (iii) shows the segmented image of the cassava leaf diseased part is highlighted.

Fig 5 (i) Original image (ii) enhanced image (iii) segmented image

4.2 Feature Extraction

Results of Feature Extraction, a result of 13 characteristics are extracted from the cassava diseases leaf and healthy leaf images to train the classifier for additional processing.

Table 3 Cassava leaf image values of GLCM Feature Extraction

Sample image	Mean	S.D	Entropy	RMS	Variance	Smoothness	Kurtosis	Skewness	IDM	Contrast	Correlation	Energy	Homogeneity
H	33.6661	61.3956	2.63239	7.43689	3337.52	1	3.61667	1.48136	255	0.596906	0.913983	0.54067	0.935357
CBB	14.7933	42.3354	1.63104	4.95279	1555.31	1	12.2386	3.12387	255	0.5072	0.845543	0.702972	0.960097
CMD	20.2535	49.6789	1.92521	6.09318	2227.71	1	8.23741	2.47786	255	0.989093	0.781656	0.641044	0.924532
CBS	16.9264	42.124	2.28053	6.72947	1621.53	1	11.6454	2.9073	255	0.597993	0.809128	0.592584	0.937369
CGM	54.4691	79.7899	3.40148	9.2912	6049.18	1	2.23024	0.962443	255	2.40923	0.768583	0.379995	0.84635

4.3 Classification results

The SVM classifier is used to classify the cassava healthy leaf and cassava diseased leaf of trained datasets. For classification purposes, the classifier with the best accuracy results is used. The results of the classifier with SVM provide 100% accuracy. SVM is used to classify Cassava leaves into two classes healthy and diseased leaves.

4.4 Disease grade evaluation

Cassava leaf disease grading for automatic is very important in the current situation. The Fuzzy logic algorithm is used for grade by the cassava leaf affected area. Fig 4 (ii) shows the cassava leaf diseases images of Fuzzy logic grade results. Pathologists will benefit from our method because it eliminates practically all of the drawbacks of manual grading in terms of complexity and time. Experiments show that the observed results are accurate and adequate.

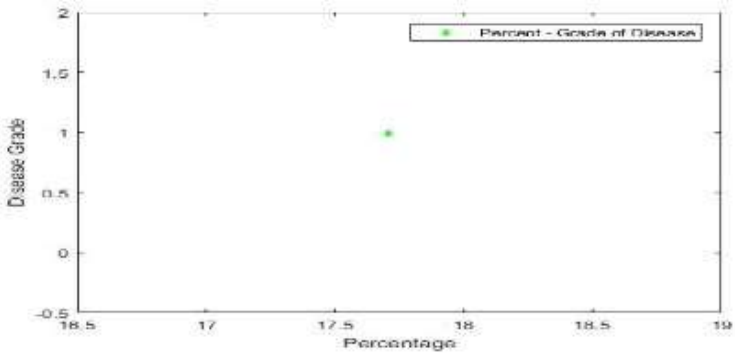

Fig 6 (i) input image **(ii) disease grade**

4.5 Conclusion

In recent days, researchers have made a number of efforts toward the development of a hybrid system for the detection of diseases in the cassava field. The major objection to proposing a method to automatically classify cassava-affected spots. From the results of research and discussion of the implementation of the fuzzy logic and SVM classifier. The SVM provides 100% accuracy and the Fuzzy logic results are accurate and adequate.

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