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# Protecting the environment from pollution through early detection of infections on crops using the deep belief network in paddy

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ABSTRACT

Paddy is the staple food for more than 50% of 138 billion Indian population. Inorder to meet with the growing demand, farmers often resort to application of synthetic fertilizers and plant protection chemicals indiscriminately. Rice is susceptible to diseases, pests, and nutrient deficiencies likewise other crops. Ignorant about the reasons for damage farmers apply synthetic chemicals that too in exorbitant rates. Excessive use of these chemical molecules alters the soil characteristics and causes environmental pollution as well. As a result, entire eco system gets affected. To overcome this, it is necessary to identify the reason for damage early and necessary treatments should be done in the beginning stages itself. Early detection can be done by assessing the leaves and culm of paddy. Assessment by naked eye may misinterpret symptoms and if artificial intelligence is used such misinterpretations can be minimised. This study proposes an automatic classification system using artificial intelligence and image processing for identification of diseased, pest infested and nutrient deficient crop using symptoms exhibited in the leaves and culm of paddy. Kaggle data set was being used to test the performance of the proposed classification system for metrics specificity, precision, sensitivity, F1-score and accuracy. The proposed work provides a specificity, precision, sensitivity, F1-score and accuracy of 97.1%, 97.6%, 96.2%, 96.8%, and 98.1% respectively. The evaluation results indicate that the proposed algorithm outperforms other recent rice leaf disease, pest and nutrient deficiency classification algorithms. Thus, precise identification of reasons for infection allows farmers to use specific control methods with less toxic chemicals or through eco-friendly methods. Thus, environmental pollution and soil characteristics can be saved and in turn can save the environment and its creatures.

## Introduction

Paddy is the most cultivated food crops in the world. India is one among the top two farm producers in the world and agriculture is an integral part of its economy. In India, rice is cultivated on 44 M Ha area, accounting 20 % of total rice production worldwide (Oo et al., 2018). Rice (Oryza sativa) is a staple for nearly-one-half of the world's seven billion people (Global Rice Science Partnership Rice Almanac, International Rice Research Institute, 2013). Paddy is the staple food for more than 50 % of 138 billion Indian population. The domestic consumption of milled rice during 2021 was around 109.25 million metric tonnes. In order to meet the demand, farmers resort to application of synthetic fertilizers and plant protection chemicals indiscriminately. Rice is susceptible to diseases, pests, and nutrient deficiencies likewise other crops.The yield and quality of rice crops get highly reduced due to different diseases and pest attack. Likewise, the yield also gets reduced due to inadequate supply of primary and secondary nutrients. The nutrients N, P and K play a crucial role in the onset of panicles, immunity of the plant and stress tolerance respectively. Both pesticides and fertilizers play a major role in crop production which in turn increases the yield. A balanced dose of fertilizer (Shankar et al., 2021) and need based application of synthetic pesticides and fungicides itself is sufficient to enhance production. Ignorant about the reasons for damage farmers select wrong treatment methods and apply synthetic chemicals that too in exorbitant rates. Excessive use of these chemical molecules alters the soil characteristics and causes environmental pollution as well (Bhatt, 2015; Zschornack et al., 2018; Jimmy et al., 2017). As a result, entire eco system gets affected. Providing more fertilizer or application of pesticides or fungicides without any purpose doesn't add benefit but only can reduce the income of the smallholder farmers (Kumar et al., 2022). Table 1 shows a comparison of fertilizer consumption bythe US, India and China for the years 2002

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**Table 1**
Consumption of fertilizer in the US, India and China (in tons).

| | Year 2002 | | | Year 2016 | | |
|---|---|---|---|---|---|---|
| | China | India | US | China | India | US |
| N | 25,223,879 | 10,469,210 | 10,945,100 | 30,624,151 | 16,735,400 | 12,038,702 |
| P | 10,706,986 | 4,029,134 | 4,015,500 | 15,785,228 | 6,705,400 | 4,274,948 |
| K | 7,773,668 | 1,597,647 | 4,502,300 | 13,847,698 | 2,508,300 | 4,789,149 |

and 2016. The usage of fertilizers has highly increased in India and China when compared to the US. The per capita grain production of China increased to 424Kg/year in 2011 from 209 Kg/year in 1949, that may be associated to the increased application of fertilizers.

It is essential to protect human health, soil health and also protect the water reservoirs from getting contaminated of fertilizers and pesticides. Precise and early identification of reasons can avoid the overuse of chemical molecules (Gavhale and Gawande, 2014). The commonly used diagnosis method is the manual judgement from the appearance of leaves and culm. There are several challenges in identifying the disease, pest and deficiency symptoms of paddy by manual observation of leaves. There are chances of misinterpretation of symptoms (Soujanya and Jabez, 2021). Non-destructive chemical and analytical methods are also used to detect nutrition deficiencies of soil and pesticidal residues in the food. However, accurate results can be obtained only upon the full-scale analysis which is highly laborious and involves financial implication as well. Computer vision-based nutrition deficiency, pest and disease classification is the fastest approach at low cost. Machine learning and deep learning algorithms play a major role in this classification. Integrated method of image processing and pattern recognition methods, such as statistical classification and artificial neural networks using multilayered perceptron neural network, can be used for identifying and classification of rice cultivars (Abbaspour-Gilandeh et al., 2020). Support vector machine in approach of K-Means and Fuzzy C-Means clustering is used to identify mineral deficient leaf of Rice Crop (Sethy et al., 2017). Convolutional Neural Network (CNN)/deep CNN shows satisfactory results whereit is difficult in feature extraction. Deep CNN was used to classify 26 diseases from 14 different species using the plant village dataset (Mohanty et al) using AlexNet (Krizhevsky et al., 2017) and GoogleNet (Szegedy et al., 2015) architectures. Deep learning technique and Convolutional neural network is being used to classify diseases in tomato (Brahimi et al., 2017; Liu et al., 2017), Rice (Lu et al., 2017) by processing the leaf images. Texture features were extracted using a local binary pattern and are classified using a bagged tree ensemble classifier in identification of diseases of Guava (Almadhor et al., 2021). Convolutional Neural Network was used for the identification of iron deficiency chlorosis in soybean (Li et al., 2020). ResNet50is used to identify nutrient deficiencies in black gram from leaf images (Han and Watchareeruetai, 2019). Auto-encoder-based inception-ResNet provided an accuracy of 91 % in the classification of nutrient deficiency in tomato (Tran et al). When comparing DenseNet-121 and NasNet-large classifiers, the classifier DenseNet-121 achieves an accuracy of 97.44 % whereas NasNet-large achieves an accuracy of 96.23 %. Transfer learning based on ensemble averaging which includes deep CNN and provided an accuracy greater than 90 %in classification of nutrient deficiency in rice (Xu et al., 2020). Several researches are being done in recent times to develop either a pest, disease or nutrition deficiency classification algorithms by using techniques *viz.,* segmentation, feature extraction and classification. This study gains importance as it proposes an automatic classification system using artificial intelligence and image processing techniques for combined identification of disease, pest and nutrient deficiency by analyzing the symptoms exhibited by leaves and culm of paddy.

## Methodology

The proposed approach uses a classification method that eliminates the redundancy features using the Mayfly optimization algorithm. The mayfly optimization algorithm hence reduces the number of features used in training/ testing the classifier, which makes the study unique than the existing studies. The optimized features are then trained using the deep belief network to classify the diseased, nutrition deficient, pest infested and healthy leaves. Kaggle data set was being used to test the performance of the proposed classification system for metrics specificity, precision, sensitivity, F1-score and accuracy.

Fig. 1. Illustrates the flow diagram of the proposed leaf disease, pest and nutrition deficiency classification system. Let $I_1$ represents the input leaf image. The sequence involves following steps (i) Preprocessing (ii) ROI segmentation (iii) Extraction of features (iv) Optimization of features and (v) Feature classification.

### *Preprocessing*

The image to be trained or tested is preprocessed using contrast enhancement (Win et al., 2015). The contrast enhancement highlights the leaf region from its background. The contrast enhancement also improves the appearance of the leaf textures and the spots which have an abnormality. Let $I_2$ represents the contrast-enhanced image given by

$$I_2(x,y) = \lfloor \frac{255}{V_{max} - V_{min}} (I_1(x,y) - V_{min}) \rceil \quad (1)$$

Where $\lfloor \rceil$ represents the roundoff function. Here $V_{max}$ and $V_{min}$ are the maximum and minimum intensity present in the image. The contrast enhancement is performed separately on R, G and B channels to obtain the contrast-enhanced leaf images.

### *ROI segmentation*

The ROI segmentation aims to segment the leaf region that has color changes or texture changes when compared to the healthy leaves. This uses two segmentation algorithms namely entropy segmentation (Zhang et al., 2004) followed by K-means clustering segmentation (Likas et al., 2003).

#### *Entropy segmentation*

The preprocessed image $I_2$ is applied for entropy segmentation which segments the image into background and foreground regions. The background region contains the region that are not related to the leaf while the foreground region includes the ROI where the color and texture differ from the healthy leaves. $I_3$ represents the ROI that was segmented by the entropy segmentation algorithm. The entropy segmentation result $I_3$ can be represented as

$$I_3(x,y) = \sum_{p=-(u-1)/2}^{(u-1)/2} \sum_{q=-(v-1)/2}^{(v-1)/2} I_2(x+p,y+q) \times \left| \log \frac{I_2(x+p,y+q)}{\bar{I}_2(x,y)} \right| \quad (2)$$

Where the mean of the neighborhood can be expressed as

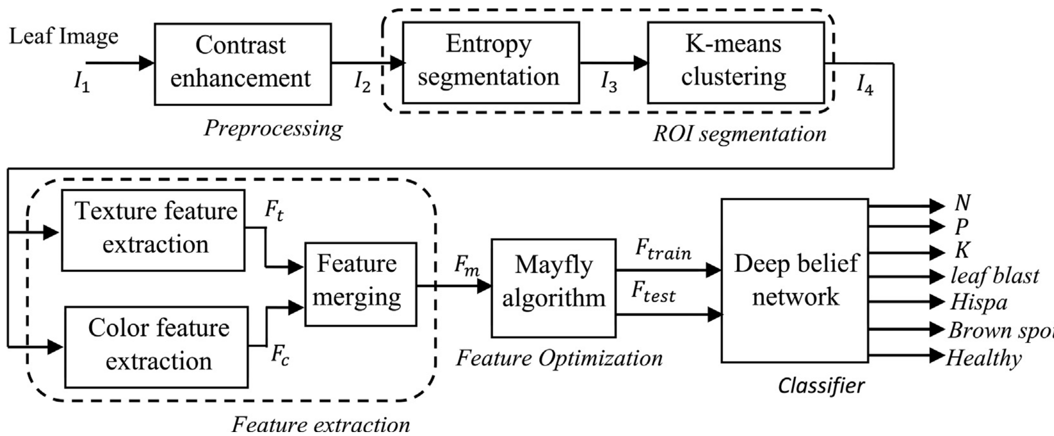


**Fig. 1.** Block diagram representation of proposed approach.

$$\bar{I}_2(x,y) = \frac{1}{uv}\sum_{p=-(u-1)/2}^{(u-1)/2}\sum_{q=-(v-1)/2}^{(v-1)/2} I_2(x+p,y+q) \tag{3}$$

Where $u, v$ represent the local neighbourhood to apply the segmentation process. After normalization, the image can be represented as

$$I_3(x,y) = \lceil\frac{I_3(x,y) - I_{3,min}}{I_{3,max} - I_{3,min}}\rfloor \times 255 \tag{4}$$

*K-means clustering segmentation*

The K-means clustering algorithm partition the image $I_3(x,y)$ into different regions based on the number of clusters. The algorithm can be summarized as follows.

**Algorithm 1.** *K-means clustering algorithm.*

*Input*: $I_3(x,y)$, number of cluster $k$, centers.$\Delta_k$

*Output*: $k$-cluster results. $I_3(x,y) = \{I_{3,1}(x,y),\ I_{3,2}(x,y)\cdots..I_{3,k}(x,y)\}$

*Step 1*: Estimate the Euclidean distance $r$, for each pixel $I_3(x,y)$ from the $k$ centroids $\Delta_k$. The distance can be expressed as

$$r = \|I_3(x,y) - \Delta_k\| \tag{5}$$

*Step 2*: Assign each pixel to a cluster $C_k$ at the nearest distance $r_{min}$.

*Step 3*: Update the centroid $\Delta_k$ with the new membership of clustering $C_k$.

$$\Delta_k = \frac{1}{k}\sum_{x,y\in C_k} I_3(x,y) \tag{6}$$

*Step 4*: Repeat step 1 to 3 till the error condition is satisfied.

From $K$ clusters, $K/2$ number of clustersis chosen whose average intensity corresponds to bright. The remaining $K/2$ number of clusters whose average intensity corresponds to dark are eliminated as background. $I_4$ represent the segmentation result obtained by the k-means algorithm.

*Feature extraction*

From the ROI extracted regions $I_4$, texture and color features are extracted. From a texture feature point, texture feature value and color feature value are extracted using the texture feature extraction (Mohanaiah et al., 2013) and color feature extraction (Chen et al., 2010) algorithms. The texture features are extracted using the Gray level co-occurrence matrix (GLCM) and the color features are extracted using the adaptive color feature extraction algorithm. Let $F_t$ and $F_c$ represents the texture and color features extracted from a feature point respectively. These two features are merged to obtain the actual feature at that point.$F_m = \{F_t, F_c\}$

*Mayfly optimization*

Two sets of mayflies are initially generated from the features. Let $F$ represent $N$ number of features obtained from a leaf image.

$$F = (F_1, F_2, \cdots ..F_N) \tag{7}$$

The mayfly optimization reduces the $N$ features to $M$ features, that only consider the best feature and eliminate the redundant features. From the change in position and direction, the velocity of the mayfly can be estimated as

$$V = (V_1, V_2, \cdots ..V_N) \tag{8}$$

The three processes in the mayfly algorithm (Zervoudakis and Tsafarakis, 2020) include (i) movement of male flies, (ii) movement of female flies and (iii) mating of mayflies. Let $E_x^t$ is the current position of male fly in time step $t$. Similarly, at time step $t+1$, the position of the male fly is $E_x^{t+1}$. The best position at next time can be estimated as

$$P_B^{t+1} = \begin{cases} E_x^{T+1} iff\left(E_x^{T+1}\right) < P_B^t \\ P_B^t otherwise \end{cases} \tag{9}$$

$f(.)$ is the function used to obtain the best position at the time step. The two offspring can be estimated as

$$OS_1 = S * P_{B,M} + (1-S) * P_{B,F} \tag{10}$$

$$OS_2 = S * P_{B,F} + (1-S) * P_{B,M} \tag{11}$$

Where $S$ is a constant value that lies between 0 and 1, $P_{B,M}$ represent the best position of male mayfly and $P_{B,F}$ represent the best position of the female mayfly. The mayfly optimization algorithm can be summarized as follows.

**Algorithm 2.** *Mayfly optimization algorithm.*

*Input*: Features.$F = \{F_1, F_2, \cdots ..F_N\}$

*Output*: Optimized features.$\widehat{F} = \left\{\widehat{F}_1, \widehat{F}_2, \cdots \widehat{F}_M\right\}$

*Step 1*: Randomly form two sets of features $F_M$, $F_F$ from the features F. $F_M$ represent the malefly features $F_F$ represents the female mayfly features.

*Step 2*: Estimate the velocity of the male mayfly $F_M$ and female mayfly $F_F$.

*Step 3*: Obtain the best position of male mayflies ($P_M$) and female mayflies ($P_F$) using equation (9).

*Step 4*: Obtain two offsprings for each pair of male and female mayflies using equations (10) and (11).

*Step 5*: Select one offspring if the difference between offspring 1 and 2 is less than the threshold $\tau$

$$OS_1 - OS_2 < \tau \tag{12}$$

*Step 6*: Note the estimated offspring as the optimized features

$$\widehat{F} = \left\{\widehat{F}_1, \widehat{F}_2, \cdots \widehat{F}_M\right\} \tag{13}$$

Where the length of optimized feature $M$ is less than $N$.

*Deep belief network (DBN)*

The deep belief network (Hua et al., 2015) contains layers of RBMs (Restricted Boltzmann Machines) (Fig. 2). There are two steps in DBN which include training layer by layer followed by fine tuning that uses an error back propagation algorithm.

Let the data be $d = (d_1, d_2, \cdots ..d_P)$ and the hidden layer be $l = (l_1, l_2, \cdots ..l_Q)$. The energy function between the visible layer $d$ and the hidden layer $l$.

$$E(d, l|\delta) = \sum_{j=1}^{P} R_i d_i - \sum_{k=1}^{Q} S_k l_k - \sum_{j=1}^{P}\sum_{k=1}^{Q} d_j w_{j,k} l_k \tag{14}$$

Here $\delta = \{w_{j,k}, R_j, S_k\}$ represents the RBM parameters $w$ represents the weight $R, S$ represents a bias of visible and hidden layers respectively. The probability distribution of the visible layer

$$P\left(d_j = 1 \middle| l, \delta\right) = sigmoid\left(R_j + \sum_k l_k w_{k,j}\right) \tag{15}$$

Similarly, the probability distribution of hidden layers is expressed as,

$$P\left(l_k = 1 \middle| d, \delta\right) = sigmoid\left(S_k + \sum_j d_j w_{j,k}\right) \tag{16}$$

Let $F_{train}$ represents the optimized features from all the train images. Using the features $F_{train}$, the DBN network is trained. In the testing phase, the test image is initially preprocessed, ROI segmented, features are extracted and further features are optimized. The optimized features applied to the pre-trained DBN network to classify the leaf in any one of the classes that include Symptoms of N, P, and K deficiency, infected with brownspot and leaf blast diseases, infested with pest hispa and healthy.

The evaluation of proposed algorithm was done for specificity, precision, sensitivity, F1-scoreand accuracy using the Kaggle nutrient deficiency dataset (https://www.kaggle.com/datasets/guy007/nutrientdeficiencysymptomsinrice) that contain the N, P, K nutrition deficiency leaves with 1156 images. Kaggle rice leaf diseases and pest dataset (https://www.kaggle.com/datasets/minhhuy2810/rice-diseases-image-dataset) with 3355 images of brownspot and leaf blast infected and hispa infested. Few of the sample images are provided in Fig. 3. Out of 4511 images from the two Kaggle datasets, 1355 images (30 % of the images) are used for testing, and the remaining 3156 images (70 % of the images) were used to train the model.

$$Specificity = \frac{True_{neg}}{True_{neg} + False_{pos}} \tag{17}$$

$$Precision = \frac{True_{pos}}{True_{pos} + False_{pos}} \tag{18}$$

$$Sensitivity = \frac{True_{pos}}{True_{pos} + False_{neg}} \tag{19}$$

$$F1score = \frac{2 \times precision \times sensitivity}{precision + sensitivity} \tag{20}$$

$$Accuracy = \frac{True_{pos} + True_{neg}}{True_{pos} + True_{neg} + False_{pos} + False_{neg}} \tag{21}$$

Here $False_{pos}$, $True_{neg}$, $False_{neg}$ and $True_{pos}$ represent the false positive, true negative, false negative and true positives in the classification result respectively.

*Estimation of error percentage*

The error percentage is defined as the number of times the tested image identifies the symptoms wrongly that of the trained images. If the accuracy is estimated at 98.1, then it is said that, out of 100 images for a particular symptom the proposed method identifies 98.1 images correctly and hence the error percentage is 1.9.

## Results and discussion

In the proposed approach the K-means clustering algorithm uses $K = 6$ clusters. Few of the segmentation results obtained on the K-means clustering algorithm are provided in Fig. 4. The segmented results thus include the abnormal region of the leaves from which the texture and color features can be extracted.

The confusion matrix obtained by the proposed method from the 1355 images used for testing is shown in Fig. 5.

The performance of the proposed approach is compared with traditional schemes namely Fuzzy C-Means + Support Vector Machine (Barpanda et al., 2017); Color feature + Support Vector Machine (Sethy et al., 2020); Histogram of Oriented Gradient + Support Vector Machine (Dalal and Triggs, 2005); NasNet-Large (Zoph et al., 2017) DenseNet121 (Yujian et al., 2019), Inception-v3 (Szegedy et al., 2016), ResNet50 (Zhang et al., 2016), Ensemble (Sharma et al., 2022) and Deep Convolutional Neural Network (Xu et al., 2020) as depicted in Table 2 which shows a better performance than the existing methods of classification.

The evaluation of proposed algorithm was done for specificity, precision, sensitivity, F1-scoreand accuracy. The proposed approach provides a Specificity, Precision, Sensitivity, F1-score, accuracy of 97.1 %, 97.6 %, 96.2 %, 96.8 % and 98.1 % respectively. This approach provides a 0.7 % higher precision and 0.66 % higher accuracy than the existing methods. The proposed method provides an AUC of 0.9876.

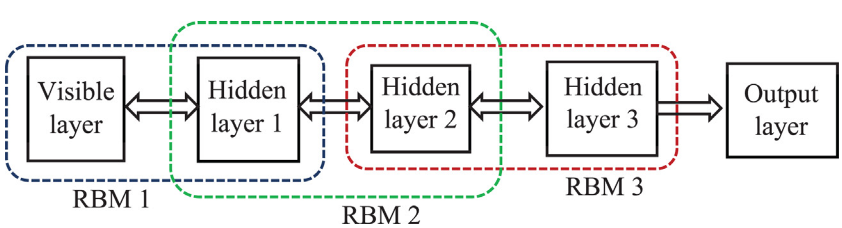


**Fig. 2.** Architecture of Deep Belief Network.

**Fig. 3.** Few of the sample rice leaf images used for classification.

**Fig. 4.** Representative rice leaf images showing segmentation results.

The proposed approach provides a 0.7 % higher precision than the Inception-v3 scheme and 0.66 % higher accuracy than the Deep Convolutional Neural Network and DenseNet121 approach.

The graphical comparison of specificity, precision, sensitivity, F1-score and accuracy are provided in Fig. 6. It shows that the proposed approach provides better performance than the other similar schemes.

The Receiver Operating Characteristic (ROC) comparison between the proposed approach and other similar schemes is provided in Fig. 7. In the ROC curve, the proposed approach provides a higher Area Under the Curve (AUC) than other similar methods. The proposed method provides an AUC of 0.9876 which was found superior than the existing classification methods.

## Conclusion

As studies shows that, most of the farmers apply fertilizers, pesticides and fungicides that too in exorbitant rates fearing crop damage without knowing the exact reasons. Excessive application of synthetic molecules pollutes air, water and even alters the soil properties. As a result, entire eco system gets affected. To overcome this, it is necessary to identify the reason for damage early and do the necessary treatments at the appropriate times. Early detection can be done by assessing the symptoms that appears in the leaves and culm of paddy. Artificial intelligence with image processing can be used effectively for early and appropriate detection of infections if any as it eliminates

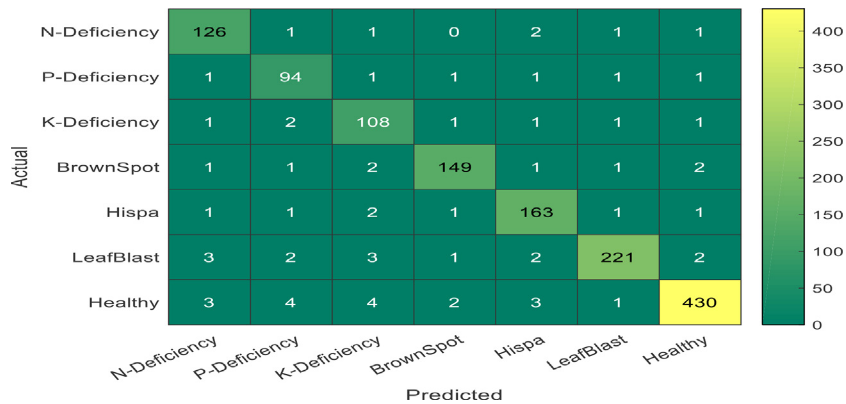


**Fig. 5.** Confusion matrix obtained for the classification results.

**Table 2**
Performance Comparison of the proposed method with traditional schemes.

| Scheme | Specificity (%) | Precision (%) | Sensitivity (%) | F1-score (%) | Accuracy (%) |
|---|---|---|---|---|---|
| Fuzzy C-Means + Support Vector Machine | 94.85 | 91.70 | 90.00 | 92.70 | 93.00 |
| Color feature + Support Vector Machine | 91.78 | 92.10 | 94.70 | 90.60 | 90.55 |
| Histogram of Oriented Gradient + Support Vector Machine | 89.34 | 95.60 | 90.50 | 88.30 | 93.76 |
| NasNet-Large | 92.01 | 96.30 | 89.90 | 94.80 | 95.88 |
| DenseNet121 | 94.49 | 93.80 | 92.10 | 89.10 | 97.44 |
| Inception-v3 | 90.67 | 96.90 | 95.20 | 95.90 | 91.67 |
| ResNet50 | 95.38 | 94.50 | 96.30 | 96.40 | 95.15 |
| Ensemble | 93.98 | 90.00 | 96.00 | 93.00 | 92.00 |
| Deep Convolutional Neural Network | 95.90 | 95.20 | 94.40 | 93.80 | 97.44 |
| Proposed | 97.10 | 97.60 | 96.20 | 96.80 | 98.10 |

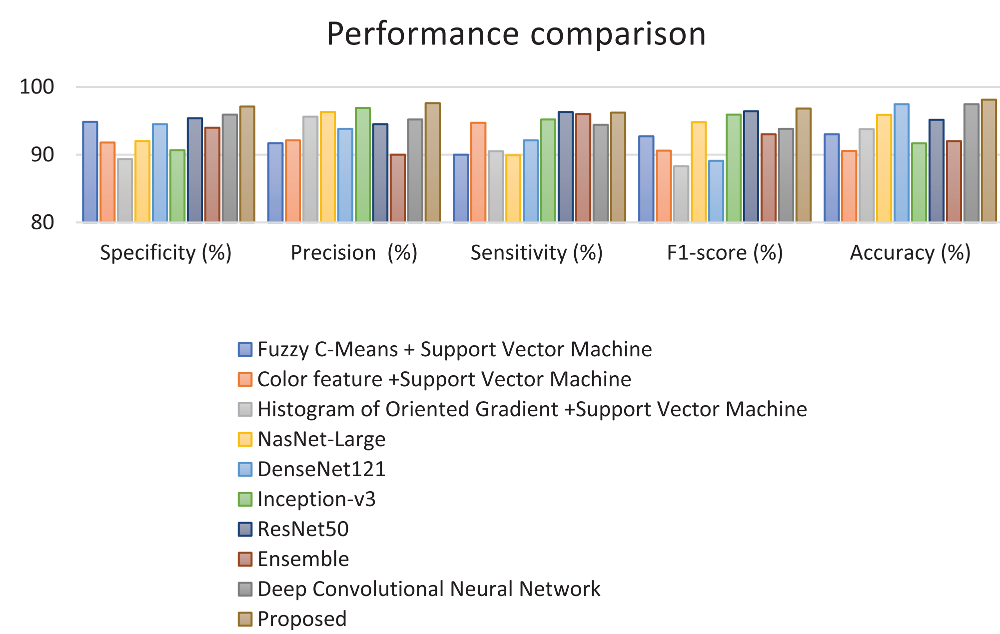


**Fig. 6.** Graphical comparison of performance between proposed and other similar methods.

or reduces the interpretation errors. In the proposed method, the leaf images are preprocessed by contrast enhancement. The ROI is then segmented using the entropy segmentation and K-means clustering algorithms. Color and texture features are then extracted from the ROI and the features are then optimized using the mayfly optimization algorithm. The optimized features are then trained and tested using the Deep belief neural network classifier. The classifier classifies the leaf images into different classes that are trained. The DBN approach

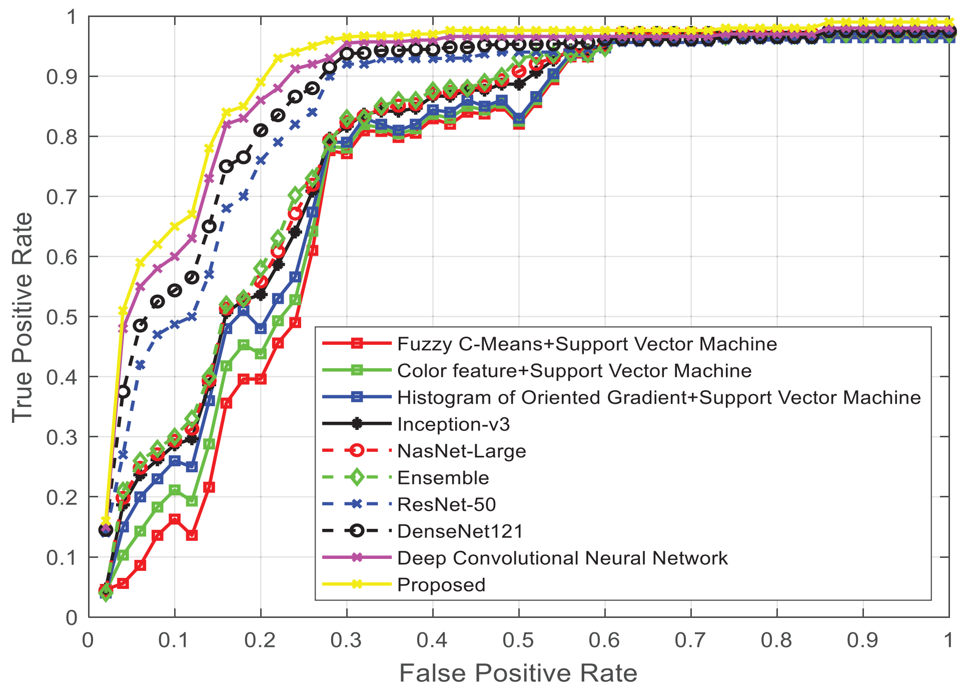


**Fig. 7.** Receiver Operating Characteristic curve comparison between the proposed and other similar schemes.

provides a higher value for the metrices of Specificity, Precision, Sensitivity, F1-score and accuracy. The AUC estimated is also found superior to the existing methods. Thus, it is concluded that the present scheme establishes its superiority in identifying the reasons for crop damage over the other existing schemes. The accurate and timely identification of the reasons for crop damage can minimizes the indiscriminate incorporation of the synthetic molecules into the environment thus reducing the pollution levels and protecting the entire ecosystem.

## Data availability statement

N, P, K deficient rice leaf image dataset used for training and testing is available in"https://www.kaggle.com/datasets/guy007/nutrientdeficiencysymptomsinrice", rice leaf diseases and pest dataset used for training and testing is available in "https://www.kaggle.com/datasets/minhhuy2810/rice-diseases-image-dataset" and all the data generated during and/or analysed during the current study are included in the manuscript.

## CRediT authorship contribution statement

**A. Pushpa Athisaya Sakila Rani:** Conceptualization, Methodology, Software, Writing – original draft, Visualization, Investigation, Writing – review & editing. **N. Suresh Singh:** Conceptualization, Methodology, Supervision, Project administration.

## Data availability

I have shared the link to manuscript.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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