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A Hybrid IHGT–Mask R-CNN Framework for High-Accuracy Plant Disease Identification

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Abstract

The model used in the study is centered on early identification of infection inflicting on leaves and the accurate division of the areas that are affected. To do it, a combined approach of Mask R-CNN and the Improved Histogram Generalization Technique (IHGT) is suggested. The preprocessing pipeline uses several convolutional networks that include five major stages, an input layer, three intermediate enhancement layers and a final output layer. The enhancement layers are aimed at improving the visual appearance of images of plant leaves by reducing noise, fixing non-clarity pixels and making the featured images look more appropriate. IHGT enhances the contrast and light consistency of the leaf images so that the network is able to detect minute patterns of diseases at an early stage of infection. The Mask R-CNN, after being improved, uses the instance segmentation to ensure that the diseased areas of every leaf are isolated perfectly. The Kaggle Plant Disease data is used to test the proposed approach and the hybrid approach proves to be effective in predicting the labeled disease classes at a better level of precision. The model can provide a powerful platform to detect early and precise plant diseases with the combination of the benefits of both modern image enhancement and deep segmentation. The proposed framework is tested on the public PlantVillage dataset containing around 54,000 images of 38 plant disease classes. With 97% overall accuracy, notable improvements in Precision, Recall, F1-score and mAP demonstrate the model's performance as both a classifier and segmentation unit. This marks the first time the Improved Histogram Generalization Technique (IHGT) has been implemented in Mask R-CNN specifically designed to work under low-contrast, noisy and real-world agricultural imaging conditions.

1. Introduction

Significant part of precision agriculture, it is impossible to imagine the way of how to enhance food security in the world without plant disease detection. The timely detection of foliar disease assists in reducing crop losses, reducing inappropriate application of pesticides and making decisions in the administration of the farm. The conventional disease surveillance tools such as visual assessment by the agronomists are usually cumbersome, subjective, and in-scaling particularly in big agricultural areas. Such constraints have increased the pace of the creation of automated methods of plant disease detection based on computer vision and deep learning. Large, annotated databases like the PlantVillage database have further led to advances in blistering and have become the standard by which to evaluate the performance of the models [1], [2].

The image-based plant disease recognition has been revolutionized by deep learning architecture, especially Convolutional Neural Networks (CNNs) because it can extract multi-scale spatial functionality directly out of the pixel intensity. The higher efficiency of CNN models in plant disease classification problems, such as ResNet and Inception or EfficientNet families, has been confirmed in several studies [3], [4], [5]. The compound-scaling approach by EfficientNet has demonstrated good accuracy-efficiency trade-offs, and is commonly used to classify leaf diseases in a variety of species [3]. CNN-based systems are found to be much better than those of handcrafted-feature systems and the matter of deep learning has become the benchmark in automated plant pathology.

Despite advances in deep learning-based detection of plant diseases, there are still many challenges that remain unresolved. Model performance is affected by factors such as poor illumination, low contrast, background noise and occlusion common to agricultural images. In addition, most existing methods are mainly proposed for classification without precise localization of diseased areas. This limitation hinders their interpretability and limits their applicability in real-world precision agriculture systems, where accurate lesion identification is critical for early diagnosis and targeted intervention.

Although CNN image-level classifiers are useful in identifying disease types, they do not have the capacity to identify the localization of the injured areas. The given limitation is the most important since disease severity, differentiation between similar symptoms, and high-interpretability systems are impossible to rely on without effective localization of lesions. The most commonly employed instance segmentation architecture is the Mask R-CNN, which has proven to provide effective results to extract pixel-level disease masks. Its capability of detection and high-quality segmentation boundaries has resulted in applications that are successful in the fields of agricultural imaging [6], [7], and [17]. It is empirically shown that when extensive mapping of the leaf symptoms is needed, instance segmentation outperforms classification-only models particularly where field conditions tend to find occlusion, cluttered backgrounds, and varying light conditions [6], [18], [19].

Agriculture presents the world with numerous imaging challenges such as uneven lights, low contrast, blur, noise, shadows, and partial occlusion. These states of affairs decrease the robustness of models and impede the detection of diseases at an early stage. Contrast limited histogram equalization, illumination normalization and adaptive histogram-based methods of the image enhancement techniques have demonstrated usefulness in alleviating these distortions [10]. Improved Histogram Generalization Technique (IHGT), contrast adaptive preprocessing, noise-reduction filters, etc. are techniques that enhance image clarity by exaggerating fine patches in lesion color and texture-patches, which are important in tasks of early detection. Research highlights that preprocessing can be used to have high segmentation and classification rates in conjunction with deep learning models [10], [12], [13].

Class imbalance is another significant issue in the plant disease classification, especially with rare diseases that have a small number of training examples. Generative Adversarial Networks (GANs) have been found to be an efficient way of generating artificial training samples to boost datasets and prevent overfitting. According to recent work, GAN-based augmentation is effective in enhancing the generalization of classifiers with respect to small data or uneven data distributions [8], [9]. It has been demonstrated that GAN-augmented pipelines can produce some of the most realistic lesion textures, which improved the performance of deep learning on a variety of crops.

Segmentation models have grown at a high rate, too. U-Net and its numerous derivatives (MultiResUNet, RMU-Net, UNet++, etc.) are still popular in biomedical and agricultural imaging segmentation [12], [13], [14], whereas the Mask R-CNN architecture is used when the detection of instances and object proposal are needed [17]. Lesion detection accuracy has also been boosted with extensions like RefineMask, small-object enhancement modules and multiscale feature extractors especially with the small or early-stage symptoms [16], [19].

The use of edge-computing systems has also received an interest in allowing real time monitoring of plant diseases in the field. As more low-power embedded systems are becoming available, scholars have come up with lightweight CNN and thermal-imaging-based disease-detection models that can be implemented on farms [6], [11]. In conjunction with IoT-based smart agricultural solutions, this possibility enables non-stop tracking of the environment and timely diagnosis of diseases [5] and eliminates the problem of connectivity in rural areas.

Based on these developments, this study proposes a hybrid framework that combines Improved Histogram Generalization Technique (IHGT) and an Enhanced Mask R-CNN (EnMask-R-CNN) model. IHGT enhances the clarity of the image by reducing noise and adapting it through the adaptive policy making the model to identify disease signs that may be unnoticed. The EnMask-R-CNN is a continuation of the Mask R-CNN and additionally centers on the optimization of the refining region proposal, multiscale mask, and superior boundary extraction. All these improvements facilitate effective identification of diverse plant diseases in natural environmental habitats.

To test our proposed system, publicly accessible datasets, like PlantVillage and field-collected samples, are used and compared to reliable baselines, such as EfficientNet classifiers [3], transfer learning and segmentation

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networks [12], [17], and hybrid optimization-based deep learning systems [20], [21], [22], and [23]. The findings show better localization of lesions, segmentation, and classification strength particularly with low contrast/noise samples on which traditional CNNs perform poorly.

Moreover, new optimization methods are added to the previous ones to enhance the convergence and performance of networks with optimizers like gray wolf, genetic algorithm and particle swarm optimization methods [21], [22], [23]. Nevertheless, such models are still difficult to properly segment when the imaging conditions are of low quality. To bridge this gap our solution will be based on adaptive pre-processing (IHGT) and segmentation-oriented deep learning (EnMask-R-CNN), which offers an effective and high-precision solution to the problem of both early and advanced-stage plant disease detection.

The greater strength and the good empirical results as well as scalability of the framework that is proposed evidence of its possible significant contribution to precision agriculture. These models can enhance healthier request attitudes in crop management, reduce yield degradation, and provide sustainable agricultural output by enhancing reliability of automatic detection of diseases, in both a smallholder and a large-scale farming setting.

This work aims to overcome such limitations by proposing a hybrid framework that utilizes the Improved Histogram Generalization Technique (IHGT) and then using Mask R-CNN for better plant disease detection and segmentation. The key contributions of this work can be summarized as follows:

i. A new hybrid framework that integrates adaptive image enhancement (IHGT) and instance segmentation (Mask R-CNN).
ii. Enhanced resistance to noise, light changes and low-contrast imaging scenarios.
iii. A better understanding of disease via accurate pixel-level localization of lesions.
iv. Detailed evaluation on standard metrics, including comparison with the state-of-the-art models.

2. A Hybrid IHGT–Mask R-CNN Framework

Table 1 gives a relative description of four generalized deep learning models, each: GoogleNet, MobileNet, AlexNet and ResNet based on their model complexity, depth and classification performance. The parameters assist in realizing the trade-offs among accuracy, computation condition, and model construction particularly in plant disease recognition and image processing applications. The values linked with GoogleNet are shown in Figure 1.

Table 1 *Reference of disease affected plants and its identification using CNN*

Model	No. of Features (M)	Total Layers	Top-1 Error (%)	Top-5 Error (%)
GoogleNet	55	18	16.4	4.62
MobileNet	27.4	45	21.48	5.34
AlexNet	7.6	88	19.7	4.5
ResNet	118	12	22.75	7.45

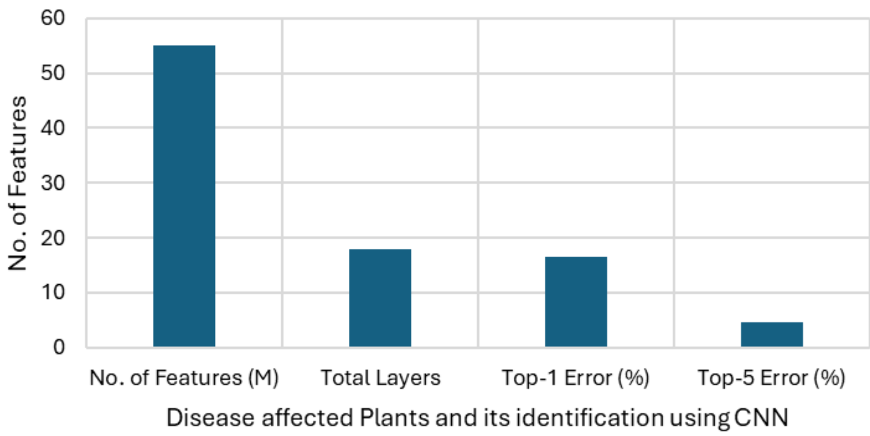

Fig. 1 *GoogleNet with its corresponding values*

MobileNet and its respective values are shown in figure 2. The Mobile net is designed in such a way that the dynamic changes can be indicated as the number of features are to be reduced according to the number of input neural networks and then by the continuous convnet with n numbers of hidden depth layers consisting into nets. The AlexNet and corresponding values are given in figure 3. This Architecture has 8 layers with numerous features built on the micro level observation of plants that can be padded to decrease the size of the feature maps.

Figure 4, ResNet44, depicts the values associated with ResNet. The vanishing gradient problem of the deep learning CNN based architecture ALexNet can then be solved in such a case where instantaneously these trainings and tests of multiple layers are also being introduced to achieve the error rate in the form of the percent (%).

To identify the label with an early spot may be uploaded as an image on a live camera or on a trained dataset. The proposed model divides the region and sliding locations and subsequently, features are tracked to go through the region proposal network (RPN). The undesired part is removed and sent to the subsequent layer in a way but adhering to the rule where the region of interest (RoI) is also monitored. The regressor box is presented in figure 5 that dimensionally reduces the 2D matrix. Table. Denotes the multi-class attributes which possess multiple images and original images, flipped images and cumulative correlation of portion highlighted. Table 2 shows the plant diseases and their types; infected areas applied with CNN.

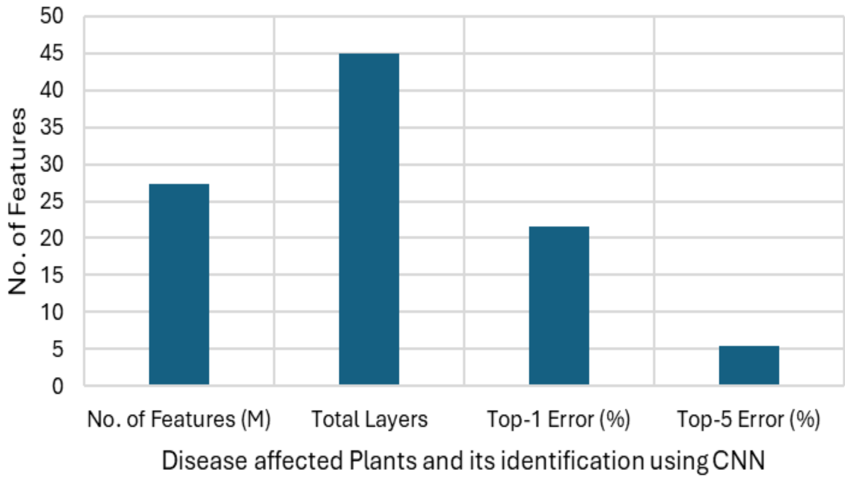

Fig. 2 *MobileNet with its corresponding values*

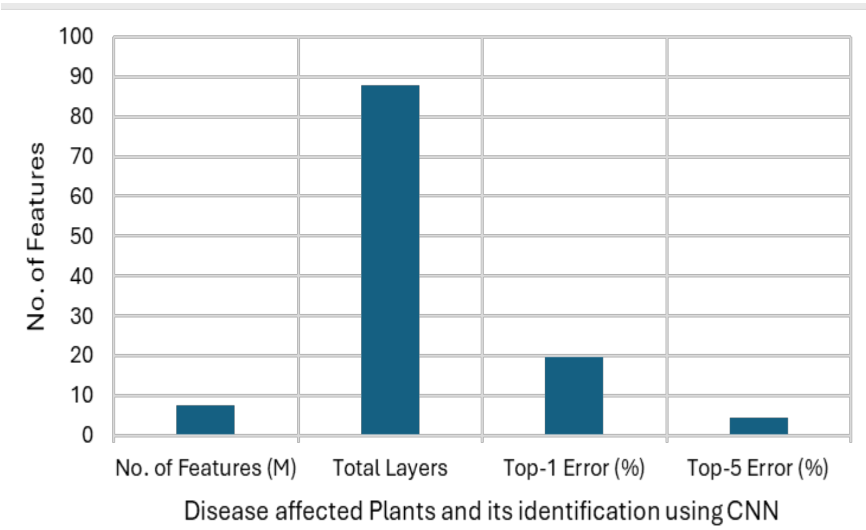

Fig. 3 *AlexNet with its corresponding values*

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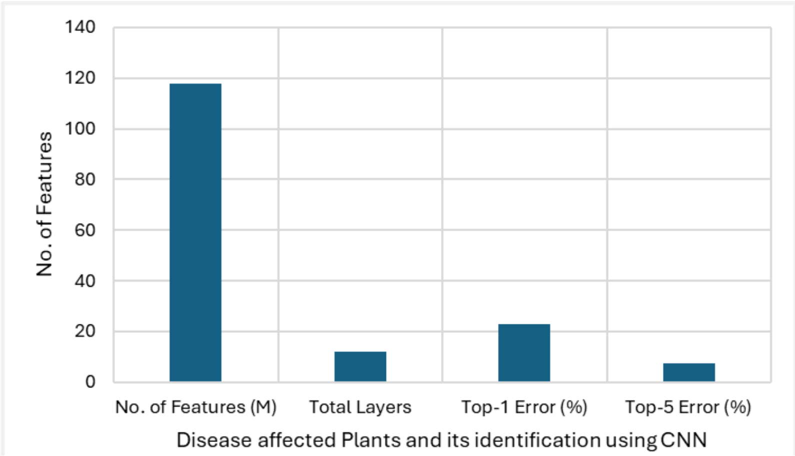

Fig. 4 *ResNet with its corresponding values*

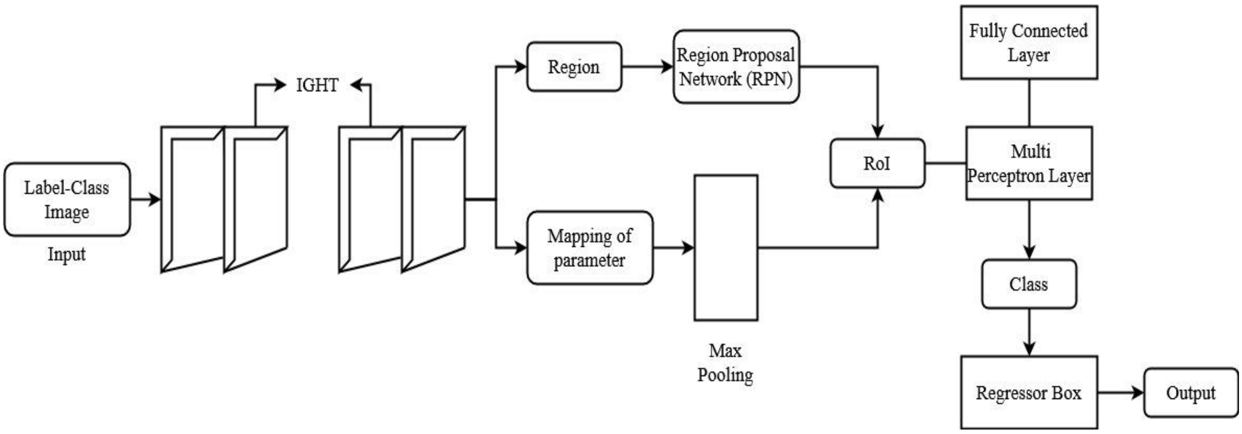

Fig. 5 *IHGT working model*

Table 2 *Various plant diseases and their types, infected areas applied with CNN*

Diseased Plant & Class	Total Images	Natural Leaf Images	Flipped / Rotated	Trained	Tested	Validated
Apple_Scab	1000	76	460	250	112	92
Cherry_Mildew	1052	65	520	230	148	89
Corn_Leaf_Blight	1000	85	540	190	115	75
Grape_Isariopsis	1076	125	470	250	140	87
Peach_Spot_Bacteria	2297	237	900	670	390	100

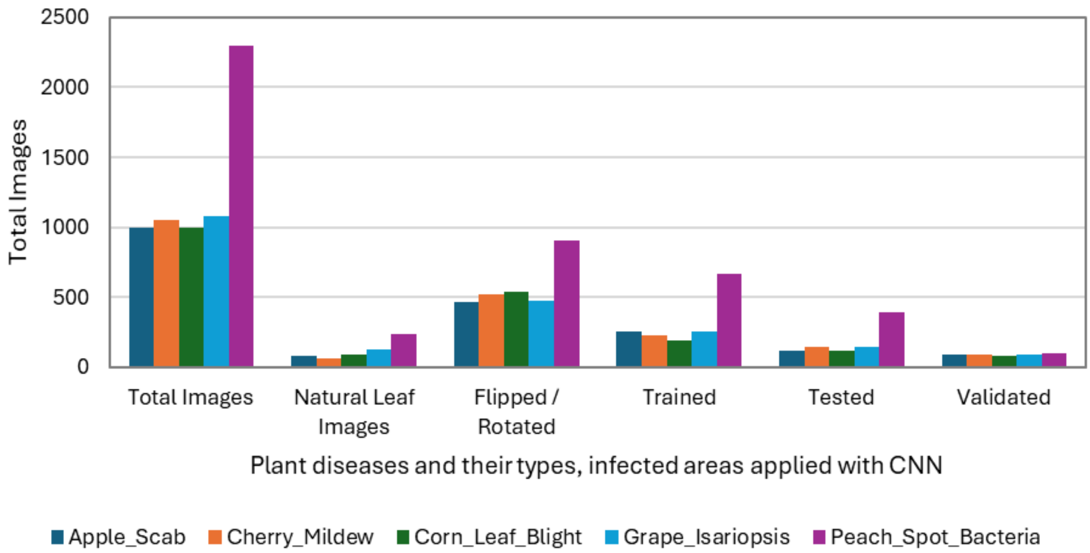

Fig. 6 *Plant diseases with infected areas*

The comparison of classes and number of epoch values of Plant disease is indicated in figure 6 to gain understanding of formation. The field of deep learning is inspired by the fact that the brain of humans is composed of multiple neurons to work effectively. CNN (Convolutional Neural Network) and RNN (Recurrent Neural Network) can be utilized to identify the hidden patterns in the data. Deep learning techniques give superior results over those in machine learning. One of the crucial peculiarities is also the absence of modules in the case of feature extraction. Data sets with vast amounts can be subjected to deep learning using a small amount of time. CNN is employed in the work of various real-time applications since images can be used to obtain effective results. We can use these images to implement convolution operation processes of CNN when it comes to feature extraction. It is also possible to use CNN to process the input with the purpose of doing image classification.

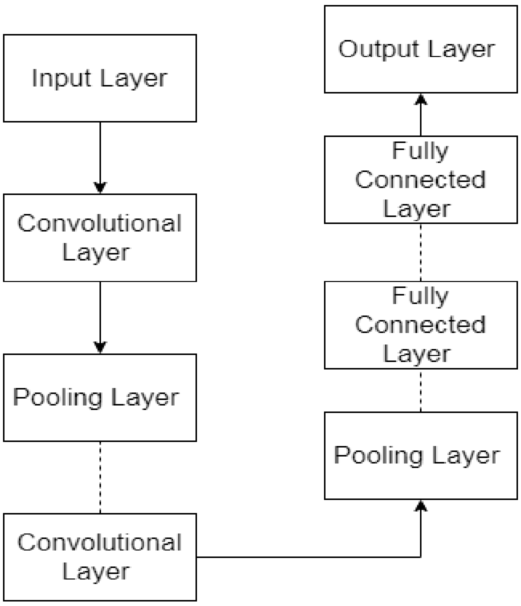

Fig. 7 *Layers of convolutional neural networks*

Convolutional neural networks have the working layers that are illustrated in Figure 7. The proposed work based on Mask R-CNN which abbreviates to Mask Region Convolutional Neural Network is used to determine and classify diseases in plants using the work proposed. Images can be enhanced using the image tool technique of Histogram Equalization (HE) tool thus improving the image quality even when the effects of lighting appear to be unfavorable. HE implements transformation of the levels of gray in an image as a histogram based on the images with gray levels. Healthcare and radar communication are the key areas of implementation of HE. There is no support in consumer electronics fields where saturation can be caused by the brightness that is potentially overbearing. The procedures of directing based on HE can be classified into two groups which are (i) there is no need to adjust parameters by human intervention (ii) the enhancement should be regulated by altering the parameters.

There is a need to devise a better method of handling the augmentations in pictures by sustaining the quality of them simultaneously. It is there that the mechanisms of the adjustments are missing in the process of regulating the improvement that causes lack of balance between parts which are both bright and dark. The images are also generated with noise bearing in mind a number of applications. The light of even the image can be dramatically altered as well. The general procedure of image retrieval is obtained in the device and on camera as input and it is sent to these databases; this sets the process of image retrieval that is sent to a neural model network capable of selecting the necessary features and preprocessing the unique features that were extracted. All the plantvillage data description is made of data augmentation that is flipped and rotated on all angles.

Using the suggested model the classification and labeling of the features that can match with the affected printed area is the graphicalization of masking the unweighted part of the input. The performance of 60% and 20% under training and testing respectively verify 20 percent of the data, which can modify the weight. The histogram has a significant role in the representation of the intensity with consideration of the image. On receiving the input of the leaf image, an intensity value is computed at each pixel. The comparison of pictures can be enhanced through the use of histogram generalization method which contributes largely in image processing. This accomplishment of this task is through the use of intensity values. Data representation to contrast the images is carried out in that way to enhance the image contrast. The value of contrast is more in the case of local areas than it was lower in previous cases.

These methods are highly beneficial in analyzing healthcare-related images and improve the voice pattern though the quality of used data is low. Overall, HGT can be employed to improve quality of the images supplied as a part of the input. HGT (Histogram Generalization Techniques) can also allow conventional methods of equalization of images where analysis of both spot which might be dark and bright have been done. An average of the pixel intensity is calculated to create the equalized ones. The process of restoring the image can also be enhanced using advanced techniques to decrease the noise and enhance the contrast of certain locations to improve the image edges. The figure 8 shows the overall architecture of the proposed model.

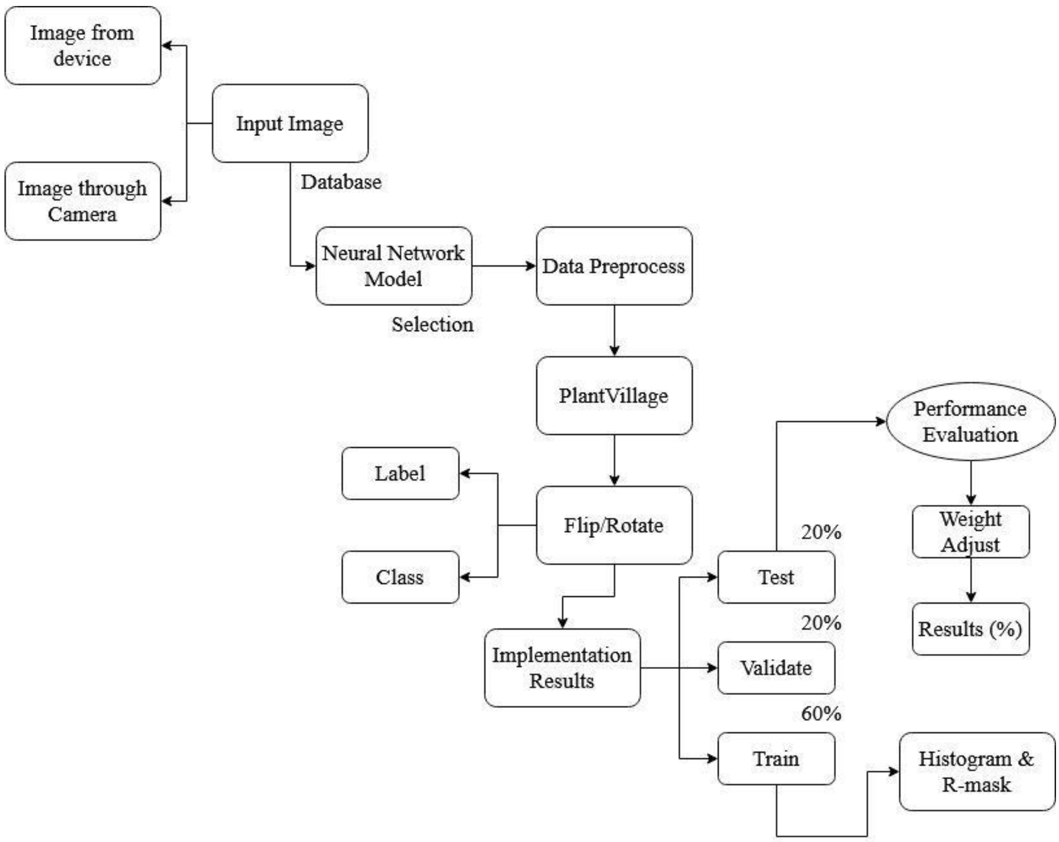

Fig. 8 *Overall architecture diagram*

Proposed framework overall workflow is composed of several steps. To improve image contrast and signal-noise ratio, we use the IHGT preprocessing method for initial enhancement of input images. The enhanced images are subsequently inputted into the Mask R-CNN model for feature extraction. This is done by generating candidate regions through RPN and refining them using ROI Align. Finally, it performs classification and pixel-level mask prediction for accurate recognition of diseased areas.

Diverse problems in realms like machine learning might be addressed with sophisticated approaches such as R-CNN (Region-Based CNN). These duties may consist of a number of processes as following: detection of the objects, categorization of the images and segmentation of the same etc. They may also be applied in reference to other areas like statistics or computer vision. This is explained by the fact that in the case of the identification process, the class of objects is known. Until the process finishes, its location is not aware of it. Due to noisiness, CNN operation becomes worse as the image comprises of several items. Identification of RoI is done with the help of CNN and classification of both foreground and background. R- CNN is amongst the more superior among the detectors that are CNN-based and can be used in object location identification and in images with multiple objects. R-CNN has the following functionality based on the base networks as depicted in Figure 9.

Some of the drawbacks of R-CNN include the higher time spent during the network training when region classification occurs, challenging them to detect objects given that an image is put to the test, and modeling of models should be carried out separately. There is an improvement in R-CNN that is necessary because of the limitations mentioned:

i. R-CNN works similarly to Fast R-CNN among others. The input image is utilized in the production of feature maps bearing in mind the CNN. Region proposals are identified and they are represented in form of squares. The pooling layer is charged with the duty to carry out tasks such as reshaping and preserving the size which is fixed. Class prediction can also be done using the softmax layer. The feed of a limited number of regions to CNN does not require any consideration of CNN that makes this algorithm faster since there is only one time of feeding.
ii. CNN is fed and taken into consideration of faster R-CNN. RPN is the abbreviation of Region Proposal Network and its operation is primarily located at the final stage of CNN. Region proposals are fed to the pooling layer and also traverses other layers which are completely connected in nature. Then, the past output is fed to the layer of softmax and the bounding box. Faster R-CNN can be used to get the correct image position of each image.
iii. Object Classification can be conducted by faster R-CNN but in this case of locating a pixel of a specific object taking the images into consideration, faster R-CNN cannot. Mask R-CNN can therefore be used to conduct instance segmentation. The detection of objects and segmentation at pixel level are the two major stages in instance segmentation. To achieve object detection, one may apply faster R-CNN and in semantic segmentation, one may apply FCN (Fully Connected Network).

The research work suggested assists in carrying out instance segmentation in which elucidation of objects can be done appropriately when segmentation is carried out on every instance. It includes two significant tasks, (i) which is classification of objects and then localization of these objects with the assistance of bounding box, (ii) classification of all the pixels as categories in which the instances of objects are not distinguished. Faster R-CNN can be further developed into Mask R-CNN that is applicable in predicting segmentation mask in each RoI. Implementing and the training process is easier in Mask R -CNN. National language processing as well as computational overhead is also lessened making the system quicker and better results are achieved.

2.1 Objective of Proposed Work

The model suggested to be used to detect and classify plant diseases is made up of the following objectives, (i) Diseased part in the leaves can be detected at earlier stages after being used with the help of Mask R-CNN and Improved Histogram Generalization Approach. This hybrid model also does instance segmentation. (ii) Purges the noise as well as the pixels without distinctness. This is executed through the prediction of the classes using the dataset provided on the kaggle.

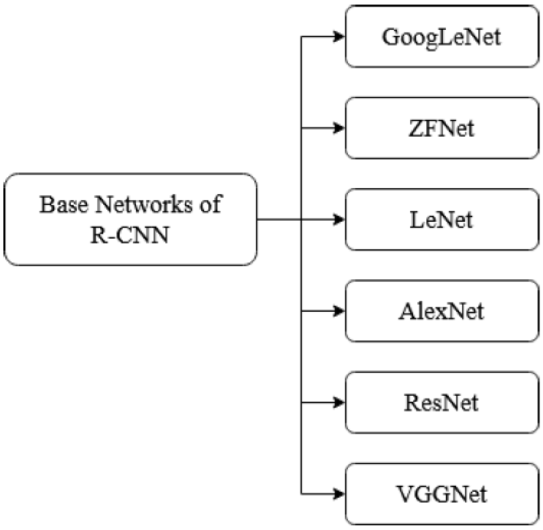

Fig. 9 *R-CNN with its base networks*

3. Proposed Model

The proposed work carries out segmentation of instances according to the label so that the diseased region is found. Every pixel that is inputted after a leaf image is obtained is used to count the location frequency by marking these parts. The localized or grouping of the localized boundary box is done and identification proceeds at the prediction level. The proposed work performs improvement of the ResNet architecture and the areas that are spotted are taken into consideration in regards to the CNN layers. The detection of such diseases is a tedious process since such classification of segmented conversion is not easy due to the errors that are likely to appear. The model functions on the different levels with the application of softmax activation as a pooling layer and fully connected layer in the neural networks with multiple spots within it. The figure 10 shows the proposed model with IHGT and Enhanced Mask R-CNN.

The data is fed in via the kaggle data that comprises of a series of images and is then trained in the model. Given that different categories of images have been used in this model, they need to be labeled. The number of identified categories amounts to 38. It is categorized according to the characteristics that are discovered on a case-by-case basis and is instance segmented because of normalization. The hybrid method that entails histogram and Mask R-CNN is presented in Figure with their workflow. Pictures are put on in series selected out of a couple of categories. In an existing system, the masking does not take these options into account since failure can occur during the process of extracting features. The process of branching and masking the affected regions and each pixel is covered is carried out with the help of mask R-CNN. RoI, which is an abbreviation of Regions of Interest, is employed in matching of pixels between the entirely connected layers. The mapping of the output must suffer a frequency offset constraint.

This proposed hybrid model is based on employing the IHGT and theMask R-CNN technique and the table gives the data of the performance metrics in terms of values of precision and the coincidence of the value of skewness and the value of mean derived through the data of the scale variations and the conversion into plants classes. The pictures to be applied to the proposed work are captured in the kaggle data set as represented in Figure 11 that passes through the stages of testing and reduces the normalization period when applied in histogram.

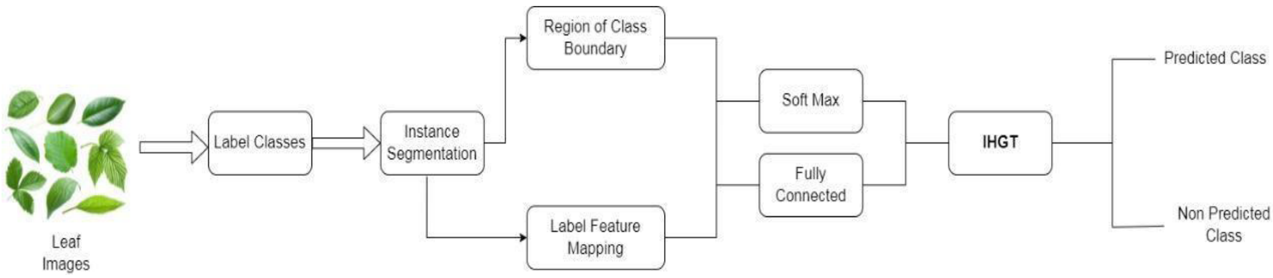

Fig. 10 *Proposed model with IHGT and Enhanced Mask R-CNN*

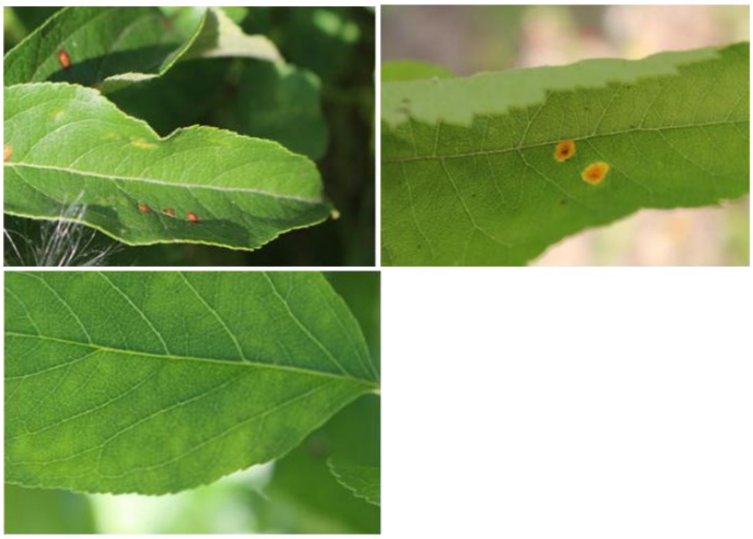

Fig. 11 *Images used for testing as samples*

3.1 IHGT Mathematical Equations

This generalization process aims to fix issues related to brightness and lighting condition in X-ray, MRI & CT images. It is denoted as the normalization of pixel intensity as follows:

$$I' = \frac{I - I_{min}}{I_{max} - I_{min}} \times 255$$

where Irepresents the input pixel intensity, and $I_{min}$and I_{max}denote the minimum and maximum intensity values, respectively. The cumulative distribution function used for histogram equalization is expressed as:

$$H_{eq}(i) = \sum_{j=0}^{i} p(j)$$

where $p(j)$represents the probability distribution of intensity levels. This transformation enhances contrast while preserving important structural details in leaf images.

3.2 IHGT Algorithm

The IHGT process can be summarized as follows:

1. Input the leaf image.
2. Some might have to convert the image into grey scale.
3. Calculate histogram of pixel intensity.
4. Remap intensities to boost contrast.
5. Apply adaptive histogram redistribution.
6. Denoise and sharpen edges.
7. Returning the enhanced image to work with it further.

3.3 Enhanced Mask R-CNN Explanation

An Improved Mask R-CNN model is built onto the standard Mask R-CNN model by enhancing segmentation performance in a condition of obstacle. It extracts features by adopting a ResNet-50/101 backbone, and a FPN to extract more multi-scale feature. The Region Proposal Network (RPN) is responsible for generating candidate regions of interest (RoIs), which are processed by ROI Align to maintain spatial precision.

The proposed network contains several significant improvements, such as optimized anchor sizes in the region proposal network (RPN), multi-scale feature representation, and a new mask prediction head for better boundary delineation. These modifications improve the specificity of small and early-stage disease regions by allowing accurate detection and segmentation. Additionally, the combination of IHGT preprocessing leads to superior feature quality that boosts robustness and improves segmentation performance.

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3.4 Dataset Description

The method is evaluated on: PlantVillage dataset and plant disease datasets from Kaggle which have a total of about 54000 images associated with them across 38 classes. It includes both healthy and diseased plant leaf classes. The images were collected under both controlled and real-world settings, providing diversity with respect to illumination, backgrounds and noise levels. The data is split into training, validation and test sets at 70:15:15 ratio. Data augmentation techniques (e.g., rotation, flipping, scaling) are applied to improve generalization and reduce overfitting. This makes sure that the model is invariant to changes in orientation and environment conditions.

4. Results and Discussion

A deep learning framework in TensorFlow/PyTorch is used to conduct the experiments on a system with a GPU accelerator. The model is trained with the batch size of 16 and a learning rate of 0.001 over 50 epochs. The Adam optimizer is used to update model weights. Standard measures of performance include Accuracy, Precision, Recall, F1-score and mean Average Precision (mAP).

The proposed work analyses several pixels, and the processing commences with layer 1. In this case the conversion of the values of true positive to grayscale occurs. The post extraction features are normalized with the layer matrix of the values represented considering the values to be represented by i as well as j. Coordinate point is denoted regarding the position where boundaries are applied to the areas and connection cultivated amid consistent degrees with angles. Table 3 shows the images for plant diseases and segmentation.

Standard classification and segmentation metrics are employed to evaluate the effectiveness of the proposed model. Precision measures the proportion of correctly predicted positive samples among all samples predicted as positive and is defined as:

$$\text{Precision} = \frac{TP}{TP + FP}$$

where TP (True Positives) represents the number of correctly identified positive instances, and FP (False Positives) denotes the number of negative instances incorrectly classified as positive.

To provide a comprehensive assessment of model performance, additional evaluation metrics such as Recall, F1-score, and Mean Average Precision (mAP) are also considered. Recall evaluates the model's ability to identify all relevant positive instances, F1-score provides a balanced measure of precision and recall, and mAP assesses the overall detection and localization accuracy across different classes.

Table 3 *Images for plant diseases and segmentation*

Layer	Feature Type	Precision	Skewness	Mean
Layer 1	Leaf Color	0.50	0.05634	0.62
Layer 2	Grayscale Image	0.11	0.07330	0.73
Layer 3	Segmentation of Instance	0.90	0.09220	0.94

Figure 12 shows the "Precision Values" achieved across three different layers or methods. The y-axis depicts the values of precision between 0 and 1.0. The data is classified into three layers in the x-axis namely: Layer 1-Leaf Color, Layer 2-Grayscale Image, and Layer 3-Segmentation of Instance.

The values of precision of each layer are as follows:
Layer 1-Leaf Color: This has a precision of 0.5.
Layer 2-Grayscale Image: It has the minimum precision value of 0.1.
Instance-Layer 3-Segmentation: The most accurate value of 0.9.

In general, Layer 3 is the most accurate, and Layer 2 is the least, which implies that there is a considerable difference in performance between the presented methods. The given figure 13 presents the values of skewness with respect to three image processing layers; Layer 1-Leaf Color, Layer 2-Grayscale Image and Layer 3-Segmentation of Instance. The value of skew is generally positive as the layers go down. The lowest skew is observed in layer 1 with the skewness of about 0.057. The value of Layer 2 is slightly higher at about 0.073 and Layer 3 exhibits the best value of skewness at about 0.092. This shows that the data distribution of the layer of the Segmentation of Instance is the most skewed out of the three methods presented.

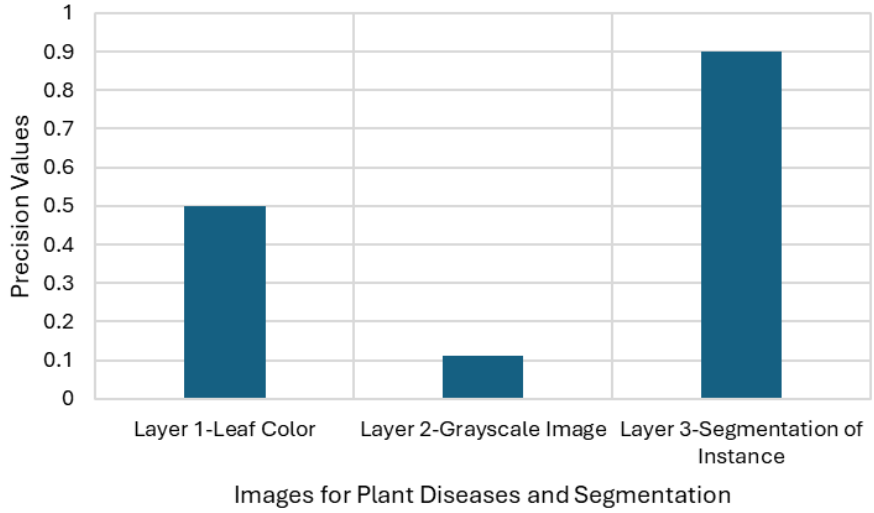

Fig. 12 *Precision values*

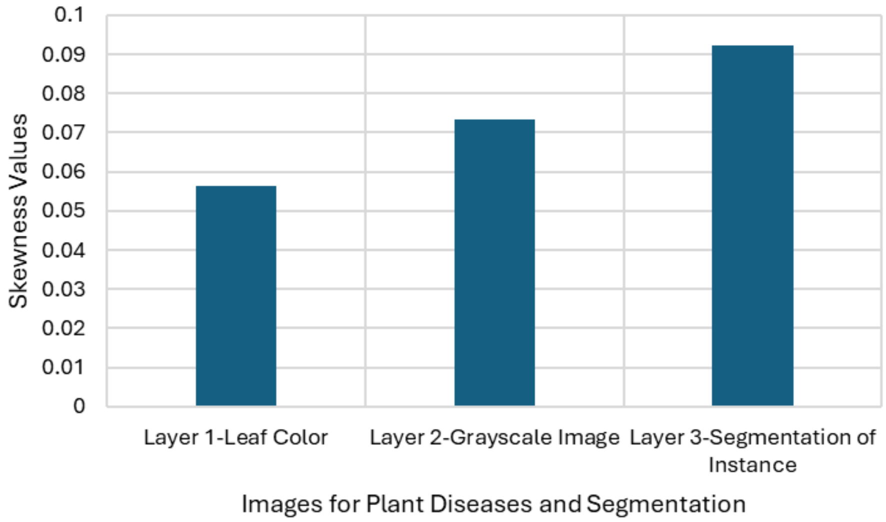

Fig. 13 *Skewness values*

Figure 14, which is called the Means Values, depicts a comparison of the mean values in three categories that are in the x-axis. The mean values are plotted on the vertical axis with the range being 0-1.0. The three layers under comparison are Layer 1-Leaf Color, Layer 2-Grayscale Image and Layer 3-Segmentation of Instance. The trend in the mean values of the layers appears to have a definite positive trend as shown in the graph. The value of Layer 1-Leaf Color is lowest with the value being around 0.62. Layer 2-Grayscale Image shows an increased mean value of around 0.73. The maximum mean of the three categories is 0.94 in Layer 3-Segmentation of Instance which is the best performing.

Prediction of healthy leaves is done using classes and their type and respective images with their size. This will be possible based on both the true positive and the true negative values. These values must be aligned with the classes and correlation is to occur with the pixel. The real negative values, conversely, are compared to the forecast. It is also useful in making a prediction on the negative labeling which gives precise classification. Precision calculation can be calculated as, Precision = TP /TPo + TNe.

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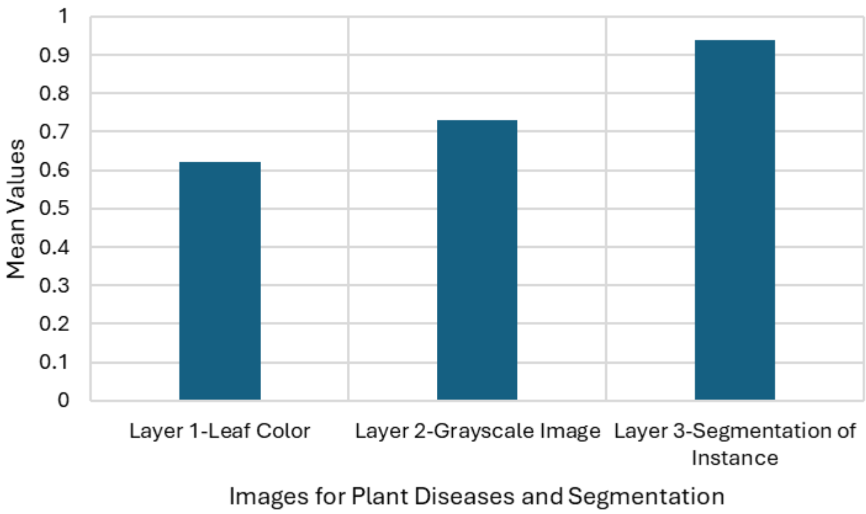

Fig. 14 *Mean values*

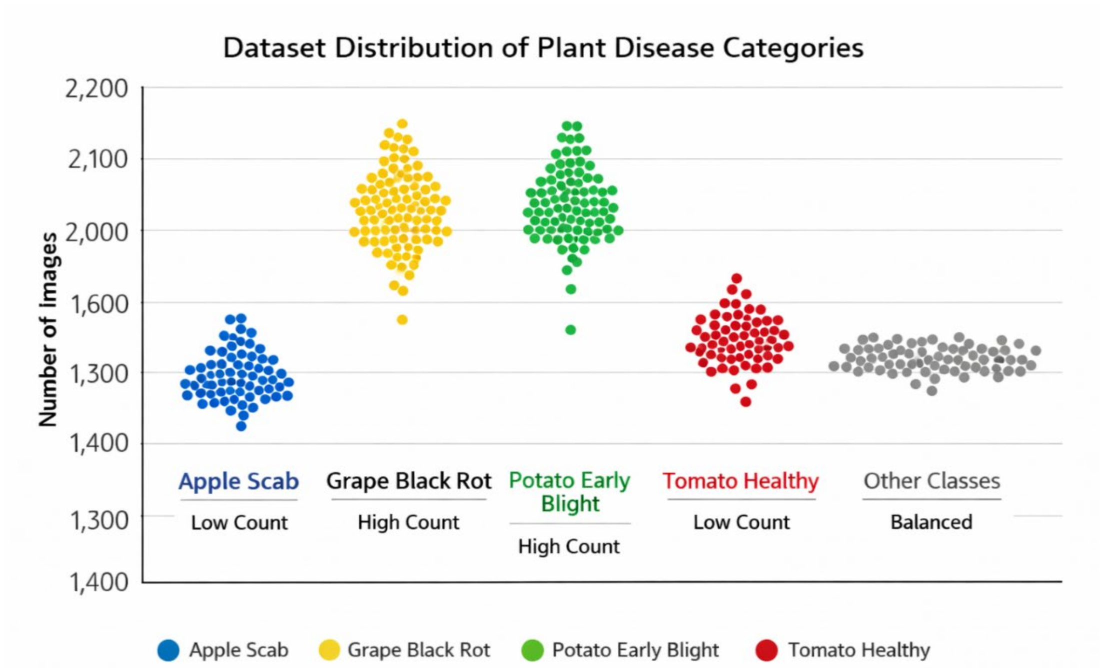

Fig. 15 *Image count from average class*

Figure 15 is a dot plot named Dataset Distribution of Plant Disease Categories that shows the amount of images that can be obtained regarding various plant conditions in a data set. The y-axis indicates the "Number of Images" and this is on a scale of about 1,200 to 2,200. The data is classified into five groups Apple Scab (blue), Grape Black Rot (yellow), Potato Early Blight (green), Tomato Healthy (red), and Other Classes (grey). The categories are also characterized by their count status; Apple Scab and Tomato Healthy are Low Count classes, Grape Black Rot and Potato Early Blight are High Count classes and Other Classes are Balanced. Particularly, the classes of High Count (Grape Black Rot and Potato Early Blight) contain around 2,000 to 2,200 images.

The classes with the Low Count (Apple Scab and Tomato Healthy) have approximately 1,200-1,600 images. The category of Other Classes is in equilibrium with about 1,400 images. The given figure 16 is a pair plot, or the scatterplot matrix, which is a popular data visualization tool in statistics and machine learning to visualize the pairwise association between two or more variables in a dataset. The given plot illustrates the correlation between the following variables but does not name them: "Number of images," "image_id," "multiple diseases," rust, and scab, and some other unnamed numerical variables.

The grid with the diagonal cells representing the univariate distribution of each variable (e.g., the number of images is represented in a bar chart with the number of images increasing) and the off-diagonal cells representing the scatter plot of all possible combinations of two different variables. The information in the scatter plots is color-coded; this implies that they could be used to represent various classes or categories in the data.

This form of visualization is very helpful during the initial exploratory data analysis (EDA) since it can help the researcher to quickly detect possible correlations, trends, or odd patterns (such as heteroscedasticity) between variables before using more complex modeling methods. The different data points represent various occurrences or observations of a study, which probably pertain to the classification or analysis of plant diseases.

The calculation of True Positive (TPo) and True Negative (TNe) is performed taking into consideration a limited region and additional conversion is performed regarding grayscale. These are the results of proposed work that can be utilized in predicting IHGT. The table that has the indices with values of true positive as well as the true negative, the dataset is shown with the pictures in the form of the plants that were healthy and the diseased plants. The confusion matrix through the hybrid model is computed using these values and matrices calculated through the use of the bounded regions. Scaling position is carried out in order to distinguish the training model and testing model. It has a number of filters in the Conv layer (38) and is linearized with the help of the softmax layer. Figure is the confusion matrix of the proposed research work whereby in the case of IHGT, skew is reduced. The fully connected layer is also utilized in mapping the features and after that, the boundaries are divided.

The proposed IHGT-Mask R-CNN framework is contrasted with some of the latest models, such as U-Net, EfficientNet, and the standard Mask R-CNN. The findings show that the proposed method is more accurate, provides higher quality of segmentation, and is more robust in noisy and low-contrast situations than these models. The IHGT integration has a major advantage in feature representation, which results in enhanced disease localization. The experimental findings prove that the visibility of disease patterns is increased with the incorporation of IHGT preprocessing, and it directly leads to the better accuracy of the segmentation. The proposed approach offers accurate pixel-level localization, unlike those based on classification, making it more applicable in agricultural contexts of the real world. The model also demonstrates good performance in adverse conditions like noises and uneven light.

The advantages of the proposed framework are that it is very accurate, more resistant to noise and lesion localization is more accurate. Nonetheless, the model is rather computationally intensive since the Mask R-CNN architecture is complicated. Moreover, it can be different based on the quality and diversity of data sets. Future research could be aimed at streamlining the model to make it real-time and applying it to multi-crop disease detection applications.

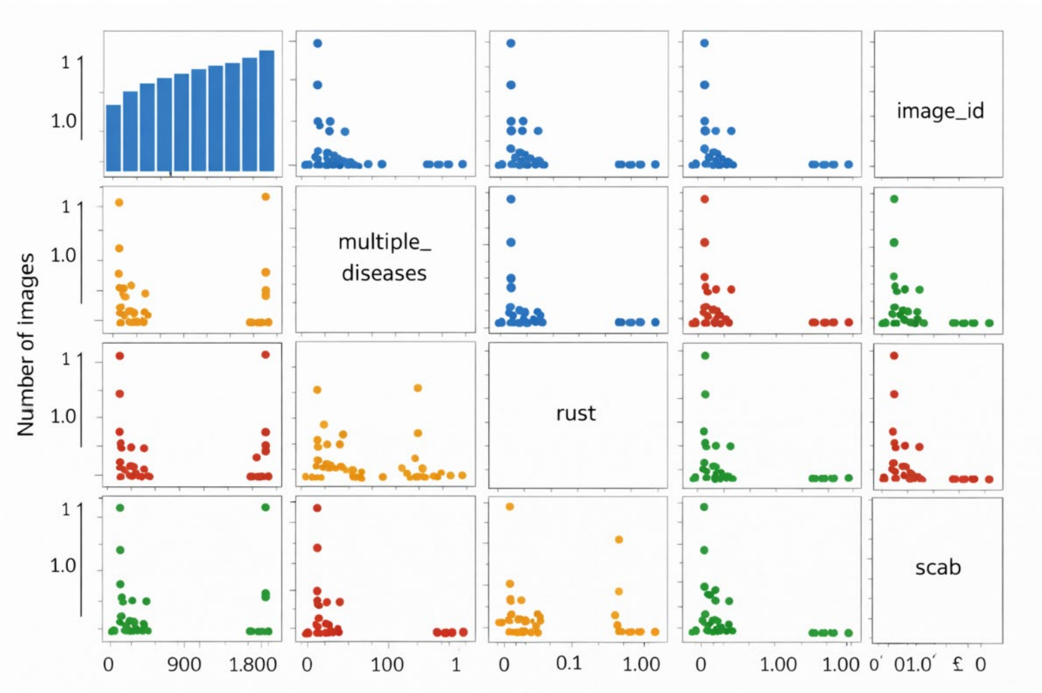

Fig. 16 *Representation of confusion matrix*

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5. Conclusion

It is possible to preserve the agricultural productivity when the plants are being preserved against the spread of diseases. Deep learning models entail the selection of features. The suggested work integrates both Mask R-CNN and IHGT to achieve superior results in relation to the current works. Bounding of affected areas is done then the matching of classes occurs at the pests. Lastly categorization is done on training model. They interfere with the growth of plants depending on the bounding tissue in case of tissues, sequence of genes with color changes of the leaves. Segmentation of the grayscale leaf is grayscale, which is in the proposed model, and the use of Enhanced Mask R-CNN approach is used to segment the leaf into each of the classes in the given data set. The changed value of the accuracy seems to be more accurate with 97 percent where the healthy leaves are depicted by categories and the stage of testing shows the identifiable leaves. The experimental values received on such parameters as precision, skewness and mean values prove that the method is grounded in deep learning methods. This further allows the agricultural field to develop better because weeds as well as diseases may be detected at an earlier stage. This paper introduces a hybrid IHGT-Mask R-CNN-based algorithm to detect and segment plant diseases with high accuracy. Combination of image enhancement and deep learning segmentation has a great performance with an accuracy of 97%. The model has a great ability of detecting and localizing the disease areas in adverse conditions. Future research will be aimed at real-time application with edge devices, combining with IoT-based smart agriculture systems, and extending the model to a variety of crop types in various environmental settings.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *K Lakshmi Devi, K.Venkata Durga Kiran;* ***data collection:*** *K.Lakshmi Devi;* ***analysis and interpretation of results:*** *K.Lakshmi Devi, K.Venkata Durga Kiran;* ***draft manuscript preparation:*** *K.Lakshmi Devi, K.Venkata Durga Kiran. All authors reviewed the results and approved the final version of the manuscript.*

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