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IoT based Wheat Leaf Disease Classification using Hybridization of Optimized Deep Neural Network and Grey Wolf Optimization Algorithm

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Abstract

Image classification has become a hot research area in identifying diseases in plants. For eliminating the financial loss of farmers, plant diseases identification by image processing models can be used to save the agricultural products. This paper presents a new IoT and cloud based classification model of wheat leaf diseases using optimal deep neural network (ODNN) model. The proposed model comprises of four processes, viz., i) acquisition, ii) preprocessing, iii) segmentation, iv) feature extraction and classification. Initially, acquisition of images takes place using Internet of Things (IoT) devices. Once the image is preprocessed, application of K-means clustering is made that extracts the diseased areas in the leaf images. Next certain unnecessary green areas are discarded from diseased area utilizing thresholding technique. Then, a set of features such as color of the leaf, texture of the leaf and shape of the leaf are extracted in the feature extracting process. At the end, ODNN model has been applied for proper image classification, which employs the Grey Wolf Optimization (GWO) Algorithm for the parameter optimization of DNN. A series of experimentation is conducted to verify the effectiveness of the presented DNN-GWO model on the identification of wheat leaf diseases.

Keywords: Leaf classification, Wheat leaf, Deep learning, IoT, Cloud computing

1. Introduction

India is basically dependent on agriculture where the livelihood of 2/3rd of the population directly or indirectly involves in agriculture. Agriculture is the fundamental economic source

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of India. People either involve directly in agriculture or it provides indirect employment to them. In simple, agriculture is the only means to feed the people. Plants are vital energy source and a great answer for the global warming problem and such plants are affected by various diseases that bring high damage in economy, society and ecology. Hence accurate and timely identification of the disease is the most significant issue. Various methods exist for this identification. In case of certain diseases either no symptoms are visible or even in case of visibility it might be in the final stage. In normal cases, powerful microscopic analysis would help where as cases of tough diagnosis needs electromagnetic spectrum to identify. Remote sensing method is the general approach for exploring the captured images that are multi and hyperspectral and this remote sensing method uses digital image processing tool for reaching the objective. Its peculiarity and the literature extensions forbid the further more discussion on the processing. [1-3].

Process and product of agricultural are the major source of growth in economy for a developing country like India. Agriculture has basic aim to feed the population. Plant disease, along with being a global threatening for food safety, it also has disastrous consequence for small farmers whose livelihood is completely dependent on the health of the crops. These small farmers contribute 80 percent of total crop production in a developing country (UNEP, 2013). The loss accounts to more than 50 percent of total yield and it is mainly due to either pest or disease[4].

Maximum population of the hungry individual belongs to this small farmer family and this makes this group as highly potential risk group in case of disruptions in food supply. Hence these diseases have the tendency to create quality reduction, less yield, slowed down economic growth etc., This scenario clearly indicates that the naked eye monitoring by an expert needs lot of effort and therefore, automation of identification of leaf diseases brings high magnitude on research. This paper focuses on the solution for reducing the cost that avoids manual monitoring and a need for expert in detecting the leaf diseases in the large fields [5].

Compared to other diseases, Puccinia rondite called as wheat leaf rust causes more universal damage to the plants. It is generally seen in wheat and also common in all cereal rust. Development of parasites along with wheat had been observed with large amount of loss due to single and homogeneous cultivation in large areas. An average of 3 percentage of loss is estimated on the whole cultivation and it increases in case of leaf rust occurrence. These situations had given immense raise to the demand of research in detection of plant diseases using Image Processing and Analysis methods [6]. These methods mainly aim at the reduction of human interference and increasing the throughput in the plant disease detection [7].

Many other studies were seen on other plants rather than wheat. Few studies focused on the automated classification system of leaf brown spots and leaf blasts seen in rice plant and the morphological changes observed in the plant due to the diseases [8]. Area of sugarcane leaf is measured with image processing technique to monitor the plant growth. It analyses the fertilizer deficiency as well as environmental stress for the estimation of stage of the disease [9, 10]. Similarly the betel leaf area is measured and that proved very minimal error [11]. More studies were seen on the identification and diagnosis of cotton plant disease. It is done through extracting features, back-propagation neural networking and segmentation process [12].

Previous work [13], presents the application of Fuzzy C-Means Clustering for identifying the affected wheat leaf from the given set of images. It was proved to be simple and quick compared to various other existing image processing techniques, yet it had the limitation of solving the ambiguity in the set of partitioned images. Wheat leaves are supposed to be affected by four different types of diseases and hence the proposed FCM technique would fix the cluster as four and aids the accurate classification. The algorithm failed in case of the set of images not covering all possible infection types that could fix in all clusters.

This work proposes an integrated image processing system for identifying and diagnosing the wheat leaf disease and overcomes the limitation of FCM technique. The system is justified by its intelligence, economic feasibility and amount of effort required for proper detection and classification. This process needs the human knowledge and expertise.

Various articles related to the plant disease identification using several methods are given in this section. [14] proposed a CNN classifier to detect cucumber disease using two different training and testing dataset that contains healthy class data and seven types of disease data. 7320 images of excellent atmosphere is found in the first dataset and 7520 images of both healthy and diseased leaves were present in the second dataset. [15] designed an automated system for integrating the process of identifying the wheat disease and the affected region using supervised deep learning framework. Also, the efficiency of the system is proved with a new dataset (Wheat Disease Database 2017) [16] of wheat disease. [17] had done an extensive survey on forty researches with deep learning technique and summarized various agricultural

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problems in food production. The team had also investigated certain problems with specific designs and techniques.

[18] illustrated complex techniques of neural network for detecting and diagnosing the crop diseases using deep learning techniques. It used a dataset of 87,848 images of 25 different crops in 58 distinct classes as training model and it produced 99.53% of accurate result with various architectures. [19] presented ANN (Artificial Neural Network) for early and précised plant disease detection. This ANN classifier along with Gabor filter (extraction function) proved 91% efficiency. In Malus domestica, [20] proposed K-mean clustering, textures, and color examinations as efficient technique for detection of plant disease. It compares the texture and color of the normal and affected field for classifying and detecting the diseased crops. [21] compared the output achieved from multiple regression, neural network, and support vector machines and proved their efficiency.

[22] examined the simulation outcome of 4 diverse transfer learning approaches for DNN centric plant classification on 4 common datasets. The experimental results show that transfer learning provides maximum merits in automatic plant investigation and also enhance the perfection of plant disease detection. [23] utilized the CNN to proceed the weed prediction in soybean image and categorized the weed from grasses and broadleaves. Dataset of images had been developed with images of types of soils, soybeans, broadleaves as well as grass weed. The CNN employed in this approach depicted a Deep Learning (DL) structure which has attained a reputed accuracy in image recognition process.

The leaf disease can be detected by the classical models like human vision relied approaches. At this point, seeking for the professional's suggestion is highly time consuming as well as costlier. The precision and correctness of human vision technique is based on the perception of a person or a professional. The ML based model allows finding the disease types and helps to make correct decision for the appropriate treatment. The major benefits of ML based approaches are, it is highly consistent when compared to human beings. Hence, the shortcomings of classical technique are that, the requirement for novel ML classification model.

This paper presents a new IoT and cloud-based classification model of wheat leaf diseases using optimal deep neural network (ODNN) model. The proposed model comprises of four processes, namely acquiring, preprocess, segment, feature extract and classify. The proposed

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ODNN model has been applied for proper image classification, which employs the Grey Wolf Optimization (GWO) algorithm for the parameter optimization of DNN. A series of experimentation is conducted to verify the effectiveness of the presented DNN-GWO model on the identification of wheat leaf diseases.

2. Proposed method

Fig. 1 shows the working principle of the proposed DNN-GWO model. Initially, a collection of IoT devices gather the images of the plant from the farming field. Then, image pre-processing takes place to raise the image quality to a certain extent. Afterwards, preprocessed image undergo segmentation using K-means clustering technique. At last, DNN-GWO based classification process takes place for classifying the plant images into Blight, Brown Spot and Smut.

2.1 Acquisition of images

The image dataset for this article is the collection of images of a digital camera that has basic color map of various wheat disease and insect pest pests [8]. It is a gallery of photo network. The investigation collected nearly 200 images of several parts of 70 wheat plant affect with various stages of disease. Major types of wheat diseases fall into the categories such as stripe rusting, leaf rusting and powdery mildews. Followed by, the illness recognition captured images are transferred to the system and precede the execution task. The dataset applied here is composed of images with disease affected leaves [17].

2.2. Pre-processing

Here, to limit the demand of storage and processing power the images in dataset were reformed into the dimension of 300x450 pixels. Here, the major objective is to avoid the image background using hue values on the basis of fusion. The execution speed of image processing techniques is increased by converting the color image into a gray scale image. Based on the sensitivity degree of human eye on RGB colors, the formula used to convert color image to gray scale image is: Gray = 0.3 x R +0.59 x G + 0.11 x B

According to the threshold value, the pictures are transformed as binary images and it is combined with RGB image for the mask development. The fusion phase removes the BG (background) by declaring the pixel value as 00 where the value 0 represent black in RGB.

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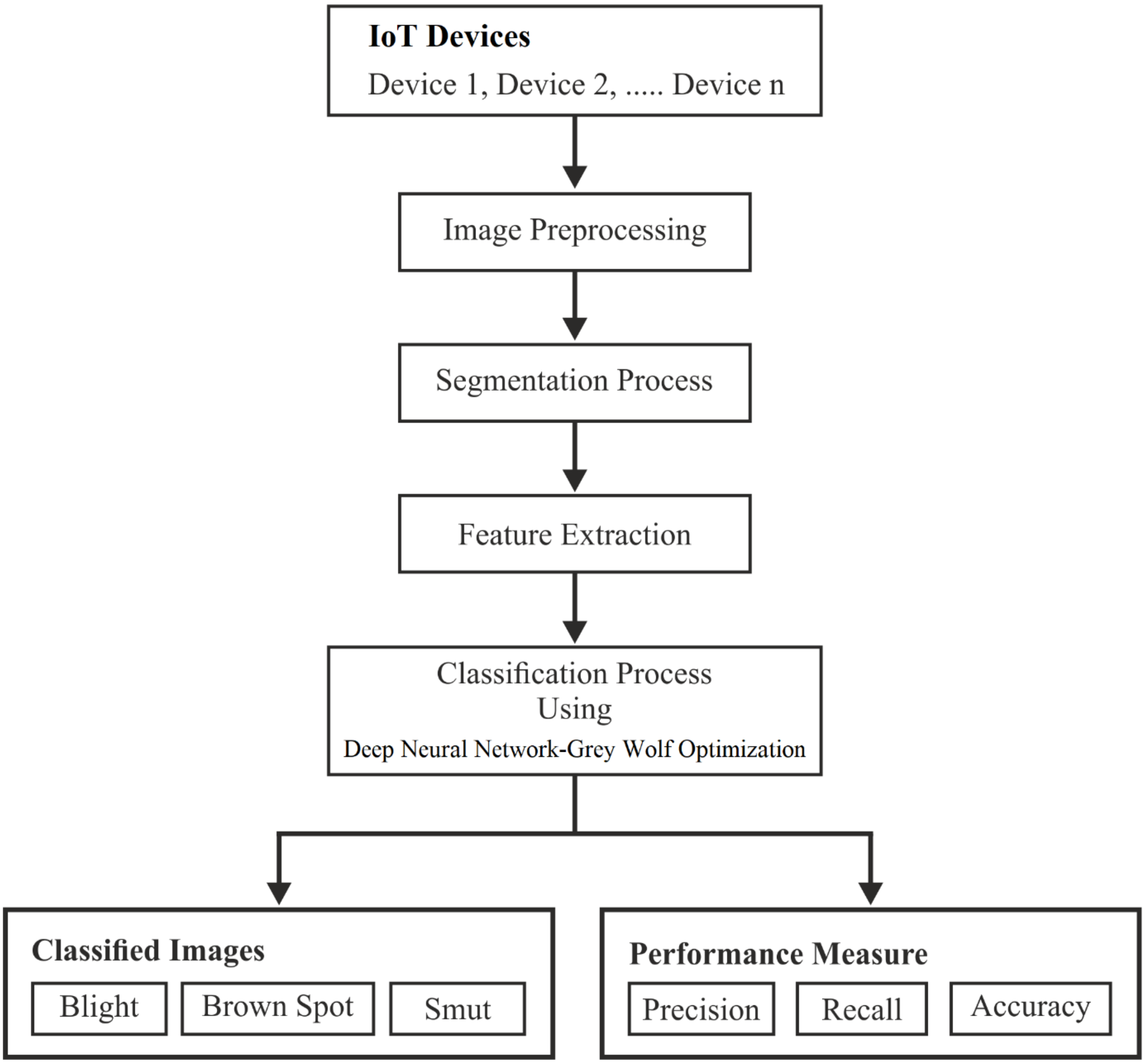

Fig. 1. Overall process of proposed DNN-GWO model

2.3. Segmentation based on K-means clustering.

The image segmenting is processed by using K-means clustering model. Clustering is defined as the process of combining the images into clusters. The infected region has been extracted using clustering task. While the clustering method is applied, clusters should be divided as diseased and non-diseased portions. It is used on hue portion of HSV approach of background rejected image. The pure color is existed in hue component; it lacks in the details of brightness and darkness. According to the examination of histogram in hue components, centroid value is produced for making accurate segments to resolve the randomness issue of cluster. Furthermore, from the affected cluster portion the irregular green portion was removed.

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Followed by, from the newly developed histogram hue values and numbers in all bins were obtained. Based on the histograms and affected images, specific threshold measure is identified to distinguish the affected and non-affected portions. For the appropriate selection of a centroid in cluster, the maximum values from hue values of good and affected portions were decided. The rate of black and chosen centroid value is provided while clustering. Once the image is clustered, the infected region is comprised with unusual green portion. The feature estimation shows that, the green pixels are highly important. Hence, the classification accuracy might be affected. In hue approach, the green color belongs to a degree that is mapped as lower and higher value.

2.4. Feature Extraction Process

In this approach, 3 categories of features like color, structure, and texture has been extracted. Among these 3 three attributes, Color features are used in filtering 14 colors of defected regions. Mean values of non-zero pixels of RGB units from infected portion of the image.

2.4.1. Extraction of color features

At the initial point, it filters the units of RGB that is comprised with the defected portions and details in different parameters. Once the feature extraction is completed, non-zero values are extracted and execute the mean2() function in MATLAB. Thus, the similar processes have been carried out for identifying the mean value of HSV and component of LAB image. Followed by, it employed std2() function in MATLAB on non-zero measures of RGB color components.

2.4.2. Shape feature extraction

The defected region of leaves can be estimated by transforming the image into binary of threshold 0.28 using MATLAB's inbuilt function as im2bw(). It results in the binary image from the range of (1,0). Then, binary image is computed with the help of bwarea() function. The number of infected areas is considered to be the main feature in blob prediction approach. Blobs are said to be the objects existed within the binary image. Binary image of a defected area is applied to find the blobs in an image. Therefore, counts of connected components are said to be count of defected portions of a mask image.

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2.4.3. Extraction of texture features

This metric is employed with GLCM for the extraction of texture attributes. GLCM contains maximum number of events related to gray level of an image. Actually, GLCM scans the image in four different directions and only some of them have been filtered. The MATLAB function and gray co-matrix() are used for developing the GLCM and its size is 8 × 8.

2.5. Deep Learning based Classification

Artificial Neural Network (ANN) principle is often labelled with the application of diverse levels of hidden unit as well as output are referred to as DL [24]. It is comprised with 2 stages as provided below:

- Pre-training level
- Fine-tuning level

2.5.1. Pre-training level

It is one of the deep structures and vital feed forward network, the Deep Belief Network (DBN) has been applied in input layer to output layer from where the hidden layers with supplement layers has been generated. According to the presence of DBN and hidden units that helps to distinguish the network and it generates the activation functions. Moreover, Restricted Boltzmann Machine (RBM) is also employed to overcome the challenging factors of possible activation function production.

Step 1: Upload the element of V for training the RBM vector.

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

The extension of Eq. (1) is provided as; w_{pq} is the symmetric correspondence with visible units v_p and hidden units h_q, α, β are said to be bias term, P, Q implies the counts of visible and hidden unit. The hidden units of RBM lack in immediate acknowledgement which results in the production of elegant impartial instance from $(V_p, h_q)_{data}$

$$\rho\left(h_q = 1 \middle| v\right) = \delta\left[\sum_{p=1}^{P} W_{pq}\, v_p + \alpha_1\right] \ldots. \quad (2)$$

Here $\delta(x)$refers the logistic sigmoid function, $\frac{1}{(1+\exp(x))}$, v_p, h_q, denotes unbiased instance. The hidden unit has been extended while the visible units are considered as synchronized from the given visible and hidden units. It results in a complicated routing as given below.

$$\Delta W_{pq}\theta(v_p h_q)_{data} - (v_p h_q)_{reconstrution} \quad (3)$$

Different RBM can be piled over the frame with the application of multi-layer model. Basically, a divergent RBM is available that has been stacked. Alternatively, hidden layer is organized into a vector, the quality of units is effectively developed using RBM layers, and shared using distributed methods in recent weight and bias. Therefore, the final layer undergoes training in a formal manner.

2.5.2. Fine Tuning Level

It is carried out on using back propagation (BP) model. The clinical images are segmented into 2 stages, output layer has been arranged from the top of DNN. In addition, N quantity of input neuron and 3 hidden layer were used in DL approach. The improved weight has to be accomplished at the training phase, and using the training data set, where the BP model is uploaded with the weights obtained from pre-training phase. As a result, the minimum error rate is measure 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

2.6. 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.

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Social dominant hierarchy

Here, α implies the dominant individual and eligible for making various decision. 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,

$$Fe = \{ f_1, f_2 ......f_n \} \tag{4}$$

Encircling prey

In hunting task, GW surrounds the prey. The nature of GWs is defined as shown Eq. (5).

$$G = | C.F_{prey}(t) - F_{wolf}(t) | \tag{5}$$

$$F(t+1) = F_p(t) - A.G \tag{6}$$

From the predefined functions, A and C are coefficient vectors

$$A = 2ar_1 - a \quad And \quad C = 2r_2 \tag{7}$$

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 is 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.

$$G^{\alpha} = | C_1.F_{\alpha} - F |, \; G^{\alpha} = | C_1.F_{\beta} - F |, \; G^{\alpha} = | C_1.F_{\omega} - F | \tag{8}$$

$$F_1 = F_{\alpha} - A_1.(G^{\alpha}), \; F_2 = F_{\beta} - A_2.(G^{\beta}), \; F_3 = F_{\omega} - A_3.(G^{\omega}) \tag{9}$$

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$$F(t+1) = \frac{F_1 + F_2 + F_3}{3} \tag{10}$$

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 $\alpha,\ \beta\ and\ \delta$ 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 is 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.

3. Experimental validation

3.1. Dataset description

The photographs of wheat plant leaves were taken from agricultural land due to the lack of dataset . Since the rice crop needs maximum amount of water, most of the farmers in India cultivate rice in rainy season. In this period, the plant highly gets affected by bacteria, fungi, or virus. Hence, the worst case is assumed for the gathered samples. It is collected with leaves of diverse degree of disease spreading is needed for the database. The images were taken through NIKON D90 digital SLR camera with the image dimension of 2848 × 4288 pixels. Additionally, some merits of images relevant to websites at the preliminary study. Sometimes the images are captured with a white backdrop, from straight sunlight. It has been arranged with 120 images, such as 40 images of all diseases. The types of all images are JPEG. Fig. 2illustrates few sample images of wheat plant diseases.

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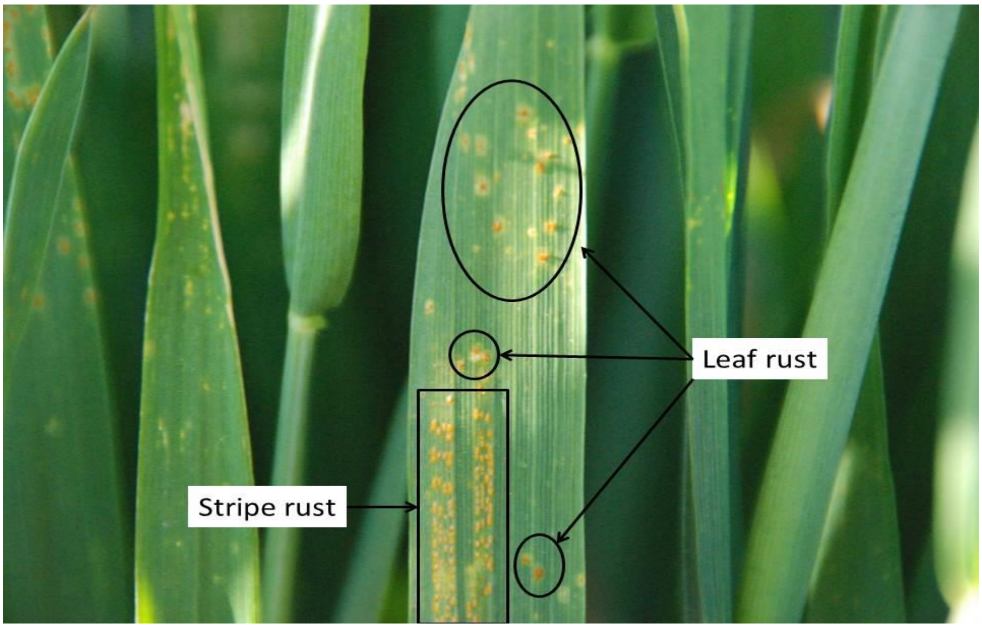

Figure.2 : Types of Rust in Wheat Plant

The Figure 2 shows the symptoms of leaf rusting and stripe rusting in the wheat plant under various weather conditions. The leaf rusting usually in orange color and stripe rust commonly identified in yellow color. The rust arrangement of leaf rust is isolated as represented as single, the stripe rust usually identified as stripe formats. The optimum temperature conditions for the leaf rust is 60-80°F and stripe rust 55-70°F.

			

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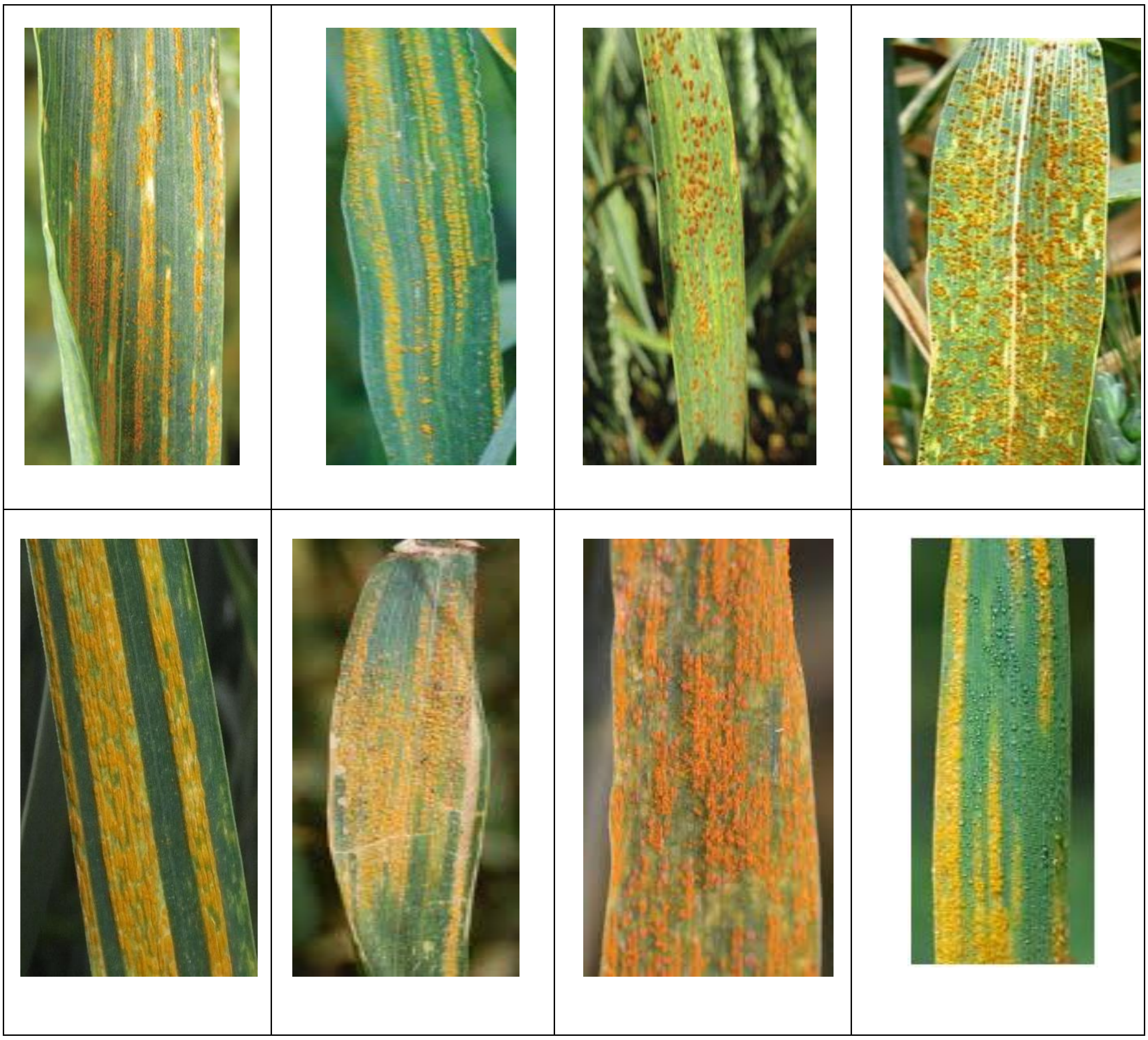

Fig. 3. Sample Images a) Bacterial leaf blight b) Brown spot c) Leaf smut

3.2. Results Analysis

Fig. 3 exhibits sample set of original input images and disease segmented images. The first column of images represents the original leaf images, gray scale converted image and the segmented image is shown in the second column.

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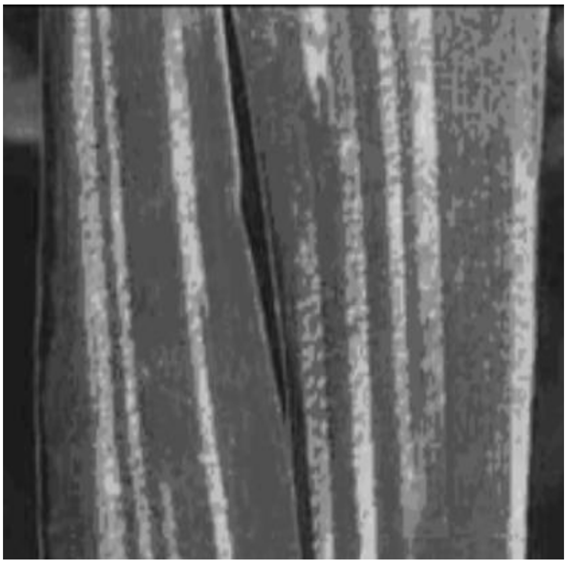
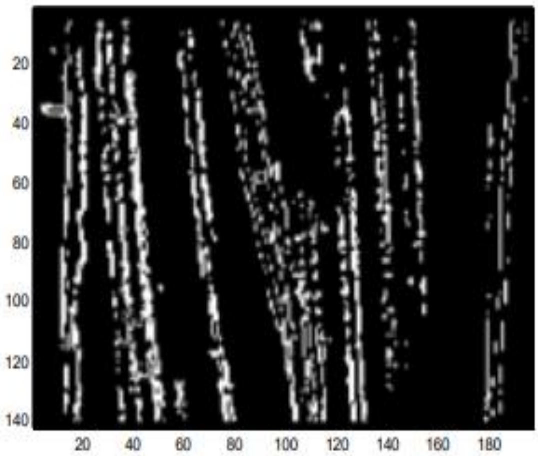
Wheat leaf with stripe rust disease



Gray Scale Converted Image



Segmented Image

Fig. 4. a) Input Image b) Disease Segmented Image

An elaborate results analysis of the DNN-GWO and other leaf disease detection and classification process takes place as provided in Table 1.k

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Table 1 Performance Analysis of Proposed Method DNN-GWO with State of Art Methods

Methods	Accuracy	Precision	Recall
DNN-GWO	97.89	96.98	97.53
Training Phase-SVM	94.23	93.98	93.43
Testing Phase-SVM	76.54	76.30	75.60
5-Fold-SVM	84.60	83.70	82.50
10-Fold-SVM	89.56	88.89	88.85

Fig. 5 displays the results of the DNN-GWO model with existing methods interms of accuracy. The figure portrayed that the testing phase-SVM model is found to the ineffective performer, which has attained the accuracy of 76.54%. Besides, the 5-fold SVM model has outperformed the testing-phase SVM model and offered a slightly higher accuracy of 84.60%. On continuing with, the 10-fold SVM model tried to show acceptable results and ended up with the moderate accuracy of 89.56%. Along with that, the training phase-SVM model has offered competitive results and attained a high accuracy of 94.23%. However, the presented DNN-GWO model has shown superior results to other models and reached to a maximum accuracy of 97.89%.

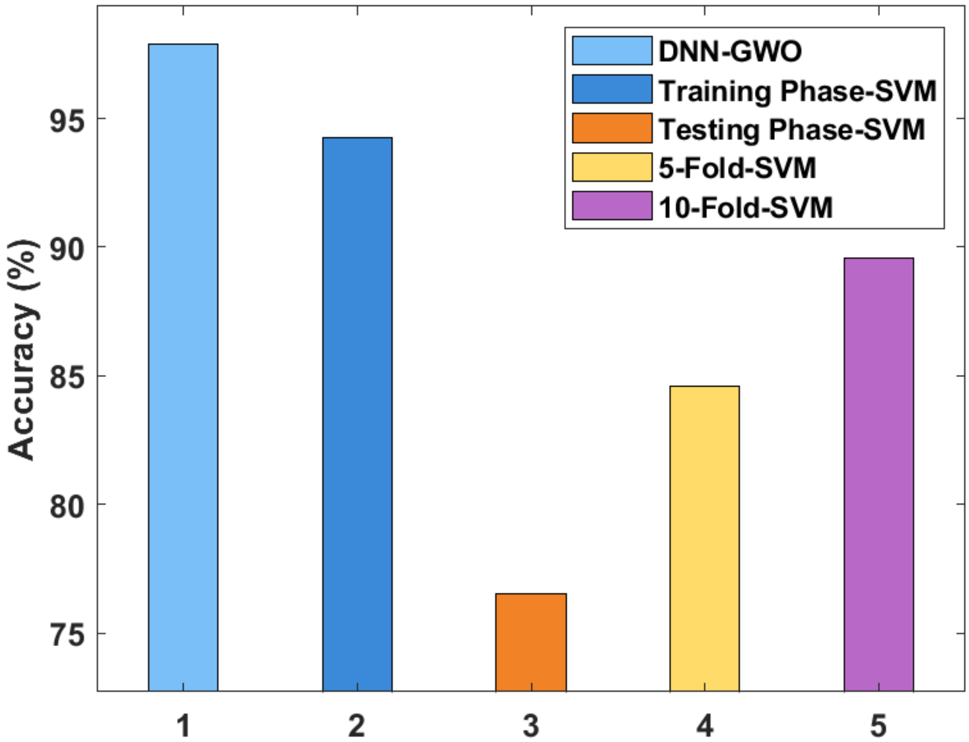

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Fig. 5. Accuracy analysis of proposed DNN-GWO model

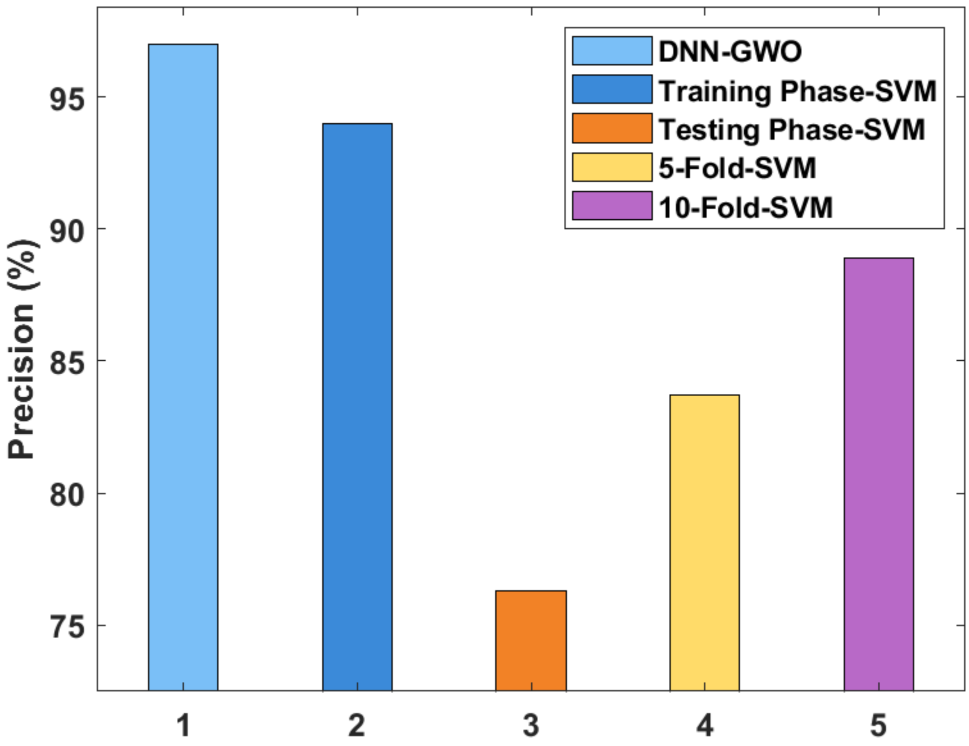

Fig.6. Precision analysis of proposed DNN-GWO model

Fig. 6 showcases the simulation outcome of DNN-GWO method with previous models with respect to precision. From the figure, it is clear that the testing phase-SVM model is an impractical performer that has reached the precision of 76.30%. On the other hand, the 5-fold SVM model performs quite-well than testing-phase SVM model and provided a slightly better precision value of 83.70%. Similarly, the 10-fold SVM model attempted to display considerable results and concluded with the precision of 88.89%. On the same way, the training phase-SVM model has achieved competing results and obtained with maximum precision of 93.98%. But, the proposed DNN-GWO approach has depicted qualified results than existing methods and attained best precision of 96.98%.

Fig. 7 showcases the results of the DNN-GWO model with conventional techniques by means of recall. The figure states that the testing phase-SVM model is a worst performer, that has reached the recall of 75.60%. Then, the 5-fold SVM model has attained as outstanding performance than testing-phase SVM model and achieved a gradual recall of 82.50%. In line with this, the 10-fold SVM model tires to demonstrate manageable results with better recall of 88.85%.

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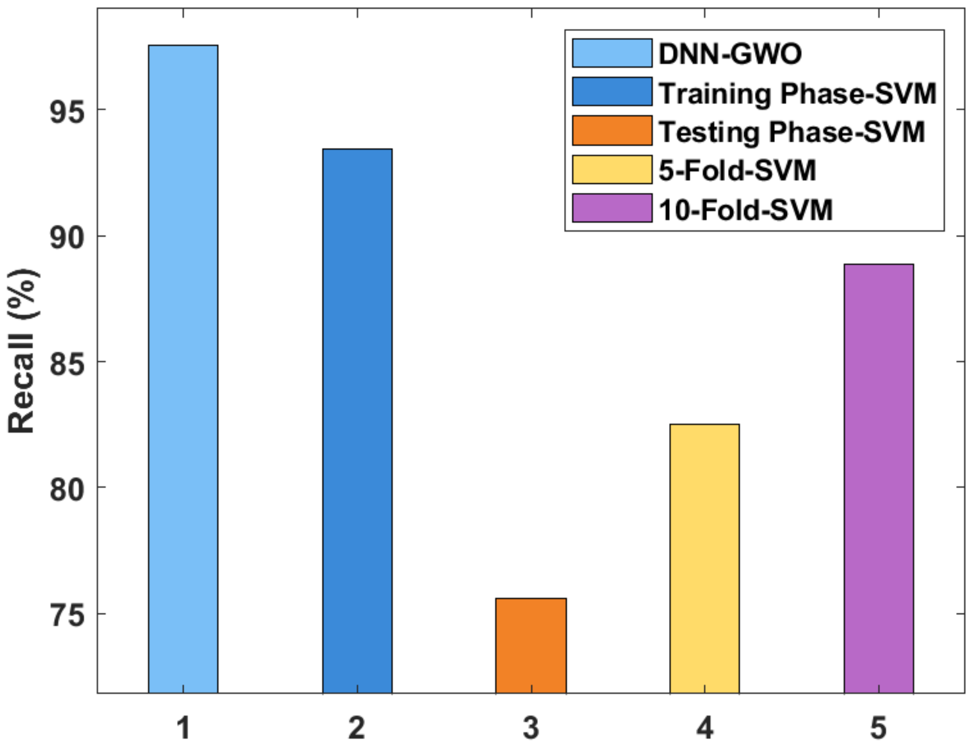

Fig.7. Recall analysis of proposed DNN-GWO model

On the same way, the training phase-SVM model has attained equivalent results with maximum recall of 93.43%. Hence, the projected DNN-GWO model has implied excellent results than compared techniques and accomplished good recall of 97.53%. Table 2 shows the Recognition rate and rank accuracy of the proposed DNN-GWO model comparing with normal human eye recognition.

Table.2 : Recognition and Accuracy of the proposed DNN-GWO Model

Measures	**Human Eye Recognition**	**Proposed DNN-GWO Model**
Recognition Rate (%)	98.6 [25]	99.96
Rank Accuracy (%)	95.6 [25]	95.92

4. Conclusion

This paper has developed an efficient IoT and cloud-based classification technique of wheat leaf diseases using DNN-OGWO model. The proposed model involves image collection, preprocessing, K-means clustering based segmenting, feature extracting and DCNN-OGWO based classifying processes. The ODNN model has been applied for proper image classification, which employs the GWO technique for the parameter optimization of DNN. The DNN-OGWO model has offered maximum plant leaf disease detection performance with the maximum precision of 95.92%, recall of 96.41% and accuracy of 96.96% respectively. In future, the DNN-OGWO model can be implemented in real time farming field to assist the farmers in the diagnosis of the plant diseases.

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