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Leaf Disease Classification Based on Edge Detection Using Training Neural Network

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Abstract: Plant pathogens influence the growth of their respective species, thus, early detection is that helped to promote plant growth. This paper deals with a new strategy to design the Plant Disease Recognition Model based upon the Leaf Image Classification utilizing simple leaves images of normal and infected plants, via the Convolution Neural Network (CNN). It can be used to detect the edge, so it makes sure of impetus features extraction from image data collection on plant diseases and also aims to recognize. Augmentation and Fine Tuning approach is used to achieve the prediction of disease in an efficient manner. In addition, Peak Signal-to -Noise Ratio, Precision metrics which are measure the output of our proposed method and make comparisons it with the existing approaches. Then, proved that our model is enhanced the efficiency and accuracy of leaf disease recognition by achieving the better metrics in term of precision and PSNR.

Keywords: Plant Disease Recognition, Augmentation Process, Convolutional Neural Networks, Edge Detection, Neural Network Training.

1 Introduction

The Indian economy depends, for the most part, on agricultural development and productivity [1]. Interrupting agricultural development through the advent of plant disease is a critical issue in our economy in a country's economic growth. Pathogenic plants encompass of fungi, cells, bacteria, viruses, phytoplasms, viroids and so on [2]. Since plant diseases are unavoidable, disease detection performs a vital role in the area of agriculture. In most types, signs of the disease occur on the leaves, stem and fruit. Generally, leaf is considered to detect the disease instead of analysis of whole plant. [3]. in this foundation, more focus was given to the seeing the quality of agricultural production by researchers and scientists. Accordingly, they find that early stage detection is protecting plant from disease. Moreover, it requires evaluation and timeous treatment to promote plant growth against severe loss.
Initially, the main method used in disease detection is by expert eye examination, which takes time and leads to discomfort [4].Furthermore, by human eyesight any kind of diseases which are microscopic in nature cannot be identifiable. Because of this, Computer Technology takes part as a prominent role in classifying and distinguishing diseased plants [5]. In which, new and emerging technologies belonged to precision agriculture, which tends to lead the implementation of innovative strategies for improving agricultural production and enhancing agricultural crops in a marketable and ecologically responsible manner [6]. By using with these techniques / tools, costs to achieve ecologically and economically sustainable agriculture could now be minimized.
Correspondingly, image processing techniques are emerging as a useful tool for increasing agricultural efficiency, farming practices, improving process accuracy and quality while reducing manual monitoring by farmers [7].]. It also provides versatility, and essentially eliminates the visual decision-making of farmers. Some researchers have therefore employed image processing techniques to identify plant diseases easily and accurately. Image selection, pre-processing of images, disease spot segmentation, extraction of features and classification of diseases are the measures taken by these scientists in detecting leaf diseases, although the lack of accuracy for automatically detecting the disease is not given for these methods [8]. To this end, researchers are beginning to focus on using new approach to improve accuracy.
In this way, a new method called artificial intelligent is a fast and non-invasive technique for plant disease diagnosis [9]. As Deep Learning architectures began to evolve additional hours, researchers applied them to the recognition and classification of images [10]. To this end, researchers are beginning to focus on using new approach to improve accuracy such architectures were also introduced for various agricultural applications. It has shown better performance in pattern recognition, segmentation of images and identification of diseases. This structured as follows: section II explains an

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overview of the work related to improving classification accuracy using Edge Detection method, and section III & IV provides the Motivation of Work and Proposed Model. Section V contains the results and the analysis of the experiments. The paper is eventually completed in Section VI.

2 Related Work

Nowadays detection and classification of disease in plants plays vital role to improve the accuracy. Moreover, it can be beneficial to recognize diseases in plants from the symptoms that appear on the leaves. Correspondingly, in [11] the color transformed method was used in Image processing techniques to identify the disease spot of the leaf. In this approach the spot disease detection is accomplished by using the threshold system Oral Tracheal Stylet Unit (OTSU). According to this process, different spots of disease are accurately identified and results are not affected by context, type of leaf, type of disease spot and camera, while veins with spot-like color are not considered. In [12], for the identification of plant diseases, using artificial neural network (ANN) and various imaging processing techniques were presented as early and reliable methods. Since the proposed method is based on the classification ANN classifier and the extraction function Gabor philtre, it provides better results with a recognition rate of up to 91%. Despite of an ANN-based classifier classifies various plant diseases and uses the combination of textures, colour and features to identify certain diseases, the accuracy of classification is required to be implemented more.

In [13], the author studied the different classification methods that can be used to diagnose plant leaf disease. The method k-nearest-neighbor (KNN) seems suitable for the given test example, as well as the simplest of all class prediction algorithms. If the training data is not linearly separable then optimal parameters in SVM are hard to analyze, which emerges as one of its drawbacks and SVM is more challenging to understand and implement. The main drawback of the KNN algorithm is that it is low accuracy and also that noisy data is not robust. To reduce noise based on edge detection, [14] proposed a tobacco leaves automatic Laplacian Grading method based on digital image processing and the theory of fuzzy sets. This technology uses computer vision for colour, scale, form, and surface texture extraction and analysis. Fuzzy comprehensive evaluation offers a high degree of trust in decision-making based on the fuzzy logic The experimental results of the two-stage Fuzzy Comprehensive Evaluation (FCE) show that the classification accuracy rate for qualified tobacco leaves is about 94 per cent, but the level of accuracy was not adequately provided .

In [15], the author suggested that plant disease be detected through the study of the leaf texture and pattern recognition. The extracted texture pattern was then graded respectively to train Multiclass SVM classificatory into safe or diseased classes. Experimental findings show that the combination of image processing techniques with DSS using multiclass SVM findings in the accuracy of grape plant disease classification up to 96.66 per cent. In Machine Learning the training method and noise control is not sufficient standard. In order to improve noise removal and precision, the author provided the system with colour, edge detection and matching histogram [16] to remove the edges of diseased leaf spot images. But, that's going to be more complicated and time consuming.

The Neural Network [17] then offered to predict the edges directly from the image patches as input. As shown in the comparison, this edge detector is fast while achieving comparable output with state-of-the-art method while identification of image leaf diseases is not well performed due to improper training. The entire process of constructing the identification model for the plant pathogens using deep Neural network is further discussed in depth. In the subsections below the complete process is separated into several necessary steps, starting with the collection of images utilizing deep neural networks for the classification process.

3 Motivation of Our Work

Research on leaf-based classification and the identification of disease leaf images are also essential to identify in plant disease recognition. Owing to noise and classification errors the edge base detection and efficient classification is a challenging one. We need to establish accurate model in order to get the better classification result. We are therefore integrating Edge Dependent Detection using enhanced Neural Network Training through the process of Augmentation and Fine Tuning to minimize noise and classification errors.

4 Proposed Method

To achieve accurate precision rates for diagnostic of plant disease based on classification of the leaf image, the noise and classification error must be reduced. Belongs to this argument, using Artificial Neural Network and Augmentation Technique, we have implemented the edge detection method to enrich noise detection and accurate precision rate by enriching the training. Our device proposed the edge detection method using Artificial Neural Network is shown in Fig.1 to recognize the diseases in the leaf.

Dataset based on the affected leaf disease is provided as input for preprocessing. In pre-processing, crop all the images manually, make the square across the leaves, underscoring the topic of focus (plant leaves). Thus it was made sure that photos encompass all the details needed to learn the features. Furthermore it is used effectively to reduce the training time.

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To obtain an accurate classification of the disease leaf, the dataset is divided into data set for training and validation. The following stage was to enhance the training data collection as well as enhanced images like the transformation and rotation techniques. Thus the edge features distinguish one class from the other by learning the edge features for network training. The output from the process of augmentation and the data area of testing then provided the input for the Convolutional Neural Network. Edges of the leaf image of the disease are detected here. Then the images of the disease leaf are precisely classified from healthy images of the leaf. Thus, our proposed method will maximize detection performance by automatically enriching the edge detection in images of disease leaf.

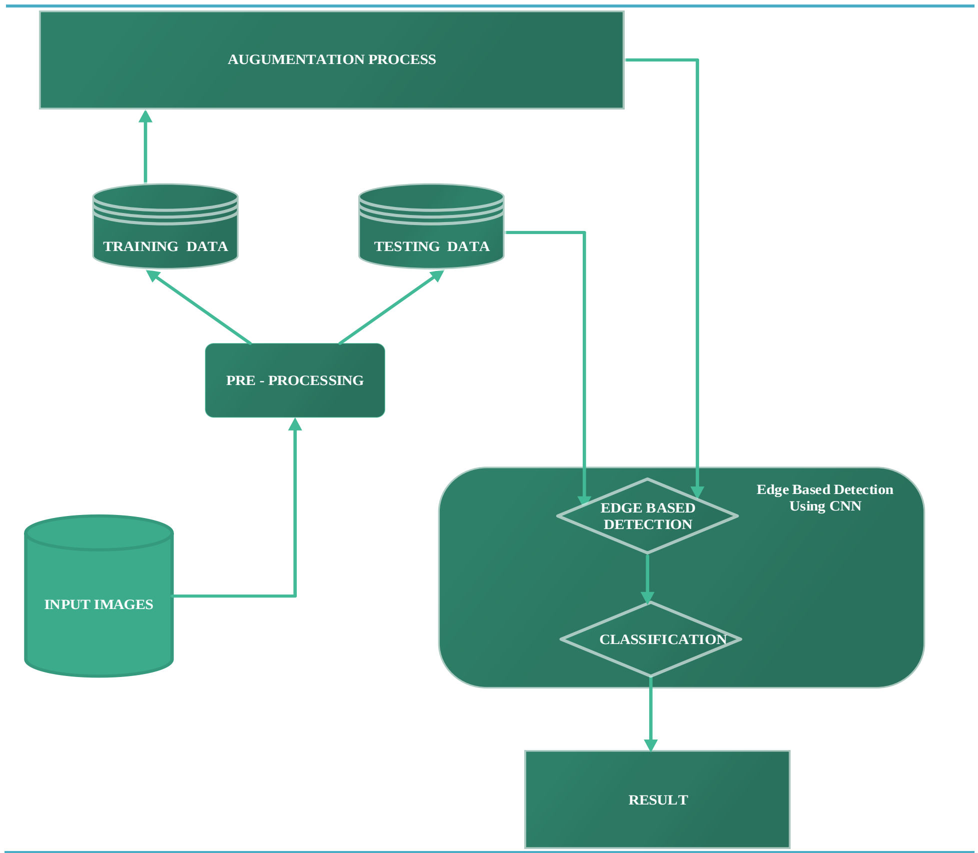

Fig.1: Proposed Method.

4.1.Pre-Processing

Images downloaded from the internet were available in different formats, and including varying sizes and reliability. For the advantage of accuracy, selected images intended to be used as a set of data into the convolutional neural network classifier were pre-processed for better extraction of the features. The image preprocessing procedure also associated manually pruning all the images[18], creating the square across the leaves, to showcase the area of focus (plant leaves). In addition, only the images were represented as applicants for the data source where better resolution of the region of interest was in. Thus images were ensured to encompass all the relevant information for the learning of features.

4.2. Augumentation Process

The major objective of bestowing augmentation is to raise the set of data and present moderate distortion of the images which aims to minimize over fitting during the training phase. In learning algorithms and also in mathematics, over fitting occurs when a mathematical model determines noisy data or inaccuracy instead of the relationship under lying [19]. The picture increase included one of many transformation methods such as affine transformation [20], perspective transformation [21], and simple rotations of pictures. To describe transformations and rotations (linear transformations and addition of vectors, exc.) where all equal lines in the first image are as yet equal in the output image, affine transformations are included. The output image required three goals from the actual image, and their respective locations, to discover a transformation matrix. A 3×3 transformation matrix was needed for perspective transformation. And after the transformation straight lines

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will stay straight. The method of augmentation was preferred to suit the requirement; in a natural environment, the leaves will vary in visual perspective. At this stage, in order to simplify the process of augmentation at different images from the dataset, a special framework was developed in Matlap with the probability of adjusting the transformation during run-time, which boosts versatility. The common approach to evaluating the performance of artificial neural networks is to split data into the training set and the test set, then train the training set on a neural network and use the predictive test set.

4.3 Disease Leaf Detection Using CNN Based On Edge Detection

Edge detection is a necessary stage towards the primary aim of computer vision and is an extensively studied topic. [22]. In other words the boundary between an object and the context is an edge. Edges contain the most important information in the image, and can present the information on the location of the object [23]. Edge detection is an important component in computer vision and other image processing, used to detect features and to analyse textures. Artificial neural network, instead of traditional methods of edge detection, can be used as a very prevalent technology. The artificial neural network [24] is more like the classic edge detection approach because it gives low operating load and is many beneficial in pruning the noise effect. More useful is an artificial neural network, as multiple inputs and multiple outputs can be used utilized the training stage. In this way, the Convolutional Neural Networks [25] (Convolutional Neural Network) are biologically motivated variants of MLPs. From the early work of Hubel and Wiesel on the visual cortex of the cat, we know a complex arrangement of cells within the visual cortex exists. Convolutional Neural Networks leverage local similarity spatially by imposing a pattern of local connectivity amid neurons of adjacent layers. In CNN, the neurons are segmented into "feature maps" inside a hidden layer [26]. Within a feature map the neurons share the same weight and bias. The hidden layer is partitioned into feature maps where each neuron searches with the certain feature in a feature map but at various image positions in the data. Hidden units may also have shift windows, resulting in a hidden unit that is invariant to translation. But now this layer recognizes only one translation invariant function, which can make it difficult for the output layer to detect any desired feature. To fix this problem, we can add multiple layers of hidden translation invariants. For partial edge detection the hidden layers trigger. So we proposed that the network should contain five learning layers and 2 convolutionary, 2 sub-sampling layers and one softmax classifier instead of completely connected layers to learn translation invariant function for accurate ranking. Pooling operation gives the translation invariance form [27]. The on-input depth slice works independently and reconstructs it spatial and temporal. To minimize over fitting, overlapping pooling is beneficially applied. The input image is thus provided by high to down-sampling layers which aims to minimize complexity of the upper layers and reduces the input dimension, while the network also has 3x3 receptive fields which handle the sampled input and output the detected image edge.

4.4 Disease Leaf Detection Using CNN Based On Edge Detection

Convolutional Neural Networking training is very close to training other types of NNs, such as ordinary MLPs. Fine-tuning aims to develope the efficiency or effectiveness of a performance or feature by creating slight changes to boost or maximize the result [28].The classification is used with the softmax classifier [29] instead of a fully connected layer which calculates the ImageNet dataset’s probability. Fine-tuned learning experiments take a little preparation, Yet they 're a lot quicker than preparation from scratch. This Softmax Classifier was removed for beginning the fine-tuning process. The new classifier Softmax has been trained from scratch utilizing the back-propagation algorithm. The algorithm for back propagation ran for number of iterations. The fine tuning process had been repeatedly modifying parameters of hidden layers and hyper parameters. In general, Back Propagation brings the best results to the Convolutional Neural Network in terms of the training algorithms. Classification of disease leaf images is thus accomplished, based on edge detection.

5 Result & Performance Analysis

To obtain the high precision for recognization of plant disease based on the classification of the leaf; our proposed model based on edge detection is a study and proved that in this section through low PSNR value and high precision than established methods.

5.1 Edge Detection Analysis

The training phase consists of various steps based on the quantity of the training epoch to reach the weight values that provides the highest performance, as the highest number of performed varies around 100 epoch to 100000 epoch. The PSNR (peak signal-to - noise ratio) is used to calculate the output of the network, when the epoch is expanded. The following Figure 3 shows a test image with the result of the output and its PSNR value at different epoch number statuses.

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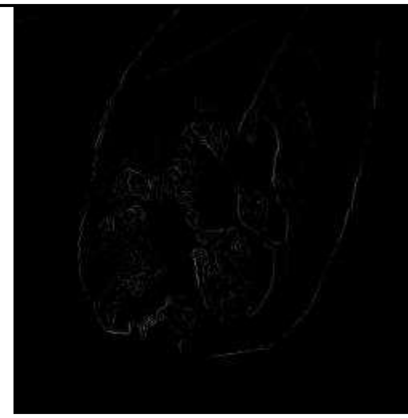
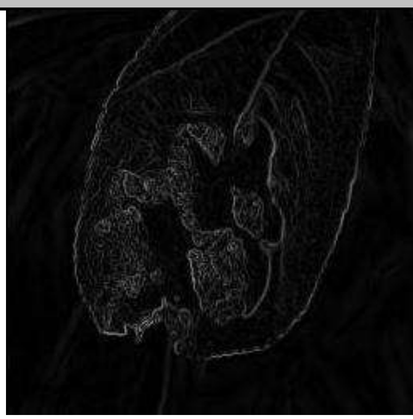
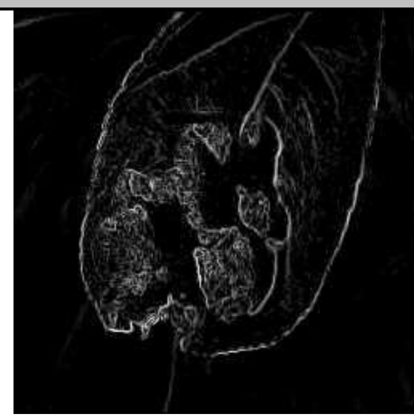
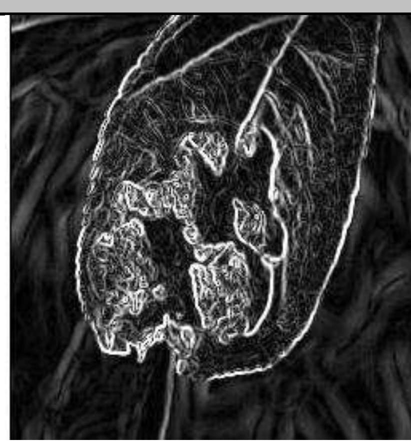
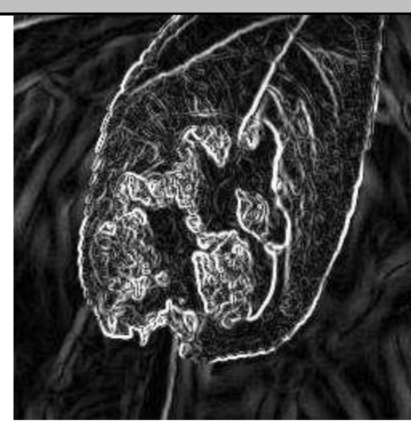
		
Input Image	epochs = 400 PSNR = + 5.73 dB	epochs = 500 PSNR = + 5.74 dB
		
epochs = 600 **PSNR = + 5.72 dB**	epochs = 800 PSNR = + 5.71 dB	Epochs =1000 PSNR = + 5.69 dB
		
epochs = 5000 **PSNR = + 5.57 dB**	epochs = 10000 PSNR = + 5.51 dB	epochs = 100000 PSNR = + 5.2 dB

Fig.2: PSNR Values Based on Epochs for Our Proposed Method.

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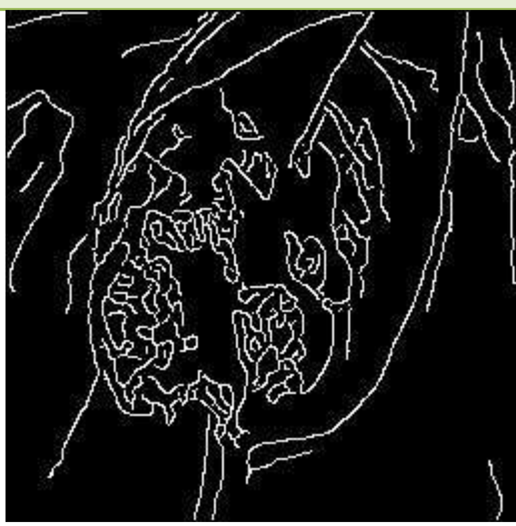
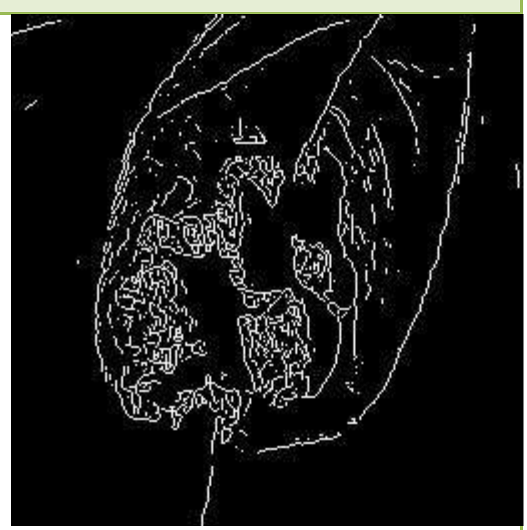
Figure.2 shows the changes in the edge detected output image of the proposed technique, it is clear that the best result that gathers more expected edge pixels with less noise, PSNR = +5.33dB is achieved when the network has been trained 100,000 times, which approves the validity and efficiency of our proposed technique, The following Figure 3 shows improvements in the noise ratio in the output edge of the observed leaf image when applied to the proposed method while raising the number of training epochs from 400 to 100000 epochs, a major change occurred when the epoch number was increased to its limit. The indicated that the best result is procured if the test image is applied either by the image intensity of the output result or by the PSNR value for the highest epochs trained network. By reducing the PSNR values, the precision of edge detection is increased to a sufficient level. The proposed technique therefore achieves an efficient edge detection method compared to various established approaches, where it gathers more predicted edge pixels and leaves a small amount of noise along with a high precision rate than other techniques as seen in Fig 3.

Original Image



CT Based Approach PSNR = 5.69 dB



Laplacian of Gaussian = 5.61dB

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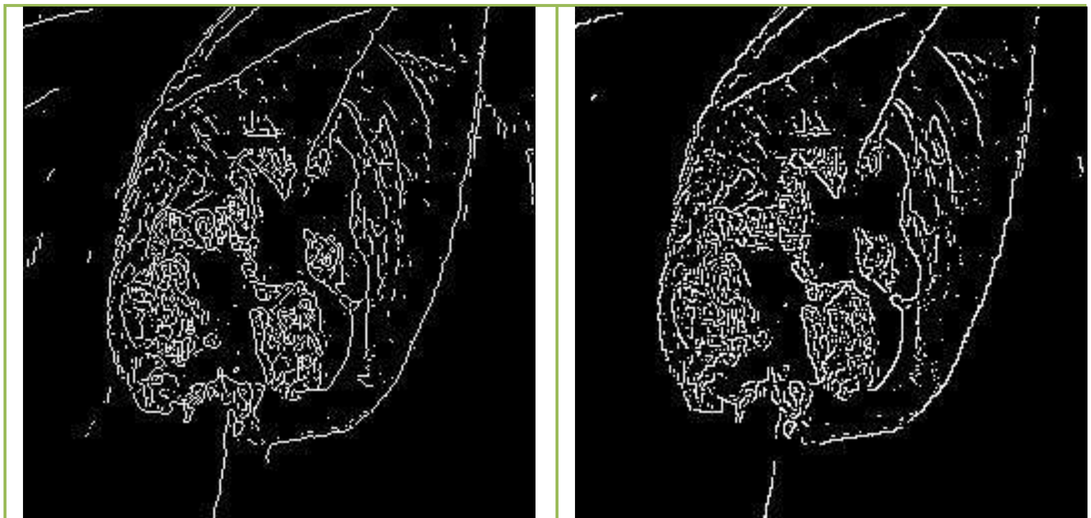

Canny PSNR = +5.5 dB	Proposed Model PSNR = +5.2 dB

Fig.3: Comparison of Detection of Edge.

In this table analysis proved that the accurate edge detection is achieved by reducing PSNR to detect the disease in the leaf image and also improving the classification accurately as Color Transformed Approach, Gaussian Method Laplacian and Canny.

5.2 Precision Analysis

The precision rate and classification accuracy are easily affected by the noise. When the number of true edge points detected is greater than the total number of points detected, the low precision occurs [30]. To know our model's classification accuracy based on edge detection through the process of augmentation and fine tuning, precision analysis is performed during training stages. The comparisons of the precision analysis are presented in Table 1 and Fig.4 in table form.

Table 1: Comparisons of Precision Analysis.

S. No	Model	Precision
1	Color Transformed Based Approach	50%
2	Laplacian of Gaussian	78%
3	Canny	90%
4	Proposed Model	97%

From Table 1, we've provided the Canny Precision Percentage, Color Transformed Based Approach, Gaussian Laplacian and Proposed Method to assess our model's accuracy. We can see that our proposed model achieves the 97 per cent high precision rate.

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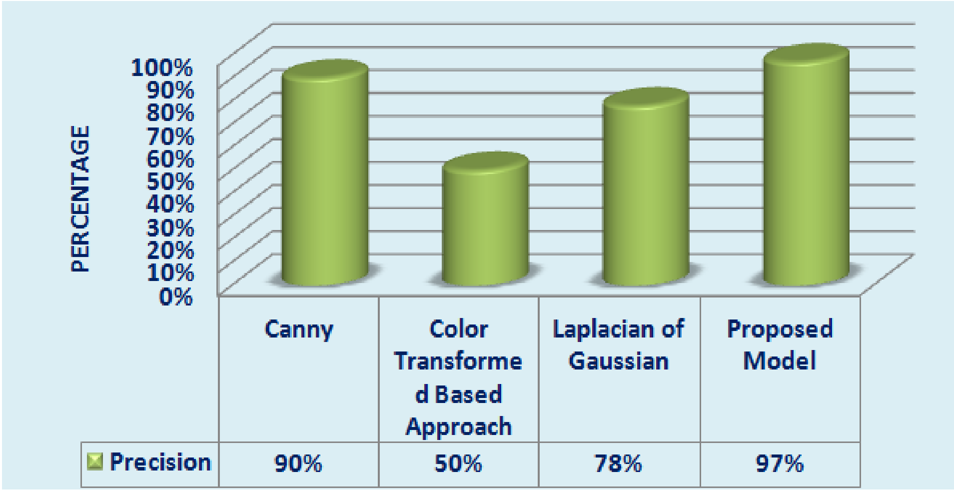

Fig.4: Graphical Analysis of Precision for Models.

Thus the classification accuracy is enhanced by increasing the prediction rate compared to the existing method.

6 Conclusion

The Neural Edge Detection Model is implemented in this paper along with the Augmentation and Fine tuning method to obtain the best classification result. In this work the edge-based detection is achieved by enhancing the PSNR value by enriching the Convolutional Neural Network training process. For training method, the augmentation and fine tuning is used here. Our system suggested has the lowest error rates and highest accuracy compared to its counterparts. Most of the current methods failed to provide better classification performance for edge-based analysis, while our proposed method provided better precision and PSNR efficiency. Our proposed method is tested using existing methods such as Canny, Color Transformed Approach, Laplacian Gaussian, and our proposed model is superior to existing methods. Very large data will be categorized using machine learning classifier for future enhancement, and classification of plant disease may be implemented using other method of extraction of features.

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