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BPSO based Feature Selection for Rice Plant Leaf Disease Detection with Random Forest Classifier

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Abstract – *Recently, Machine Learning and computer vision have generated interest and have found new applications in engineering. In agriculture, "smart" systems have become important tools for detecting anomalies that decrease the quality and quantity in the harvest of agricultural products. This paper intended to detect three rice diseases, namely Brown-spot, Bacterial Leaf blight, and Leaf smut, using the Random Forest Classifier technique of machine learning with image processing. The color moments are extracted for color features, while the Gabor Wavelet and Harris Corner methods are used for texture features extraction of PlantVillage Dataset images for rice plant leaf disease detection. The binary particle swarm optimization (BPSO) is then applied for the feature selection from the extracted features. Finally, Random Forest Classifier is used for the classification of extracted features to obtain the simulation results in terms of precision, sensitivity, and accuracy using a confusion matrix plot.*

Keywords – *BPSO, Gabor Wavelet, Harris Corner, Random Forest Classifier.*

I. INTRODUCTION

It is well known that the prevention and timely diagnosis of any disease will bring us the strategic advantage over said disease, and in agriculture, it is no exception since knowing what ails a crop or plant increases the chances of success in treatment.

In developing countries, over 80% of agricultural production is produced by smallholder farmers [1], and reports of crop losses of over 50% due to pests and diseases are common [2]. Moreover, the majority of people suffering from poverty and hunger (50%) live in these productive areas [3], making smallholder farmers a very vulnerable group to food disruptions caused by pathogens.

There are methods to determine the diseases of any plant, such as taking samples of vegetative tissue to a specialized laboratory or taking an expert agronomist to the cultivation site; in either of the two methods, the disadvantage lies in the time necessary to obtain the results.

That is why the use of artificial vision and pattern recognition techniques has been considered, as well as some classification algorithms that automatically determine the possible disease, facilitating the task of specialists to develop their work and that they can find a timely diagnosis for its treatment. As Barbedo [4] says, tools for automatic recognition of plant diseases have the potential to become a valuable source of information to aid decision-making in agriculture.

The next section shows the significant works related to the detection of diseases in various types of plants, using different machine learning algorithms but always following the same methodology.

II. LITERATURE REVIEW

DerwinSuhartono et al. (2013) used a system of fuzzy logic and decision trees, and with the help of a human expert, they were able to make a recognition of coffee diseases, where they obtained the characteristics of the symptoms that occur in the plant and thus be able to do your decision tree. The results they obtained are within 85% accuracy. Although this research does not deal with artificial vision techniques, it can be noted that a very important step has been taken for the detection of diseases, using expert systems applying decision trees with fuzzy logic [5].

Bhange and Hingoliwala (2015) propose a web tool where the farmers who grow the pomegranate will upload an image of the fruit to be analyzed, and with the trained model, it can be verified whether or not the fruit is infected. The technique used is based on extracting the characteristics of the pomegranate images, such as color, morphology, and the color coherence vector, on later performing the classification using the SVM algorithm, giving them an accuracy of 85% with a 10-megapixel camera. Knowing that farmers will not always have the optimal capture means to upload the images to the system, the authors carried out significant tests with the cameras of mobile devices with resolutions of 5 and 3 megapixels and obtained results of 82% and 79%, respectively [6].

Mengistu et al. (2016) used an ANN, KNN, Naive Bayes, a hybrid of self-organizing maps (SOM) and radial base function (RBF), all this in order to determine the best algorithm to classify diseases of rust, coffee wilt (CWD) and the CFD that affects the coffee fruit. In their work, they state that they obtained 58.16% for KNN, for Naive Bayes, they obtained 53.47%, for ANN 79.04%, and for the combination of RBF and SOM, they obtain 90.07% accuracy, which shows a great improvement with respect to the previous algorithms. However, they note that the latter takes longer in training [7].

Singh and Misra (2017) carried out tests to obtain recognition of diseases or burns presented in the leaves. The study crops were banana, beans, lemon, and roses. After processing the images, they propose to do the segmentation using genetic algorithms and do the clustering. For the extraction of characteristics, they used the color concurrency method since they consider it better to use the color image than the traditional grayscale. To make the classification, they used MDC with K-Mean obtaining 86.54%, MDC with an algorithm proposed by them, obtaining an improvement of 93.63%, and SVM with a proposed algorithm obtaining a significant improvement of 95.71%. All these percentages describing a general average of the four study cultures [8]

Barbedo et al. (2016) propose algorithms to identify multiple plant diseases based on color analysis and using a pair-wise classification algorithm. According to them, their methodology allows them to work in uncontrolled conditions and thus be able to fight a large number of diseases. This method has been tested on an unlimited series of symptomatic leaf images associated with 74 diseases, 4 parasites, and 4 abiotic disorders affecting 12 different plant species. The results obtained had an accuracy of 40% to 80% [9].

Qin et al. (2016) tell us they have found a viable solution to diagnose and detect four diseases of alfalfa. They extracted 129 texture, color, and shape characteristics from 1,651 images using ReliefF, 1R, and CFS methods. To classify the diseases, they used SVM, KNN, and Random Forest, obtaining that the best classifier was SVM and the ReliffF method for obtaining the characteristic, since they achieved 97.64% in precision for the training set and 94.74% for the test set [10].

Pujari et al. (2016) compared the SVM and ANN algorithms to classify diseases in various crops that have been attacked by fungi, bacteria, nematodes, and nutrient deficiencies. They mention that the symptoms of plant diseases exhibit different properties such as color, shape, and texture, and based on this, the characteristics are obtained. They consider color as an important dimension but applying dimensionality reduction, and they discover by experimentation that, out of 24, only 8 characteristics are significant for the classification of diseases. In the end, they put the two algorithms to the test and found that with SVM, they obtained 92.17% precision and that with ANN only 87.48%, which is why they show that, for this case, SVM is a better classifier [11].

Kiani and Mamedov (2017) try through their work to prove that it is not necessary to use a complex neural network or algorithm to verify whether or not there is a characteristic disease in strawberry leaves. For the authors, it is better to use fuzzy logic algorithms for classification than any other method that consumes more computational resources, such as neural networks. The results obtained are encouraging since they achieved a 97% optimization in the segmentation and classification of diseases with a processing time of 1.2 seconds. With this type of technique, they verify that it is feasible to be implanted in an integrated circuit, adapted to a robot with artificial vision and that it could make an automated inspection in a modern botanical center [12].

Mohanty et al. (2016) conducted 60 experiments using deep convolutional neural networks to identify 14 crop species and 26 diseases, using trained models such as AlexNet [13] and GoogleNet [14]. They use the approach of Krizhevsky et al. [15], demonstrating for the first time that end-to-end supervised training with a CNN architecture is a potential option for large numbers of classes, going beyond the traditional approach of using hand-built features. In the PlantVillage dataset of 54,306 images, containing 38 classes of 14 plant species and 26 diseases (or none), this goal has been achieved, as indicated by a maximum accuracy of 99.35%. Thus, without any development of traits, the model correctly classifies plants and diseases into 38 possible classes out of 993 out of 1000 images. The authors noted that a lot of computational work is required for training, but for classification, it is less than a second; they believe it could be implemented on a cell phone [16].

Ashkar and Abu-Nasser (2018) conducted a study consisting of analyzing 9000 images of tomato leaves to create a model that can be used on a smartphone to identify 5 types of diseases. Your model will be based on a deep convolutional network but will have two parts: the first part of the model (extraction function), which is the same for the color focus and layer focus. Gray consists of 4 convolutional layers with Relu activation function, each followed by a Max Pooling layer, and the second part will contain two solid layers that contain two focuses, color, and grayscale. In the end, they demonstrated that working with color characteristics gives them 99.84% better results with respect to the gray scale with 95.54% [17].

Barbedo (2019) has been working with convolutional neural networks of various crops, looking for disease levels in plants, being able to classify healthy crops with 89% accuracy, slightly ill with 31%, moderately ill 87%, and seriously ill with 94%. Although the results are satisfactory, he concludes that the classification of plant diseases from digital images is very difficult. On the other hand, the limitations of the data set in terms of quantity and variety of samples continue to prevent the emergence of truly comprehensive systems from performing disease classification functions [18].

Khan et al. (2019) propose the use of VGGNet [19] and AlexNetOWTBn [15] as architectures of a deep convolutional network to automate the process of classifying diseases that occur in tomato leaves. The diseases to be classified were early blight, powdery mildew, and mildew. The collected images are pre-processed using image processing techniques such as noise reduction, regression, and image processing enhancement which helps in reducing costs and computation time. Later he extracted the characteristics of the data set using convolution maps where images of healthy and infected leaves were applied to the input data. Although the architecture has presented very precise results, for this study, they only obtained 32.23% using the AlexNetOWTBn architecture and 33.27% for VGG [20].

In the following sections, we will detail the preprocessing, feature extraction, feature selection, and classification steps for the rice plant leaf disease detection, and then we will present the experimental results and discuss our working perspectives.

III. PROPOSED METHODOLOGY

This research work presents the rice plant leaf disease detection using color moments, Gabor wavelet, and Harris Corer-based feature extraction followed by BPSO based feature selection with Random Forest classifier. Figure 1 shows the generalized block diagram for the proposed work.

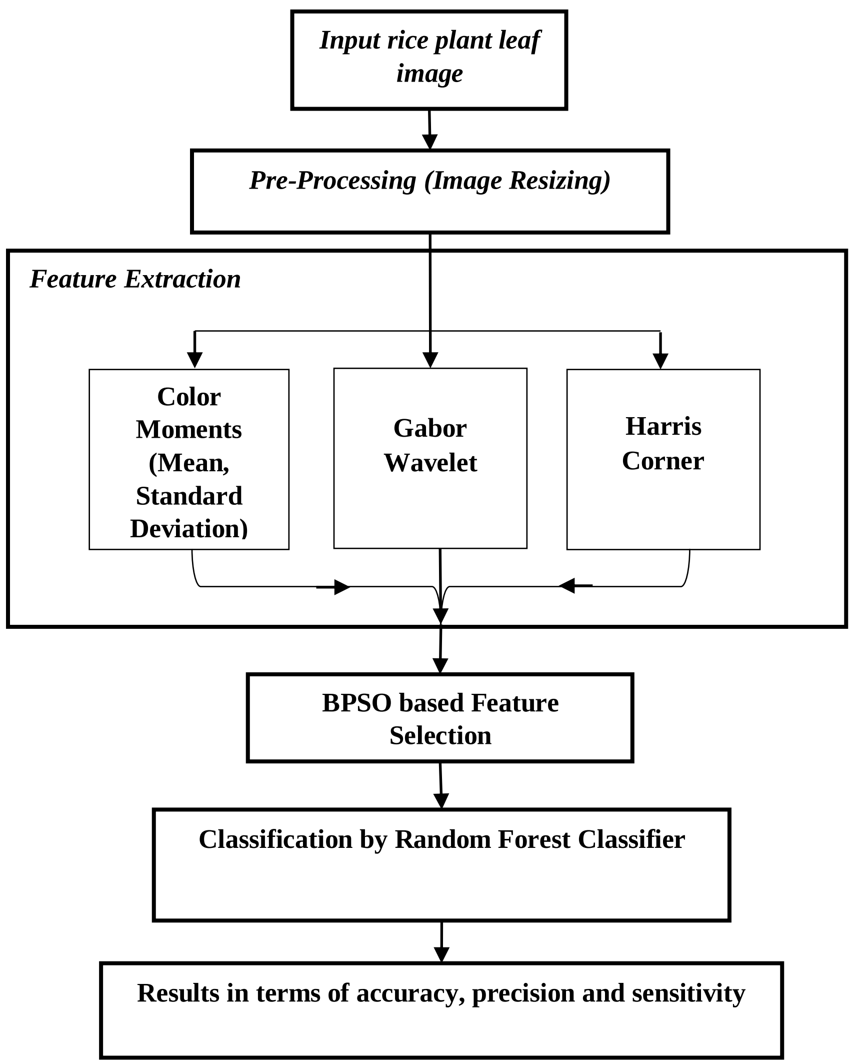
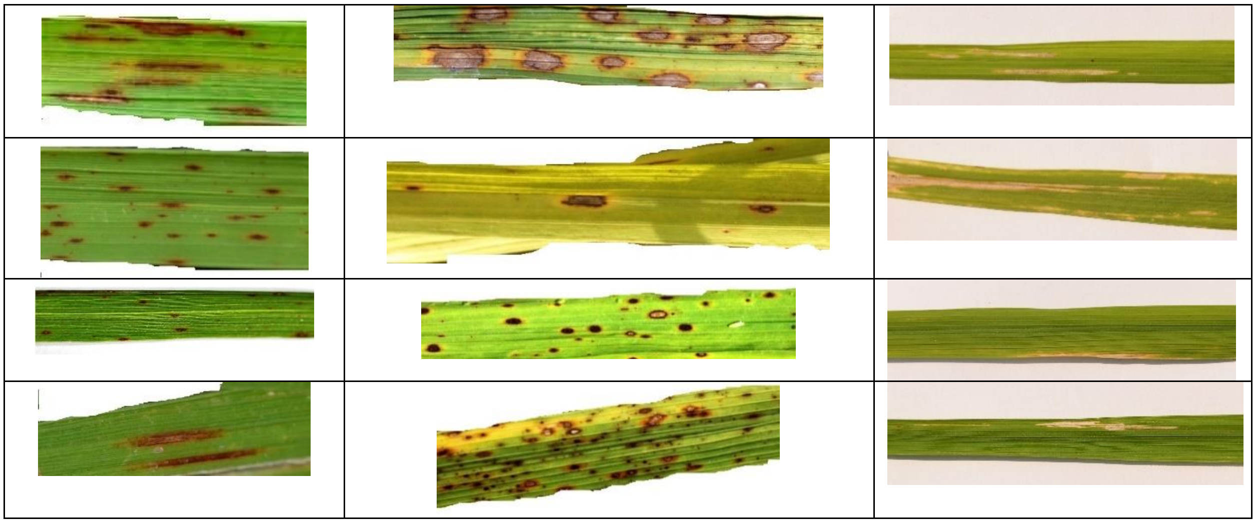


Figure 1: Block diagram for proposed rice leaf disease detection



A. Preprocessing

The pre-processing is achieved by resizing the input image into 300×450 pixels.

B. Feature Extraction

a) Color Moments

Color moments are calculated to evaluate the brightness and intensity of an image. The color moments used in this paper to extract color images are the mean and standard deviation. The mean can be understood as the average of the colors in the image, and the square root of the variance can be defined as the standard deviation. The histogram method uses the full-color distribution. We have to store a lot of data. Instead of calculating the complete distribution, only dominant color characteristics such as mean and standard deviation are calculated [22].

Moment-1:

$$Mean = E_i = \sum_{j=1}^{N} \frac{1}{N} P_{ij} \tag{1}$$

Moment-2:

$$Standard\ Deviation = \sigma_i = \sqrt{\left(\frac{1}{N}\sum_{j=1}^{N}\left(P_{ij} - E_i\right)^2\right)} \tag{2}$$

b) Gabor Wavelet Transform

The directional decompositions for image analysis were probably initiated by Gaussian windowing in the 2D Fourier domain and continued 4D filters, as well as the directional Gabor wavelets proposed by J. Daugman [23]. The use of Gabor's wavelets for the image is often linked to the consideration of the human visual system.

Gabor wavelets are constructed by isotropic Gaussian windowing of a complex plane wave of frequency F in direction θ [24]:

$$\psi^{\theta}(x) = \frac{e^{-\|x\|^2/2}}{2\pi} e^{-j(x^T \omega_0)} \tag{3}$$

Where, $\omega_0 = F[\cos(\theta)\,;\sin(\theta)]^T$

The decomposition depends on the number of orientations K that one fixes and that one can distribute evenly in $[0,\pi]$.

$$\theta \in \Theta = \left\{\frac{k\pi}{K};\, 0 \le k \le K\right\} \tag{4}$$

We can then decompose any real 2D signal (x) by scalar product with the following atoms:

$$\left\{\psi_{j,u}^{\theta}(x) = 2^{-j}\psi^{\theta}\left(2^{-j}(x-u)\right)\right\}_{\theta\in\Theta, j\in\mathbb{Z}, u\in\mathbb{R}^2} \quad (5)$$

c) Harris Corner Method

It was invented by Harris and Stephens. We take an image $I(x,y)$ we start by taking the derivatives of the image inline and in column [25]:

$$I_x(x,y) = \frac{\partial I}{\partial x}(x,y) \quad (6)$$

$$I_y(x,y) = \frac{\partial I}{\partial y}(x,y) \quad (7)$$

For the calculations we will need three matrices with the derivatives with the squares and their multiplications:

$$A(x,y) = I_x^2(x,y) \quad (8)$$

$$B(x,y) = I_y^2(x,y) \quad (9)$$

$$C(x,y) = I_x(x,y) \cdot I_y(x,y) \quad (10)$$

These three matrices must be smoothed by a Gaussian low pass filter. However, you can choose the filter that is best [26].

$$k(x,y) = k(x,y) \cdot Hgauss \quad (11)$$

Where, $k = A, B$ or C and $Hgauss$ is the Gaussian filter. This is a convolution.

We can now calculate the cornering force for each pixel. It is calculated such that:

$$Q(x,y) = (AB - C)^2 - \alpha \cdot (A+B)^2 \quad (12)$$

Where α is the sensitivity of the detector?QIt is called the corner response function (CRF) and returns large values when a corner is detected. The larger α, the lower the sensitivity and the lower the number of corners. Typically α is between 0.04 and 0.06 but does not exceed 0.25. Thresholding is carried out to eliminate the low values of the CRF.

$$Q(x,y) < th = 0 \quad (13)$$

Generally, this threshold (th) is between 10^4 and 10^7

We can then arrange the detected corners in descending order and carry out detection of local maxima to eliminate the too-close corners. The local maxima must be made from the corner of the highest value and eliminate the corners of low value.

C. BPSO based Feature Selection

Particle swarm optimization is an intuitive method. It is an advanced algorithm with the inclusion of some herd behavior in nature. The particle swarm optimization algorithm that occurs by observing the behavior of birds, fish, and bees is population-based [27].

Binary Particle swarm optimization was introduced by Kennedy and Eberhart [27]. If the elements of the problem can be sorted or grouped, binary particle swarm optimization can be used to solve such discrete problems [28]. Research on many optimization problems, such as path problems or schedules, takes place in a discrete space.

For the research area $S = \{0,1\}^D$, the fitness function f maximizes, i.e. $(\max f(x))$. The i^{th} particle in D dimension is defined as:

$$X_i = (x_{i1}, x_{i2}, \dots x_{id})^T,\ x_{id} \in \{0,1\}, d = 1,2,\dots,D \quad (14)$$

The velocity vector in D dimension can be represented as:

$$V_i = (v_{i1}, v_{i2}, \dots v_{id})^T,\ v_{id} \in [-V_{max}, V_{max}], d = 1,2,\dots,D \quad (15)$$

Where V_{max} is the maximum velocity vector?
The previous best position can be given as [28]:

$$p_i = (p_{i1}, p_{i2}, \dots p_{id})^T,\ p_{id} \in \{0,1\}, d = 1,2,\dots,D \tag{16}$$

Definitions according to the given notation can be given as:
Equation of Velocity:

$$v_{id} = v_{id} + c_1 rand_1(p_{id} + x_{id}) + c_2 rand_2(p_{gd} - x_{id}) \tag{17}$$

Equation of position:

$$X_{id} = \begin{cases} 1 & if U(0,1) < sigm(v) \\ 0 & otherwise \end{cases},\quad d = 1,2,\dots D; i = 1,2,\dots,N \tag{18}$$

Transfer function:

$$sigm(v_{id}) : \frac{1}{1+\exp(-\lambda v_{id})} \tag{19}$$

g: index of the best performing particle
p_{gd}: best part
N: the width of the fortification
c_1, c_2: social and cognitive component constants
$rand_1, rand_2$: $U(0,1)$random numbers
$sigm(v_{id})$: sigmoid transform function.

D. Classification by Random Forest Classifier

Finally, after extracting the features of all the images, we proceeded to separate them into two classes: test and test, because for the training of the model, we will work with the test class, and to verify the model, we will use the test class. Random forest classifier is used as the learning algorithms, explained as follows.

Random Forests are based on a heuristic division of the description space. The construction of the decision structure of a tree is carried out by recursive partitioning of this space, which makes the final decisions strongly dependent on the upstream divisions. The search space of the possible decision tree structures is then strongly restricted by these dependencies.

In particular, there have been many techniques that take advantage of the opportunity to create diversity in three communities. Breiman presented a formal framework for this category of methods called random forest (RF).

A random forest is a classifier consisting of a set of base classifiers such as a decision tree shown:

$$\{h(x, \Theta_k),\ k = 1, \dots L\} \tag{17}$$

Random forests are composed of a set of binary decision trees in which randomness has been introduced.

Random forests were introduced by Breiman (2001) by the following very general definition [29]:

Let $\left(\hat{h}(\Theta_1), \dots, \hat{h}(\Theta_q)\right)$ a collection of tree predictors, with $\Theta_1, \dots, \Theta_q$ random variables independent of $\mathcal{L}_n$. The predictor of random forests $\hat{h}_{RF}$ is obtained aggregating this collection of random trees as follows:

- $\hat{h}_{RF}(x) = \frac{1}{q}\sum_{l=1}^{q} \hat{h}(x, \Theta_l)$ Average of individual tree predictions in regression.
- $\hat{h}_{RF}(x) = \operatorname{argmax}_{1\le k\le K} \sum_{l=1}^{q} 1_{\hat{h}(x,\Theta_l)=k}$ A majority vote among individual prediction trees in classification.

The term random forest comes from the fact that individual predictors are, here, explicitly predictors per tree and that each tree depends on an additional random variable (that is, in addition to $\mathcal{L}_n$).

In terms of precision, the results obtained with this approach are comparable to those obtained directly using the one against the rest method. For practical problems, the choice of approach will depend on the available limitations, and relevant factors include the precision required, the time available for development, the processing time, and the nature of the classification problem.

IV. SIMULATION RESULTS

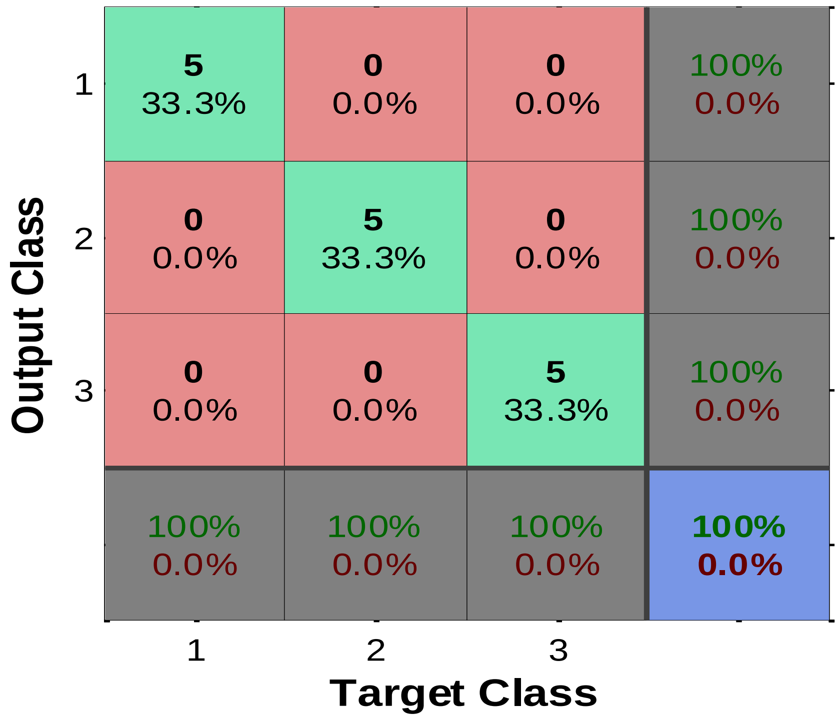


Figure 2: Confusion matrix plot of proposed rice plant leaf detection using random forest classifier

Table 2: Parameter values for three classes

Parameter	**Class**		
	1	**2**	**3**
TP	5	5	5
FP	0	0	0
FN	0	0	0
TN	10	10	10

Figure 2 shows the confusion matrix plot for proposed random forest classifier-based rice plant leaf defect detection. It can be seen that the confusion matrix contains results for three different classes which resemble different leaf diseases. Calculation of confusion matrix for different classes is given as follows:

For Class 1:

TP=5, TN=10, FP=0, FN=0

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} = \frac{5 + 10}{5 + 10 + 0 + 0} = 100\%$$

$$Precision = \frac{TP}{TP + FP} = \frac{5}{5 + 0} = 100\%$$

$$Sensitivity = \frac{TP}{TP + FN} = \frac{5}{5 + 0} = 100\%$$

For Class 2:

TP=5, TN=10, FP=0, FN=0

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} = \frac{5 + 10}{5 + 10 + 0 + 0} = 100\%$$
$$Precision = \frac{TP}{TP + FP} = \frac{5}{5 + 0} = 100\%$$
$$Sensitivity = \frac{TP}{TP + FN} = \frac{5}{5 + 0} = 100\%$$

For Class 3:

TP=5, TN=10, FP=0, FN=0

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} = \frac{5 + 10}{5 + 10 + 0 + 0} = 100\%$$
$$Precision = \frac{TP}{TP + FP} = \frac{5}{5 + 0} = 100\%$$
$$Sensitivity = \frac{TP}{TP + FN} = \frac{5}{5 + 0} = 100\%$$

The final accuracy of the proposed approach is calculated by taking the mean of all three classes, i.e., 100%.

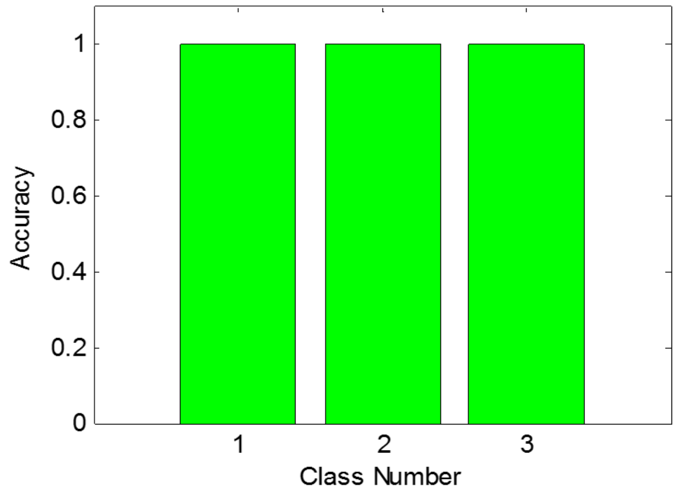


Figure 3: Accuracy graph for proposed work

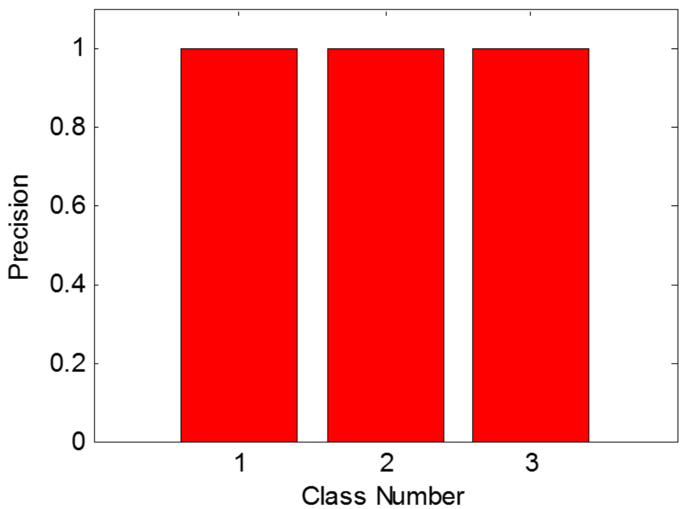


Figure 4: Precision graph for proposed work

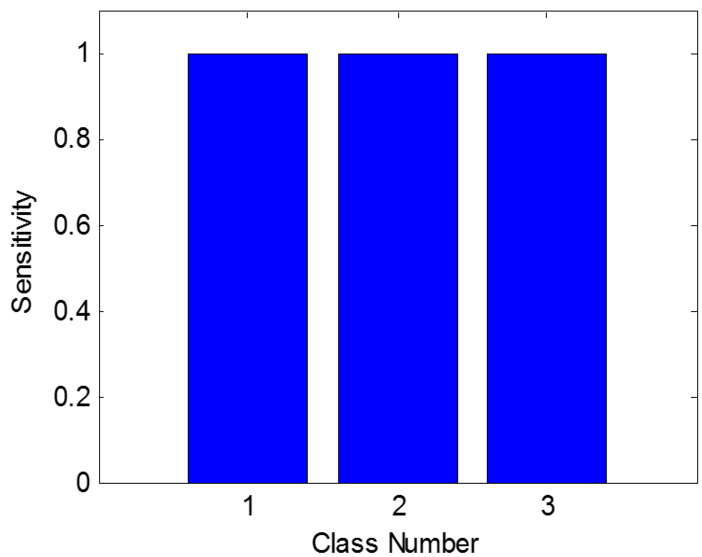


Figure 5: Sensitivity graph for proposed work

V. CONCLUSION

This article discusses the automatic detection of rice plant diseases by harvesting and analyzing rice plant leaves using image processing techniques using machine learning. It includes image capturing/extracting, image preprocessing, feature extraction, feature selection, and classification. The development of an automatic detection system using sophisticated information technologies such as image processing helps farmers detect diseases at an early or early stage and provides useful information to control them. Machine learning technology is integrated into the agricultural sector. Using a random forest classifier algorithm, different classes of leaf diseases were identified and analyzed. In this context, feature selection makes it possible to fill in the information gaps caused by the use of various diseases in rice plant images. It is a good choice for farming communities, especially in remote villages. This acts as an efficient system in terms of shortening grouping times and reducing the area of the contaminated area. The proposed rice plant leaf disease detection system achieves a maximum accuracy of 100%.

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