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Independent Gaussian Gray Level Geometric Neural Network Classifier For Plant Leaf Disease Prediction

Mohammed Zabeeulla A N[1] , Dr. Chandrasekar Shastry[2]

[1]Research Scholar, JAIN (Deemed-to-be University), Bangalore, Karnataka, India.

[2]Dean, PG Studies, FET, JAIN (Deemed-to-be University), Bangalore, Karnataka, India.

Abstract

Swift and precise plant leaf disease prediction is dangerous to surging agricultural fertility within a feasible manner. Conventionally, human experts have been reckoned upon to identify variation in plants leaf because of diseases, pests, or paramount climate. But, the excessive, laborious during certain scenario found as unrealistic. To address such issues, application of image processing methods to detect plant leaf disease is a more familiar topic. Therefore, Independent Gaussian Gray Level Geometric Neural Network Classifier (IGGL-GNNC) for plant leaf disease prediction is proposed. This IGGL-GNNC method is split into three sections. They are image enhancement and pre-processing using Independent Component Gaussian Median Preprocessing model. Second, feature extraction using pre-processed plant leaf images by means of Gamma Corrected Gray Level Run Length Feature Extraction model. Finally, Sine Cosine Position Update Predictor Neural Network classifier is applied for extracting images to enhance the classifier performance using geometric functions. Four metrics are computed to evaluate the proposed IGGL-GNNC method namely, sensitivity, specificity, prediction accuracy and PSNR for different plant leaf images acquired from Plant Village Image dataset. Results indicate that proposed method can effectively detect plant leaf disease in plant leaf images.

Keywords: Independent Component, Gaussian Median, Gamma Corrected, Gray Level Run Length, Sine Cosine, Position Update, Predictor Neural Network

1. Introduction

Abundance of erstwhile efforts has examined image identification with specific classifier is utilized that classifies given input images as normal or abnormal. Specifically, plant leaves are the foremost origin of plant disease recognition, and the features of the diseases kick off for materializing the leaves. Yet the artificially-outlined features necessitate exorbitant tasks and expert knowledge, which have an undeniable distinction. On the whole, it is not tranquil in determining that features that are found to be optimal and vigorous four identification of disease from several features being extracted. In composite background circumstances, many techniques give out for significantly partition the leaf and respective lesion image from its background, therefore corresponding in erratic disease recognition results. Hence, automatic plant disease image recognition is still considered to be a demanding issue owing to difficulty of diseased leaf images.

An automatic tassel detection method was proposed in [1]. To start with, a color attenuation prior model was utilized for obtaining scene depth of saturation map to eliminate saturation present in the image. Followed by which next, the area of interest was extracted in Itti visual attention detection algorithm. Lastly, classification was carried out through using texture features and vegetation indices for removing the false positive rate. With this precision, recall and f-measure were found to be improved.

A method called, Inception – Visual Geometry Group Network (INC-VGGN) was proposed in [2] to recognition of plant leaf diseases. INC-VGGN method was split into two sections. The first section involved a pre-trained module that utilized basic feature extractor and the second section involved supplementary structure which employed multi-scale feature maps to plant leaf disease recognition.

Enhanced VGGNet with Inception module was chosen through changing final convolutional layers through extended convolutional layer. Subsequently batch normalization was performed and Swish activation function was employed to obtain multi-scale features of images. Finally, a fully-connected Softmax layer was employed to detect the class of plant disease images.

1.1 Problem Definition

Recent developments in crop management system have led to the growth of plant leaf disease prediction through new deep learning based method. With the aid of deep learning based techniques, a prediction algorithm is trained utilizing certain features in plant leaf image, that can differentiate between plant leaf images provided as input and therefore contributing to precision accuracy. These features or plant leaf images obtained from the Plant Village dataset are extracted and analysis is made for plant leaf disease prediction. The existing attention detection based methods [1] though extract features with higher reliability based on the area of interest, but, the sensitivity factor and the specificity with which the area of interest were extracted was not focused. Also, with deep learning mechanisms employing convolutional layers via batch normalization was achieved [2] with higher detection, however, the time and the noise involved were not analyzed. Therefore, there is need of designing an efficient plant leaf disease prediction algorithm with increased performance by removing the noise present in the images and improve classification performance, prediction accuracy by extracting and segmenting the region of interest in a more accurate and efficient manner.

To solve said problem, this paper presents an Independent Gaussian Gray Level Geometric Neural Network Classifier (IGGL-GNNC) that pre-processes the plant leaf images by removing impulse noise and enhances the sensitivity and specificity rate or the detection of plant leaf disease in an accurate manner. IGGL-GNNC method that can enhance prediction accuracy through segmenting region of interest based on geometric properties. Lastly, classifier performance improvement is examined through using deep neural network for contaminated leaf region detection.

1.2 Contributions

The contributions of this work are listed below.

- Independent Gaussian Gray Level Geometric Neural Network Classifier (IGGL-GNNC) method employed to increase performance accuracy on plant leaf images and improve prediction accuracy with enhanced classifier performance.

- This method can intuitively visualize the process of obtaining highly sensitive and computationally efficient pre-processed leaf images from Independent Component Gaussian Median analysis based on adjacent measurement of pixels, which increases the sensitivity and specificity of the method.
- Gamma Corrected Gray Level Run Length Matrix algorithm has strong robustness and accurate precision and can be used by agriculturist and horticulturists in identifying and analyzing the fertility of soil.
- Finally, the Sine Cosine Position Update Predictor Neural Network classifier model by partitioning the area of interest predicts leaf area in an accurate manner.
- To calculate the performance of IGGL-GNNC method with existing technique, we tested it in the Plant Village dataset based on different metrics like, sensitivity, specificity, prediction accuracy and processing time.

The paper is organized as follows. Literature survey is reported in Section 2. Section 3 describes proposed method Gaussian Gray Level Geometric Neural Network Classifier (IGGL-GNNC). In section 4 experimental settings and result discussion with the aid of table and graphical representation. The paper is summarized in section 5.

2. Literature survey

Issue related to significant plant disease prevention is strictly associated with complications of feasible agriculture and weather change. Suitable and expedient disease prediction together with untimely protection has not been paramount.

A novel method to the improvement of plant disease identification was designed in [3] on the basis of leaf image categorization via deep convolutional networks, therefore increasing precision. For huge numbers of applications, the method failed to be manageable owing to limitations involving computational factors, features of grouping and the results of local Traveling Salesman Problems were included in [4], therefore ensuring large-scale applicability.

One of the paramount factors that have negative influence on food safety is the pesticide residue. With the objective of attaining efficient prediction of pesticide remains present in apples, an algorithm utilizing machine-vision-based segmentation and hyperspectral techniques has been proposed in [5] for partitioning foreground and background apple areas of image, therefore improving the detection accuracy with minimum average time. Yet another machine learning method for grading tomato on the basis of mean g-r region of interests was presented in [6], therefore achieving the highest accuracy.

Plant disease can straightly result in dwarf development resulting in bad consequences on returns. Different conditions are the most laborious and demanding issue because of the geographic dissimilarities which leads to obstacle plant disease detection. Particle swarm optimization was applied in [7] for detecting leaf disease present in the sunflower. Convolutional Neural Networks were proposed in [8] for effective soybean disease identification. In [9] Chan Vese algorithm was applied based on the localized leaves using region proposal network resulting in accuracy concentration.

One of the important forage grasses consisting of different types of nutrients are Alfalfa. Disease occurrence in alfalfa plants has a significant impact in alfalfa yield and quality, influencing the healthy development of alfalfa. Some of the diseases occurring on these types of leaves are said to have indistinguishable symptoms, causing in problems in attaining accurate diagnosis disease identification at early stage. Pattern recognition algorithms were applied in [10] to concentrate on recognition accuracy to a greater extent. Besides, classification method through optimization technique employing Salp Swarm Algorithm designed in [11] to focus on the dimensionality related issue. However, in the complex environment, the role played by optimization technique was found to be less. To address this issue, machine learning system used for enhancing diseased plant prediction accuracy was designed in [12].

In [13] Review of neural networks for plant disease prediction with hyperspectral data was presented. Numerous works have been performed in area of factor causing plant disease identification. In [14], recent trends and demand to detect plant disease through computer vision and advance imaging techniques were proposed. The article in [15] has reviewed certain neural network methods that are utilized in processing plant leaf image data with distinction on crop disease detection. However, with the expensive and maximum resource utilized in disease detection, a review of automated plant leaf disease detection methods was investigated in [16].

A review focusing on the seed quality prediction using x ray images were proposed in [17]. In [18] a survey involving many methods for providing detailed outline concerning present development of agriculture automation was proposed. Imaging techniques concerning plant leaf disease detection using computer vision approaches was investigated in [19].

Motivated by the above studies, Gaussian Gray Level Geometric Neural Network Classifier (IGGL-GNNC) for plant leaf disease prediction is proposed. The IGGL-GNNC method aims to offer a three-fold contribution to the existing methods on agriculture and farming. First, by employing an Independent Component Gaussian Median Preprocessing, it reveals noise minimized enhanced image, therefore contributing to the performance or prediction accuracy by removing the noise present on the images. Next, Gamma Corrected Gray Level Run Length Feature Extraction is introduced for enhancing prediction accuracy through partitioning area of interest part of input plant leaf images. Finally, Sine Cosine Position Update Predictor Neural Network classifier provides a more complexity picture of the classifier performance by extracting the image features more accurately and effectively.

3. Methodology

This section presents the proposed Independent Gaussian Gray Level Geometric Neural Network Classifier (IGGL-GNNC) for plant leaf disease prediction and the architecture of the proposed method is presented as figure 1. The images collected from the plant village dataset are initially pre-processed by passing the image to the Independent Component Gaussian Median Preprocessing model. The plant disease usually affects the leaf region due to the presence of impulse noise, and thus the noise is eliminated during this pre-processing stage. Then, the leaf image is subjected for the feature extraction to carefully extract the region of interest by means of Gamma Corrected Gray Level Run Length Feature Extraction. Finally, the resultant output is provided to the Sine Cosine Position Update Predictor Neural Network for the disease prediction.

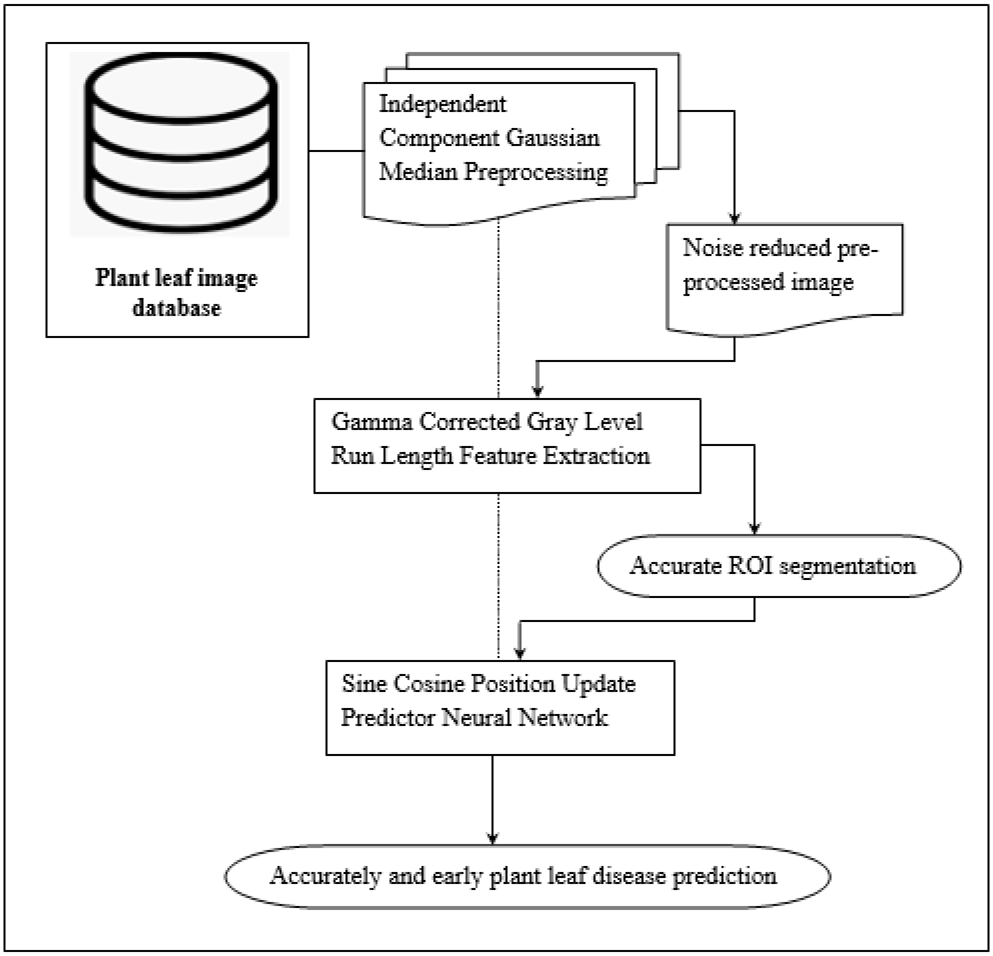


Figure 1: Architecture of Gaussian Gray Level Geometric Neural Network Classifier

As shown in the above figure, the architecture of IGGL-GNNC is split into three sections, namely, pre-processing, feature extraction and classification. The elaborate description of the proposed method is explained in the following sections.

Independent Component Gaussian Median Preprocessing model

Plant leaf images acquired by the camera are sometimes found to be corrupted due to the presence of impulse noises. As a result, the plant leaf image pixels are getting impaired due to these impulse noises. Then, the objective here remains in discarding this type of impulse noise in the highest number through safeguarding the dominant image features. To eliminate the impulse noises, different types of filters are present and in our work, an Independent Component Gaussian Median Preprocessing model. Hybrid median filter is used that safeguards the corner with the removal of impulse noise and also produced enhanced images as output. Fig 2 shows the block diagram of Independent Component Gaussian Median Preprocessing model.

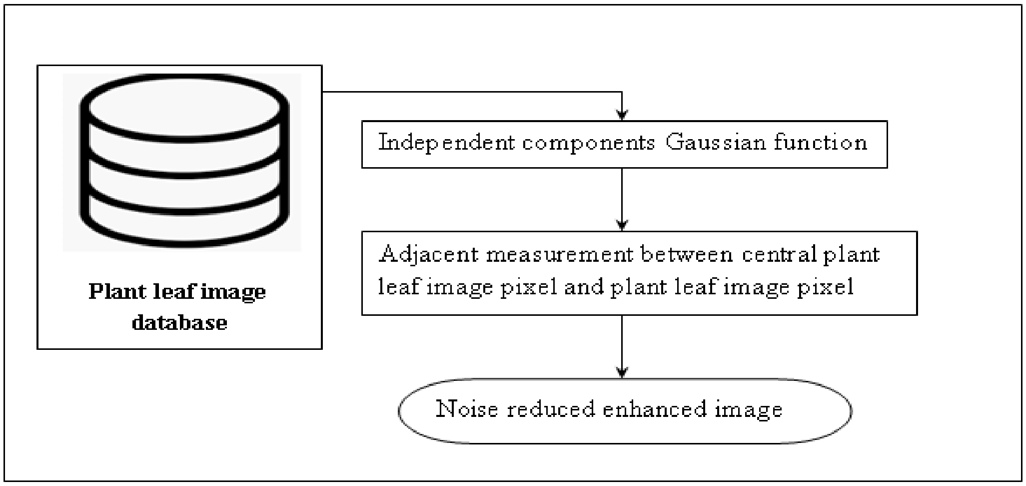


Fig 2 Block diagram of Independent Component Gaussian Median Preprocessing model

The Independent Component Analysis separates a multivariate plant leaf image 'PI' into additive subcomponents '$\mathrm{PI1}_1, \mathrm{PI1}_2, \ldots, \mathrm{PI1}_n$ '. This is conducted with the assumption that the fragments or subcomponents are non-Gaussian images and hence are said to be independent from each other. Then the components or images 'PI_i' of the observed random vector plant leaf image '$\mathrm{PI} = (\mathrm{PI}_1, \mathrm{PI}_2, \ldots, \mathrm{PI}_n)^T$' are produced as a volume of the independent components '$\mathrm{IC}_i, i = 1,2, \ldots, n$', mathematically expressed as follows.

$$\mathrm{PI}_i = W_{a1}\mathrm{IC}_1 + W_{a2}\mathrm{IC}_2 + \cdots + W_{an}\mathrm{IC}_n \quad (1)$$

In equation (1), sum of independent components is attained through additive function of products weights 'W_{ab}' and independent components 'IC_i'. With the objective of enhancing the image while identifying the independent components a Gaussian function is applied for the corresponding plant leaf image 'PI_i' is estimated as given below.

$$\mathrm{Prob}(\mathrm{PI}_i|W, \theta) = \sum_{j=1}^{n} W_j \mathrm{Prob}\left(\mathrm{PI}_i|\theta_j\right) \quad (2)$$

From the above equation (2), '$\theta = \{\theta_1, \theta_2, \ldots, \theta_n\}$' represents the pixel values of all the plant leaf image components, 'W_j' refers to the weight of the 'jth' component. In the process of imaging, a significant amount of impulse noise specifically contaminates the image enhancement process. Aiming at solving this issue, Independent Component Gaussian Hybrid Median Filter algorithm is introduced. When dealing with '$\mathrm{PI}(p, q)$' with median represented by '$M(p, q)$', then, the respective weight '$W(a, b)$' is mathematically obtained as given below.

$$\mathrm{vol} = \sum_{a=p-W}^{p+W} \sum_{b=p-W}^{p+W} \frac{1}{1+[f(a,b)-M(p,q)]^2} \quad (3)$$

$$W(a, b) = \frac{1/[f(a,b)-M(p,q)]^2}{\mathrm{vol}} \quad (4)$$

From the above equations (3) and (4), '$f(a, b)$' represents the respective gray value of the plant leaf image '$\mathrm{PI}(p, q)$'. It can be seen that the bigger the difference values between '$f(a, b)$' and '$M(p, q)$', the smaller the value of corresponding ‘$W(a,b)$’ will be. When ‘$f(a,b)$’ is equal to ‘$M(p,q)$’, ‘$W(a,b)$’ will be the maximum. Then, the corresponding output value is mathematically expressed as given below.

$$O(p,q) = \sum_{a=p-W}^{p+W} \sum_{b=q-W}^{q+W} W(a,b) * f(a,b) \quad (5)$$

Due to the reason that much relevancy is said to prevail between central pixel and its neighborhood similarity value between every pixel and the center pixel is mathematically formulated for eliminating the impulse noise as given below.

$$\mathrm{Sim}\,(a,b) = \varphi[f(a,b) - f(p,q)], a \in (p-W, p+W); b \in (q-W, q+W) \quad (6)$$

From above equ (6), it is inferred that the similarity resultant value lies between ‘0’ and ‘1’. If the gray value of the plant leaf image pixel is adjacent to that of the central plant leaf image pixel, the similarity value will be larger and vice versa. In this manner, the large similarity value is retained or considered as the pre-processed and enhanced image, whereas the lesser similarity value is considered as the impulse noise and therefore eliminated from further processing. The pseudo code representation of Independent Component Gaussian Hybrid Median Filter algorithm is given below.

Input: Plant leaf image database, plant leaf images ‘$PI = PI_1, PI_2, PI_3, \dots PI_n$’
Output: Noise minimized enhanced image ‘PPI’

Initialize gray value of the plant leaf image ‘$f(a,b)$’
Begin
For each plant leaf images ‘PI’
Split plant leaf images ‘PI’ into independent components as in (1)
Obtain plant leaf image enhanced result as in (2)
Evaluate weights as in (4)
Evaluate output value of central pixel as in (5)
Obtain similarity result to eliminate impulse noise as in (6)
Return (‘PPI’)
End for
End

Algorithm 1 Independent Component Gaussian Hybrid Median Filter algorithm

The above algorithm 1 explains the step by step process for minimizing the impulse noise and creating improved image. It attained through Independent Component Gaussian function and Filtering the minimum important part of image for further processing by similarity function. With these two functions utilized during the pre-processing, not only the impulse noise is minimized but also enhanced image or enhanced pre-processed image is obtained as output.

3.1 Gamma Corrected Gray Level Run Length Feature Extraction model

Feature extraction under differing radiance is the distinguished demanding issue in plant leaf disease prediction. With the changes in radiance, the appearance of plant leaf image differs diligently. These complete characteristics make the plant leaf disease classification task demanding. To overcome this problem, feature extraction is carried out through Gamma Corrected Gray Level Run Length Feature Extraction model. With the Gamma Corrected Gray Level Run Length Matrix (GC-GLRLM), geometric properties for extracting robust features with the assistance of gamma corrected group of gray level pixels and its run lengths concerning Region of Interest (ROI) are used. Fig 3 shows the block diagram of Gamma Corrected Gray Level Run Length Feature Extraction model.

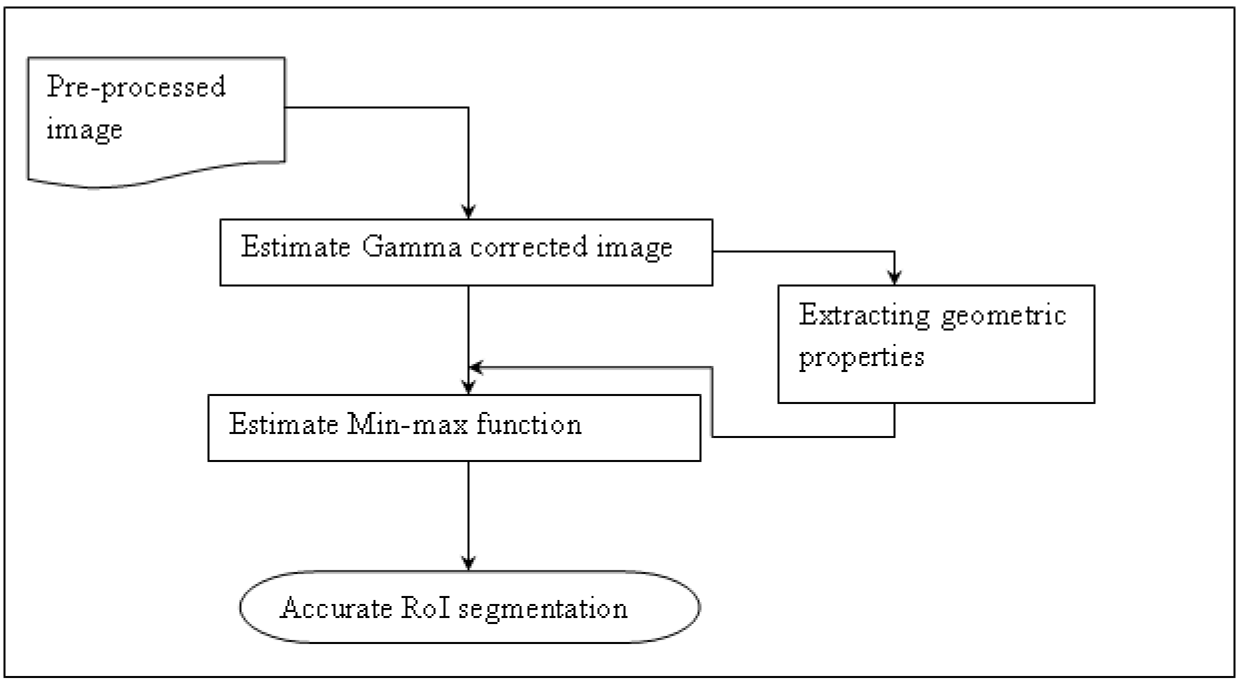


Fig 3 Block diagram of Gamma Corrected Gray Level Run Length Feature Extraction

As shown in the above figure, to start with the pre-processed image, a nonlinear transformation that restores the pre-processed plant leaf image pixel with intensity 'I' is referred to as gamma correction. The gamma correction has the effect of improving the pre-processed plant leaf image visibility. This is performed mathematically as given below.

$$GCI = Rad_{PPI}(p, q) * Ref_{PPI}(p, q) \quad (7)$$

From the above equation (7), the gamma corrected image 'GCI' is obtained based on the product of the radiance of the pre-processed image '$Rad_{PPI}(p, q)$' and the reflectance of the pre-processed image '$Ref_{PPI}(p, q)$' respectively. With improved visibility, processing time involved in prediction is said to be reduced. Next, Gamma Corrected Gray Level Run Length Feature Extraction is designed that segments the Region Of Interest (ROI) according to geometrical properties, therefore contributing to prediction accuracy. The gray level pixels denotes to the pixel set possessing similar plant leaf gray level pixels that are successively dispersed in ROI along certain directions. Alternatively, the number of pre-processed plant leaf pixels is referred to as the length of the gray level iterations. Therefore, the gray level pre-processed plant leaf pixels and length of gray level pre-processed plant leaf pixels simultaneously describe a coordinate. This is mathematically formulated as given below.

$$\mathrm{MinGLW} = \sum_{p \in N(Rad)} \sum_{q \in N(Ref)} \frac{p^2 GCI_{p,q}}{q^2} \Big/ \sum_{p \in N(Rad)} \sum_{q \in N(Ref)} GCI_{p,q} \tag{8}$$

From the above equations (8), minimum gray length weight 'MinGLW' is obtained based on the gamma corrected radiance image '$p^2 GCI_{p,q}$' to the reflected image 'q^2' with respect to the gamma corrected images '$GCI_{p,q}$'.

$$\mathrm{MaxGLW} = \sum_{p \in N(Rad)} \sum_{q \in N(Ref)} \frac{q^2 GCI_{p,q}}{p^2} \Big/ \sum_{p \in N(Rad)} \sum_{q \in N(Ref)} GCI_{p,q} \tag{9}$$

In a similar manner, from the above equations (9), maximum gray length weight 'MaxGLW' is obtained based on the gamma corrected reflected image '$q^2 GCI_{p,q}$' to the radiance image 'p^2' with respect to the gamma corrected images '$GCI_{p,q}$'. The pseudo code representation of Gamma Corrected Gray Level Run Length Matrix is given below.

Input: Plant leaf image database, plant leaf images '$PI = PI_1, PI_2, PI_3, \ldots . PI_n$'
Output: Accurate segmented feature extraction '$FE = \{FE_1, FE_2, FE_1^N, FE_2^N\}$'
1: **Initialize** Pre-processed images '$PPI = PPI_1, PPI_2, \ldots, PPI_n$', radiance '$Rad_{PPI}(p,q)$', reflectance '$Ref_{PPI}(p,q)$' 2: **Begin** 3: **For** each plant leaf pre-processed images 'PPI' 4: Estimate Gamma corrected image as in (7) 5: **For** each Gamma corrected image 'GCI' 6: Evaluate minimum gray length weight as in (8) 7: Evaluate maximum gray length weight as in (9) 8: Evaluate features extracted '$FE = MinGLW, MaxGLW$' 9: **Return** (features extracted 'FE') 10: **End for** 11: **End for** 12: **End**

Algorithm 2 Gamma Corrected Gray Level Run Length Matrix

As given in the above Gamma Corrected Gray Level Run Length Matrix algorithm for enhancing prediction accuracy with minimum processing time. Geometric properties are extracted through using Gamma Correction function which leads to minimize processing time. Next, with extracted features, prediction accuracy is improved by segmenting the region of interest part by means of min-max function. The features finally are extracted from min function '$\{FE_1 \dots . FE_1^N\}$' and max function '$\{FE_2 \dots . FE_2^N\}$' respectively.

3.2 Sine Cosine Position Update Predictor Neural Network

Finally, Classifier performance is enhanced through extracting the image features by means of accurate extraction of segmented features in an efficient manner. In our work, Sine Cosine Position Update Predictor Neural Network classifier model is used to enhance the classifier performance for infected leaf area prediction. Fig 4 shows the block diagram of Sine Cosine Position Update Predictor Neural Network classifier model.

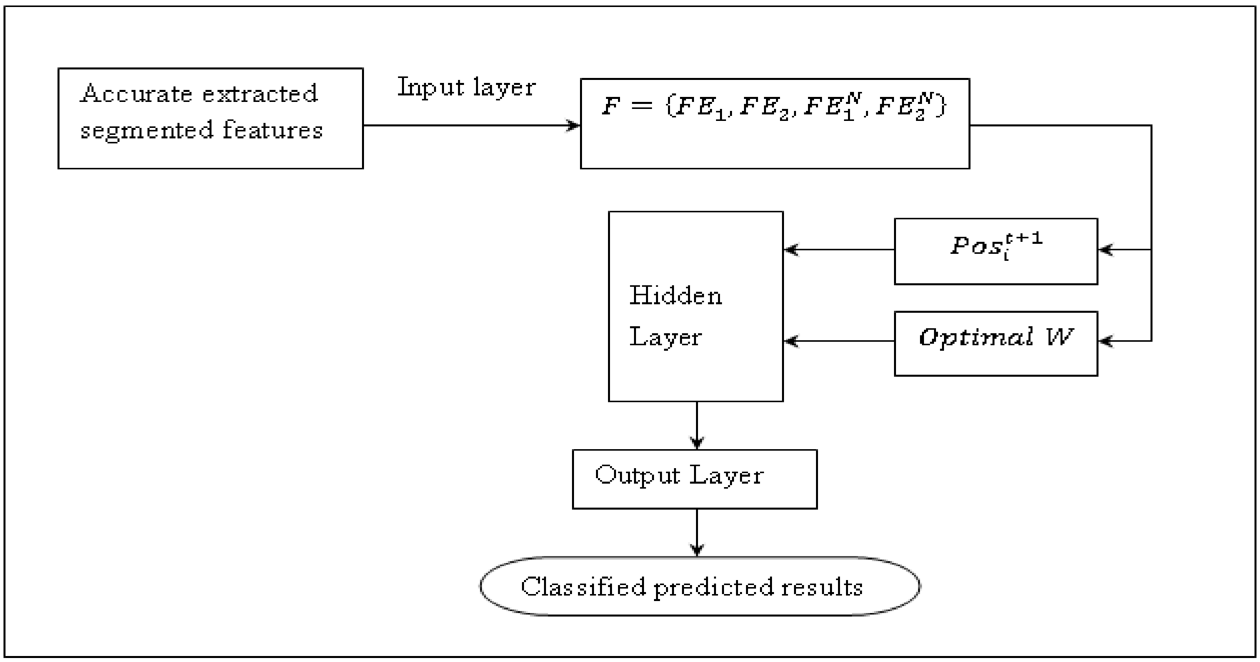


Fig 4 Flow process of Sine Cosine Position Update Predictor Neural Network classifier

In fig 4 , extracted features are attained using Gamma Corrected Gray Level Run Length Matrix algorithm from pre-processed plant leaf image. It includes the size as 'M' and extracted features are given to the input unit, and it is expressed as follows.

$$F = \{FE_1, FE_2, FE_1^N, FE_2^N\} \quad (10)$$

From the above equation (10), 'F' has a total of '12' features from the Plant Village Dataset with an overall of features extracted based on two different functions respectively. Also 'FE_1' indcates to the '1st' feature given as input to the Sine Cosine Position Update Predictor Neural Network classifier model. With 'M' number of extracted features used in our work, the neurons included in our work for input is

'$M = 12$'. Moreover, for the 'M' neurons associating the hidden units, the Sine Cosine Position Update Predictor Neural Network classifier model is provided with the weights as in (4).

$$\eta = W_O * \left[\text{Log Sig}\left(\sum_{i=1}^{M} FE_i * W_i + B_H\right)\right] + B_O \quad (11)$$

From the above equation (11), 'B_H', 'B_O', 'W_O' represents the bias of the hidden layer, bias of the output layer and the weight of the output layer respectively. For the output evaluation, the weights '$\frac{1/[f(a,b)-M(p,q)]^2}{vol}$' and the biases '$B_O$', '$W_O$' are chosen in a best way depend on position update through using sine cosine function.

The Sine Cosine Position Update Predictor Neural Network classifier algorithm has infected plant leaf to be detected and adjacent pixel for changing the search space. Therefore, position of the infected plant leaf to be predict the used to attain the enhanced optimal position, and Sine Cosine Position Update Predictor Neural Network classifier algorithm has choose for classifying extracted plant leaf image features to improve the classification performance.

$$Pos_i^{t+1} = \begin{cases} Pos_i^t + rv_1 \sin(rv_2) * \left[rv_3 Pos_t(a,b) - Pos_i^t\right];\ rv_4 < 0.5 \\ Pos_i^t + rv_1 \cos(rv_2) * \left[rv_3 Pos_t(a,b) - Pos_i^t\right]; rv_4 \geq 0.5 \end{cases} \quad (12)$$

From the above equation (), with the random variables 'rv_1', 'rv_2', 'rv_3' and 'rv_4' in the range of '$[0,1]$', 'Pos_i^t' signifying the position of the extracted plant leaf image for '$i - th$' solution at time 't', the classified results are obtained in an optimal manner. The pseudo code representation of Sine Cosine Position Update Predictor Neural Network classifier is given below.

Input: Plant leaf image database, plant leaf images '$PI = PI_1, PI_2, PI_3, \ldots. PI_n$'
Output: Correctly detected classified results
1: **Initialize** features extracted 'FE' 2: **Begin** 3: **For** each plant leaf pre-processed images 'PPI' 4: Evaluate predictor neural network classifier as in (11) 5: Evaluate Sine Cosine Position Update as in (12) 6: **Return** (classified results) 7: **End for** 8: **End**

Algorithm 3 Sine Cosine Position Update Predictor Neural Network classifier

As given in the above Sine Cosine Position Update Predictor Neural Network classifier algorithm, the objective remains in enhancing the classifier performance so that accurate and robust plant leaf disease prediction is made. To achieve this objective position updates based on geometrical features (i.e., sine and cosine functions) are utilized and fed as input along with extracted features for classification. With this, the predictor neural network classifier classifies the results in an accurate and efficient manner.

4. PERFORMANCE EVALUATION

The illustration of Independent Gaussian Gray Level Geometric Neural Network Classifier (IGGL-GNNC) method for plant leaf disease prediction is experimented using Plant Village Dataset to evaluate its performance is presented in Python tool. Experiments of IGGL-GNNC method is performed with windows 10 OS, 4 GB RAM, and Intel I3 processor. The performance of the IGGL-GNNC is evaluated using four different metrics, sensitivity, specificity, prediction accuracy and processing time. To conduct fair evaluation Plant Village Dataset [20] is used in our work and performances are evaluated for three different methods, IGGL-GNNC, automatic tassel detection [1] and INC-VGGN [2] respectively.

4.1 Dataset

The IGGL-GNNC method is uses the number of images collected from the Plant Village Dataset [20]. Dataset comprises of the leaf organ in addition to its ground truth value. Dataset comprises of 38 group of species and disease and a total of 54,303 normal and abnormal leaf images.

4.2 Qualitative analysis

Processes	**Results of the application of the proposed IGGL-GNNC**
Input leaf image collected from plant village dataset	
Independent Component Gaussian Hybrid Median Filter	Gaussian Median Pre-Processing 

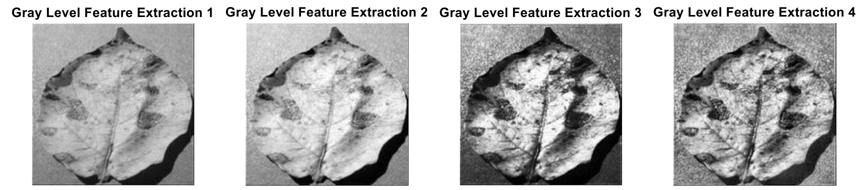
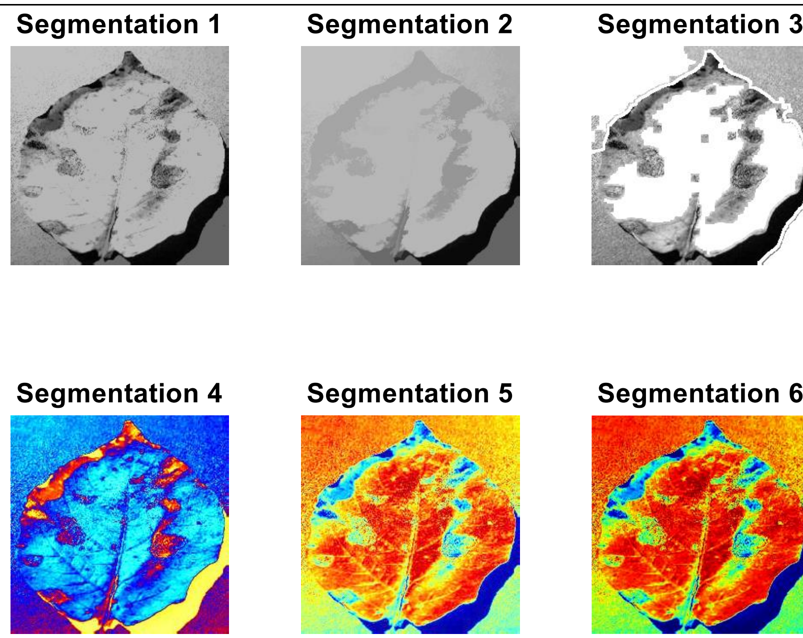
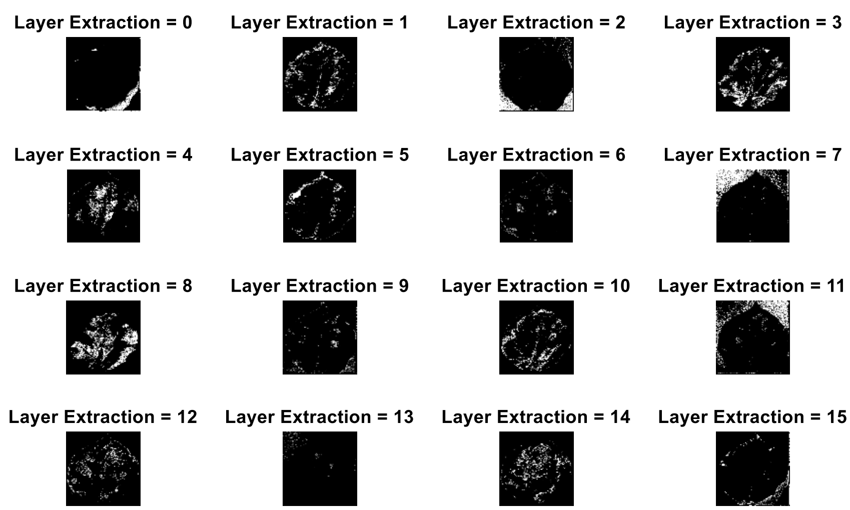
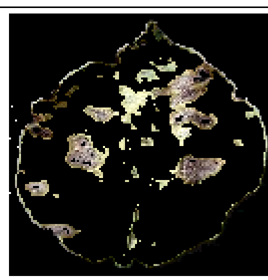
Gamma Corrected Gray Level Run Length Feature Extraction	
ROI Segmentation	
Sine Cosine Position Update Predictor Neural Network Classification	
Prediction Classified output	

Fig 5 Qualitative results of IGGL-GNNC method

Fig 5 given above illustrates qualitative outcomes of IGGL-GNNC method. Initially plant leaf image obtained from https://www.kaggle.com/emmarex/plantdisease/discussion [20] are provided as input with which the pre-processing Independent Component Gaussian Hybrid Median Filter method is employed for eliminating impulse noise. Then image improvement is carried out through adjacent measurement between central plant leaf image pixel and plant leaf image pixel. Subsequently, geometric properties are obtained through the Gamma Corrected Gray Level Run Length feature extraction model. By segmenting the region of interest via geometric properties, accuracy is said to be improved. Finally, Sine Cosine Position Update Predictor Neural Network classifier is applied to predict the infected leaf area.

4.3 Impact of sensitivity

It is referred as ability to detect a true positive (TP). In other words, sensitivity in our work estimates the proportion of positive values.

$$\mathrm{Sen} = \sum_{i=1}^{n} \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \quad (13)$$

In equation (13), 'Sen' is calculated depend on 'TP' (i.e., plant leaf disease correctly detected) and false negative 'FN' (i.e., incorrectly plant leaf disease detected) respectively. The sensitivity rate is measured in units of percentage (%).Table 3 reports the simulation results of Sensitivity versus a number of images.

Table 1 Tabulation of sensitivity

Number of images	Sensitivity (%)		
	IGGL-GNNC	automatic tassel detection	INC-VGGN
20	94.73	89.47	84.21
40	93.15	88.35	83.55
60	92.05	88	83.05
80	92	87.45	82.55
100	90.85	87	82.15
120	90.55	86.55	82
140	90.3	86.35	81.55
160	89.55	86	81
180	89.4	85.45	80.35
200	89.25	84	80

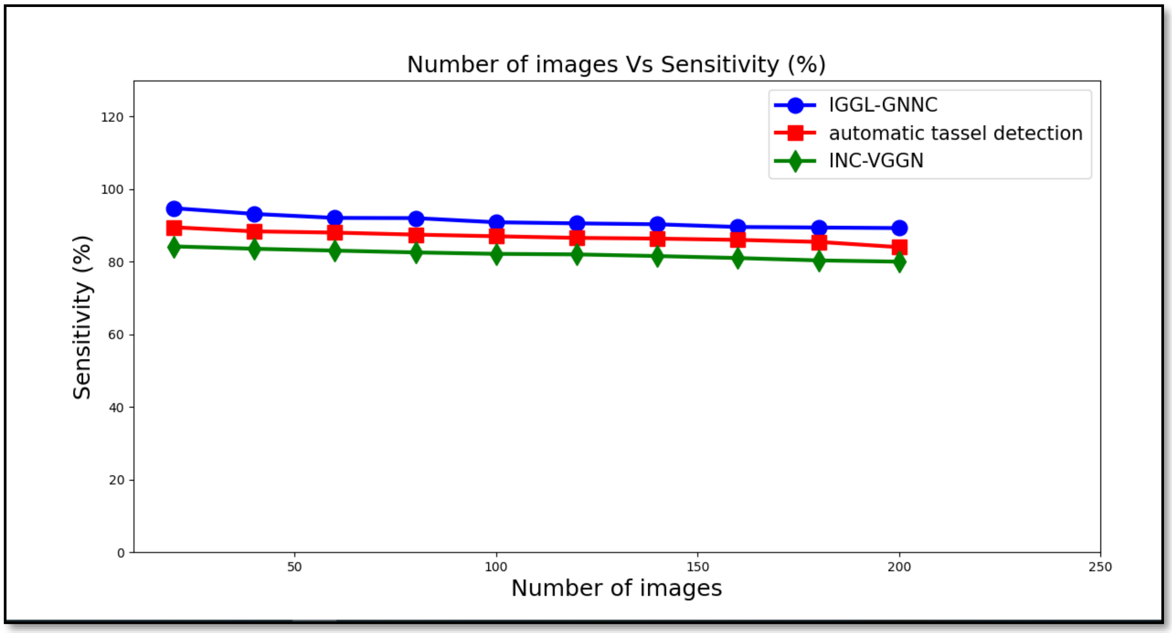


Figure 6 Graphical representation of sensitivity

The above fig 6 provides overall sensitivity rate of the training plant leaf images utilized during the learning process in the range of 20 to 200 obtained at different time intervals. It shows that the overall sensitivity rate decreases to the optimal value using IGGL-GNNC method upon comparison with [1] and [2]. Also simulation with 20 plant leaf images found a TPR of 18, 17 and 16 , FPR of 2, 3 and 4 using three methods. With this, the sensitivity rate was observed to be 94.73%, 89.47% and 84.21%. From this result, the sensitivity rate of IGGL-GNNC method was observed to be better than [1] and [2] due to the application of Sine Cosine Position Update Predictor Neural Network classifier model. From that , position updates are obtained depend on the geometrical features (i.e., sine and cosine functions).Then the classification is performed to increase the sensitivity using IGGL-GNNC method by 5% than the [1] and 11% than the [2].

4.4 Performance analysis of specificity

Specificity is referred to as the ratio of negatives which are properly recognized (the proportion of the plant leaf disease that does not have the condition (i.e., negative traits that are correctly identified as not having the positive traits condition). In other words, it refers to the detections characteristics of true negatives in the plant feature subset within a class in a dataset.

$$\mathrm{Spe} = \sum_{i=1}^{n} \frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FP}} * 100 \tag{14}$$

In equation (14), ‘Spe’ is estimated depend on true negative ‘TN’ (correctly unwanted plant leaf disease detected as true negative) and false positive ‘FP’ (incorrectly plant leaf disease detected as false positive). The specificity rate is measured in terms of percentage (%). Table 2 given below illustrates the comparative analysis of specificity using three methods, IGGL-GNNC, automatic tassel detection [1] and INC-VGGN [2] respectively.

Table 2 Tabulation of specificity

Number of images	Specificity (%)		
	IGGL-GNNC	automatic tassel detection	INC-VGGN
20	90	85	80
40	89.25	84.85	79.55
60	89	84	79.3
80	88.55	83.75	78.55
100	88.3	83.5	78.15
120	88	83	78
140	87.9	82.55	77.95
160	87.55	82.15	77.55
180	87.3	82	77.25
200	87	81.35	77

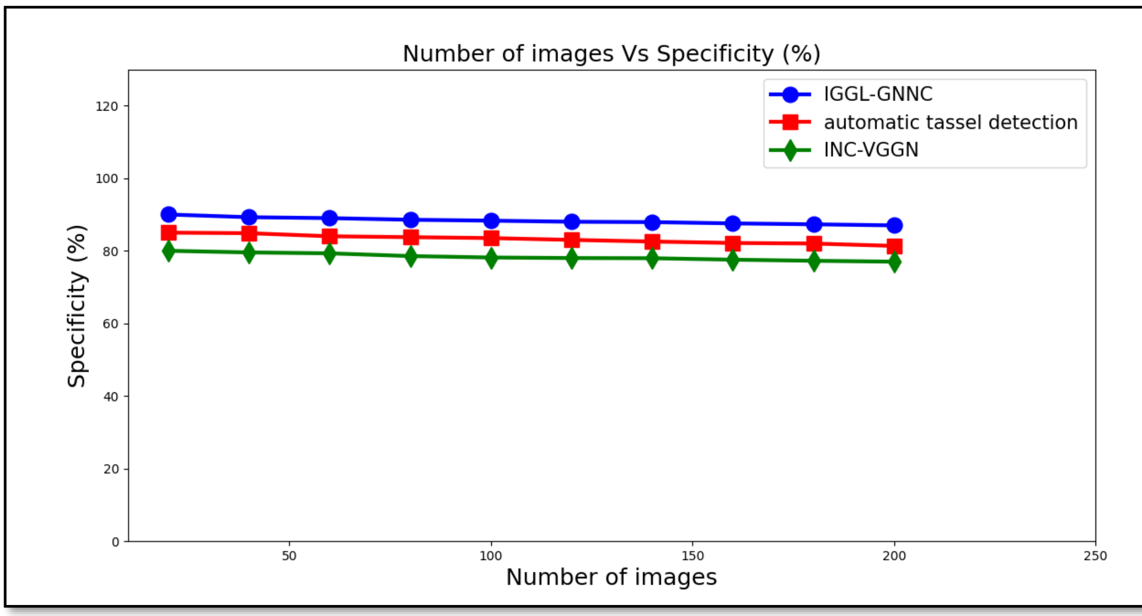


Figure 7 Graphical representation of specificity

Figure 7 strikes specificity rate values for the proposed IGGL-GNNC method and its contemporary methods, automatic tassel detection [1] and INC-VGGN [2] respectively. It can be observed that specificity rates are significantly higher using IGGL-GNNC method when compared to the other two techniques. Though the specificity rate is found to be decreasing with the increase in plant leaf images provided as input, with simulations conducted using 20 plant leaf images, false positive rate using three methods were observed to be 2, 3 and 4. Therefore, the specificity is observed to be 90% using IGGL-GNNC method, 85% using [1] and 80% using [2]. The improvement in specificity rate using IGGL-GNNC was owing to the application of Gamma Corrected Gray Level Run Length Matrix resultant output to the classifier model.

Bias and weights were chosen for every pre-processed plant leaf images depend on the position update through using sine cosine function which enhanced specificity using IGGL-GNNC method by 6% than the [1] and 13% than the [2].

4.5 Performance analysis of prediction accuracy

In this section, the analysis of prediction accuracy is made. Prediction accuracy (PA) refers to the accuracy level attained while detecting plant leaf disease. PA is formulated as given below

$$PA = \sum_{i=1}^{n} \frac{PI_{cd}}{PI_i} * 100 \quad (15)$$

From the above equation (15), the prediction accuracy 'PA' refers to the samples provided as input 'PI_i' and the plant leaf images corrected detected 'PI_{cd}'. It is measured in units of percentage (%). In Table 3 we show the performance analysis of prediction accuracy for IGGL-GNNC, automatic tassel detection [1] and INC-VGGN [2] respectively.

Table 3 Tabulation of PA

No. of images	PA (%)		
	IGGL-GNNC	automatic tassel detection	INC-VGGN
20	95	90	85
40	94.25	89.55	84.55
60	93.25	89.3	84.3
80	93	89.15	84
100	92.15	89	83.15
120	92	88.55	83
140	91.55	88.3	82.55
160	91.35	88.15	82.15
180	91	88	82
200	90.55	87	81.55

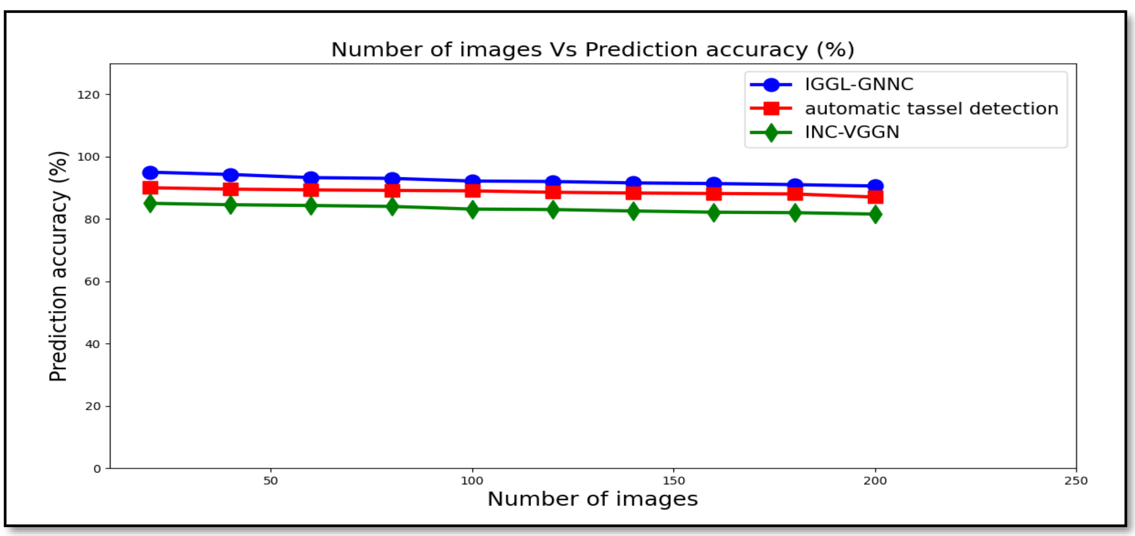


Figure 8 Graphical representation of prediction accuracy

Figure 8 strikes a comparison of prediction accuracy values with existing methods automatic tassel detection [1] and INC-VGGN [2] and examined that the IGGL-GNNC method provides higher values of plant leaf disease prediction accuracy and the accuracy is nearly 94.25%. IGGL-GNNC method is highly accurate and provides accurate smart farm and agriculture model to horticulturists requesting for plant cultivation in gardens to produce food and medicinal ingredients when compared to other contemporary methods such as automatic tassel detection [1] and INC-VGGN [2] respectively. This is because of Independent Component Gaussian Hybrid Median Filter algorithm. By using this algorithm, impulse noise present in the plant leaf images are ignored. Then the Independent Component Gaussian function used to provide the enhanced image this in turn prediction accuracy of IGGL-GNNC method by 4% than the [1] and 11% than the [2] respectively.

4.6 Performance analysis of processing time

Finally, in this section, the processing time involved in analyzing the plant leaf disease is presented. This is mathematically formulated as given below.

$$\mathrm{PT} = \sum_{i=1}^{n} \mathrm{PI_i} * \mathrm{Time}\ [\mathrm{LDD}] \quad (16)$$

In equation (16), processing time 'PT' is calculated depend on samples involved in simulation '$\mathrm{PI_i}$' and time utilized in plant leaf disease detection '$\mathrm{Time}\ [\mathrm{LDD}]$'. PT is measured in units of milliseconds (ms). Table 4 given below shows the processing time for three different methods, IGGL-GNNC, automatic tassel detection [1] and INC-VGGN [2] respectively.

Table 4 Tabulation of processing time

Number of images	Processing time (ms)		
	IGGL-GNNC	automatic tassel detection	INC-VGGN
20	3.1	3.5	3.8
40	4.55	7.45	10.15
60	5.35	10.15	14.35
80	7.25	11.55	15
100	11.55	14.15	17.35
120	13.15	20.35	25.15
140	18.35	25.15	38.35
160	25.55	35.55	45.25
180	30.15	45.85	55.15
200	35.45	50.35	65.35

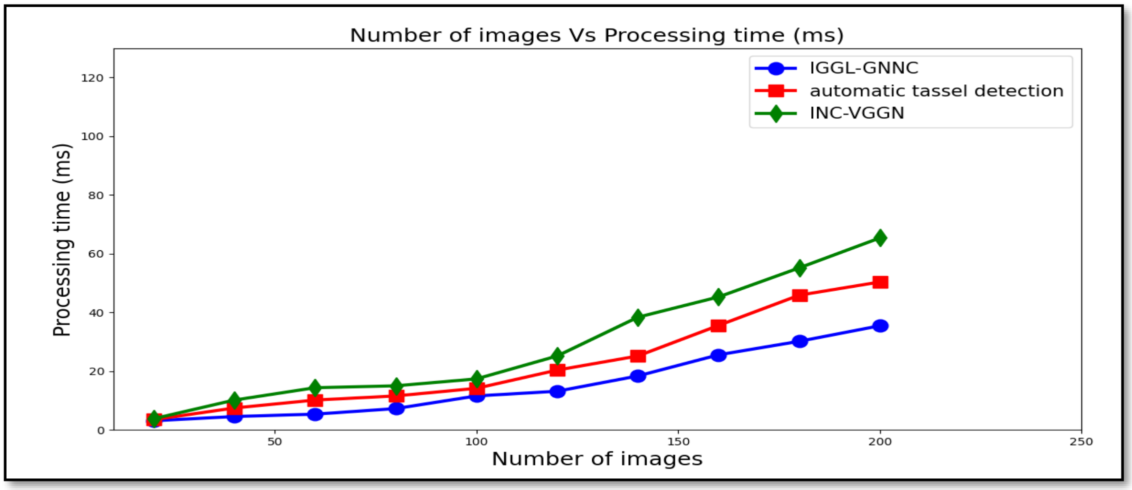


Figure 9 Graphical representation of processing time

To further explore the significance of the proposed IGGL-GNNC method, we show the average processing time of IGGL-GNNC, automatic tassel detection [1] and INC-VGGN [2] respectively with respect to varying plant leaf images in figure 9. It can be seen that the processing time performance varies with plant leaf images provided as input for simulation. While this variation mainly depends on the species and disease intensity, the proposed IGGL-GNNC method shows performance improvement over other existing methods [1] and [2]. In other words, though increasing the plant leaf image outcomes in the increase of processing time, but simulations conducted with 20 plant leaf images shows a processing time of 3.1ms using IGGL-GNNC method, 3.5ms using [1] and 3.8ms using [2] respectively. With this result the processing time improvement was found in IGGL-GNNC method due to the application of Gamma Corrected Gray Level Run Length Matrix algorithm. By applying this algorithm, geometric properties were applied via region of interest segmentation. Also, the gamma corrected image was obtained on the basis of the product of radiance of the pre-processed image and the reflectance of the pre-processed image. Therefore, processing time involved in detecting plant leaf images was minimized using IGGL-GNNC method by 31% than the [1] and 46% than the [2].

5. Conclusion

This work is managed for connecting with evolving a pertinent classifier system that can obtain the plant leaf images that are available as database, recognize the ubiquity of plant leaf images and predict the presence/absence of disease with concentrate on the cultivation and processing of different types of plants globally. The performance of this IGGL-GNNC method was evaluated using four parameters namely sensitivity, specificity, processing time and prediction accuracy and the results were evaluated with existing methods. These outcomes were discussed in previous section show that the sensitivity, specificity and prediction accuracy value using IGGL-GNNC method is higher compared to the existing methods that were compared. Besides, precision accuracy for IGGL-GNNC method was nearly 94.25% for plant leaf disease prediction. Similarly, the processing time for IGGL-GNNC method showed minimal time for extracting geometric features which is another powerful indicator of maximum degree of accuracy. The discussed results have revealed that the IGGL-GNNC method obviously excels existing method in terms of accurate classification of plant leaf images with respect to cultivation of plants globally.

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