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RICE PLANT DISEASE IDENTIFICATION DECISION SUPPORT MODEL USING MACHINE LEARNING

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Abstract

In this paper, we propose a decision support system for Indian rice farmers for identifying diseases. In a country like India, food security is an essential concern. Additionally, diseases in plants can cause a significant loss. Early-stage detection of diseases can help in improving the production of rice. In this context, first we investigate the recent contributed efforts in the field of plant disease detection by analysing plant leaves using machine learning and image processing techniques. Next, the datasets and relevant algorithms are concluded. Then, a machine learning model has been presented. The model includes the edge feature extraction using canny edge detection technique, colour features are extracted using grid colour movement, and the texture analysis is performed using Local Binary Pattern (LBP). In the next step, using the extracted features, we have prepared a combined feature vector to train the Machine Learning (ML) algorithms namely Support Vector Machine (SVM) and Artificial Neural Network (ANN). These machine learning algorithms are organized in such a manner that the proposed decision support model can identify and differentiate the leaf plants. Additionally, it also recognizes the rice plants when we query. Secondly, the model is also able to recognize rice plant diseases. The first scenario of the experiment has been carried out using Plant Village dataset. The second scenario of experiment uses the rice plant disease dataset obtained from Kaggle with three classes. The second dataset used which is known as the Mendeley dataset which contains five different diseases as class labels. The experimental study with the implemented system confirms the superiority of ANN to be used with the proposed decision support system as compared to the SVM algorithm in terms of accuracy and time consumption. Finally, future work has also been highlighted.

Keywords:

Plant Disease Detection, Machine Learning, Image Processing, Food Security, Early Disease Detection

1. INTRODUCTION

In India, agriculture is a major source of livelihood for more than 80% population. It not only provides employment to 52% of labours but also contributes to GDP up to 15% [1]. However, we know the conditions of farming in this country and lack of focus and resources. One of the major factors which impact the performance of Indian crop production is plant disease. Plant diseases are the key reason for 10–16% losses in the global crops each year [2]. However, in India we follow the traditional approaches of disease identification which are time consuming as well as require higher level of expertise. Recently, Machine Learning (ML) techniques have become popular in various real-world applications which use them for object recognition and classification tasks [3]. The combination of Image processing and ML enables us to process the image data and recover required knowledge. These techniques can also be used for the detection of diseases.

The proposed work is motivated to design a low cost, enhanced and accurate disease detection model which can be used by farmers to detect the possible rice plant disease in early stage by using the plant leaf image. Most of plant diseases are initially present on the leaf and then become viral. This results in low production and bad quality of crops. Therefore, in this paper we have proposed a decision support system for Indian framers. This support system is an on-demand and low-cost technique where a farmer can take a image of rice plant image from the farm and send the image to a cloud server. The server will analyse the image and send a message to the farmer whether the plant is healthy or diseased.

Therefore, in this paper we first explore the different techniques and methods that are utilized for recognizing the plant diseases. Next, architecture has been presented and the implementation of the model has been carried out. Finally, based on the experiments the results are analysed. Lastly, we provide the future road map for extending the proposed working model.

2. LITERATURE REVIEW

In this section, recent contributions and developments are offered which will help us to understand the working of plant disease detection models.

2.1 SURVEY AND REVIEWS

The major cause of low crop yield is disease. It can be prevented by plant diseases detection systems. Shruthi et al. [4] presents the stages of plant diseases detection system and compared ML techniques for plant disease detection. It observed that Convolutional Neural Network (CNN) gives high accuracy and detects more diseases. However, plants are diseased through their leaves. Leaves are important for fast growth of plants. Spraying pesticides to the plants can affect the human health. Kumar et al. [18] survey on different plant diseases and advanced techniques to detect them.

Similarly, Shah et al. [21] present a survey of different image processing and ML techniques used for rice plant diseases identification. They not only survey techniques but also discuss concepts applied to plant disease detection. The survey is based on criteria, which includes size of dataset, no. of classes, pre-processing, segmentation techniques, types of classifiers, accuracy of classifiers, etc.

Dhingra et al. [24] address disease recognition and classification of plant leaves. A discussion on the disease's classification performance is presented based on techniques from 1997 to 2016. Finally, they discussed the challenges and future improvements.

2.2 DATASET AND QUALITY

Singh et al. [17] explore the possibility of computer vision for early plant disease detection. They present PlantDoc; a dataset for visual plant disease detection. That dataset contains 2,598 image data in total across 13 plant species and up to 17 classes, of annotated images. To show the efficacy, 3 models for classification were used. The results show that modeling used this dataset can increase the classification accuracy. On the other hand, images taken from distance are insufficient in resolution and can degrade accuracy.

Cap et al. [5] propose a pre-processing method to improve the plant disease diagnosis systems performance. The investigation includes two super-resolution techniques by comparing them on high-resolution, low-resolution, and super-resolved images of cucumber. The model generates super-resolved images which is able to recover the symptoms. It improves the accuracy by 26.9%.

2.3 DEEP LEARNING

Fujita et al. [6] propose a plant-disease detection system using 7,520 cucumber leaf images of healthy and infected. The leaves were photographed on site; image must contain a leaf roughly at its centre, thus providing a variety of parameters including distance, angle, background, and lighting. Half of the images used were taken in bad conditions. The CNN attained 82.3% accuracy under the 4-fold cross validation. Most Deep Learning (DL) models for diseases detection suffer from the fatal flaws that were tested on independent data.

Sharma et al. [7] investigate this problem using segmented image to train the CNN. The F-CNN is trained with full images and S-CNN was trained with segmented images which improve accuracy to 98.6% with 10 diseases. Using tomato plant, it shows that the confidence of S-CNN model is improves significantly. New DL models offer to be effectively sent on portable.

Utilizing a dataset of cassava, Ramcharan et al. [8] applied exchange figuring out how to recognize three infections and two sorts. The prepared model accuracy was 98% for BLS, 96% for RMD, 95% for GMD, 98% for CBSD, and 96% for CMD. The model accomplished a general precision of 93%. Results show that move learning offers a quick, reasonable, and effectively deployable procedure.

According to Ferentinos et al. [9] CNN models are used for plant disease detection by analyzing leaves images. Training was performed with 87,848 image databases, it consists of 25 different plants in 58 classes, with healthy plants. The best performance reached a 99.53% success rate.

Too et al. [10] concentrated on tuning and evaluation of deep CNN algorithms for plant disease classification. The architectures include Inception V4, VGG 16, ResNet with 50, 101 and 152 layers and DenseNets with 121 layers. The 38 different classes including diseased and healthy images are used. DenseNets has a tendency to improve in accuracy with growing epochs, with no over-fitting and deterioration. It requires lesser number of parameters and time to achieve performances of an accuracy of 99.75%.

Using PlantVillage dataset, a series of deep CNN are trained. The shallow networks trained and deep models fine-tuned by Wang et al. [11]. The deep VGG16 is best model, which yields an accuracy of 90.4%. To detect verticillium wilt in strawberry accurately, Nie et al. [25] propose a network based on Faster R-CNN and multi-task learning. The SVWDN detects verticillium wilt according to the symptoms. They construct a dataset that contains 3,531 images with 4 categories. They achieved a MAP of 77.54% and 99.95% accuracy.

2.4 SVM

Automatic recognition of plant diseases may benefit in monitoring huge fields. D. O. Shamkuwar et al. [12] developed a system which recognizes crop diseases. In this model, the users have to take an image and by using SVM, plant disease can be predicted. M. Islam et al. [16] present an approach using image processing and ML to diagnose diseases. This method classifies potato plants from a database ‘Plant Village’. The segmentation and SVM demonstrate an accuracy of 95%. S. A. Nandhini et al. [19] developed a web enabled disease detection system based on compressed sensing. Statistical thresholding is proposed for segmentation. The segmented leaves are uploaded to the cloud. The measurements are retrieved and the features are extracted. The analysis is done using SVM. The WEDDS was evaluated using Raspberry pi. The consequences demonstrate that technique offers an accuracy of 98.5%. To increase the productivity in agriculture, early detection of diseases needed. S. Iniyan et al. [27] have a concise discussion with detection of diseases using ML techniques, especially with SVM and ANN. They have concluded with the pros and cons of every method.

2.5 DECISION TREE AND OTHERS

Ramesh et al. [13] used the Random Forest to identify between healthy and diseased leaves. They include various phases namely dataset creation, feature extraction, training the classifier and classification. The datasets are trained to classify the images using extracted features HOG.

Garud et al. [22] presented the plant leaf diseases detection. The steps are image acquisition, pre-processing, segmentation using k-medoids, texture extraction, and classification using ANN. Similarly, Khirade et al. [14] discussed the methods used for the detection of diseases.

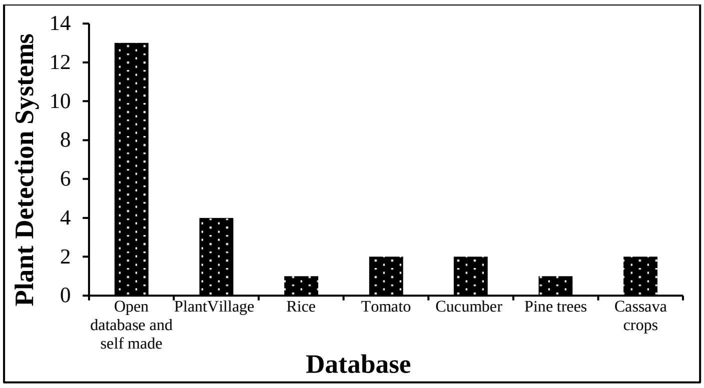
Pourazar et al. [20] zeroed in on the need of radiometric adjustment to recognize unhealthy trees dependent on elevated multi-ghostly images. Two locales were chosen and multispectral images were gathered. The effect of radiometric rectification recognition was surveyed in: 1) examination of detachability between the sound and sick classes; 2) impact on precision. The outcomes showed the irrelevant impact of radiometric adjustment on distinctness. The radiometric adjustment negligibly affected precision. The precision and kappa esteems, utilizing five phantom groups and DVI, NDRE, NDVI, and GNDVI vegetation records utilizing irregular backwoods. An illness named little leaf is dangerous in pine trees. Some technique is beneficial in monitoring in big farms and early-stage detection of diseases.

Singh et al. [15] present an algorithm for image segmentation which is used for detection of plant diseases. Image segmentation is done using genetic algorithm. To minimize the losses, it is essential to detect the pathogens. Ray et al. [23] provide an overview of conventional methods, current trends and advances on biosensors. Biosensors would become a promising and alternative, but they still have to be subjected to some modifications and proper validation.

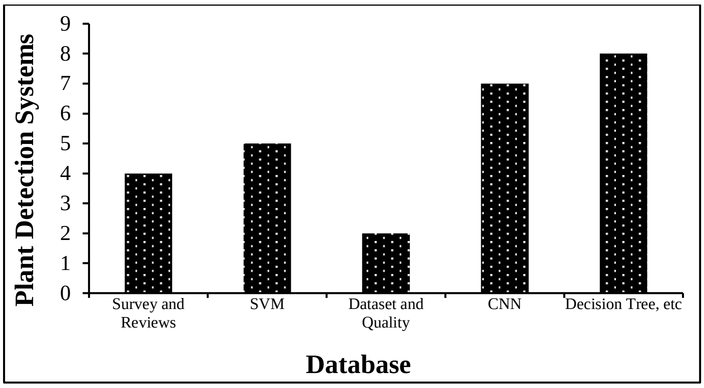
Owomugisha et al. [26] suggest the use of visible and infrared spectral information for disease detection in cassava crops. They monitor the plants and collecting both spectra and plant tissue for chemistry analysis. The results demonstrate that suitably trained classifiers are able to detect cassava diseases. They consider Generalized Matrix Relevance Learning Vector Quantization (GMLVQ) and alternatively, a combination of Principal Component Analysis (PCA). The early detection of diseases will be beneficial to avoid losses. Panigrahi et al. [28] focus on supervised ML techniques such as Naive Bayes (NB), Decision Tree (DT), KNN, SVM, and Random Forest (RF) for maize plant disease detection. The techniques are analyzed and compared to select the suitable model with highest accuracy. The RF results with the highest accuracy of 79.23%.

Table.1. Review Summary

Ref.	Article type	Algorithm	Crop Type
[4]	The stages of plant diseases detection system and compare ML techniques	CNN	-
[18]	Survey on different plants disease and advance techniques to detect diseases.	Different ML techniques	-
[21]	presents a survey of different image processing and ML techniques	Segmentation and classification	Rice
[24]	A discussion on diseases detection performance based on traditional methods from 1997 to 2016	Classification	-
[17]	Explore the possibility for early plant disease detection and present PlantDoc: a dataset.	Dataset	13 plant species
[5]	Improving the performance of disease diagnosis using super-resolution techniques	Pre-processing	Cucumber images
[6]	Classification based on CNN attained an average of 82.3% accuracy	CNN	Cucumber leaf images
[7]	Using segmented image to train the CNN models	Segmentation and CNN	Tomato plant
[8]	Applied transfer learning to train a deep CNN to identify three diseases and two types of pest	Deep CNN	Cassava
[9]	CNN models were developed	CNN	A database of 87,848 images
[10]	CNN for image-based plant disease detection	Deep CNN	38 different classes
[11]	A series of deep CNN are trained	Threshold-based segmentation and deep CNN	PlantVillage dataset
[25]	A disease detection network based on Faster R-CNN and multi-task learning	CNN	Strawberry
[12]	A system which recognizes crop diseases	SVM	-
[16]	Integrates image processing and ML to allow diagnosing diseases	Segmentation and SVM	Plant Village
[19]	Web enabled disease detection system based on compressed sensing	SVM	-
[27]	Early detection of diseases	SVM and ANN	-
[13]	Makes use of Random Forest in identifying between healthy and diseased leaf	Random Forest	-
[20]	Focused on the necessity of radiometric calibration to distinguish diseased trees based on aerial multi-spectral images	Random Forest	-
[14]	Discussed the methods used for the detection of diseases	Segmentation	-
[15]	An algorithm for image segmentation technique using genetic algorithm	Image Segmentation	Pine Trees
[22]	Method covers the steps of image processing	k-medoids, ANN	-
[23]	Overview of conventional methods, current trends and advances on biosensors	Biosensors	-
[26]	Use of visible and near infrared spectral information facilitates disease detection	Generalized Matrix Relevance Learning Vector Quantization, Principal Component Analysis	Cassava crops
[28]	Focuses on supervised machine learning techniques	Naive Bayes, Decision Tree, KNN, SVM, Random Forest	-



(a)



(b)

Fig.1. Datasets used (a) and Classifiers (b) for Designing the Plant Disease Detection System

3. REVIEW AND CONCLUSION

Additionally, the graphical representation of summarized review has been reported using Fig.1(a) and Fig.1(b). The Fig.1(a) shows the work based on different crops or datasets. In Fig.1, the frequency of articles is reported in Y axis and X axis reports the plant names. According to the observations, for identifying the disease using leaf image analysis, most of the works are based on either open database of plant images or constructed by their own. In addition, PlantVillage dataset is the most popular for experimental images of diseased as well as healthy plants. On the other hand, the Fig.1(b) shows the algorithms used for analysing the image data. In the figure, the X axis shows the algorithms used and Y axis shows the frequency of research work. During this review, we found that there are two kinds of approaches:

- Extraction of different kinds of features from the image and make use of a supervised learning technique to classify them.
- Segmentation of image to recover the features from image and use of CNN to learn and classify them.

4. PROPOSED WORK

The aim of the proposed work is to develop an efficient and accurate plant disease detection technique for rice plants. In order to identify the disease, the rice plant leaves are used with ML and image processing techniques. Therefore, in this section we provide the complete discussion about the proposed ML model.

4.1 SYSTEM OVERVIEW

The proposed model is an initiative to design a decision support system according to the need of Indian Farmers. Initially, the proposed model is aimed to provide the support the farmers of rice, because the rice is a main food base in India. Additionally, a significant number of farmers suffer because of the different diseases in rice plant which results in low production of crops. The proposed initial model will include the following features:

- **Differentiate the Different Plant Leaves**: In this phase, the model will verify the leaf. It will be able to recognize the different plant leaves by their names.
- **Accurately Identify the Rice Plant**: In this phase the model will simulate its ability to recognize the rice plant leaf accurately from other plants.
- **Classify the Plant Leaf as Healthy or Diseased**: If a rice plant has been detected, then it will be analysed to identify whether image contains a healthy or diseased plant.

In order to organize the above discussed features in a real-world application, a conceptual model has been demonstrated in Fig.2. According to the process demonstrated in this figure, a farmer will first click an image and will upload to the server. The server will receive the farmer’s image, and then will apply the above discussed components to the image and recognize whether the image is infected or it is a healthy rice plant image. When the model concludes the results, then it will send the message to the framer providing the status of the plant infection. This section just provided an overview of the proposed concept; the next section discusses the server component of given model.

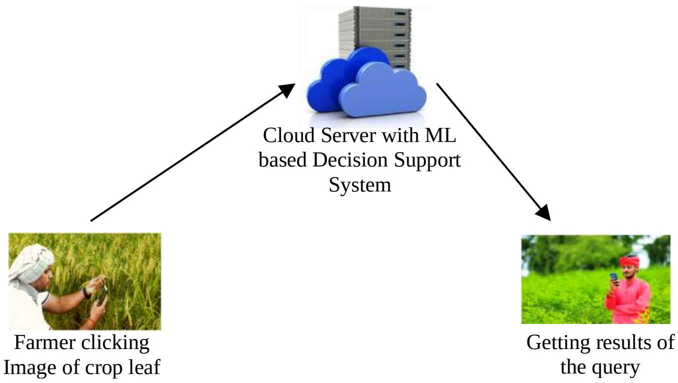


Fig.2. Core Concept of ML Based Decision Support System

4.2 SERVER COMPONENTS

In order to design the required module of decision support system, the basic machine learning component is demonstrated in the Fig.3. In this diagram, we have utilized two different kinds of datasets such as:

4.2.1 PlantVillage Dataset:

This dataset is taken from the online experimental data repository Kaggle [29]. In this dataset 38 directories are present for demonstrating the diseased and healthy plant leaves. The aim behind making use of this dataset is to demonstrate how the ML techniques can distinguish two different kinds of plant leaves automatically.

4.2.2 Rice Leaf Diseases Dataset:

This dataset is also obtained from the Kaggle [30]. This dataset consists of 120 jpg images of disease infected rice leaves. The images are grouped into 3 classes based on the type of disease. There are 40 images in each class. The Classes are Leaf smut, Brown spot and Bacterial leaf blight. The aim to use this dataset is to demonstrate how the ML algorithms can identify the type of disease in rice plants.

The datasets of these two types are processed using the three popular image feature descriptors namely, canny edge detection, local binary pattern and grid colour movement. The process of these techniques is described in brief as:

4.3 CANNY EDGE DETECTION

The purpose of edge discovery is to reduce the quantity of data while stabilizing the structure to be utilized [31, 32]. The canny edge detection utilizes the following procedure in 5 stages:

- **Smoothing**: It is predictable that all the images captured from a camera will comprise of several quantity of noise. Therefore, images will be processed by first applying a Gaussian filter.
- **Finding Gradients**: The gradient scales are calculated and then the Euclidean distance.

$$|G| = \sqrt{G_x^2 + G_y^2} \tag{1}$$

It is simplified by applying Manhattan distance measure to reduce the complexity.

$$|G| = |G_x| + |G_y| \tag{2}$$

where, G_x and G_y are the inclines in the x-and y-directions separately.

The Euclidean distance measure has been smeared to the image. Image of the gradient magnitudes indicates the limits; However, the limits are usually broad and do not designate precisely. To make it conceivable, the bearing of the limits must be defined as:

$$\theta = arc\,\mathrm{Tan}\left(\frac{|G_y|}{|G_x|}\right) \tag{3}$$

4.3.1 Non-Maximum Suppression:

The aim is to transform the “blurred” edges to “sharp” edges. That is performed by protecting all local maxima in the image, and erasing everything else using the following process:

- Round the incline way θ to nearest 45◦, to the use of connected neighbors.
- Compare the edges of the present pixel with the edges of the pixel.
- When the edge strength is higher the keep the edges otherwise remove them.

Double Thresholding: The edge-pixels residual afterwards the non-maximum conquest step is noticeable with their asset’s pixel-by-pixel. Numerous of these will provide advantages, but certain caused by noise or colour differences. The easy method of identifying difference we can use a threshold to limit stronger edges. The Canny procedure utilizes double thresholding. The high threshold is noticeable as strong whereas the edge pixels have fewer values than low threshold are removed.

Tracking Edge: the suitable edges are obtained as certain edges which consists the edge feature. Weak edges comprise if edges are associated to strong limits. The logic is to reduce noise and other basic differences to find a strong edge. Thus, strong limits will only be due to true limits in the image. The weak limits can either be due to true limits or noise/colour differences. Weak limits due to true limits are much more probable to be associated straight to strong limits. Edge tracking can be performed by BLOB-examination. The edge pixels are identified on the basis of 8-connected pixels. BLOBs containing at smallest edge pixel then preserved, while other BLOBs are suppressed.

4.3.2 Local Binary Pattern:

The LBP [33] of an image is calculated by equating its neighbours:

$$LBP_{P,R} = \sum_{p=0}^{p=1} s\left(g_p - g_e\right) 2^p \tag{4}$$

$$s(x) = \begin{cases} 0 & x \geq 0 \\ 1 & x < 0 \end{cases} \tag{5}$$

where, g_e is the gray pixel value of the central pixel, g_p is the value of neighbours, P is the number of neighbours and R is the radius. Assume the coordinate is (0,0), then the coordinates of g_p are:

$$\left(R\cos\left(\frac{2\pi p}{P}\right), P\cos\left(\frac{2\pi p}{P}\right)\right) \tag{6}$$

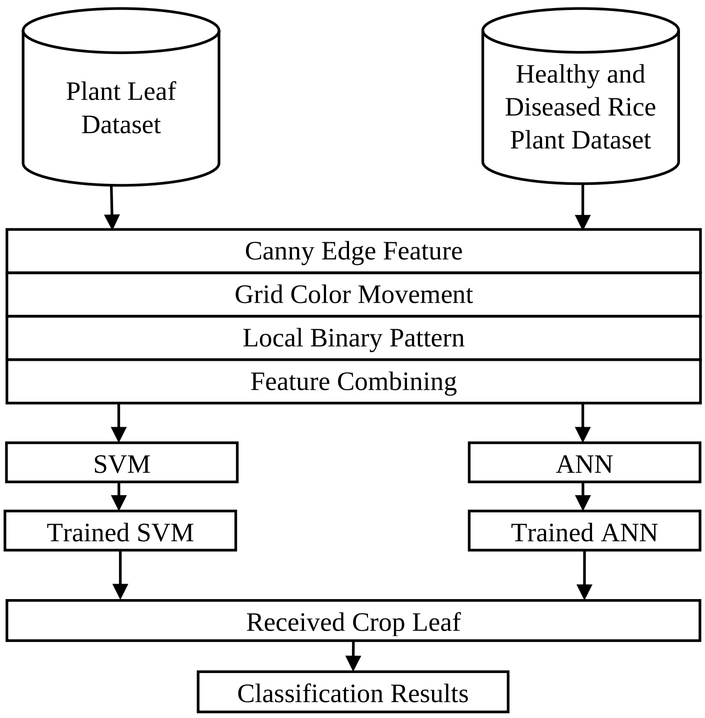


Fig.3. ML Module of the Proposed System

The gray neighbours that are not in the image can be projected by exclamation. Presume the image is of size $I*J$ then LBP of every pixel is recognized, as histogram to signify the image:

$$H(k)=\sum_{i=1}^{I}\sum_{j=1}^{J} f\left(LBP_{p,r}(i,j),k\right);k\in[0,k] \tag{7}$$

$$f(x,y)=\begin{cases}0 & x=y\\ 1 & otherwise\end{cases} \tag{8}$$

where, K is the greatest LBP value. The U value of an LBP is described as the number of spatial evolutions (bitwise 0/1 changes)

$$U\left(LBP_{P,R}\right)=\left|s\left(g_{p-1}-g_e\right)-s\left(g_0-g_e\right)\right| + \sum_{p=1}^{p-1}\left|s\left(g_p-g_e\right)-s\left(g_{p-1}-g_e\right)\right| \tag{9}$$

The unchanging LBP refers to the designs which have partial changeover ($U\leq 2$) in the spherical binary performance. The plotting from $LBP_{P,R}$ to $LBP_{P,R}^{u^2}$ which has $P*(P-1)+3$ different outputs, is executed with a lookup table of 2^p components to attain rotation, a locally rotation in irregular design could be described as:

$$LBP_{P,r}^{r_iu^2}=\begin{cases}\sum_{p=0}^{p-1} s\left(g_p-g_e\right) & if\ U\left(LBP_{P,R}\right)\leq 2\\ P+1 & otherwise\end{cases} \tag{10}$$

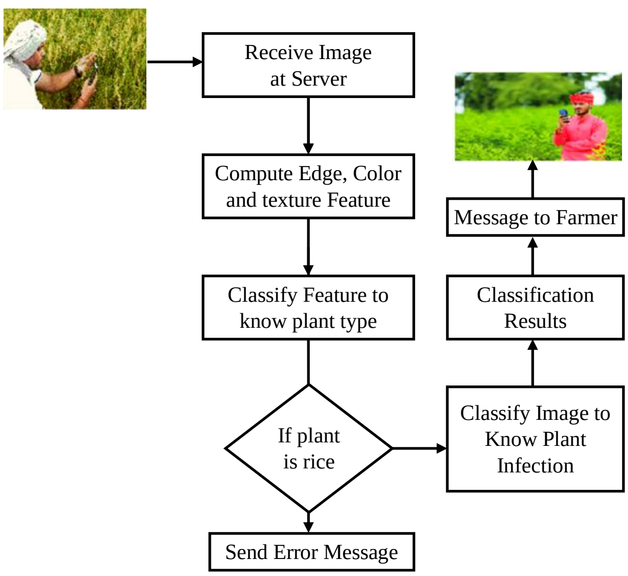


Fig.4. Process involved in Proposed Decision Support System

The mapping from $LBP_{P,R}$ to $LBP_{P,R}^{u^2}$ which has P+2 distinct output values.

4.3.3 Grid Colour Moment:

Colour feature is most widely utilized in small level feature. Paralleled with shape and texture feature, colour feature shows better stability and more insensitive due to the transformation and scaling of image. Colour feature is utilized as tool in content-based image retrieval (CBIR). The colour feature vector is also called “Grid-based Colour Moment” to compute this feature we will follow the following steps: [34]

Step 1: Change the image from RGB for HSV

Step 2: Uniformly divide the image into 3×3 blocks

Step 3: For each blocks

Step 4: Compute its mean color (H/S/V)

$$x'=\frac{1}{N}\sum_{i=0}^{N}x_i \tag{11}$$

where N is the number of pixels within each block, x_i is the pixel strength in H/S/V channels.

Step 5: Calculate its variance (H/S/V)

$$\sigma^2=\frac{1}{N}\sum_{i=1}^{N}\left(x_i-x'\right)^2 \tag{12}$$

Step 6: Compute its skewness (H/S/V)

$$\gamma=\frac{\frac{1}{n}\sum_{i=1}^{N}\left(x_i-x'\right)^3}{\left(\frac{1}{n}\sum_{i=1}^{N}\left(x_i-x'\right)^2\right)^{3/2}} \tag{13}$$

Step 7: Each block will have 3+3+3=9 features, and thus the whole image will have 9×9=81 features. Now need to normalize the 81 features.

Step 8: Calculate the mean and normal nonconformity from the exercise dataset

$$\mu=\frac{1}{M}\sum_{i=1}^{M}f_i \tag{14}$$

$$\sigma^2=\sqrt{\frac{1}{M}\sum_{i=0}^{M}\left(f_i-\mu\right)^2} \tag{15}$$

where M is the number of images in the dataset, and f_i is the article of the i^{th} sample.

Step 9: Implement the “whitening” alter for all the data, and get the regularized feature:

$$f_i'=\frac{f_i-\mu}{\sigma} \tag{16}$$

Table.2. Performance for Plant Leaf Recognition

Class	Accuracy (%)		F-Score (%)		Training Time	
	SVM	ANN	SVM	ANN	SVM	ANN
2	98.3	100	95.8	100	10	37
3	96.8	99.3	93.5	98.4	34	43
4	94.5	97.7	93.9	94.6	86	59
5	90.6	94.2	89.4	90.5	112	71
6	87.3	92.8	84.2	89.1	178	95
7	84.8	90.5	82.7	87.3	220	108
8	80.4	91.7	80.2	85.9	289	132

After computing the different feature vectors from the described approaches, we have combined the outcomes of these vectors in order to create a new dataset the dataset instances that can be described using the following notation.

$$I=C_f+L_f+CM_f+Class$$

We have two kinds of training feature samples. First is containing the different kinds of plant leaves and second vector contains the training sample of healthy and diseased plants. Using these two datasets, we train two different models namely SVM and ANN. The trained SVM using the plant leaves is denoted here as SVM_{PL} and the SVM which is trained on healthy and diseased rice plants is denoted as SVM_R.

Similarly, we also denoted ANNs as ANN_{PL} and ANN_R. The trained models will be used for performing the classification of queried image and replied with the relevant outcomes. The Table.2 demonstrates how the required decision support system utilizes the trained models for providing services.

According to the given diagram, the farmer will click an image his farm and upload it to server. When the server receives an image, then first the image is processed with the three feature selection techniques namely colour, texture and edge. These features are combined and then queried to the trained models ANN_{PL} and SVM_{PL}. Both the models are trying to recognize the image is for rice plant or not. If the image is recognized as another plant, then the server sends an error message to the farmer to resend the image of rice plant. On the other hand, if the image is for rice plant, then the SVM_R and ANN_R models are used for classifying the features as the diseased plants or healthy plant leaf. The support system will send the identified infection to the target client. In this section, we have explained working of the proposed model. The next section provides the performance analysis of the model for demonstrating the correctness and efficiency of the model.

5. RESULT ANALYSIS

The proposed machine learning and image processing techniques-based framer decision support system is implemented using JAVA technology and their performance has been measured and reported in this section. The proposed model has been experimented with the following two scenarios:

Study the performance during the plant leaf classification: In this phase, the model is trained and tested with the plant village dataset for recognizing the different kinds of plant leaves using both the machine learning models and their performance in terms of accuracy, f-score and time has been measured and reported.

Study the performance of the model for plant disease identification: In this scenario, the algorithms are trained with the rice plant disease dataset and the aim is to classify the rice plant leaves into their relevant classes.

5.1 PLANT LEAF CLASSIFICATION

The performance of the proposed plant leaf classification model implements the SVM and ANN classifiers, additionally the performance in terms of accuracy, f-score and time consumption is measured. The accuracy of a classification model demonstrates the correctness in classifying the target patterns. Here the target is to recognize the given plant leaf is rice plant leaf or not. In addition, to demonstrate the effectiveness the f-score of the models has also been measured, based on the precision and recall. The performance of plant leaf detection is demonstrated in Table.2.

In Table.2, the accuracy of recognition using both the learning algorithms i.e. SVM and ANN is reported. According to the given line graphs the X axis of the diagram shows the number of classes involved in learning and Y axis shows the obtained recognition accuracy in terms of percentage (%). Similarly, we also measure the performance of the models in terms of f-score which is demonstrated in Table.2. As similar to the previous Fig.5(a) contains similar X axis and Y axis contains the f-score in percentage (%).

According to the obtained results the ANN is more accurate as compared to SVM with increasing size of classification problem. According to the findings we can say that the number of classes to learn can impact on performance of classifiers.

Table.3. Performance of Diseased Rice Plant Detection

Dataset	Accuracy		F-score		Training Time	
	SVM	ANN	SVM	ANN	SVM	ANN
Kaggle	92.4	99.5	90.2	99.1	98	74
Mendeley	83.6	92.7	84.8	89.7	370	183

In addition, the performance of the plant disease detection technique has also been investigated. The obtained time requirements of the algorithm are given in Table.3. According to the performance, we can say when the amount of learning data is limited, then SVM algorithm provides better efficiency as compared to ANN, but as the amount of learning data increased, we found that the required time of learning of the SVM algorithm is increases significantly. Thus, we can say the ANN not only provides the higher accuracy but also provides the robustness in learning with the large set of training sample in lesser amount of time. Thus, in the near future, the more ANN architectures are expected to be involved for study and improvement in time and accuracy of the proposed model.

5.2 RICE PLANT DISEASE DETECTION

In this section, the performance of the model is demonstrated for classifying the rice plant images into three types of infections. In addition, we have also evaluated the model using one more publicly available rice plant disease dataset for a set of classes' Bacterial blight, Blast, Brown Spot and Tungro. It consists of 5932 images. The performance of the model in terms of training time is described in Table.3 for both the datasets and learning algorithms. According to the obtained results in terms of training time, we found that the SVM is more expensive when we utilize the large amount of data. Therefore, in order to classify the large data, the ANN is better than in SVM.

Additionally, the observed performance values are given in Table.3. According to the obtained results, the ANN model is more accurate and efficient in this experimental analysis.

6. CONCLUSIONS

The entire world started getting benefits of the Information Technology and Communication (ITC) technology. These technologies are being accepted in a number of applications around the world. The technologies are making complex and laborious tasks easy by introducing the automation and efficient computing. Among them in the domain of agriculture, the technology is also enhancing for automation and designing intelligent and dedicated support systems. But in India, we are nowhere in this domain. In order to enhance the productivity, we need to introduce the technology in agriculture in the Indian farming perspective.

An initiative for Indian farmer has been taken place by introducing the low-cost decision support system to take care of the crops. In this context, first we reviewed the recent development in plant disease detection which affects the crops production up to 15-20%. If we are able to prevent the crops from diseases, we can reduce a significant loss. Therefore, in this paper a solution is proposed which automatically detects the rice plant disease by analyzing the plant leaf images. A decision support system has been proposed which will take the raw image from the farmer mobile and identify the rice plant disease. The model uses the colour, edge and texture feature analysis. Additionally, the obtained features are trained with the two popular machine learning approaches namely SVM and ANN. The performance of the classifiers in the two different scenarios has been evaluated to design the entire functional module and experimentally the proposed model has been tested. According to the results, we found that the ANN is a suitable, efficient and accurate manner for utilizing in pattern recognition applications. In the near future, we will explore more kinds of ANN architectures for improving the performance of the proposed model as well as extend the features of the proposed decision support system.

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