Feature Selection Using Quantum Inspired Island Model Genetic Algorithm for Wheat Rust Disease Detection and Severity Estimation

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Abstract: In the context of smart agriculture, an early disease detection system is crucial to increase agricultural yield. A disease detection system based on machine learning can be an excellent tool in this regard. Wheat is one of the world's most important crops. Leaf rust is one of the most significant wheat diseases. In this work, we have proposed a method to detect the leaf rust disease-affected areas in wheat leaves to estimate the severity of the disease. The method works on a reduced Color-GLCM (C-GLCM) feature set. The proposed feature selection method employs Quantum Inspired Island Model Genetic Algorithm to select the most compelling features from the C-GLCM set. The proposed feature selection method outperforms the classical feature selection methods. The healthy and diseased leaves are classified using four classifiers: Decision Tree, KNN, Support Vector Machine, and MLP. The MLP classifier achieved the highest accuracy of 99.20% with the proposed feature selection method. Following the detection of the diseased leaf, the k-means algorithm has been utilized to localize the lesion area. Finally, disease severity scores have been calculated and reported for various sample leaves.

1 INTRODUCTION

Smart agriculture is getting more attention from researchers in many areas because it has an enormous research scope. It aims to apply technology to increase the productivity and efficiency of farming (Zinke-Wehlmann and Charvát, 2021). In the current century, global food production is highly affected by climate change caused by changing temperature and precipitation, sea level rise, and increasing frequency of other extreme climate events worldwide. The climate-smart agriculture is a multifaceted approach to achieve food security while combating climate change (Lipper et al., 2018). Annually, it is cultivated on 217 million hectares, making it the most widely grown crop in the globe (Erenstein et al., 2022). Wheat is the second most consumed food cereal globally, after rice (Erenstein et al., 2022) and also in India (Mottaleb et al., 2023). According to the study, climate change will substantially impact wheat production in India (Kumar et al., 2014). Wheat disease is one of the primary causes of decreased production. Fungal-induced disease result in annual yield losses ranging from 15% to 20%. Leaf rust is a prominent fungal disease affecting wheat, resulting in significant yield losses (Figueroa et al., 2017). The widespread wheat leaf rust disease, caused by the fungus Puccinia triticina, is an example of a disease impacted by climate change (Caubel et al., 2017). Early detection and continuous field monitoring can prevent the spread of disease throughout a field. Thus, computer vision and machine learning can play a crucial role in automatically detecting disease, enabling the field to initiate treatment sooner. In this study, the controlled wheat leaf image and leaf rust affected leaf are classified using a reduced feature set selected by the proposed quantum inspired island model genetic algorithm. In addition to using k-means clustering to identify the lesion area, a severity score is also calculated. Various analysis has been performed to study the robustness of the proposed system.

The overall contributions of this work have been outlined in the following.

- A color GLCM-based automated Wheat leaf rust recognition system has been proposed.
- The proposed quantum inspired island model genetic algorithm is used to determine the optimal

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color GLCM features.

- The proposed model is also compared with the classical, quantum-inspired, and classical island model genetic algorithms.
- The performance of the reduced feature set has been tested with four classifiers.
- The result has been analyzed according to different evaluation parameters.
- In addition, a severity score for leaf rust disease has been calculated.

This paper is organized as follows: section 1 provides an initial idea and need for smart agriculture and the scope of computer vision for disease detection. A brief discussion of recent works in computer vision-based wheat disease detection has been done in section 2. The prerequisite concept of quantum computing, island model genetic algorithm, and color GLCM features have been briefly discussed in section 3, and experimental setup has been mentioned in section 4. The proposed method has been presented in detail in section 5. The result of the proposed method has been shown and discussed in section 6. Finally, the paper has ended with a conclusive discussion in section 7.

2 LITERATURE SURVEY

Many researchers in recent years have developed computer vision-based methods for identifying and categorizing wheat diseases. A method proposed for leaf rust detection and grading in an embedded framework based on the green channel of the captured color image has been implemented (Xu et al., 2017). Spots are identified by applying edge detection, background elimination, and flood-filling algorithm consecutively. The system's disease reorganization and ranking accuracy are 96.2% and 92.3%, respectively. An investigation on the leaf rust disease at the canopy scale and under high, medium, and low Leaf Area Index levels has been done (Azadbakht et al., 2019). Based on the reflectance data of a specific spectrum range from a radiometer, they estimated disease severity levels at the canopy scale using Gaussian process regression (GPR), random forests regression, v-support vector regression, and random forests regression. The v-SVR achieved the R^2 measures, all being around 0.99 at all three LAI levels, which is the highest compared to other algorithms. The work on Powdery mildew(PM) disease detection of wheat from hyper spectral images has been done (Zhao et al., 2020). They applied and compared three dimensional reduction algorithms and identify PM-sensitive bands. The support vector machine, RF, and a probabilistic neural network built three machine learning models. The PCA-dimensionality-reduced SVM model got the best classification accuracy at 93.33%. The diagnosis of wheat stem rot disease has been recognized by a deep convolutional neural network (Kukreja and Kumar, 2021). They have utilized the CGIAR dataset and secondary data sources to obtain images of stem rust. They obtained a high classification accuracy of 97.16%. A machine learning based approach for classifying brown and yellow rusted diseases in wheat has been developed (Khan et al., 2022). They have collected the image data from Pakistani fields considering the capturing device's illumination and direction. Then, segmentation and resizing methods distinguish healthy and afflicted areas to preprocess the data accurately. Training different classifiers is based on various features, including Haralick texture, color histogram, and hue moments. Thus, the suggested fine-tuned framework outperforms the other methods with 99.8% accuracy. The pre-trained deep learning models have been deployed by to classify Wheat yellow rust disease grade (Shafi et al., 2023). The researchers employed the U2 Net model to extract leaf area, whereas for classification purposes, they utilized the Xception model and ResNet-50. The ResNet-50 model ultimately attained the highest level of accuracy, measuring at 96.00%, in the context of severity grading. A brief comparison of the proposed method with some existing works has been shown in Table 1.

3 MATERIALS & METHODS

A brief introduction of *Quantum Computing* and the *Island Model Genetic Algorithm (IMGA)* has been discussed in this section.

3.1 Quantum Computing

The laws of quantum physics are the foundation for quantum computing. Qubits, which are superpositions of 0 and 1, are the smallest information units used in quantum information processing (Deutsch, 1985). Because the qubit cannot be directly represented in a conventional computer, researchers are interested in utilizing the various aspects of quantum computing that are implementable in a classical computer. In the given setting, the concept of Quantum Inspired Evolutionary Algorithm (QIEA) combines the principles of evolutionary computing and quantum computing (Han and Kim, 2002).

Table 1: Recent works on wheat leaf disease recognition.

SL No	Objective	Disease Name	Performance
1	Disease reorganization (Xu et al., 2017)	Leaf rust	96.20%
2	Disease severity (Azadbakht et al., 2019)	Leaf rust	99.00%
3	Disease detection (Zhao et al., 2020)	Powdery mildew	93.33%
4	Disease detection (Kukreja and Kumar, 2021)	Stem rust	97.16%
5	Disease detection (Khan et al., 2022)	Leaf rust	99.80%
6	Disease severity (Shafi et al., 2023)	Leaf yellow rust	96.00%
7	Disease detection & severity, Proposed	Leaf rust	99.20%

Qubit. Here, a qubit can be defined as a linear superposition of two fundamental states, commonly realized through systems such as electron spins, specifically the ground state (0) and the excited state (1) in QIEA. The qubit is represented as a two-state column vector in the 2-D Hilbert space as shown by Equation 1 and Equation 2. α_0 and α_1 are two probabilistic amplitudes of the state $|0\rangle$ and $|1\rangle$ in the equation 1 Equation 2 demonstrates the necessary and sufficient condition for all qubits to be in the linear superposition. Consistent with Equation 2 and Equation 3, the probabilistic amplitudes are specified as $\frac{1}{\sqrt{2}}$.

$$|\psi\rangle = \alpha_0 |0\rangle + \alpha_1 |1\rangle \tag{1}$$

$$|\alpha_0|^2 + |\alpha_1|^2 = 1 \tag{2}$$

$$|\psi\rangle = \frac{1}{\sqrt{2}}|0\rangle + \frac{1}{\sqrt{2}}|1\rangle \tag{3}$$

Quantum Gate. In quantum computing, the quantum gates operate on qubits, and various quantum gates are available, including the Hadamard gate and the Rotation gate. Both gates have been utilized in the proposed quantum inspired island model genetic algorithm. The Hadamard gate(H) is represented by Equation 4. It defines the superposition of qubit states.

$$H = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \tag{4}$$

This H gate is utilized to prepare quantum chromosomes. The quantum rotation gate rotates a qubit following the optimal quantum solution in quantum inspired metaheuristic algorithms. This gate is essential for the algorithm to converge. The update process of a single qubit is shown in Equation 5. The qubit is updated by rotation gate by the Equation 5, where the left-hand side indicates the updated qubit. The updated qubit is generated on the right-hand side by multiplying the rotation gate $U(\Delta\theta i)$ the original qubit. The rotation gate $U(\Delta\theta i)$ is expressed in a matrix form as shown in Equation 6, and $\Delta\theta i$ is the rotation angle.

$$\begin{bmatrix} \alpha'_{0i} \\ \alpha'_{1i} \end{bmatrix} = \mathrm{U}(\Delta\theta_i) * \begin{bmatrix} \alpha_{0i} \\ \alpha_{1i} \end{bmatrix} \tag{5}$$

$$U(\Delta\theta i) = \begin{bmatrix} \cos(\Delta\theta_i) & -\sin(\Delta\theta_i) \\ \sin(\Delta\theta_i) & \cos(\Delta\theta_i) \end{bmatrix} \tag{6}$$

3.2 Island Model Genetic Algorithm

The Island Model Genetic Algorithm(IMGA) is a distributed model of the genetic algorithm introduced by David E. Goldberg (Goldberg, 1989). It includes multiple sub populations or islands. Each island functions as a distinct GA that evolves independently, and individuals occasionally migrate between islands to exchange genetic information. This migration enhances the algorithm's convergence speed and solution quality performance by facilitating information exchange and diversity preservation. The IMGA has several powerful features, including parallelism and exploration, information exchange, island diversity and sub populations, migration strategies,Topology and Connectivity. Based on the characteristics mentioned above, researchers have presented various models for various problems. The University Course Timetabling Problem was solved by introducing a localized island model genetic algorithm with a dual dynamic migration policy (Gozali et al., 2019). The job-shop scheduling problem has been efficiently solved and tested with 52 benchmark instances using a modified version of the island model genetic algorithm (Kurdi, 2016). The IMGA model has been utilized for feature selection in non-traditional credit risk analysis (Liu et al., 2019) .

3.3 Color-GLCM: Texture Features

Gray-level co-occurrence matrix (GLCM) features have been extensively utilized for pattern recognition by researchers. A color-based texture analysis based on the color co-occurrence matrix (CCM) was utilized in this study to identify leaf rust disease. The CCM is computed using four distance values, $d = 1$, 2, 4, and 8 and thirteen (13) directions considering the 3D color channels (Ortiz et al., 2013). The ten (10) features used by us are known as Haralick features (Haralick et al., 1973) extended in 3D GLCM (color-GLCM) as reported in (Ortiz et al., 2013). The ten features under consideration are *energy*, *entropy*, *correlation*, *contrast*, *homogeneity*, *Variance*, *sum average*, *dissimilarity*, *cluster shade*, and *cluster tendency*.

4 EXPERIMENTAL SETUP

The details of experiment related information and dataset are given here.

Dataset. In this experiment, healthy and disease-affected wheat images have been considered (Mendeley, 2020). In total, 250 healthy and 250 leaf rust diseased leaves have been considered for this experiment.

Parallel Environment. The experiment was conducted using a hexacore $i7$ laptop and Matlab 2016a. The proposed quantum inspired island model genetic algorithm has been implemented using 'par for' in Matlab.

5 PROPOSED METHOD

This section will discuss the proposed system for wheat leaf rust detection and severity measurement technique in detail. Figure 1 shows all the steps involved in the system. Initially, wheat leaf images including 250 healthy and 250 disease-affected images, have been considered for feature extraction. The first step is preprocessing the input healthy and disease-affected wheat leaf images. Preprocessing includes scaling the original leaf images to reduce the computation time for later stages. It also includes registration of a few samples image which are not correctly aligned and removing an extra black background. After preprocessing is over, the next step is to extract color GLCM features from both types of leaf images. Total 520 $(10 \times 4 \times 13)$ are extracted from control and disease-affected images. Once the features are extracted, the zero feature values are eliminated from the vector; and finally, the feature vector of size 340 is prepared. Once the color features are ready, the proposed quantum inspired island model genetic algorithm for feature selection is applied. The detail of the proposed feature selection method will be discussed in section 5.1. In the next step, the different classifier models are trained and tested with the selected features. So, the outcome of the classification step is to identify either the healthy wheat leaf or disease affected leaf. If the leaf is detected as healthy, then there is no need for further processing, whereas if the leaf is detected as diseased affected, another three steps are involved. In subsequent phases, the k-means clustering is applied with the value of $k = 3$ to localize the disease-affected area of the diseased leaf. The reason to keep the value of $k = 3$ is to make three clusters which include black background, unaffected leaf area, and affected leaf area. Then lesion area of the leaf is extracted, and finally, the disease severity score is calculated according to Equation 7. Severity score ζ is the percentage of the ratio of the number of pixels affected by the disease $(Lesion_{area})$ to the total number of pixels $(Leaf_{area})$ in the leaf area.

$$\zeta = \frac{Lesion_{area}}{Leaf_{area}} \times 100 \tag{7}$$

5.1 Proposed Quantum Inspired Island Model Genetic Algorithm for Feature Selection

This section briefly explains the proposed quantum inspired island model genetic algorithm (QIIMGA) feature selection strategy. The architecture of the proposed model has been shown in Figure 2. In this proposed method, the initial feature vector of length L is subdivided into four equal lengths of L_k where $(L/4 = L_k)$. The original feature dataset DS is subdivided into length of L_k and represented DS_1, DS_2, DS_3, and DS_4, Similarly, feature set is subdivided into FS_1, FS_2, FS_3, and FS_4. Four group of dataset and feature set are represented by DS_p and FS_p where $p \in 1,2,3,4$. DS_p and FS_p are given as input on each island where the quantum inspired genetic algorithm (QIGA) is applied. These four islands are executed in parallel on four individual cores of the system as mentioned at Line 1. Here, each QIGA optimizes the feature set as per the objective function value. These four islands have been explored in parallel in multi-core architecture. Once each QIGA reaches the $maximum\_iteration$ with value 20, it returns the optimized feature set vector $(\hat{FS_p})$ along with feature dataset $(\hat{DS_p})$. After getting the output from each island, the selected dataset is combined to obtain DS_m as shown at Line 7. Similarly, each island's selected feature set vectors are combined to obtain the integrated feature set FS_m at Line 8. Now, DS_m and FS_m, are further sent back to the $main\_QIGA$ module. The final optimized feature set (FS_F) is produced by the $main\_QIGA$ along with final optimized feature dataset (DS_F) at Line 10. The length of FS_F is reduced to a great extent compared to the size L of the original feature set FS. The basic structure of the QIGA algorithm is given in Algorithm 2. Both $main\_QIGA()$ and $sub\_QIGA()$ have the same steps and structure as

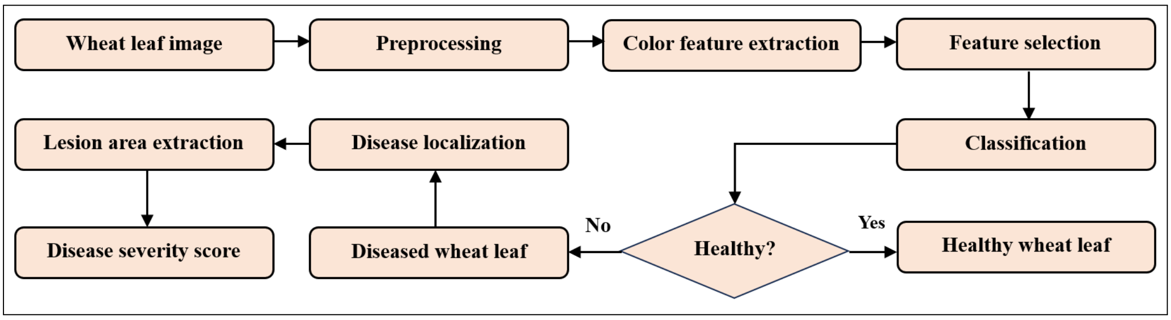


Figure 1: Proposed system for wheat disease detection and severity measurement.

given in Algorithm 2. Here, The quantum population is initialized by Hadamard gate with quantum chromosome length d at Line 2 and quantum population size $n = 20$. The value of d depends on the feature set length. Then, measurement operator is applied on each quantum chromosome to get bit from qubit which produces the binary chromosome, and evaluation is done according to the objective function at Line 9 and Line 4. Here, the objective function is has been built based on classification accuracy and number of selected features. The chromosome that obtains superior classification accuracy while utilizing fewer features will be favored as a good chromosome. From the population, the best quantum chromosome is obtained after the ranking. The selection, crossover, mutation, and update operations are applied sequentially within the for loop at Line 6- 17. With in the **for** loop, after execution of genetic operators, evaluation is done at Line 10 and based on the fitness value the previous global fitness and quantum solution are updated at Line 12 and Line 14 when the **if** condition is satisfied. Then the complete quantum population is updated according to the best quantum chromosome so far using rotation gate as described in 3.1. Finally, the optimized sub feature dataset $\hat{\hat{DS}}$ with feature set $\hat{\hat{FS}}$ are returned to the *QIIMGA* at Line 19.

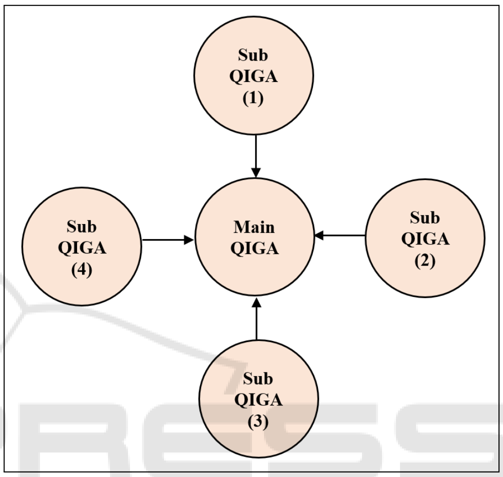
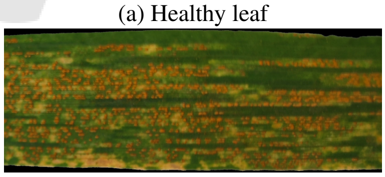


Figure 2: Proposed architecture for quantum inspired island model genetic algorithm for feature selection.

(a) Healthy leaf

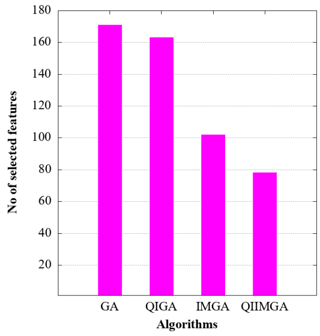


(b) Leaf rust affected leaf

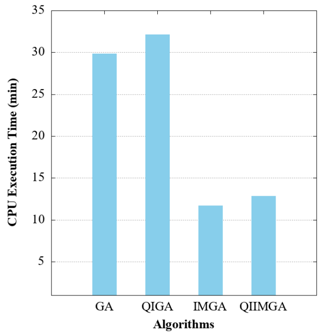
Figure 3: Wheat sample leaf images.

6 RESULT & ANALYSIS

This section provides an analysis of the results of the experiment. The sample images of wheat leaves without and with leaf rust have been shown respectively in Figure 3 (a) and (b). Leaf rust causes noticeable color changes, as shown in Figure 3(b). Table 2 displays the results of a comprehensive parametric study of the four classifiers using each feature selection approach. Here, four classifiers which include decision tree (DT), k-nearest neighbor (KNN), support vector machine (SVM), and multi-layer perceptron (MLP) are used. Also, five feature reduction methods, including principal component analysis (PCA), genetic algorithm (GA), quantum inspired genetic algorithm (QIGA), island model genetic algorithm (IMGA), and quantum inspired island model genetic algorithm (QIIMGA), have been applied in this study. It is observed that all the classifiers have more than 90% accuracy of all kinds of feature selection strategies. More specifically, the SVM and MLP have more than 95% in all



(a) No of selected features.



(b) CPU execution time.

Figure 4: Performance of QIIMGA feature selection.

Algorithm 1: QIIMGA for feature selection.

Input: $DS \longleftarrow$ Sub feature data set
$L \longleftarrow$ Length of feature vector
$L_k \longleftarrow$ Length of sub feature vector
Output: DS_F, FS_F

`// p loop will be executed parallelly`
do in parallel
  for $p \leftarrow 1$ **to** 4 **do**
    $[\hat{DS}_p, \hat{FS}_p] \longleftarrow Sub\_QIGA(DS_p, FS_p)$
  end for
end
$DS_m \longleftarrow \hat{DS}_1 \cup \hat{DS}_2 \cup \hat{DS}_3 \cup \hat{DS}_4$
$FS_m \longleftarrow \hat{FS}_1 \cup \hat{FS}_2 \cup \hat{FS}_3 \cup \hat{FS}_4$
$[DS_F, FS_F] \longleftarrow Main\_QIGA(DS_m, FS_m)$
return $[DS_F, FS_F]$

cases. The number of selected features by different methods have been shown in Figure 4 (a). It is observed that selected features by GA, QIGA, IMGA, and QIIMGA are 171, 163, 102, and 78, respectively. In the case of PCA, the 80 component values have been considered, which is near the number of features optimized by the proposed QIIMGA. Figure 5 (a) shows that the out of four classifiers, MLP has obtained maximum accuracy of 99.20%. The performance of the MLP with different feature selection (FS) strategies has been demonstrated in Figure 5 (b). A comparative study on the average execution time of each feature selection method has been shown in Figure 4 (b). In both cases, quantum inspired GA and IMGA versions take slightly more time than their classical versions. After successfully detecting the diseased leaf, the k-means has applied with a value of $k = 3$ to localize the lesion area on the leaf. Original diseased leaf sample images have been shown in Figure 6 (a), (b), (c), and (d). Results of k-means clustering have been presented in Figure 6 (e), (f), (g), and (h). The lesion area of each sample has been shown in Figure 6 (i), (j), (k), and (l). Finally, the severity score is calculated for each sample, and obtained the

Algorithm 2: QIGA.

Input: $\hat{DS} \longleftarrow$ sub feature dataset.
$\hat{FS} \longleftarrow$ sub feature vector.
Output: $\hat{\hat{DS}} \longleftarrow$ optimized sub feature dataset.
$\hat{\hat{FS}} \longleftarrow$ optimized sub feature vector.

begin
  $[qpop] \longleftarrow initialize(d)$
  $[mepop] \longleftarrow measurement(qpop)$
  $[g_{fit}, gbest_{qs}, gbest_s] \longleftarrow evaluation(mepop)$
  for $i \leftarrow 1$ **to** $Maximum\_Iteration$ **do**
    $[spop] \longleftarrow selection(qpop)$
    $[cpop] \longleftarrow crossover(spop)$
    $[mpop] \longleftarrow mutation(cpop)$
    $[mepop] \longleftarrow measurement(mpop)$
    $[l_{fit}, lbest_{qs}, lbest_s] \longleftarrow evaluation(mepop)$
    if $l_{fit} > g_{fit}$ **then**
      $g_{fit} = l_{fit}$
      $gbest_{qs} = lbest_{qs}$
      $gbest_s = lbest_s$
    end if
    $[qpop] \longleftarrow update(mpop)$
  end for
end
return $[\hat{\hat{DS}}, \hat{\hat{FS}}]$

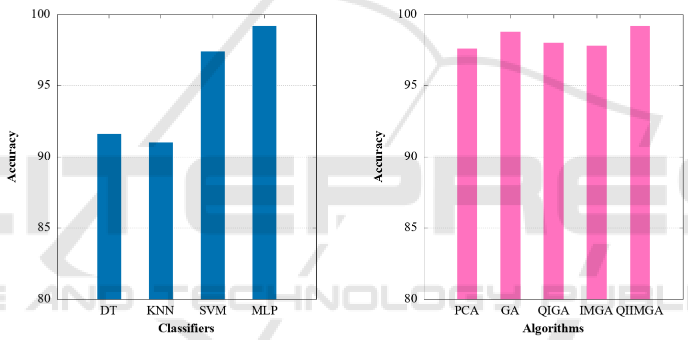
severity scores ζ are 8.57%, 14.23% 12.63%, and 40.20% respectively.

7 CONCLUSION

This work proposed a wheat leaf rust disease recognition method based on an optimized color feature set. The proposed quantum-inspired island genetic model reduces the number of color features. The result shows that the proposed QIIMGA feature selection approach outperforms others concerning the number of features. The performance of the proposed method is comparable with other state of the art works. Fi-

Table 2: Performance of different classifiers based on the selected features by various feature selection strategy.

Method	Classifier	Accuracy	Error	Sensitivity	Specificity	Precision	FPR	F1-Score
PCA	DT	0.904	0.096	0.904	0.904	0.904	0.096	0.9040
	KNN	0.932	0.068	0.932	0.932	0.9320	0.068	0.9320
	SVM	0.962	0.038	0.964	0.960	0.9602	0.040	0.9621
	MLP	0.976	0.024	0.988	0.964	0.9648	0.036	0.9763
GA	DT	0.926	0.074	0.936	0.916	0.9176	0.084	0.9267
	KNN	0.926	0.074	0.972	0.880	0.8901	0.120	0.9293
	SVM	0.982	0.018	0.996	0.968	0.9689	0.032	0.9822
	MLP	0.988	0.012	0.996	0.980	0.9803	0.020	0.9881
QIGA	DT	0.936	0.064	0.940	0.932	0.9325	0.068	0.9363
	KNN	0.926	0.074	0.968	0.884	0.893	0.116	0.9290
	SVM	0.972	0.028	0.980	0.964	0.9646	0.036	0.9722
	MLP	0.980	0.020	0.988	0.972	0.9724	0.028	0.9802
IMGA	DT	0.912	0.088	0.932	0.892	0.8962	0.108	0.9137
	KNN	0.928	0.072	0.972	0.884	0.8934	0.116	0.9310
	SVM	0.960	0.040	0.992	0.928	0.9323	0.072	0.9612
	MLP	0.978	0.022	0.980	0.976	0.9761	0.024	0.9780
QIIMGA	DT	0.916	0.084	0.912	0.920	0.9194	0.080	0.9157
	KNN	0.910	0.090	0.960	0.860	0.8727	0.140	0.9143
	SVM	0.974	0.026	0.984	0.964	0.9647	0.036	0.9743
	MLP	0.992	0.008	0.996	0.988	0.9881	0.012	0.9920



(a) Different classifier. (b) Different FS strategy.

Figure 5: classification performance of the proposed system.

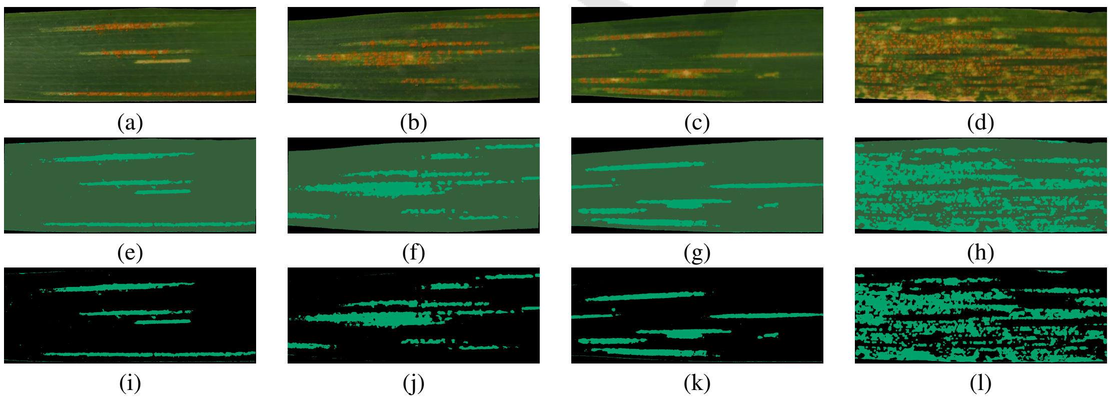


Figure 6: (a), (b), (c), and (d) Original sample images, (e), (f), (g), and (h) segmented images, and (i), (j,), (k), and (l) disease affected area.

nally, the work measures the severity of the disease using a k-means clustering algorithm. Further investigation may be carried out with this system for other leaf diseases that cause color variations in the lesion area.

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