VOL. 16, NO. 24, DECEMBER 2021 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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A NOVEL DESIGN FOR PESTDETECTION BASED ON FEATURE EXTRACTION WITH ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Identifying the pest and eradicating one of the significant and challenging tasks to the farmers in the agriculture field. It is considered to be one of the devaluating processes while farming and it pushes cultivation productivity to face a downfall. Usually farmers follow conventional approaches to the diminish growth of pests and propagate the productivity. Recently researchers incorporate machine learning methods to classify the categories of pest present in the paddy crop through various images practically. This paper deals with Artificial Neural Networks that is used to identify ten kinds of pest. There are 3549 images available in the data repository. An augmentation methodology is incorporated to support large dataset via machine learning process. A noise removed leaf images are preprocessed and given as input. Sobel operator based edge detection is used to Segment the ROI of processed images Advanced Feature extraction methods are incorporated to clearly sort out the three important criteria of the images like Shape, Intensity and Texture. The proposed model validates the images through ANN and accurate results are produced in pest image classification.

Keywords: ANN, noise removal, feature extraction, filtering, pest detection.

1. INTRODUCTION

Early pest identification of pests in crops has been a serious challenge for farmers in recent years. Agriculture is the primary source of income for the majority of the population. The most essential thing now is to boost crop productivity. Pest infection on plants, however, is an issue. To address this issue, a variety of ways have been explored. The field is farmed with a variety of crops. This article is mostly concerned with paddy crops. Thrips, green leafhoppers, and paddy stem borer are the most frequent pest illnesses in paddy crops. Image processing techniques can help farmers discover pest shape, affected area of pest in leaf, color variation owing to pest infected region, change of form and size of each leaf can be identified independently and easily to solve these problems. Automatic detection is the most effective method for detecting pests in crops, and classification algorithms are employed to identify them based on image attributes. A review of several image processing techniques is applied to paddy crop leaves in this research.

Pest is an organism which is harmful to human and human needs. Pests mainly damage the agricultural crops due to which there is a loss the farmers. In the Modern era due to increase in population there is a shortage of food. Global warming is another reason due to which there is shortage of food. Due to the global warming there is a change in climatic conditions and rise sea levels. These factors affect the growth of the agricultural crops. Pest detection should be done so as to detect the pest present on a crop. There are various methods invented to detect the pests. For the practical implementation of pest detection and classification of the embedded systems are used widely for easy implementation of software with hardware. The early pest detection techniques involved the single pest detection in a single image but in the recent developments involved multiple pest detection in a single image due to which all the pests present on the crops are detected. Pest detection is not sufficient for efficient crop growth. Pests must be classified so as to use proper pesticides on the pests. Permethrin is a pesticide used to kill grass hopper in the crops. The same pesticide cannot kill another pest like ladybug. So pests must be classified to use a proper pesticide on the pests.

The remaining of the paper is laid out as follows. Section 2 describes the research that has been done in relation to our proposed project. The technique for detecting and classifying pests is presented in Section 3. Section 4 assesses and compares the proposed work's performance to that of other current algorithms. Section 5 brings the paper to be concluded.

2. RELATED WORKS

There has been some previous work the subject of crop pest detection that has been automated. The white insects were detected from leaves using the Relative Difference in Pixel Intensities (RDI) technique [1]. It also counts the white flies in order to evaluate their density in the field. Both green house and agricultural crops benefit from this algorithm. It evaluates 100 photos and has a 97% accuracy rate. When dealing with overlapping white flies, it works well, but it does not detect the white fly's entire shape. This can result in false positives. [2] Proposes a method for distinguishing between white fly and aphid. It also contains a way for determining which leaves are damaged and which are not. This approach employs a support vector machine to extract various visual attributes for use as input the classification process. The 'Watershed approach' takes the most but is the best for occluded objects, while Otsu's method takes the least time [11]. This approach is overly sensitive to noise and produces false positives even when there isn't much noise.

The scientists used classification as a learning strategy to detect white flies in one of the ways evaluated. It compares and contrasts several classifiers such as k-NN, RBF, ANN, and SVM. By using input parameters such as color, shape, and texture data, the support vector machine outperforms conventional classifiers. It makes use of lot of image attributes that aren't relevant, resulting in incorrect findings. Another way for detecting white flies is to use background subtraction of photos with white flies to measure white fly size and count the white flies [3]. The Sobel edge detection operator is then used to detect the edges of whiteflies in the image, allowing them to be easily distinguished. This method detects three times faster and covers three times as much leaf surface as the previous technique. In the presence of noise, edge detection algorithms perform poorly because noise is also considered as an edge.

3. PROPOSED WORK

The experimental outcomes of our planned study are detailed in this section. As a result, this project entails the creation of a pest detection model that identifies leaf images. The operations and techniques used in the suggested model are clearly displayed in Figure-3. This study offers a new model called Pest Detection Model (PDM), and the operations and strategies used in the suggested model are clearly displayed in Figure-1. The model is divided into five stages, as shown in Figure 3.

a) Pre-processing

b) Leaf Segmentation

c) Advanced Feature Extraction (AFE)

d) Classification using ANN

e) Performance Evaluation

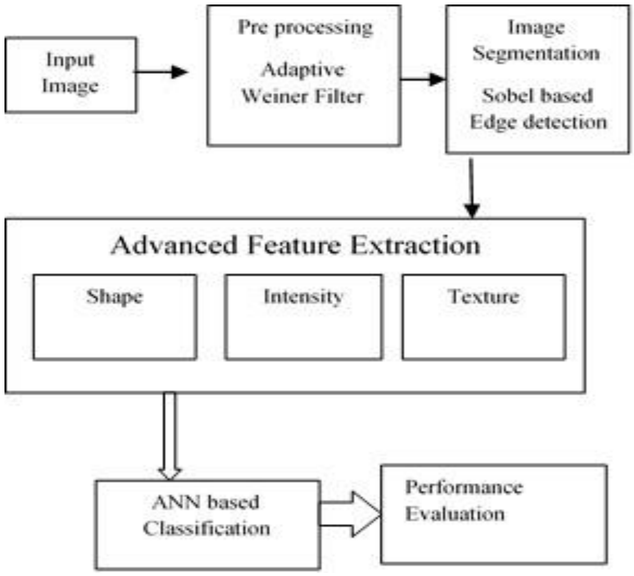

Figure-1. Operation and techniques.

a) Pre-processing - In this model, the later leaf images are acquired from image database. Moreover, the images contain some noises such as labels containing leaf information, included by the artifacts. Those noises and artifacts are to be removed in this pre-processing stage. For digital images pre-processing, Adaptive Weiner Filter is used in this work. Let the considered DM contains some white Gaussian noise, can be given as,

$$b(x, y) = a(x, y) + n(x, y) \qquad (1)$$

Where, '$a(x, y)$' is the noise occurs at the pixel location (x,y) and '$n(x, y)$' is the white Gaussian noise, wherein, '$b(x, y)$' is the location of noisy pixel. Here, the main intention is to reduce noise '$n(x, y)$' and to gain the linear determination '$\hat{a}(x, y)$' of $a(x, y)$ that also reduces the mean square error rate. Moreover, the scalar form of Weiner Filter is given as,

$$\hat{a}(x, y) = \frac{\sigma_a^2(x,y)}{\sigma_a^2(x,y)+\sigma_n^2(x,y)}[b(x, y) - \mu_b(x, y)] + \mu_b(x, y) \qquad (2)$$

Where, '$\sigma_a^2(x, y)$' and '$\mu_b(x, y)$' are the mean and variances of image signals. And, it is considered that the mean value of signal noise is equal to 0, then, the value of '$\mu_b(x, y)$', '$\sigma_a^2(x, y)$' and '$\mu_b(x, y)$' are to be calculated. Furthermore, with the assumption that the mean and variance values of noise are known, then, the rest are considered to be measured. Here, the values of local mean and variances are measured with the mean window size under uniform motion $(2m + 1) \times (2m + 1)$. In this proposed model, the Adaptive Weiner Filter with (3×3) neiborhoods is used on the input leaf images.

b) Leaf - Segmentation - Segmenting the leaf image is an important process in PDM model and a typical segmentation process involves in diving the image area into sections having similar properties based on texture, contrast and so on. Here, Sobel Operator based edge

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detection technique is used for cancer region segmentation and its objective is to detect the accurate location and categorize the pest detection. The Sobel operator contains 3×3 convolution kernels, and X and Y direction kernels. The kernels are designed to counter exactly to the edges that are denoting on X and Y-axis with respect to the pixel grids. Further, those kernels are processed individually to the input DM for generating the separate computations of the gradient element in each orientation. Here, I_x is considered to gradient in X-directional columns and I_y is taken to gradient in Y-directional rows. Both values are integrated to detect the accurate gradient magnitude (GM) at each pixel and orientation. The GM is computed as follows:

$$|GM| = \sqrt{{I_x}^2 + {I_y}^2} \quad (3)$$

And, the approximate GM is further calculated as,

$$|GM| = |I_x| + |I_y| \quad (4)$$

Further, the angle of edge orientation (A) with respect to the pixel grid is used to compute the spatial gradient of the input DM, which is given as,

$$A(\theta) = \arctan\,(I_x/I_y) \quad (5)$$

c) Advanced Feature Extraction (AFE)

The features of the input digital leaf images from the image database are extracted to train the Artificial Neural Network for Accurate pest detection. The Advanced Feature Extraction (AFE) process is used here to calculate the physical factors that can be visualized with the segmented pest region. Moreover, the objective of AFE is to determine the mathematical way to define the image details. In PDM, these extracted features are used for find the pest kind from the obtained image dataset. Moreover, this process provides great impact on enhancing the classification accuracy, and also in reducing cost and time. For Advanced Feature Extraction, Shape based features, Texture and Intensity based features are derived from the segmented image.

A. Shape based Feature Extraction:

The shape features are defined based on the pixels in and around the segmented region or the Region of Interest (ROI). The factors considered are given as follows:

a. $$Circularity = \frac{4\pi ROI_A}{ROI_P}, \quad (6)$$

where 'A=area of segmented region' and 'P= perimeter of segmented region'.

b. $$Compactness = \frac{(ROI_P)^2}{ROI_A} \quad (7)$$

c. $$Ellipse\ Ratio = \frac{ROI_A}{Ellipse_A} \quad (8)$$

d. $$Solidity = \frac{ROI_A}{Convex_{full_A}} \quad (9)$$

B. Texture based Feature Extraction

The roughness of the segmented image is analyzed in this section. And, the texture-based feature extraction evaluates the intensity variations among pixels by considering the following features.

a. $$Energy = \sum_{x=1}^{a} \sum_{y=1}^{b} IP(x,y)^2, \quad (10)$$

where 'IP' is the intensity pixel rate of image co-ordinates 'x' and 'y'.

b. $$Contrast = \sum_{x=1}^{a} \sum_{y=1}^{b} (x-y)^2\, IP(x,y) \quad (11)$$

c. $$Correlation = \sum_{x=1}^{a} \sum_{y=1}^{b} \frac{(x-\mu_x)(y-\mu_y)IP(x,y)}{\sigma_x \sigma_y} \quad (12)$$

d. $$Homogeneity = \sum_{x=1}^{a} \sum_{y=1}^{b} \frac{IP(x,y)}{1+|x-y|} \quad (13)$$

e. $$Entropy = -\sum_{x=1}^{a} \sum_{y=1}^{b} IP(x,y) \log\,[IP(x,y)] \quad (14)$$

C. Intensity based Feature Extraction

In this section, the intensity-based features are derived based on the probability of pixel rates in the segmented image.

a. $$Mean\ (\mu) = \frac{1}{ab} \sum_{x=1}^{a} \sum_{y=1}^{b} IP(x,y) \quad (15)$$

b. $$Standard\ Deviation\ (\sigma) = \sqrt{\frac{1}{ab-1} \sum_{x=1}^{a} \sum_{y=1}^{b} |IP(x,y) - \mu|^2} \quad (16)$$

c. $$Variation\ Co-efficient = \frac{\sigma}{\mu} \quad (17)$$

d. $$Skewness = \frac{1}{ab} \sum_{x=1}^{a} \sum_{y=1}^{b} \left(\frac{IP(x,y)-\mu}{\sigma}\right)^3 \quad (18)$$

In this proposed model, Artificial Neural Network (ANN) is used for classification and appropriate decision making in the field of pest detection.

d) ANN Classification - For automated and accurate classification of images, Artificial Neural Networks is used in this work, which is operated with one step only training process for solving the approximation issue. The training process is corresponding to surface determination in multi-dimensional space that defines best fit for training with image samples. Here, the advanced features that are extracted from previous section and some other additional features are giving to the ANN for result classification, providing efficient decision making on pest. The structure of ANN for the proposed PDM model is presented in the Figure-2. The structure contains three layers, namely, Input layer, Hidden Layer and Output layer. The input layer obtains the Leaf data from the AFE along with common information. The hidden layer comprises of neurons, in which the processing is carried out for decision making and the output layer provides the final classification results.

ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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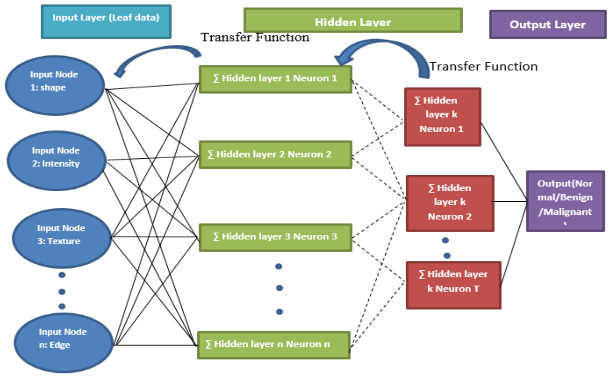

Figure-2. AN Structure for PDM Model.

Performance Evaluation - The performance of the proposed PDM model is evaluated with the measures, such as, sensitivity, specificity, accuracy and precision rate. Those computations are processed with the four factors called True Positive (P), True Negative (Q), False Positive (R) and False Negative (S). The formulae for measuring the four evaluation factors, Accuracy (DA), Sensitivity, Specificity and Precision are presented below.

a. $$(\,Accuracy) = \frac{P+Q}{P+Q+R+S} \quad (19)$$

b. $$Sensitivity\ (Recall\ Rate) = \frac{P}{P+S} \quad (20)$$

c. $$Specificity = \frac{Q}{Q+R} \quad (21)$$

d. $$Precision = \frac{P}{P+R} \quad (22)$$

Using the aforementioned equations, the performance efficiency of the proposed model in detecting pest is evaluated.

4. RESULTS AND DISCUSSIONS

For training the ANN, the images from Leaf database are divided into two sets, one set is for training with 80% of Leaf image samples and another is for testing, which contains the remaining 20% of images. The implementation is carried out in MATAB and the obtained results for the evaluation factors and compared with the existing works for breast cancer detection, such as, Support Vector Machine (SVM), Probabilistic Neural Networks (PNN) and K-Nearest Neighbour (KNN).

Figure 3 Sample Dataset

Figure-4. Pest detected image 1.

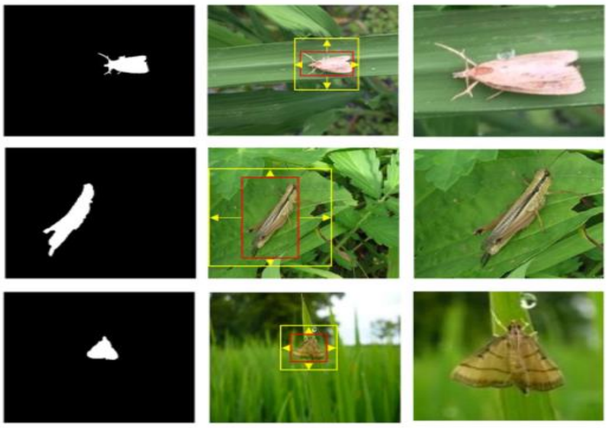

Figure-5. Pest detected image 2.

VOL. 16, NO. 24, DECEMBER 2021 ISSN 1819-6608
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Figure-6. Sheath blight detected image 2.

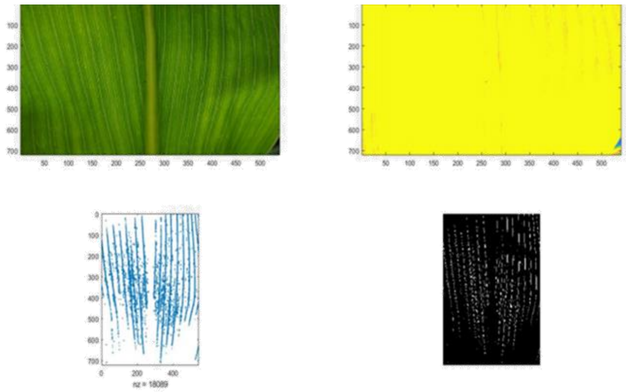

Figure-7. Moisture content extraction with sparsity levels.

An image gradient was created to reduce noise in the gradient and to detect correct characteristics from these pixels, as well as statistics for each image. Simply put, the effect of noise on an intensity image can be decreased by smoothing over irregular areas on paddy fields. The image gradient pixel is a small quantity of noise image to horizontal direction measuring using the sobel gradient operator. To put it another way, healthy zones within sick areas were also destroyed. Because the paddy fields photos are afflicted with illness and biomass, we added noise to the image on red-pixels for unhealthy image 5.

Table-1. Comparison of sensitivity.

Images/Methods	SVM	PNN	KNN	PDM
Image 1	82.34	83.45	86.67	92.45
Image 2	83.24	85.23	85.46	94.56
Image 3	82.11	82.54	86.90	95.21
Image 4	81.45	84.89	87.25	95.34
Image 5	82.45	85.90	89.45	96.76

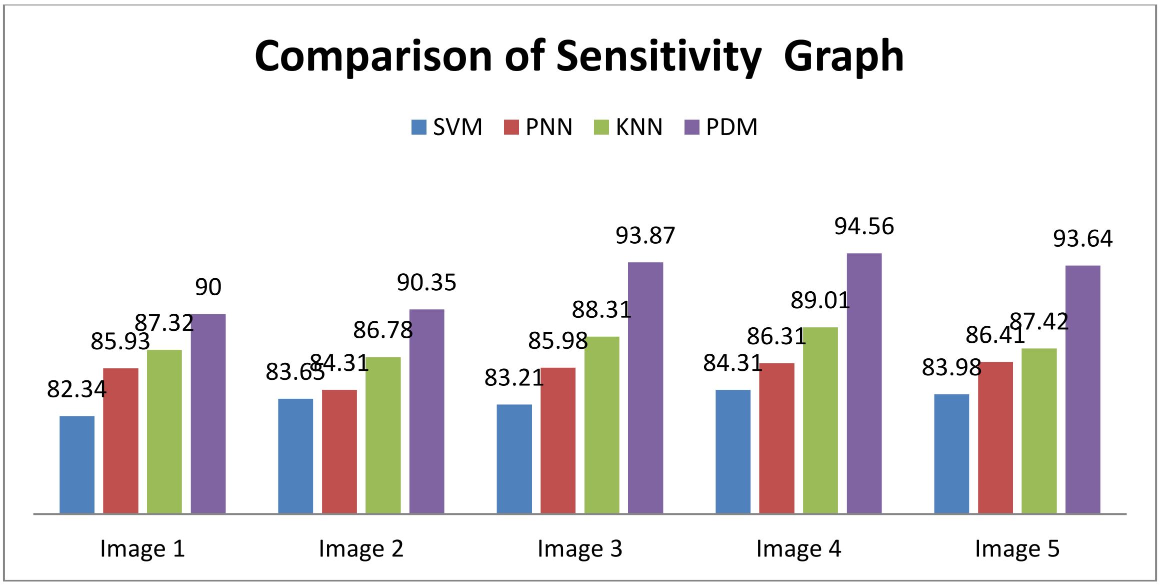

Figure-8. Graph for sensitivity.

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Table-2. Comparison of specificity.

Images/Methods	SVM	PNN	KNN	PDM
Image 1	72.34	81.45	82.27	90.09
Image 2	73.24	82.45	84.87	93.21
Image 3	75.11	81.09	81.92	91.21
Image 4	80.45	83.89	83.24	93.78
Image 5	81.45	81.23	84.52	92.56

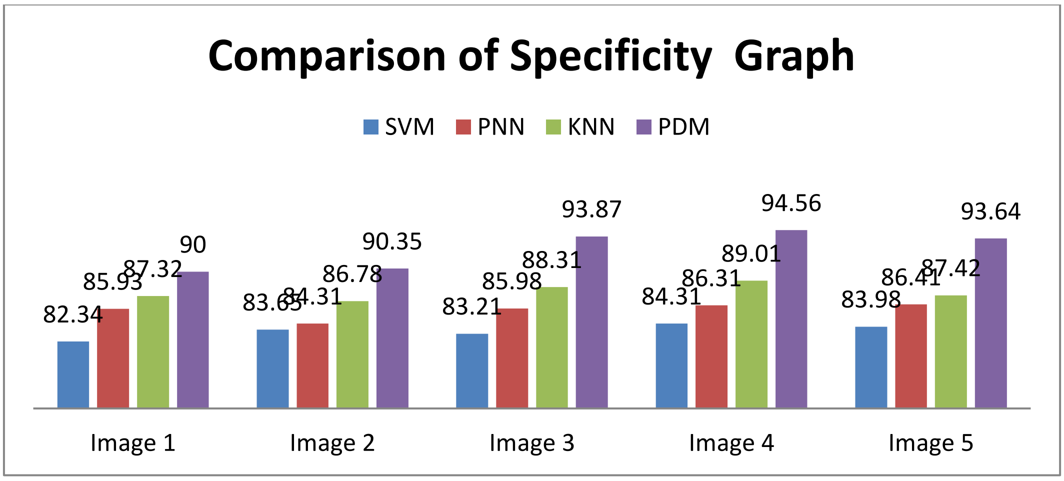

Figure-9. Graph for sensitivity.

Table-3. Comparison of precision.

Images/Methods	SVM	PNN	KNN	PDM
Image 1	81.45	79.76	81.93	91.54
Image 2	76.24	85.45	83.21	92.31
Image 3	72.11	83.07	82.73	90.43
Image 4	82.45	81.23	81.45	91.72
Image 5	73.24	80.74	83.65	92.01

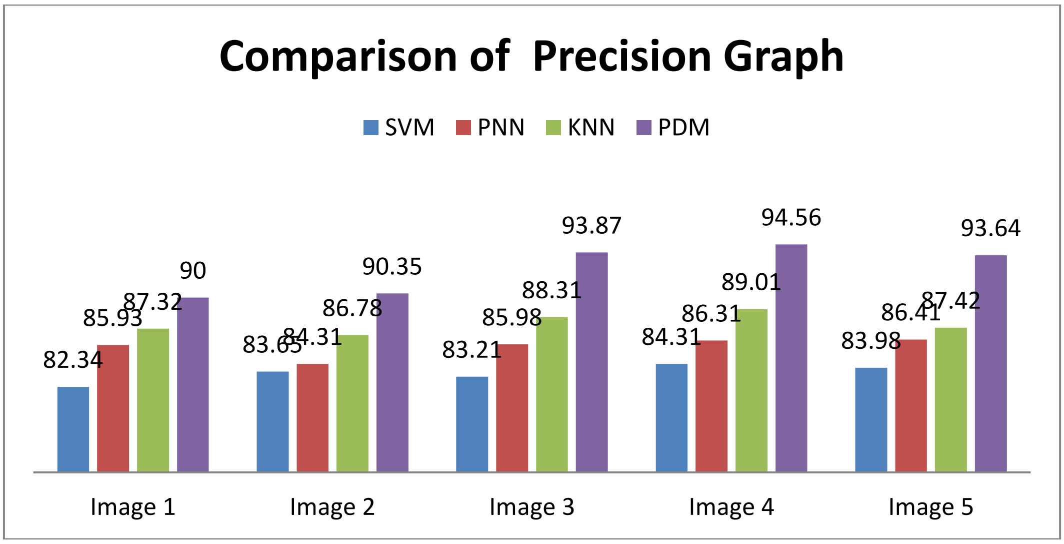

Figure-10. Graph for precision.

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Table-4. Comparison of accuracy.

Images/Methods	SVM	PNN	KNN	PDM
Image 1	82.34	85.93	87.32	90.00
Image 2	83.65	84.31	86.78	90.35
Image 3	83.21	85.98	88.31	93.87
Image 4	84.31	86.31	89.01	94.56
Image 5	83.98	86.41	87.42	93.64

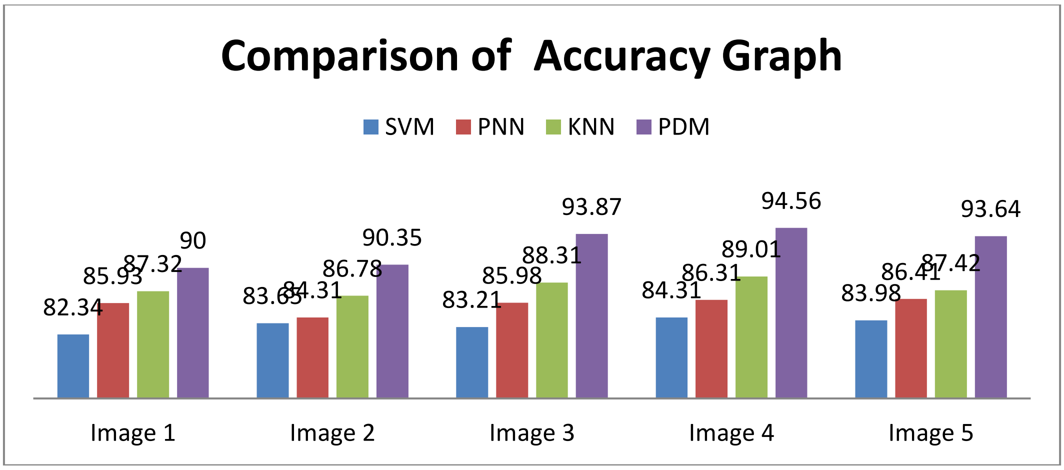

Figure-11. Graph for accuracy.

While considering about the Sensitivity, Specificity, Precision, Accuracy and error rates in classification, with the effective implementation of the advanced techniques in the proposed model, error rate are minimal than others in disease pest detection. And, the results are portrayed in Figures 8, 9, 10, 11, for processing around 70 input images from the dataset. Moreover, the processing time is also considered as the important factor here, as time plays a vital role in pest disease. By utilizing Artificial Neural Networks (ANN) for training and testing with extracted features with AFE based on shape, texture and intensity of the segmented image, the diagnosis process takes minimal time for the proposed model when comparing others.

5. CONCLUSIONS

Feature extraction-based Artificial Neural Networks are used in this paper to reduce noise in color aberrant areas caused by illness and biomass on rice fields. The proposed algorithm Detection of Abnormal Region for Pest Prediction in Paddy Field 85 was tested on abnormal areas in paddy fields, with the results indicating that on abnormal areas of the initial partition with segmentation for modified gradients images to finding in color abnormal areas that insects, biomass, and fertilizer on paddy fields. Because certain color aberrant patches seem like plants, it's difficult to spot abnormal spots in paddy fields. The proposed method for detecting aberrant areas in rice fields with accuracy. Based on the findings of an experiment, an algorithm for abnormal identification in paddy fields was presented. These studies are in their early stages, and we will focus our future efforts on automating them; nonetheless, methods for detecting color illness in plants still need to be improved.

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