Comparative Analysis of Rice and Wheat Plant Leaf Disease Classification

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***Abstract*— The field of plant disease detection using image classification has recently exploded in popularity. Using image processing algorithms, plant illnesses can be identified to help farmers to save their agricultural products and avoid financial losses. Smart Grids, Surveillance, Smart houses, and so on are just a few examples of how IoT is being used today. Using IoT and networking technologies, Precision Agriculture aims to boost the yield of the farm's crops. There is a lot of interest in using machine learning (ML) techniques to identify illnesses in plant photos. Several steps are included in the procedure, including picture acquisition, preprocessing, segmentation and feature extraction. To begin, images will be captured via IoT devices and stored on a cloud server, where they will be processed for classification. The rice plant photos are being preprocessed in the cloud to improve the image quality. A Comparative analysis of rice plant and wheat plant disease identification and classification is presented. The disease detection of a wheat leaf is then segmented using the fuzzy c-means (FCM) and multi-class classification is performed using probabilistic neural networks (PNN). For rice plant disease classification, Deep Neural Network (DNN) and Grey Wolf Optimization Algorithm (GWO) are used to evaluate the comparative performance. The effectiveness of the proposed method's classification performance was compared by a thorough experimentation.**

Keywords: Wheat Plat Leaf, rice plant leaf, Fuzzy C-Means, Machine Learning, Probabilistic neural network.

I. INTRODUCTION

Providing food, shelter, and a clean breathable atmosphere are just a few of the many functions that plants play in Earth's ecosystem. Plants are also key sources of alternative energy, such as bio-fuel, and medicinal properties [1]. Deforestation in order to clear the way for modernisation is, however, putting more and more flora on the verge of extinction. A plant database with an integrated search engine is a significant step toward the conservation and preservation of plants and other sorts of flora diversity. Among cereals, wheat is the most important staple food grain of the country as well as of the globe which serves the need of more than one billion people of almost 43 countries. It is a good source of feed various domestic products. consumed by human beings and wheat straw by cattle, processed industrial food products like bread, biscuits, cakes pastries etc., apart from major food. In view of the ever-growing population in the world accompanied by the decrease in area of arable land, the breeders are facing a challenge to enhance productivity in unit area per unit time, particularly in areas where the harvest has reached a ceiling by using conventionally bread varieties [2]. In order to have a break through, heterosis (hybrid vigor) exhibited in the F1 hybrids has taken advantage, in rice even though it is a self pollinated crop. Based on the spectacular success achieved in China in developing the genetic tools viz., cytoplasmic male sterile lines, maintainers and restores commercial hybrids were developed which currently occupies 55% of the rice growing areas in China [3].

Plant Breeders all over the rice growing countries are adapting this technique to their advantage. In fact, hybrid rice technology augors well for a further revolution in- grain production which is desperately needed to meet the escalating demand [4]. Growth and yield of the plant are heavily dependent on biochemical reactions. Hybrid vigor has been demonstrated by biochemical analyses of the isozyme patterns of hybrids and their parents. As the world's population grows and arable land diminishes, rice breeders face a challenge to enhance rice production per unit area per unit time, particularly in areas where the harvest has reached a ceiling. [5]. In view of the fact that to sustain self-sufficiency in rice, India will have to add around 30 million tons during the next ten years to meet the demand created by increasing number of rice consumers and rising incomes. To meet this challenge, heterosis breeding (hybrid vigor) the construction of hybrids using Fi cultivars' superiority over locally existing high yielding varieties has recently been recognized as a realistic and significant technological innovation for boosting and stabilizing rice's yield potentials. In the Peoples Republic of China during 1992-94 hybrid rice was grown in 18.1 million hectares which constituted 54% of rice growing area (33 million hectares) and contributed 64% of the total rice production with a distinct yield advantage of at least 2t/ha: over the best check [6]. Based on the spectacular success of hybrid rice' in China rice breeders in India have been encouraged to accept this challenge for the future by paying serious attention to intensify the development and use of this technology to suit different agro-climatic situations [7].

Apparently in any hybrid breeding programme for the low light monsoon areas, the selection of parental lines with adaptability to low light stress situations may be an essential. Step and hence the selection of restorers should be based on their adaptability to low light situations. However [8], since hybrid vigor is highly cross specific, extensive testing of the restorers and the hybrids developed from such restorers for inherent low light adaptability is warranted to identify the desired combinations for low light environment. To evaluate the nitrogen response of the Fi hybrids and their parents during the wet season to identify the productive hybrids even for low nitrogen inputs which is commonly practiced during the wet season. The heterotic in yield and various physiological parameters in the hybrids in relation to the -N levels is also investigated. To analyse the physiological efficiency of

the commonly used restorers in hybrid rice programed along with their relative adaptability to low light situations. The physiological traits' associated with the low light adaptability also needs to be investigated [9]. The efficiency, of restorers in different duration groups was also assessed so as to identify physiologically. efficient restorers in early, medium and late duration groups for possible use in evolving hybrids with varying durations and to suit different agro-climatic situations in which rice is cultivated in the country. Experiments were conducted in the field as well as in green house conditions to investigate the physiological analysis of grain yield of Fi rice hybrids generally deals with physiography and climatology, cultural practices and standard techniques adapted in the investigation, observations and chemical analysis, while the experimental portion contains details of various trials conducted during the period [10]. The biometrical information gathered on the above aspects related to values for grain yield and its attributes would be of immense utility in planning of efficient breeding programed for the improvement of wheat crop in order to develop better genotypes in comparison to existing ones under stress environments. A large sum of plant leaf classification approaches have been proposed over the last decade for identifying and recognizing various species of plants using image processing and pattern recognition techniques. These have addressed various challenges of building automated plant classification and recognition systems. However, leaves being natural objects have an almost infinite amount of variation with regards to their physical properties which can also change over time. This makes plant classification challenging problems in computer vision. A large number of problems still do not have satisfactory solutions and provide motivations for the current work.

The ODNN (optimal deep neural network) model is used in this paper to offer a new IoT and cloud-based classification ideal for wheat leaf diseases. Acquiring, preprocessing, segmenting, extracting features, and classifying are the four operations in the proposed model. It has been used for proper picture classification using the crow-search (CS) technique for the parameter optimization of DNN, which is implemented in the suggested ODNN model Tests are being carried out to verify the DNN-CS model's efficiency in detecting wheat leaf diseases.

II. Literature Review

Zhang et al, [11] Manifold learning based dimensionality approach is utilised in plant leaf recognition because the algorithms may choose a subset of useful and well-organized discriminative features in the leaf pictures. LDTSA, which employs manifold learning dimensionality reduction, is utilised for plant leaf recognition because it allows for an estimate to be made of how much data will be generated from the within-class and neighbourhood matrices in order to minimise their size.

For the identification of overlapping rubber tree leaves, Anjomshoae et al. [12] employed a template-based method. In the beginning, the Scale Invariant Feature Transform is used to extract critical points for features (SIFT). The SIFT method's steps include determining the scale space extreme by Gaussian difference, locating the key point via main curvature, assigning orientation via gradient directions, and defining the key point.

In Vijayalakshmi et al. [13], the characterization of texture, shape, and colour features of leaves is used to classify them. The feature includes Haralick texture based features, Gabor features, shape features, and colour features. Area, centroid, make up the proposed system's shape features. It's recommended that six colour features will be used in the proposed work, such as the mean and standard deviation for hue, saturation, and intensity (HSI).

The approach proposed by Kalengkongan et al. [14] uses dynamic threshold polygonal approximation to retrieve landmarks of leaf form. It is found that polygonal approximation is an effective method for selecting the optimum spots to represent the variety in leaf form in this study. The authors regulate the fitting of a succession of line segments over a digital curve with a leaf form using a dynamic threshold.

Wu et al. [15] use morphological criteria to identify leaves. The RGB photos of the leaf are first transformed to grayscale. For the binary images to be created from the grayscale images a Laplacian filter is used. Digital morphological leaf traits, which are derived from five basic aspects, have been grouped into 12 categories. Five basic geometrical properties are used to extract 12 morphological features, including Aspect ratio, Form Factor, Rectangularity, Narrow Factor, Perimeter Diameter, Perimeter Physiological Length, and Perimeter Physiological Width, and 5 Vein features. A leaf's area, leaf perimeter, and the five vein characteristics are all included in the diameter measurement.

III. Materials and Methods

a) Acquisition of images

Photographs from a digital camera were used to create the image dataset for this article [8], which includes images of numerous wheat and rice diseases and insect pests. An online photo gallery is featured here. Nearly 200 photos of 70 wheat plants in various stages of illness were gathered as part of the inquiry. Stripe rusting, leaf rusting, and powdery mildews are some of the most common wheat illnesses. Following that, the acquired photos of sickness recognition are transferred to the system and the execution task begins. Images of diseased leaves form the basis of this dataset.

b) Preprocessing

While the pre-processing step has been carried out, the crop images are resized into a dimension of 897 × 3081 pixels to minimize necessity of storage as well as processing energy. Moreover, the basic function is to eliminate the background from an image. Empirically, it has been applied with 4 models to avoid the background from a leaf, initially, use a mask produced on the basis of actual image, employ an originated according to Hue element measures of images from HSV color space, utilize the mask obtained from Value elements of image in HSV color space, and application of a mask attained from Saturation element values of image from HSV color space. RGB image has been transferred to HSV color. Then, due to the existence of S component which has whiteness, it selects the saturation element of HSV image for future computation. Followed by, a mask is developed to eliminate

the background images and assign the values as 0 that shows a black color, in RGB. Hence, the background less image has leaf part, and disease spots.

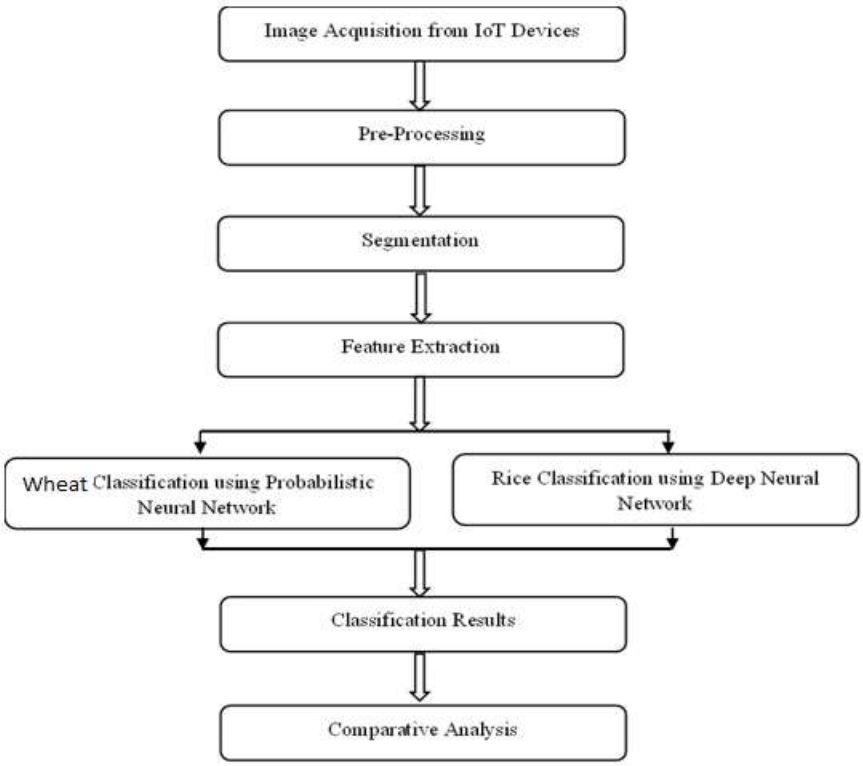

Fig.1: System framework

IV. FCM-PNN Model for Wheat Classification

Several steps are included in the procedure, including picture acquisition, preprocessing, segmentation and feature extraction. IoT devices will take the image and store it on a cloud server, where the categorization procedure is carried out. The wheat plant is being preprocessed to improve the image quality in the cloud. Then, using the FCM clustering algorithm, the diseased areas of the leaf image are identified. Color, shape, and texture are the three kinds of features that are extracted following this step. It is finally used for multi-class classification with the help of PNN.

a) FCM based segmentation process

The FCM is the mainly utilized technique for image segmentation. The FCM's achievement is mostly related to the formation of fuzzy groups and the membership of fitting. An objective function of the regular FCM is provided with

$$J_{FCM} = \sum_{i=1}^{C} \sum_{n=1}^{N} u_{in}^{m} d_{in} \tag{1}$$

$$U = \left\{ u_{in} \in [0,1], \sum_{i=1}^{C} u_{in} = 1 \forall n, 0 < \sum_{n=1}^{N} u_{in} < N \forall i \right\}$$

here U indicates the matrix (i.e., every element u_{in} indicates the degree of fitting of nth pixel to ith cluster), $d_{in} = \|x_n - v_i\|^2$ is the square Euclidian distance among pixel data x_n and the ith cluster center- or mean model v_i and $m \in [1, \infty]$ is model sum to manage the fuzziness.

b) PNN based classification

The PNN have 3 layers such as input, output and hidden layers. As depicts in figures, it is assume that the PNN have the ability to classify the group of 2 classes; but, it is lengthened to classify upto some number of classes. If number of elements in the feature vector is N, the input layer has N nodes, one for all of the input modules of the feature vector. All components in the input feature vector are given as input to all other nodes near the hidden layer.

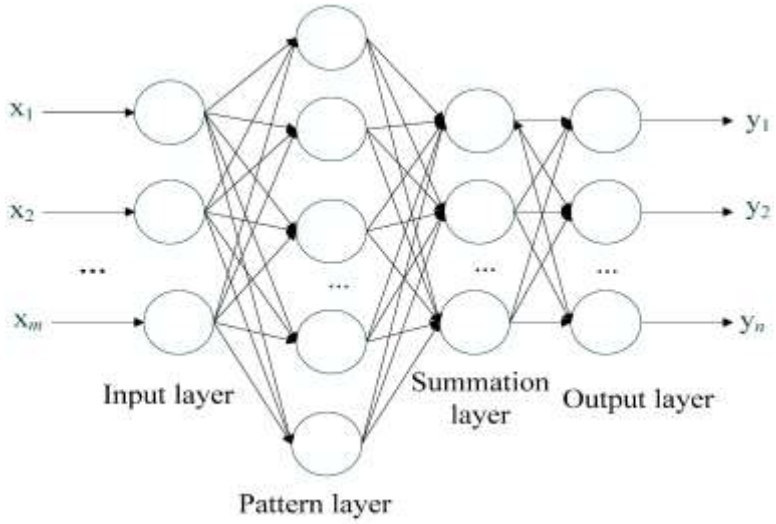

Fig. 2. Architecture of PNN

All hidden nodes are collected into sets as depicted in Fig. 2. The PNN exposed under is selected for the group of only 2 classes; the hidden node is collected of 2 groups denoting 2 various classes. The Gaussian function is validated to its connected feature vectors in similar class. In the resultant node, all Gaussian value endures similarity to individual set are totaled. The sum of the probability in the sum function is unity and subsequently the total creates a possibility density function. The groups of 2 resultant nodes are similar to 2 individual classes.

A mathematical depiction of PNN classification is provided here. PNN is a data classifier method that has executed the Bayesian decision principle as represent here. If it is regarded that (1) data model u $\in G^n$ that includes some of suitable classes $r = 1, \cdots, R$; (2) the probability of u appears in the class r is equivalent to i_r; (3) the classifier cost to u into class r is c_r; (4) the PDF $v_1(\mathrm{u})$, $v_2(\mathrm{u})$, . . . , $v_R(\mathrm{u})$ to all class is known. Then, depends on Bayes theorem, if $r \neq s$, the vector x endure classifier into the class label r, if $i_r c_r v_r(\mathrm{u}) > i_s c_s v_s(\mathrm{u})$. Usually, $i_r = i_s$ and $c_r = c_s$, so, if $v_r(\mathrm{u}) > v_s(\mathrm{u})$, the vector u endure classifier into the class r.

In real time image classifier problem, some data on the PDF $v_r(\mathrm{u})$ is not given as shared of the dataset is not known. Thus, some estimates of the PDF have been calculated. It is obtained with the utilization of Parzen method. In general, the Gaussian function is a substitute to PDF as it performs the criterion required with Parzen's method. It is consideration of using the Gaussian density to PDF suggests the possibility of growing a feed-forward classifier method. It has group of input layers indicated with group of attributes u, the pattern and summation layers contain of R-neurons in all individual one finds the signal only to patterns that appears in the r-th class

$$v_r(u;\sigma) = \frac{1}{l_r(2\pi)^{n/2}\sigma^n} \sum_{p=1}^{l_r} exp\left(-\sum_{q=1}^{n} \frac{\left(u_{pq}^{(r)} - u_q\right)^2}{2\sigma^2}\right), \qquad (2)$$

where l_r is the count of samples of class r, σ denotes the smoothing variable, $u_{pq}^{(r)}$ is the q-th module of the p-th training vector $(p = 1, \ldots, l_r)$ that is present in the class r and u_q is the q-th manage of the indefinite vector u. Finally, the resultant layer is the estimation of the class of u in terms of Baye's decision rule. The result of all summation layer neurons are provided as

$$R^*(\mathrm{u}) = \arg \max_{\mathrm{r}} \{v_r(\mathrm{u})\}, \qquad (3)$$

where $R^*(\mathrm{u})$ denotes the forecast class of the pattern u. As v_r signified in Eq. (4). depends on scalar σ, it is considered as PNNS. If particular classes differ in their densities are considered, next the summation layer signal holds different shapes depends on the value of the smoothing variable interms of the classes. It is referred with PNNC method and is indicated in Eq. (4):

$$v_r(u;\sigma_C) = \frac{1}{l_r(2\pi)^{n/2}(\sigma^{(r)})^n} \sum_{p=1}^{l_r} exp\left(-\sum_{q=1}^{n} \frac{\left(u_{pq}^{(r)} - u_q\right)^2}{2(\sigma^{(r)})^2}\right), \qquad (4)$$

where $\sigma_C = [\sigma^{(1)}, \ldots, \sigma^{(R)}]^T$ is the smoothing variable vector contains of $\sigma^{(r)}$ modulus connected to the r-th class.

V. DNN- GWO for Rice Disease Classification

To begin, a network of Internet of Things (IoT) devices collects photos of the plant in its natural habitat. Then, the image is pre-processed to a certain level to improve its quality. After that, K-means clustering is used to

segment the preprocessed image. DNN-CS based classification is finally used to classify the plant pictures into Blight, Brown Spots, and Smuts.

a) Deep Learning based Classification

The principle of Artificial Neural Network (ANN) is often referred to as DL [24] because of the use of many levels of hidden unit and output. Here are the two stages that make up this process:

- Pre-training level
- Fine-tuning level

Pre-training level

Applied in the input layer to the output layer, the Deep Belief Network (DBN) has developed the hidden layers and supplement layers. This is a vital feed forward network. The activation functions are generated by the presence of DBN and hidden units, which helps to differentiate the network. Additionally, the Restricted Boltzmann Machine (RBM) is used to address the difficulties of possible activation function creation.

Step 1: Upload the element ofV for training the RBM vector.

$$F(v,h) = -\sum_{p=1}^{P}\sum_{q=1}^{Q} W_{pq} v_p\, h_q - \sum_{p=1}^{P} \alpha_p\, v_p - \sum_{q=1}^{Q} \beta_q\, h_q \ldots\ldots \qquad (5)$$

P,Q are the counts of visible and hidden units, respectively, with respect to Wpq, which is a bias term, and being a v_p and h_q symmetrical correspondence. There is no immediate recognition of RBM's concealed units, resulting in the construction of an elegant, unbiased example from $(V_p, h_q)_{data}$

$$\rho(h_q = 1|v) = \delta\left[\sum_{p=1}^{P} W_{pq}\, v_p + \alpha_1\right] \ldots. \qquad (6)$$

Here $\delta(x)$refers the logistic sigmoid function, $\frac{1}{(1+\exp(x))}$, v_p, h_q, is a sign of an objective case. All visible and hidden units have been synced, however only the hidden one has been extended. As a result, the following route has been created.

$$\Delta W_{pq} = \theta(v_p h_q)_{data} - (v_p h_q)_{reconstrution} \qquad (7)$$

Using a multi-layer model, different RBMs can be stacked on top of one another. Diverse RBMs can be found layered on top of each other. Hidden layers can be arranged into a vector, and the quality of units can be produced using RBM layers and distributed approaches in recent weights and biases. As a result, formal training is required for the final group.

Fine Tuning Level

On the basis of back propagation (BP) model, it is carried out. Clinical images are divided into two stages and the output layer is arranged at the top of DNN. In addition, the DL method utilised N input neurons and 3 hidden layers. In order to achieve the new weight, the BP model must be loaded with the pre-training weights from the training data set during the training phase. As a result, the minimum error rate is measured and higher accuracy of DL classification has been attained using excellent weight. Finally, according to the best weight, the acquired images were categorized into 2 classes namely,

- Diseased Plants
- Healthy Plants

b) Grey Wolf Optimization Algorithm

The GWO model is developed from the chasing hierarchy and social leadership of grey wolves (GW). GWO is composed of 3 fittest candidate solutions called alpha, beta, and delta to overcome the challenging issues in search space. Generally, GW resides in groups. Followed by, optional wolves present a set of sponsorship to alpha in assortment development or similar gathering process.

Social dominant hierarchy

Here, α implies the dominant individual and eligible for making various decisions. From the group of GW, the decision making process is carried out by a leader role. In subsequent phase of GWO, it is called beta and named subordinate wolves. It is indirectly

referred as assistants for alpha. Finally, minimum level GW is omega ω ; it is the most inferior individual that has to act according to the rule of dominant GW [6]. According to 3 GW based phases, the optimization process is computed to decide best feature in the applied dataset. Hence, the population size of optimization is illustrated as,

$$Fe = \{ f_1, f_2 ..... f_n \} \quad (8)$$

Encircling prey

In hunting task, GW surrounds the prey. The nature of GWs is defined as shown in Eq. (9).

$$G = | C.F_{prey}(t) - F_{wolf}(t) | \quad (9)$$

$$F(t+1) = F_p(t) - A.G \quad (10)$$

From the predefined functions, A and C are coefficient vectors

$$A = 2ar_1 - a \quad And \quad C = 2r_2 \quad (11)$$

r_1 *and* r_2 are considered to be the random values ranged within $[0,1]$ and a is linearly reduced from {2, 0}.

Hunting

It is operated under alpha GWs. β *and* δ which are assumed to be the portion of GW behavior. The mathematical representation of chasing is processed in dark wolves and underlying optimal solutions are alpha, beta, and delta which is accomplished and alternate search operators are appreciative to refresh the situations as represented by given function.

$$G^{\alpha} = | C_1.F_{\alpha} - F |, G^{\alpha} = | C_1.F_{\beta} - F |, \; G^{\alpha} = | C_1.F_{\omega} - F | \quad (12)$$

$$F_1 = F_{\alpha} - A_1.(G^{\alpha}), F_2 = F_{\beta} - A_2.(G^{\beta}), \; F_3 = F_{\omega} - A_3.(G^{\omega}) \quad (13)$$

$$F(t+1) = \frac{F_1 + F_2 + F_3}{3} \quad (14)$$

Where t denotes the current cycle and F_{α}, F_{β} *and* F_{ω} defines the position vector of GW α, β, and δ. The α, β *and* δ determines the food and other GW upgrades the position in over the food.

Attacking Prey

The ability of dark wolves leads in global optima; which is referred as exploitation ability A. The adaptive evaluation of constraint a *and* A enables GWO to modify investigation and application. By reducing A, most of the cycles are scalable to investigate and another half is concentrated on $(|A|<1)$. The GWO composed of 2 principal units are accumulated.

Search Prey

The exploration principle depicts by applying A with random qualities and performs well and acquires inquiry professional to roam from the prey, whereas $(|A|>1)$, the wolves are defined to move away from the prey.

VI. RESULTS AND DISCUSSION

Table.1 shows the results of the DNN-GWO for rice plant and FCM-PNN for wheat plant with existing methods in terms of accuracy. The results shows that DNN-GWO model has offered competitive results and attained a high accuracy of 95.67%. However, the presented DNN-GWO model has shown superior results to other models and reached to a maximum accuracy of 86.61%..

Table 1 Comparative analysis in terms of accuracy, precision , recall, specificity and AUC

Evaluation Parameters	Measured Value (%)	
	Wheat Plant	**Rice Plant**
Precision	85.57	94.57
Recall	77.39	74.77
Accuracy	86.61	95.67
Specificity	79.55	72.00
Sensitivity	89.03	89.00
AUC	0.96	0.98

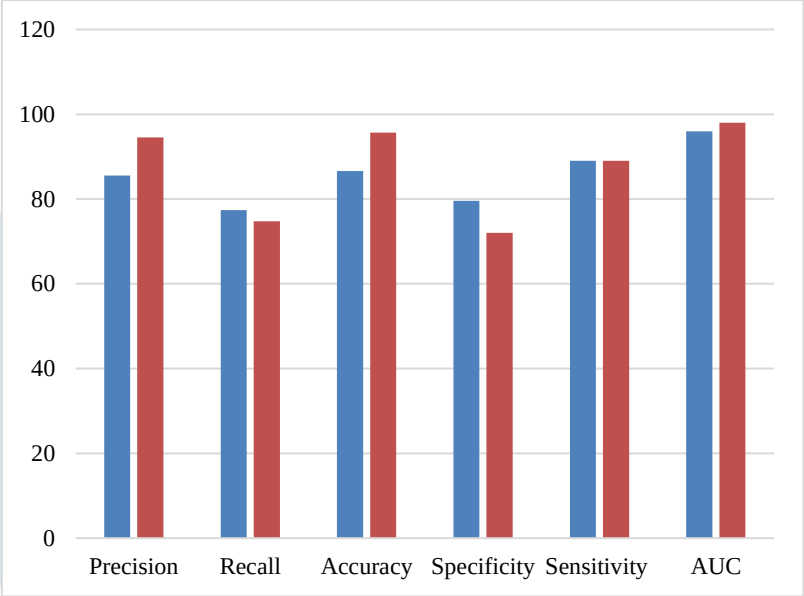

Fig. 3: Comparative analysis of FCM-PNN and DNN-GWO in terms of accuracy, precision and recall

Table. 2 – Comparative Analysis with Existing Benchmark methods

Methods	Measured Value (%)	
	Wheat Plant	**Rice Plant**
DNN-GWO	95.67	97.89
FCM-PNN	96.54	86.61
Training Phase-SVM	93.33	94.23
Testing Phase-SVM	73.33	76.54
5-Fold-SVM	83.80	84.60
10-Fold-SVM	88.57	89.56

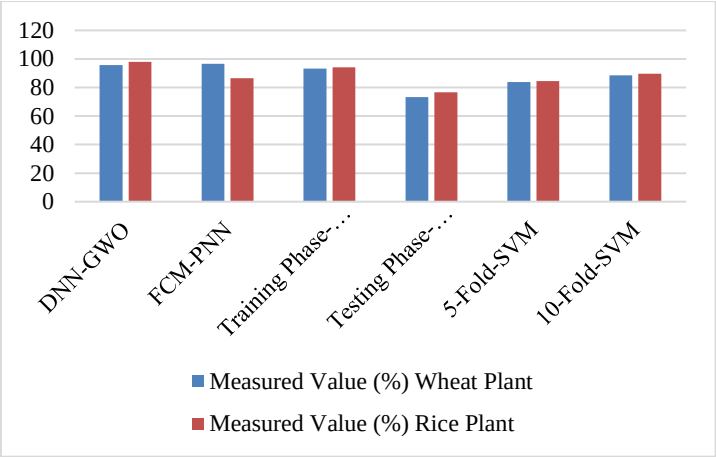

Fig. 4: Comparative analysis of FCM-PNN and DNN-GWO in terms of accuracy

VII. CONCLUSION AND FUTURE WORK

This paper has introduced an actual rice plant disease empathy and classification model for the identification of different kinds of diseases. The proposed model involves FCM based segmentation and PNN based classification to classify wheat plant diseases, at the same time the rice plant disease classification performed using DNN- GWO Model. The effectiveness of the presented FCM-PNN and DNN- GWO model has been tested using a benchmark image dataset. The comparative analysis has been performed and results presented and it shows that DNN-GWO model used for rice plant shows high accuracy than FCM-PNN model. Based on the results, the techniques used for rice plant classification offers better detection than methodologies proposed for wheat plant classification. As a part of future work, hybrid deep learning model can be used to improve the performance of the disease detection.

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