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# Automation of Leaf Disease Prediction Framework based on Machine Learning and Deep Learning in different Crop Species

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**ABSTRACT**

The phenomenon of plant leaf illness has fatalistic influences on production and assists in promoting safety in products concerning agriculture. Owing to the reason that the leaf is major vulnerable portion of a plant it is influenced easily upon comparison with the other parts. Plant disease detection by means of numerous automatic models is advantageous as it minimizes immense work of big farm monitoring, and also at the early stage assists in detection of the disease symptoms. Several frameworks have been designed for plant disease. But the error rate and overhead incurred in plant leaf disease diagnosis was not focused. In this research, characterize and investigate the plant leaf disease prediction using three novel proposed frameworks using Plant Village dataset. They are Gaussian Distributive Czekanowskis Region-based Deming Regression (GDCR-DM), Covariance Kalman Geometric Graph-based Bernoulli Classifier (CKGG-BC) and Independent Gaussian Gray Level Gaussian Gray Level Geometric Neural Network Classifier (IGGL-GNNC). The GDCR-DM framework identifies the plant leaf disease in an accurate manner with minimum false positive rate employing Czekanowski's dice and Deming regression function. Next, to reduce noise involved during preprocessing and segmentation, CKGG-BC framework is proposed that with the aid of Covariance Kalman filter function and Multiple Kernel Learning Classifier not only reduces the error but also enhances true positive rate considerably. Finally, IGGL-GNNC framework is designed that Sine Cosine Position Update using geometric functions for realistic disease prediction. The different parameters were evaluated for distinct plant leaf images obtained from Plant Village Image dataset.

**Keywords:** Gaussian Distributive, Czekanowskis, Deming Regression, Covariance, Kalman Filter, Graph-based Bernoulli, Gaussian Gray Level, Neural Network

## 1. Introduction

A plethora of quondam endeavors has investigated image recognition for which definite classifier has been employed for classification of input images into healthy or diseased. To be more specific, plant leaves form the principal source of plant disease identification. Nonetheless the artificially-defined features entail outrageous chores that have an unquestionable distinction. For the most part, it is not placid in deciding the features that are hinged to be efficiently detect the plant disease form numerous features being extracted.

Also, under the synthesized circumstances, most methods give out to notably portioned the leaf and respective lesion image from its environment, therefore emerging in inconsistent disease recognition results. Therefore, automatic plant leaf disease detection and identification is yet contemplated as a demanding concern owing to its laborious process involved in identifying diseased leaf images.

An automatic tassel detection method has been introduced in [1] with color attenuation prior model. With this model, presence of saturation in the image was discarded. Next, an Itti visual attention detection algorithm was applied to extract the important area of interest. With obtained area, texture features and vegetation indices were utilized to perform the classification for minimizing the false positives, there contributing to both precision and recall also.

In [2], Inception – Visual Geometry Group Network (INC-VGGN) to discover the plant leaf infection. In INC-VGGN basic feature extractor was utilized and then multi-scale feature maps were used for plant leaf disease detection. Initially, Inception module has been selected. An improved VGGNet was adapted by changing its last layers by an added convolutional layer. Next, convolved output was obtained by batch normalization. Next, multi scale image features were extracted by means of Swish activation function, following which fully connected layers were retained in global pooling for minimizing dimensionality. Finally, with the aid of Softmax layer plant disease class prediction was made.

In order to find the corn leaf illness, a method termed Dense convolutional neural network (DenseNet) have been introduced [3]. With the lack of proper and precise image segmentation, the method was not able to focus on the disease detection accuracy.

Based on transfer learning, pretrained AlexNet and GoogleNet convolutional neural networks (CNNs) utilized in [4] for soybean illness classification. Also, five-fold cross-validation function was used. To start, preprocessed images were applied as input to the pre-trained GoogleNet CNN framework. Also, retraining was done on the preprocessed images for classifying soybean disease into four distinct class species, therefore improving accuracy to a greater extent.

Binary classification of disease detection was performed in [5] using support vector machines via single class. Despite classification performance being improved the rate at which the accuracy could be evolved was not focused. To address this issue, convolution neural network based on deep learning was designed in [6]. With this deep learning method, soybean as a grain plant disease was made in an efficient manner via classification on the basis of the segmented leaf images. Despite improvement observed in terms of identification accuracy, concept of noise filtering was not performed, therefore compromising better image quality.

Numerous leaf disease prediction frameworks were designed with enhanced result of plant leaf disease detection accuracy. But, classification of plant leaf consumes a significant amount of noise that has to be considered during analysis. Many research works have been designed for attaining efficient and higher plant leaf disease detection accuracy with minimum overhead. However, the plant leaf disease detection still remained a major concern with maximum prediction accuracy. Few research works have been designed to enhance classification performance. With this, prediction accuracy gets compromised. Hence, above issues are overcome by proposing three different proposed frameworks.

The objective of the research work is described as follows.

- To correctly detect the plant leaf disease with lesser error, the three proposed methods are introduced.
- To increase the classification accuracy in the affected leaf area prediction by introducing the better classifier framework called, Gaussian Distributive Czekanowskis Region-based Deming Regression (GDCR-DM)
- To improve the prediction accuracy rate and true positive rate, Covariance Kalman Geometric Graph-based Bernoulli Classifier (CKGG-BC) is developed for extracting the geometric properties of the infected leaf areas.
- To enhance the classifier performance by extracting the image features more accurately and effectively using Independent Gaussian Gray Level Geometric Neural Network Classifier (IGGL-GNNC).

The rest of the paper is arranged into different sections as given below. The literature review is discussed in Section 2. The proposed three frameworks with a neat diagram are elaborated in Section 3. Section 4 presents the experimental settings for designing three frameworks namely, GDCR-DM, CKGG-BC and IGGL-GNNC. Section 5 presents the evaluation metrics and discussion in detail via table and graphical representation. At last, the paper is concluded in Section 6.

## 2. Literature Review

Owing to dearth of required framework, the food security is the crop diseases. Numerous endeavors have been deployed to put a stop to on account of infection. Self reliant of the method, illness identification accurately during its first occurrence still remains a critical step for significant disease management. Supplementary, in the present day situation, such endeavors have moreover been aided by bestowing information for disease diagnosis, capitalizing the increasing Internet perforation globally.

In [7], convolutional neural network models were utilized with the objective of plant disease diagnosis involving plain leaves images. With this classification into either strong or diseased were diagnosed in an accurate

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manner. However, with the lack of proper image segmentation process, disease identification accuracy was not focused, therefore compromising the time consumed in identification. To address this issue, k-means clustering algorithm was proposed in [8] with the aid of covariance matrix differentiated between healthy and diseased leaves in a timely and accurate fashion. Yet another method based on improved k nearest neighbor algorithm was designed in [9] to classify the images with the purpose of identifying disease spots present in rice leaves.

A method to diagnosis the disease at an early staged was proposed in [10] employing deep feature learning. Despite improvement in accuracy level, the noise involved during analysis was not focused. To concentrate on this aspect, multiple linear regression was designed in [11] for plant disease detection.

Computer vision models that can identify plant diseases in the agricultural field would be beneficial instruments for disease management and confrontation breeding. Producing sufficient data for training these methods is laborious and cumbersome owing to the reason that only professionals can exactly estimate the symptoms.

In [10], a Deep convolutional neural network has been applied to distinct 14 crop species for disease diagnosis and evolved significant results. But, the huge farm was observed for 14 crop species, steps. For discovering the sunflower leaf disease, an optimization method was introduced in [13] called, particle swarm optimization.

In [14], the neural network mechanisms were analyzed for plant leaf disease detection with hyperspectral data. An image processing and machine learning methods have been developed in [15] to perform the holistic review of current work in crop pesticide area and disease recognition. In [16], the leaf infection is classified, by using deep learning algorithms.

Plant diseases are an exemplar for securitizations of food around the globe, as well as globally evince to be intricate fatal repercussions for small farmers whose routine subsistence hugely is dependent on robust yield. The 80 percent of agricultural production is generated by small farmers in India. In the beginning period, the plant leaf disease identification is a major part. For enhancing the validation accuracy, multiple convolutional neural networks were introduced in [17]. In [18], to increase the accuracy, a new method based on classification called, sine cosine algorithm has been designed by rider neural network.

During the leaf image classification, a novel technique was presented in [19] with deep convolution networks, therefore contributing to precision. For immense applications involving algorithms are in the recent years found to be not practicable due to the disadvantages like, computational characteristics, clustering. To address this issue, Traveling Salesman Problems was designed in [20], therefore ensuring large-scale applicability.

One of the foremost characteristics that have fatalistic impact on food safety is the pesticide remnants. The machine-vision-based segmentation and hyperspectral technique was designed in [21] for obtaining pesticide residue identification. With this segmentation process separately performed for both foregrounds and background apple image regions, the detection accuracy was said to be improved in a timely manner. Yet another machine learning technique with the purpose of tomato grading based on the region of interests was proposed in [22], therefore attaining accuracy.

Plant disease can absolutely out turns in dwarf evolution emerging in inadequate repercussions on returns. Several prevailing climatic conditions are some of the most laborious and complication issue for researchers due to the geographic disparities that in turn hurdle the plant disease accurate identification. To address this issue, a particle swarm optimization method has been discussed [23]. The comprehensive analysis of plant disease identification was investigated in [24]. On the basis of the localized leave extraction employing Chan Vese algorithm [25] and region proposal network plant disease accuracy was ensured.

## 3. Methodology

The proposed research work implement three different proposed frameworks to identify plant leaf disease for maximum accuracy, true positive rate with minimum processing time. The developed research work is performed within three different sections as shown in the figure given below.

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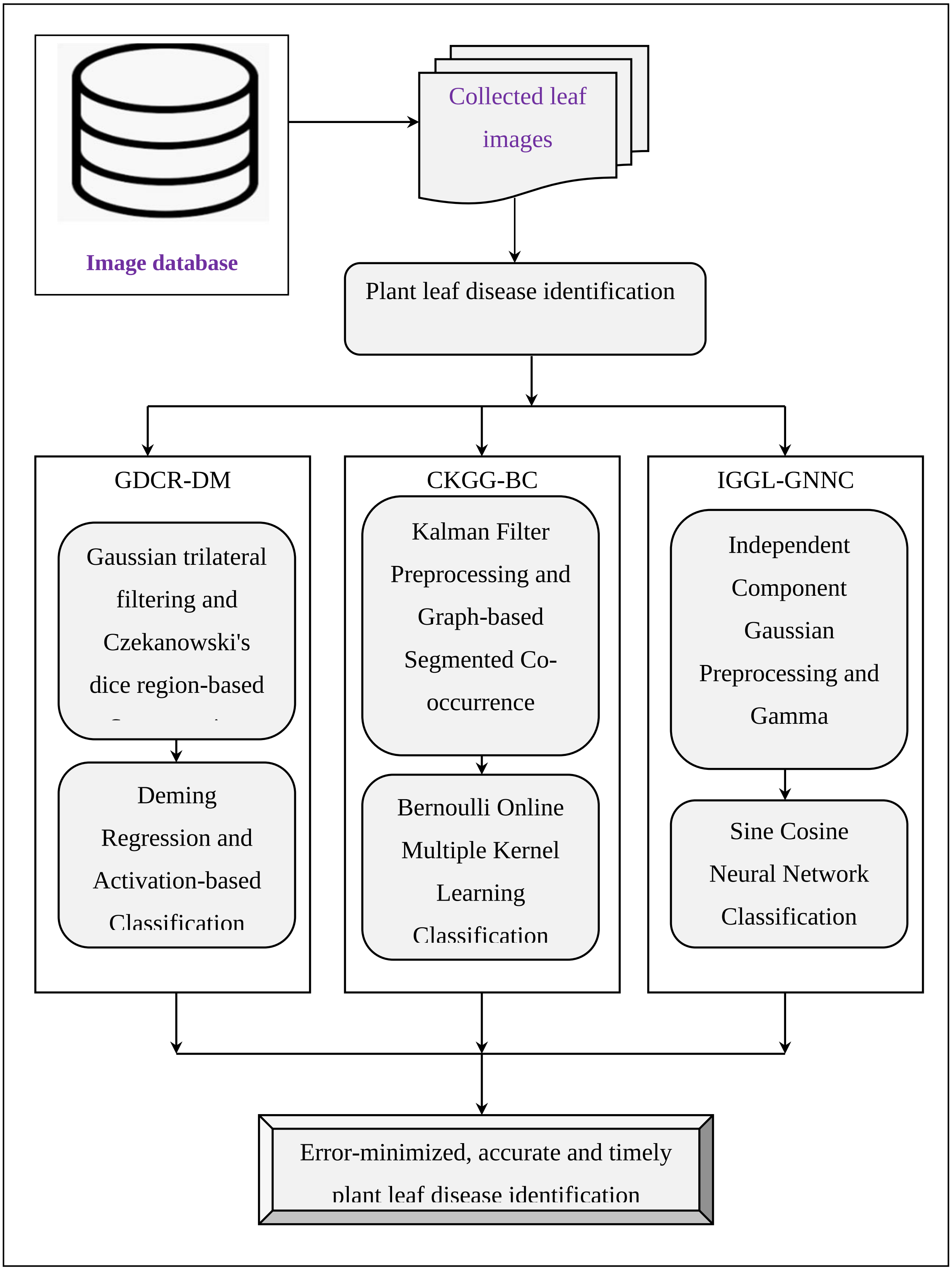

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Figure 1 given above illustrates the architecture overview of three proposed frameworks for accurate plant leaf disease identification in a timely manner. The brief explanation about the three proposed frameworks is provided in the subsections given below.

### 3.1 Gaussian Distributive Czekanowskis Region-based Deming Regression (GDCR-DM)

The GDCR-DM employs deep multilayer feed forward neural learning model consisting of numerous layers with the purpose of learning the provided input plant images and acquiring accurate disease identification. The GDCR-DM is designed with the novelty of Gaussian trilateral filtering model, Czekanowski's dice similarity coefficient, Deming regression function, and tanh activation function to classify leaf image as normal or disease. The feed forward neural learning model employs four distinct processing steps in numerous layers. Initially, multiple plant leaf images are acquired from dataset. Then acquired images are sent to input layer where preprocessing is performed in the first hidden layer for image smoothening using Gaussian trilateral filtering model. Next with the purpose of identifying the region of interest, Czekanowski's dice region-based segmentation model is applied in the second hidden layer. Followed by which to extract essential features, Deming regression function is applied in the third hidden layer. Finally, features extracted are analyzed with the objective of classifying leaf image into normal or disease by means of activation function.

#### 3.1.1 Gaussian trilateral filtering and Czekanowski's dice region-based Segmentation

The feed-forward model of the network acquired input plant image '$pi_1, pi_2, pi_3, \ldots .pi_n$' in hidden layers and finally transformed into an output layer. The accuracy of performance was affected by using unnecessary noisy pixels. In our work, preprocessing is performed in the first hidden layer by means of Gaussian Distributive Trilateral that with the aid of Gaussian distribution function enhance the input image quality, paving means for accurate disease identification.

$$\text{(psi) } \Psi\left(c_{i,j}\middle|c_{nn}\right) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\left[\frac{1}{2\sigma^2}\left|c_{i,j}-c_{nn}\right|^2\right]} \quad (1)$$

From the above equation (1), '$\Psi\left(c_{i,j}\middle|c_{nn}\right)$' denotes the likelihood between center pixel '$c_{i,j}$' and neighboring pixels '$c_{nn}$' with the deviation denoted as '$\sigma$'. Maximum likelihood between center and neighboring pixels are represented as ordinary pixels and on the other hand, the pixel that diverges from center value is referred to as noisy pixels that are eliminated from further processing. From filtering window, noisy pixels are eliminated, therefore enhancing the peak signals to noise ratio. Next, to separate similar pixel characteristics in the second hidden layer, image segmentation is performed by employing Czekanowski's dice quantitative index. This is mathematically stated as given below.

$$(eta)\eta = 1 - 2 * \left[\frac{c_i \cap c_j}{c_i \cup c_j}\right] \quad (2)$$

From the above equation (2), Czekanowski's dice similarity coefficient is denoted by '$\eta$' with preprocessed pixel image denoted by '$c_i$' and adjacent pixel '$c_j$' with statistically mutual dependence of '$\cap$' and mutual dependence between pixels as '$\cup$'. The resultant similarity coefficient results in integer value ranging between 0 and 1. On the basis of the similarity value, similar pixel from input images is segmented. With this, the segmented region of interest is obtained in a computationally efficient manner.

#### 3.1.2 Deming regression and Activation-based classification

With the segmented extracted region of interest, to enhance disease identification rate or accuracy feature extraction is performed in the third hidden layer. With the presence of both local and global features, extracting them separately are said to be laborious process, therefore resulting in complexity. Here, Deming regression is utilized to identify the best-fit features using the following function.

$$R = \alpha_0 + \alpha_1 r_k \quad (3)$$

From the above equation (3), the regression output '$R$' is obtained utilizing the regression coefficients '$\alpha_0$' and '$\alpha_1$', segmented region '$r_k$' respectively. Finally, third hidden layer output provides the actual classification results. By using this function, the best features such as shape, color, and texture are identified and are transferred to the output layer. In this layer, in order to examine the extracted features and offer the classification outcomes, tanh

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activation function is employed. By applying this activation function, the variation amid extracted features and disease leaf feature.

$$\delta_f = \frac{(e^v - e^{-v})}{(e^v + e^{-v})} \quad (4)$$

From the above equation (4), $\delta_f$ represents a tanh activation function, '$v$' indicates variation between the two features. With investigating the variations, the activation function returns the two outcomes as '-1' and '+1'. Here '+1' symbolizes the image is classified as abnormal and '-1' designates the leaf image is classified as normal. Followed by, the out of sample error is evaluated as the differentiation among the expected and observed error.

$$Error_{os} = [Er]_{ep} - [Er]_{ob} \quad (5)$$

From the above equation (5), $Error_{os}$ denotes an out-of-sample error, $[Er]_{ep}$ is refers to the expected error, $E_{od}$ represents an observed classification error. When the observed error is maximum than the expected error, then the weights among the layers are updated and the process is repeated. Otherwise, the process gets stopped. This is aids to achieve the precise classification results with lesser error rate. The algorithmic process of the GDCR-DM is described as given below,

| Input: Plant leaf image database, plant leaf images ' $pi_1, pi_2, pi_3, \dots . pi_n$' |
|---|
| Output: Increase Plant leaf disease detection accuracy |
| Step 1: Begin<br>Step 2: Gather plant leaf images $pi_1, pi_2, pi_3, \dots . pi_n$ as input **….. input layer**<br>Step 3: For each plant leaf images $pi_i$<br>Step 4: Apply preprocessing technique -------- **first hidden layer**<br>Step 5: Arrange the pixels in the filtering window<br>Step 6: Take the center value<br>Step 7: Evaluate the likelihood between the center and neighboring pixels $\Psi(c_{i,j} \vert c_{nn})$<br>Step 8: Determine the noisy pixels and eliminate from the filtering window<br>Step 9: Obtain quality enhanced plant leaf image<br>**Step10: End for**<br>Step 11: For each preprocessed image $pi_i$<br>Step 12: Compute the similarity between pixel in the preprocessed image '$c_i$' and adjacent pixel '$c_j$' **…… second hidden layer**<br>Step 13: Discover Czekanowski's dice similarity coefficient '$\eta$'<br>Step 14: Segment image into dissimilar regions '$r_k$'<br>Step 15: Extract region of interest 'ROI'<br>Step 16: End for<br>Step 17: for each segmented region ' $r_k$'<br>Step 18: Examine the images regression output **….. third hidden layer**<br>Step 19: Extract the different features such as shape, color, texture feature<br>Step 20: End for<br>Step 21: Examine the features **…..output layer**<br>Step 22: If $(\delta_f = +1)$ then<br>Step 23: Image is categorized as 'abnormal or disease affected'<br>Step 24: else<br>Step 25: Image is categorized as 'normal'<br>Step 26: End if<br>Step 27: Estimate out-of-sample error rate<br>Step 28: If ( $arg\ min\ Error_{os}$) then<br>Step 29: Stop the process<br>Step 30: else<br>Step 31: update the weights between layers<br>Step 32: Repeat the process |

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| |
|---|
| **Step 33: End if**<br>**End** |

**Algorithm 1** Gaussian Distributive Czekanowskis Region-based Deming Regression

Algorithm 1 demonstrates the step-by-step algorithmic processes of the proposed GDCR-DM. Initially, in the input layer, the plant leaf images are collected from the dataset. The filtering technique is employed in the first hidden layer for eliminating the redundant noisy pixels. Therefore, the quality of enhanced images is obtained and sends to the second hidden layer. The segmentation is carried out in the second hidden layer to split the images into a number of regions. Deming regression is employed to carried out feature extraction in the third hidden layer. The features such as shape, color, texture are extracted and it transferred to the output layer. The tanh activation function is utilized to examine the extracted features with the normal leaf features. According to the tanh activation function value, the proposed DCR-DM accurately matches each of the images as abnormal or normal. Once the classifier obtained lesser error, the process gets stopped. Otherwise, the weights among the layers are updated. Then, the process is iterated.

### 3.2 Covariance Kalman Geometric Graph-based Bernoulli Classifier (CKGG-BC):

The proposed CKGG-BC is performed to discover the plant leaf disease. The proposed CKGG-BC framework consists of three parts. The CKGG-BC is designed with the innovation of Covariance Kalman Filtered Preprocessing model, Geometric Graph-based Segmentation, co-occurrence matrix and Bernoulli Online Multiple Kernel Learning Classifier model for plant leaf disease identification. First, the preprocessing model used for enhancing plant leaf images. Next, Feature Extraction is performed to extract the leaf region and division of impure leaf region in accurate manner. Finally, the classification error is reduced, by using Classifier model.

#### 3.2.1 Kalman Filter preprocessing and Graph-based Segmented Co-occurrence Feature Extraction

Initially, state equation of plant leaf images is utilized in this model to estimate leaf image state. With the presence of noise and interference, optimal estimate is made using Kalman filter via state equation and observation equation to perform preprocessing. Followed by, the population covariance matrix is achieved as given below.

$$\mu = Mean[PL] = \begin{Bmatrix} \mu_1 \\ \mu_2 \\ \dots \\ \mu_n \end{Bmatrix}; \Sigma = \mathrm{COV[PL]} = \mathrm{Mean}\ [(\mathrm{PL_S} - \mu)(\mathrm{PL_{Ob}} - \mu)] = \begin{pmatrix} \sigma_{11}\sigma_{12} \dots & \sigma_{1n} \\ \sigma_{21}\sigma_{22} \dots & \sigma_{2n} \\ \dots & \dots \\ \sigma_{n1}\sigma_{n2} & \sigma_{nn} \end{pmatrix} \quad (4)$$

From above equation (4), covariance to obtain preprocessed images are obtained based on plant leaf state vector '$\mathrm{PL_S}$', plant leaf observation vector '$\mathrm{PL_{Ob}}$', mean value '$\mu$' respectively. Next, feature extraction process is split into two sections, region of interest identification and feature extraction. To identify region of interest, Geometric Pixel Graph-based model is applied to preprocessed images as given below.

$$SI = D(S_c, S_{sd}) = \begin{cases} True, If\ Diff\ (S_c, S_{sd}) > MID(S_c, S_{sd}) \\ False, Otherwise \end{cases} \quad (5)$$

From the above equation (5), the segmented images are obtained based on preprocessed color segmented leaf image '$S_c$' and preprocessed spatial distributed segmented leaf image '$S_{sd}$'. Followed by which the actual feature extraction is performed employing co-occurrence matrix. With the geometric leaf image infected portions are extracted accurately with good true positive rate.

#### 3.2.2 Bernoulli Online Multiple Kernel Learning Classification model

Lastly, the objective of increasing leaf prediction and extracting leaf images with minimum error, classification is developed. The model initially learns the classifier for kernel or segmented infected plant leaf images, then integrates the classifiers using linear weights. For every single kernel classifier, the number of segmented impure image is limited with reduce the false positive rate. With this objective, optimal kernel collections are estimated for each segmented region of interest image on the basis of Multiple Kernel Learning. Followed by which to minimizing

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classification error, rather than employing traditional Kernel Learning Classifier, Bernoulli trial is employed, therefore corroborate the objective. The algorithmic steps of the CKGG-BC are illustrated below in algorithm 2.

| |
|---|
| **Input**: Plant leaf image database, plant leaf images '$PI = pi_1, pi_2, pi_3, \dots . pi_n$' |
| **Output**: Correct plant leaf disease prediction with lesser classification error |
| **Step 1: Begin**<br>Step 2: **Fo**r each plant leaf images<br>Step 3: Measure state equation and the observation equation<br>Step 4: Measure state vector and the observation vector<br>Step 5: Attain principal component with mean and variance<br>Step 6: Attain covariance between the two vectors<br>Step 7: Obtain overall covariance<br>Step 8: Update state estimation<br>**Step 9: End**<br>Step 10: **For** each preprocessed plant leaf image<br>Step 11: Calculate channel information (i.e., color and spatial distribution)<br>Step 12: Find region of interest<br>Step 13: Perform graph-based segmentation based on color and spatial distribution<br>Step 14: Calculate infected leaf image<br>**Step 15: End**<br>**Step 16: Initialize** Threshold, kernel functions<br>Step 17: **For e**ach input vector<br>Step 18: Obtain obtaining the optimal collections of '$m$' kernels<br>Step 19: For each new segmented non-infected image<br>Step 20: Perform Bernoulli trial<br>Step 21: Perform classification with optimal margin classification error<br>**Step 22: Return** (plant leaf disease detection)<br>**Step 23: End for**<br>**Step 24: End for**<br>**End** |

**Algorithm 2** Covariance Kalman Geometric Graph-based Bernoulli Classifier

Algorithm 2 describes the step-by-step process of the CKGG-BC to correctly predict the plant leaf disease with minimal classification error. Initially, Covariance Kalman Filtered Preprocessing model is utilized to enhance the plant leaf images. Next, feature extraction process is used to extract the geometric properties of the infected leaf areas with higher accuracy and true positive rate. Then, the Multiple Kernel Learning is utilized to measure the optimal collections of '$m$' kernels. Finally, the Bernoulli trial is used to perform the classification with lesser error.

### 3.3 Gaussian Gray Level Geometric Neural Network Classifier (IGGL-GNNC)

Finally, Independent Gaussian Gray Level Geometric Neural Network Classifier (IGGL-GNNC) for plant leaf disease prediction is proposed. The IGGL-GNNC is designed with the innovation of Gaussian function, Gamma Correction function, and Sine Cosine Position Update Predictor Neural Network classifier to find the plant leaf disease. Three parts are involved in the IGGL-GNNC framework, namely, preprocessing using Independent Component Gaussian Median Preprocessing model, feature extraction using Gamma Corrected Gray Level Run Length Feature Extraction model and finally, classification using Sine Cosine Position Update Predictor Neural Network classifier.

#### 3.3.1 Independent Component Gaussian Preprocessing and Gamma Corrected Feature Extraction

The Independent Component Gaussian Preprocessing splits numerous plant leaf images into additive subcomponents. Then, with the purpose of improving image portions while identifying independent components Gaussian function is applied to respective plant leaf image. During the preprocessing, a small portion of impulse noise is said to contaminate image, therefore compromising the image quality. To address this issue, hybrid median filtering model based on the independent components are applied. Then, the respective output is mathematically stated as given below.

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$$O(p,q) = \sum_{a=p-W}^{p+W} \sum_{b=q-W}^{q+W} W(a,b) * f(a,b) \tag{6}$$

From the above equation (6), the output value '$O$' is obtained based on the respective weight '$W$' of independent components '$a, b$' and the gray value '$f$' of independent components '$a, b$' respectively, therefore obtaining preprocessed leaf images. However, with radiance changes, plant leaf image differs diligently in appearance, therefore complicating the disease identification process. To concentrate on this issue, geometric properties for extracting robust features employing Gamma Corrected Gray Level Run Length Matrix is used that with the aid of gamma corrected gray pixel pair ensures accurate segmented feature extraction.

### 3.3.2 Sine Cosine Neural Network classifier model

Finally, with the entire feature set extracted, position update is performed by utilizing sine cosine function. With the purpose of predicting the infected plant leaf, with the position of the infected plant leaf subjected to the classifier model, the sine cosine function is mathematically stated as given below.

$$Pos_i^{t+1} = \begin{cases} Pos_i^t + rv_1 \sin(rv_2) * [rv_3 Pos_t(a,b) - Pos_i^t];\ rv_4 < 0.5 \\ Pos_i^t + rv_1 \cos(rv_2) * [rv_3 Pos_t(a,b) - Pos_i^t]; rv_4 \geq 0.5 \end{cases} \tag{7}$$

From the above equation (7), '$rv_1, rv_2, rv_3, rv_4$ ' refers to the arbitrary or random variables ranging between '$[0,1]$', the position of the infected plant leaf image at time '$t$' for '$i - th$' iteration '$Pos_i^t$' is obtained, therefore ensuring optimal classified results. Finally, the plant leaf disease prediction with plant leaf images is performed to identify the presence of any disease and if so to inform for timely solution. With plant leaf disease detection, accurate analysis is said to be made in a timely manner. With the detected or the infected plant leaf images at an early stage, further deterioration can be avoided. The algorithmic description of proposed Independent Gaussian Gray Level Geometric Neural Network Classifier is described in following algorithm.

| |
|---|
| Input: Plant leaf image database, plant leaf images '$PI = PI_1, PI_2, PI_3, \ldots . PI_n$' |
| Output: Error-minimized, accurate and timely plant disease identification |
| **Step 1: Initialize** gray value of the plant leaf image '$f(a,b)$'<br>Step 2: **Initialize** radiance '$Rad_{PPI}(p,q)$', reflectance '$Ref_{PPI}(p,q)$'<br>Step 3: **Begin**<br>**Step 4:** **For** each plant leaf images '$PI$'<br>Step 5: Split plant leaf images '$PI$' into independent components<br>Step 6: **For** each independent components<br>Step 7: Calculate weight for each independent components<br>Step 8: Calculate output value of central pixel for each independent components<br>Step 9: Calculate similarity found from each independent components to eliminate impulse noise<br>Step 10: **End for**<br>Step 11: Estimate Gamma corrected image based on product of radiance and reflectance of the pre-processed image<br>Step 12: Evaluate maximum and minimum gray length<br>Step 13: Obtain features extracted (maxgraylength, mingraylength)<br>Step 14: Evaluate predictor neural network classifier using bias of hidden layer, bias of output layer and weight of output layer<br>Step 15: Evaluate sine cosine function for each extracted plant leaf image features<br>Step 16: **Return** classified results<br>Step 17: **End for**<br>Step 18: **End** |

**Algorithm 3 Independent Gaussian Gray Level Geometric Neural Network Classifier**

The algorithmic process of proposed IGGL-GNNC framework is designed in the above algorithm 3. It explains plant leaf disease identification and prediction at an early stage. Let us consider the number of plant leaf images. After that, Independent Component Gaussian Median Preprocessing is applied to obtain node reduced plant leaf images. In addition, Gamma Corrected Gray Level Run Length Feature Extraction model is applied to segment accurate region of interest. Sine Cosine Position Update Predictor Neural Network uses to segment and extract plant leaf images. The IGGL-GNNC determines the accurate plant leaf illness and reduces the error.

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## 4. Experimental section

Simulation analysis on different proposed frameworks, such as GDCR-DM, CKGG-BC and IGGL-GNNC for plant disease prediction is carried out by implementing in the Python tool. For implementation, the configuration settings of PC are performed with windows 10 OS, 4 GB RAM, and Intel I3 processor. To conduct experimental evaluation, Plant Village Dataset is used for Plant leaf Disease Detection. The dataset is taken from the https://www.kaggle.com/emmarex/plantdisease/discussion. This dataset includes a variety of plant's RGB plant leaf images namely pepper, potato, tomato, with dissimilar sizes. The dataset consists of leaf organ in addition to its ground truth value. It includes 38 types of species and infection with a total of 54,303 normal and abnormal leaf images.

## 5. Comparison Analysis

Different proposed framework and existing automatic tassel detection [1] and Inception – Visual Geometry Group Network (INC-VGGN) [2] is compared in this section. Here, the simulation is conducted on parameters namely disease identification accuracy, sensitivity, false positive rate and processing time.

### 5.1 Disease identification accuracy

One of the paramount metric in plant disease identification is the disease identification accuracy. It refers to the accuracy level obtained while identifying plant leaf disease. It is computed in percentage (%) and expressed as follows,

$$Acc = \left[\frac{n_{cc}}{n}\right] * 100 \tag{8}$$

From the above equation (8), '$Acc$' denotes the accuracy, '$n$' represents the number of leaf images, and '$n_{cc}$' indicates the plant leaf images correctly classified to be normal as normal or diseased as diseased.

**Table 1 Tabulation for disease identification accuracy**

| Number of images | Disease identification accuracy (%) | | | | |
|---|---|---|---|---|---|
| | Proposed IGGL-GNNC | Proposed CKGG-BC | Proposed GDCR-DM | Existing automatic tassel detection | Existing INC-VGGN |
| 20 | 85 | 80 | 72 | 69 | 63 |
| 40 | 85.25 | 82.15 | 73.5 | 70.5 | 64.15 |
| 60 | 86 | 83 | 75 | 71 | 66 |
| 80 | 86.15 | 83.15 | 76.15 | 72.15 | 68.5 |
| 100 | 86.55 | 84 | 77 | 73 | 69 |
| 120 | 87.35 | 85 | 78 | 75.45 | 69.5 |
| 140 | 88 | 85.45 | 80.15 | 77 | 70 |
| 160 | 88.45 | 86.15 | 82.45 | 78.15 | 72.15 |
| 180 | 90 | 87 | 86 | 80 | 75 |
| 200 | 92 | 90 | 88 | 85 | 79 |

Table 1 show the experimental result of disease identification accuracy occurred during classifying input plant leaf images. In table 1, the numbers of plant leaf images is used range of 20 to 200 for proposed and existing frameworks. In all the frameworks, the input images is increased, then, disease identification accuracy neither increases nor decreased. From the tabulated values, proposed IGGL-GNNC framework, CKGG-BC framework and GDCR-DM framework is compared with other existing frameworks such as automatic tassel detection [1] and INC-VGGN [2]. From the result of experimental work, proposed IGGL-GNNC framework resulted with maximum disease

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identification accuracy of plant leaf disease identification. With help of above table values, the graph is presented below to estimate the performances of proposed frameworks.

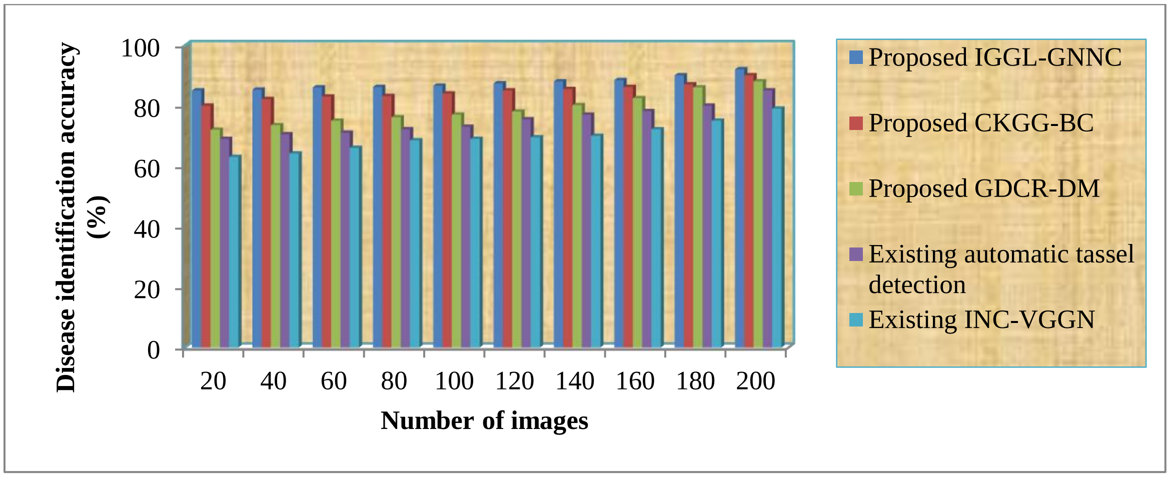


**Figure 2 Graphical representation of plant disease identification accuracy**

Figure 2 demonstrates the plant disease identification accuracy for proposed and existing methods. As shown in the above figure, accuracy rate using the proposed frameworks provides better performance. Moreover, while increasing the number of plant leaf images, the accuracy taken to classify the plant leaf images also varies. For example, 20 different plant leaf images are considered from dataset for experimental purpose. From the performance analysis, existing automatic tassel detection [1] and INC-VGGN [2] obtains 69% and 63% of accuracy, whereas 85%, 80% and 72% is achieved in proposed IGGL-GNNC framework, CKGG-BC framework and GDCR-DM framework. From the result, proposed IGGL-GNNC framework achieves better results of plant leaf disease identification accuracy. By applying Independent Component Gaussian Median Preprocessing model only after image enhancement and preprocessing, further process is carried out. This in turn improves the plant leaf disease identification accuracy using upon IGGL-GNNC framework. Consequently, IGGL-GNNC framework, CKGG-BC framework, and GDCR-DM framework is enhanced by 21%, 17%, and 9% respectively than the existing works. Therefore, accuracy rate for plant leaf disease identification using IGGL-GNNC framework obtains better result when compared with existing method such as automatic tassel detection [1] and INC-VGGN [2].

### 5.2 Sensitivity

The sensitivity is second importance parameter. In other words, sensitivity is referred to as the potentiality of a screening test to detect a true positive, i.e., plant leaf disease correctly detected.

$$Sen = \sum_{i=1}^{n} \frac{TP}{TP+FN} * 100 \quad (9)$$

In equation (9), '$Sen$' denotes the sensitivity, '$TP$' represents the true positive rate '$TP$' (plant leaf disease correctly detected) and false negative '$FN$' (i.e., incorrectly plant leaf disease detected) respectively.

**Table 2 Tabulation for sensitivity**

| **Number of images** | **Sensitivity (%)** | | | | |
|---|---|---|---|---|---|
| | Proposed IGGL-GNNC | Proposed CKGG-BC | Proposed GDCR-DM | Existing automatic tassel detection | Existing INC-VGGN |
| **20** | 84 | 77 | 71 | 68 | 66 |
| **40** | 84.15 | 78.55 | 71.15 | 69.35 | 66.45 |
| **60** | 85 | 80 | 72 | 70 | 67 |
| **80** | 85.85 | 81.45 | 73.55 | 71.55 | 67.55 |

| | | | | | |
|---|---|---|---|---|---|
| **100** | 86 | 82 | 74 | 72 | 68 |
| **120** | 86.45 | 83.15 | 76.35 | 73.15 | 68.45 |
| **140** | 87 | 84 | 77 | 74 | 69 |
| **160** | 87.15 | 85.45 | 78.15 | 75 | 70 |
| **180** | 88 | 85 | 79 | 75.25 | 71.25 |
| **200** | 91 | 86 | 81 | 76 | 72 |

The above table lists out the performance results of sensitivity. The different proposed frameworks according to distinct plant leaf images as illustrated in table 2. For experimental purpose, distinct plant leaf images are considered in the range of 20 to 200. Followed by, the sensitivity also correspondingly varies in all the other frameworks and methods as growing the number of input plant leaf images. From the experimental analysis, IGGL-GNNC framework attains enhanced sensitivity than the existing methods namely automatic tassel detection [1] and INC-VGGN [2] respectively. Based on the above table values, the graphical representation is as shown in below figure to analyze proposed performances.


**Figure 3 Graphical representation of sensitivity**

The experimental result analysis of sensitivity with respect to distinct plant leaf images is illustrated in above figure 3. The figure shows comparison result of proposed IGGL-GNNC framework, CKGG-BC framework and GDCR-DM framework with existing automatic tassel detection [1] and INC-VGGN [2] method. For example, let us consider 20 plant leaf images for experimental purpose. From the experimental result existing automatic tassel detection [1] and INC-VGGN [2] obtains 68% and 66% of sensitivity, whereas 84%, 77% and 71% is achieved in proposed IGGL-GNNC framework, CKGG-BC framework and GDCR-DM framework. The IGGL-GNNC framework achieves improved performance of sensitivity. This is because of performing Independent Component Gaussian Hybrid Median Filter algorithm. By employing the Independent Component Gaussian function and Filtering less significant image portions are eliminated from further processing, therefore improving sensitivity. Therefore, IGGL-GNNC framework improves sensitivity by 23%, CKGG-BC framework by 17% and GDCR-DM framework by 7% than the conventional approaches. Therefore, IGGL-GNNC achieves efficient sensitivity rate result while comparing with other methods namely automatic tassel detection [1] and INC-VGGN [2].

### 5.3 False positive rate

The third parameter of false positive rate is utilized in measuring the plant leaf disease identification. It is defined as the number of input plant leaf images is wrongly detected to the total plant leaf images and it computed in percentage (%).

$$FPR = \left[\frac{n_{ic}}{n}\right] * 100 \tag{10}$$

In equation (10), '$FPR$' indicates the false positive rate, and '$n_{ic}$' is refers to the number of images wrongly categorized.

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**Table 3 Tabulation for false positive rate**

| Number of images | False positive rate (%) | | | | |
|---|---|---|---|---|---|
| | Proposed IGGL-GNNC | Proposed CKGG-BC | Proposed GDCR-DM | Existing automatic tassel detection | Existing INC-VGGN |
| **20** | 4.85 | 5 | 8 | 10 | 12 |
| **40** | 5 | 7.5 | 10 | 12.5 | 15 |
| **60** | 5.15 | 7.95 | 10.35 | 12.15 | 14.15 |
| **80** | 5.35 | 8 | 10.85 | 12 | 13.55 |
| **100** | 5.85 | 8.35 | 11 | 11.55 | 13.15 |
| **120** | 6 | 10 | 11.35 | 12.55 | 14 |
| **140** | 5.55 | 9.15 | 11 | 12 | 13.15 |
| **160** | 5.15 | 8.45 | 10.85 | 11.35 | 12 |
| **180** | 6 | 8 | 10 | 11 | 12.55 |
| **200** | 6.35 | 8.85 | 10.35 | 11.65 | 13 |

The comparison of false positive rate are described in table 3 based on the input plant leaf images. Moreover, comparison results of false positive rate with proposed and existing methods are presented above. Here, the proposed IGGL-GNNC framework, CKGG-BC framework and GDCR-DM framework is compared with the existing automatic tassel detection [1] and INC-VGGN [2] respectively. With the aid of above table values, the graphical representation is portrayed in below figure for performances analysis of proposed frameworks.

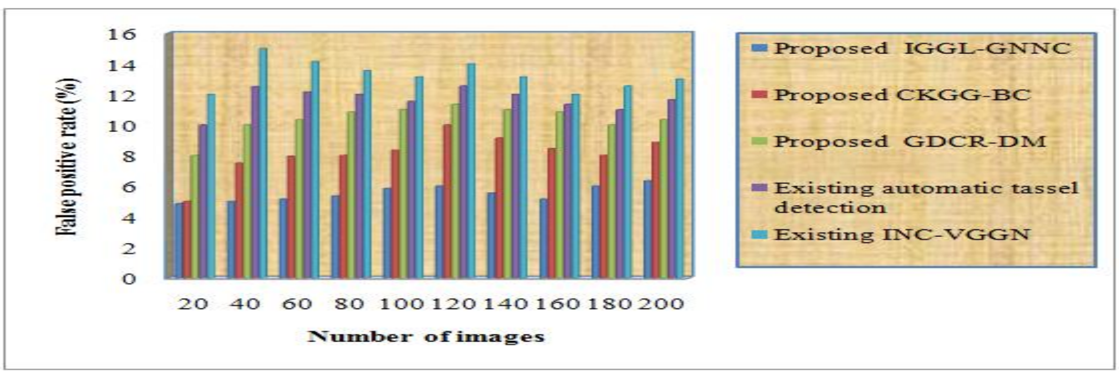


**Figure 4 Graphical representation of false positive rate**

The performance analysis of false positive rate is shown in figure 4. The proposed IGGL-GNNC framework, CKGG-BC framework and GDCR-DM framework with existing automatic tassel detection [1] and INC-VGGN [2] methods is considered in above figure. To conduct fair comparison between the frameworks and methods, sample plant leaf images in the range of 20 to 200 was considered. Here, 20 sample plant leaf images are considered for example to show experimental performance result. From the performance analysis, existing automatic tassel detection [1] and INC-VGGN [2] obtains 10% and 12% of false positive rate, whereas 4.855, 5% and 8% of false positive rate is achieved using proposed IGGL-GNNC framework, CKGG-BC framework and GDCR-DM framework. From the figure, proposed IGGL-GNNC framework reduces the false positive rate than other methods. The reason behind the improvement in the false positive rate is due to the application of Gamma Corrected Gray Level Run Length Feature Extraction model. By applying this model, with the plant leaf pre-processed images, Gamma corrected image is estimated and only using the corrected image, further region of interest segmentation is performed. As a result, the proposed IGGL-GNNC framework, CKGG-BC framework, GDCR-DM framework reduced by55%, 35%, 16% as

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compared to the traditional works. Therefore, IGGL-GNNC framework achieves minimum false positive rate while comparing with other methods namely automatic tassel detection [1] and INC-VGGN [2].

### 5.4 Processing time

Finally, processing time involved in plant leaf disease identification is made. The processing time here refers to the time consumed in processing the plant leaf images for identification of disease, i.e., either affected or not affected with disease. The processing time is estimated in milliseconds (ms) and mathematically stated as given below.

$$PT = \sum_{i=1}^{n} PI_i * Time\ [LDD] \tag{11}$$

In equation (11), '$PT$' symbolizes the processing time, ''$Time\ [LDD]$' indicates time taken to predict the leaf disease', and '$PI_i$' represents the plant leaf images

**Table 4 Tabulation for processing time**

| **Number of images** | **Processing time (ms)** | | | | |
|---|---|---|---|---|---|
| | Proposed IGGL-GNNC | Proposed CKGG-BC | Proposed GDCR-DM | Existing automatic tassel detection | Existing INC-VGGN |
| **20** | 7 | 11 | 12 | 17 | 21 |
| **40** | 8.25 | 11.45 | 12.15 | 18.55 | 25.55 |
| **60** | 8.55 | 11.85 | 12.65 | 19.35 | 27.25 |
| **80** | 8.95 | 12 | 13.15 | 19.95 | 28 |
| **100** | 9.35 | 12.35 | 13.55 | 21.45 | 28.35 |
| **120** | 9.95 | 12.05 | 14 | 23 | 28.55 |
| **140** | 10.25 | 12.45 | 14.7 | 24.35 | 29.95 |
| **160** | 10.75 | 13 | 15.35 | 27 | 30 |
| **180** | 11 | 13.85 | 16 | 29.55 | 31.35 |
| **200** | 11.35 | 14.35 | 16.15 | 31.35 | 35.45 |

Table 4 indicates the complete evaluation outcomes of the processing time regarding the numbers of plant leaf images in the ranging between 20 and 200 images. Followed by, time consumed in extraction and segmentation increases, therefore increasing the time consumed in plant leaf disease identification in all the methods though improving the plant leaf image results. Here, above table provides the comparison of IGGL-GNNC framework, CKGG-BC framework and GDCR-DM framework with existing methods namely automatic tassel detection [1] and INC-VGGN [2]. Therefore, processing time using IGGL-GNNC framework provides efficient result as compared to conventional techniques.

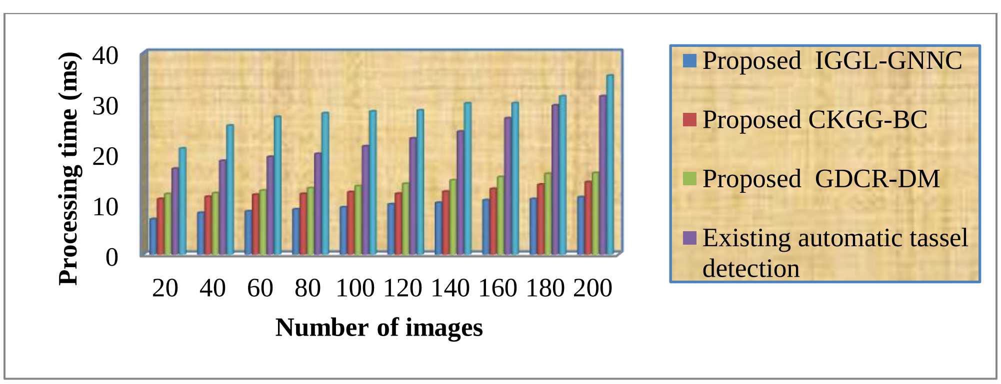


**Figure 5 Graphical representation of processing time**

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Finally, the above figure 5 illustrates the experimental analysis of processing time based on different sample plant images for performing experimental purpose. Figure shows the comparison of proposed IGGL-GNNC framework, CKGG-BC framework and GDCR-DM framework with existing automatic tassel detection [1] and INC-VGGN [2]. For example let us consider 20 sample plant leaf images for experimental performance. From the performance result, existing automatic tassel detection [1] and INC-VGGN [2] obtains 17 ms and 21 ms of processing time, whereas 7ms, 11ms and 12ms is achieved in proposed IGGL-GNNC framework, CKGG-BC framework and GDCR-DM framework. From above figure, IGGL-GNNC framework results with minimum processing time than the other proposed frameworks and existing methods. The proposed IGGL-GNNC framework uses Sine Cosine Position Update Predictor Neural Network classifier algorithm for detecting plant leaf disease. By using this algorithm, position updates based on the geometrical features (i.e., sine and cosine functions) are utilized for classifying therefore reducing the processing time to a greater extent. Hence, processing time is reduced by 62% in proposed IGGL-GNNC framework, CKGG-BC framework reduced by 51% and GDCR-DM framework reduced by 45% when compared with other methods. From the result analysis, IGGL-GNNC framework provides efficient result of processing time than existing automatic tassel detection [1] and INC-VGGN [2].

## 6. Conclusion

In this research, different proposed methods such as IGGL-GNNC framework, CKGG-BC framework and GDCR-DM framework is developed to predict the plant leaf disease by extracting accurate ROI segments with minimum false positive rate and time. Therefore, the plant leaf disease detection performance is enhanced. With the process of noise minimized enhanced image and segmentation models, proposed work are performed. Thus, it provides better plant leaf detection by classifying plant leaf images with minimum time utilization. Initially, IGGL-GNNC framework is proposed for plant leaf disease identification. The Gaussian distributive trilateral filtering technique is carried to perform preprocessing for enhancing image quality. With the preprocessed images, Czekanowski's dice indexive region-based segmentation technique is applied to find region of interest. Thus, minimum processing time and is ensured during detection. Next, CKGG-BC framework is proposed for plant leaf disease detection by applying Covariance Kalman Filtered Preprocessing for image enhancement from Plant Village dataset. With the preprocessing images, the impure leaf areas are accurately segmented, by using Geometric Graph-based Segmented Co-occurrence Feature Extraction. Then, Bernoulli Online Multiple Kernel Learning Classifier utilized for predicting plant leaf disease .After that, Bernoulli Online Multiple Kernel Learning Classifier is utilized to predict the plant leaf disease. Finally, GDCR-DM framework is explained to identify plant leaf disease with maximum accuracy. The Independent Component Gaussian Median Preprocessing model preprocesses the plant leaf images by focusing on the noise aspect. With the preprocessed images, a Gamma Corrected Gray Level Run Length Feature Extraction is utilized to obtain accurate ROI segmentation. Thus the plant leaf images are significantly detected by classifying with minimum error. From the simulation result, proposed frameworks reduce the processing time taken to detect plant leaf disease with minimum false rate.

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