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Crop Disease Detection Using 2D CNN Based Deep Learning Architecture

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Abstract: Growth in the economy of the nation is mainly based on agricultural production. Harmful plant areas are recognized as the major reason for crop productivity. Huge time, very hard work, and monitoring the farm continuously are required for the detection of disease and classification in the previous conventional approach. In recent years, researchers and technology advancement focuses on this region making it probable to acquire a solution optimized for it. For the identification and detection of disease in agricultural products, several well-known approaches of neural networks, machine learning, and image processing are used. The crop disease detection based on preprocessing and segmentation process using filtering and neural network technique is proposed. The dataset here has been collected based on the pre-historic cultivation data and disease-affected data of the crop and live images from the field have been collected and the dataset has been created. This data has been initially processed using a pre-processing technique based on convoluted Gaussian filtering. Then the processed image has been segmented using an active contour neural network (ACNN) to formulate new loss functions which incorporate the region and information about size in the disease detection while training. By using 2D CNN the processed and segmented image has been classified for detecting the crop disease. From the results of the experiment, the proposed method is a vigorous method for crop disease detection and also segmented main diseases of plant leaves like Cercospora Leaf Spot and Bacterial Blight, Powdery Mildew and Rust.

Keywords: *disease detection, neural network, pre-processing, convoluted Gaussian filtering, DCACNN, loss functions.*

1. Introduction

Production and quality of agricultural products are reduced due to diseases. Therefore, earlier diagnosis of diseases in plants is more important for curing and controlling them. The best seeds of plants are taken and a perfect environment is delivered which are suitable for plant's growth, so many diseases are there which affect the plants [1]. Earlier detection of diseases in the plant is very important in agriculture for minimizing the damage, decreasing the cost of production, and increasing income. Diseases are not only identified by the human eye. So many years before, diseases are observed only by the naked eye having the examples of pretentious plants or the persons with the disease prediction skill observe the farm, and conservative measurements were taken by the farmers depending on their suggestions [2]. Skilled person's identification is a challenging task and their suggestions will not often cure the diseases. A huge period is required and costs are very high due to the need for experts. Any Country's root is agriculture so that the identification of disease in the agricultural product is more important [3]. Thus, few accurate, fast, automatic, and low-cost approaches are used for detecting diseases. The latest advancement of technology in the image processing and Machine Learning (ML) field will provide the economical knowledge of pesticides in farmers. In the products of agriculture, diseases are caused by mainly two factors: non-living and living agents. Living agents are viruses, fungi, bacteria, and insects. Non-living agents are temperature changes, increased moisture, light insufficiency, and decreased nutrients, and air pollution. Identification of leaf, detecting leaf diseases and diseases in fruits, etc. are the diseases for which some agricultural applications are established. The digital camera captures digital images which are required by these applications. The information needed for the examination of diseases is extracted by the images captured which are applied with image processing and machine learning techniques [4]. The utilization of crops can be classified into four different types such as cash, food, plantation, and horticulture. Plants get affected by two major diseases as biotic and abiotic. Fungi, bacteria, and viruses in plants are caused by biotic disease [5], whereas abiotic can cause plants in terms of weather conditions, chemicals, etc... Leaves of different plants bear different diseases that have to be identified with the support of color, texture, and shape. Based on color intensity, the histogram technique was used on paddy leaves to

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identify the infected regions. The disease detection mechanism involves several phases. It consists of two major parts such as training and testing. The Training part begins with the collection of images from the stem, root, leaves, etc... These images are pre-processed by evacuating blur effect, noise effect, and even correcting the RGB/grey level [6]. In the phase of segmentation, it removes the background image from the ROI and also detects the affected part during training. The feature Extraction phase is utilized for extracting the features and producing feature vectors. These feature vectors are utilized to train the classifier. In the training part, the test image goes through all phases and recognizes either infected or healthy from the trained classifier. The effectiveness and compatibility of the model are evaluated using performance metrics. It is also called a recognition rate and success rate. These rates depend upon the comparison of a model, type of classifier, techniques used, and accuracy of recognition from one over another [7].

This paper organization is followed as Section 2 exhibits related works on crops. Section 3 describes the proposed crop diseases detection design. The experimental results are depicted in Section 4. The conclusion is presented in Section 5.

2. Literature Review

This session explains how to use an image segmentation technique to detect and classify different forms of leaf diseases in plants. According to article [9], the Grape plant is home to 80 percent to 85 percent of illnesses. Grape productivity and output are gradually declining. For picture segmentation, the study's authors employed the K-means cluster technique and neural networks, and for illness classification, they used neural networks. There are four processes for identifying plant leaves and classifying them, according to study [10]. This is how the phases are. 1) The pre-processing step of the image 2) K-means clustering Image segmentation using a clustering technique 3) Extraction of features 4) Classification of Diseases Statistical Grey level Co-Occurence matrix is used to extract features from photos. The categorization is done with the help of a Support Vector Machine (SVM). The design technique in paper [11] is divided into five parts. Image capture, image pre-processing, classification, extraction of features, and segmentation are some of the phases. This approach employs a color-based and cluster-based segmentation procedure, and a Support Vector Machine (SVM) tools for classification. Cotton is one of India's most significant crops, according to paper [12], and the most of illnesses affect cotton plant leaves only in their early stages. The color-based approach is used for segmenting pictures in order to identify the discovered region for identifying the many forms of illness that affect cotton plants. The characteristics are extracted using a grey level co-occurrences matrix. The SVM classifier is used to categorise the illness. The author of [13] proposes that image processing techniques such as pre-processing of pictures, image segmentation, image feature extraction, and image classification might help identify chilli plant leaves illness sooner. Early disease detection and image processing techniques are both economical and simple to use for farmers. The real-time edge detection of rubber plant diseases is shown in article [14]. They employed the Sobel edge detection technique to detect the edges of plant leaf diseases.

Production losses are arisen due to the critical problems of diseases occurring in plants in farming is described by D. M. Sharath, et.al (2019). This also affects the farming production’s quality. Plant health monitoring is very difficult to monitor and classify the various infections manually. For this purpose, experts are required and this process will consume a lot of time. Several stages for detecting the infection are incorporated in this method. Depending on the obtained output, plants that are affected by the disease are monitored using these changes. Recognition of plant infection is implemented with the techniques that use the infectious plant images [15]. Through image processing, various plant diseases are characterized by G. K. Sandhu, et.al (2019). In recent years, several researchers are attracted by this method of plant disease detection. Normal plant leaves or infected plant leaves are classified by these algorithms. Moreover, various problems are developed in this method. The problems are The images captured without light are present in the recognition system with the conversion of these images into digital form and environmental conditions. Accuracy and capability to detect disease by these recognition approaches are concluded. The limitation present in this method requires more future research. A major source of food is farming and it is not a technique was stated by A. Devaraj, et.al (2019) in [17]. Agriculture is the main source of income for 70% of the population in countries of Asia. But, various kinds of diseases decrease the crop’s quality. This efficient method for disease detection will prevent farming loss. Classification and disease detection is performed by software is developed in this work. Various phrases are incorporated in the process of disease detection. So, the implementation of techniques in image processing makes the detection and classification of disorders in leaves easier in the sector of farming.

3. Model: System Design

Crop disease detection in the leaves is the major motivation of this work. An ensemble model based on pre-processing and segmentation process using convoluted Gaussian filtering and deep convoluted active contour neural network (DCACNN) for the crop diseases detection from the leaves is proposed. Images are crop disease benchmark dataset of tomato and brinjal leaves is used to perform experiments. The live dataset has been gathered and the pre-historic dataset has been collected from the cultivation land. 1000 Healthy Leaves images are present in this dataset and crop disease leaves.Architecture for crop disease detection using convoluted Gaussian filtering and deep convoluted active contour neural network (DCACNN) has been given in fig.,-1.

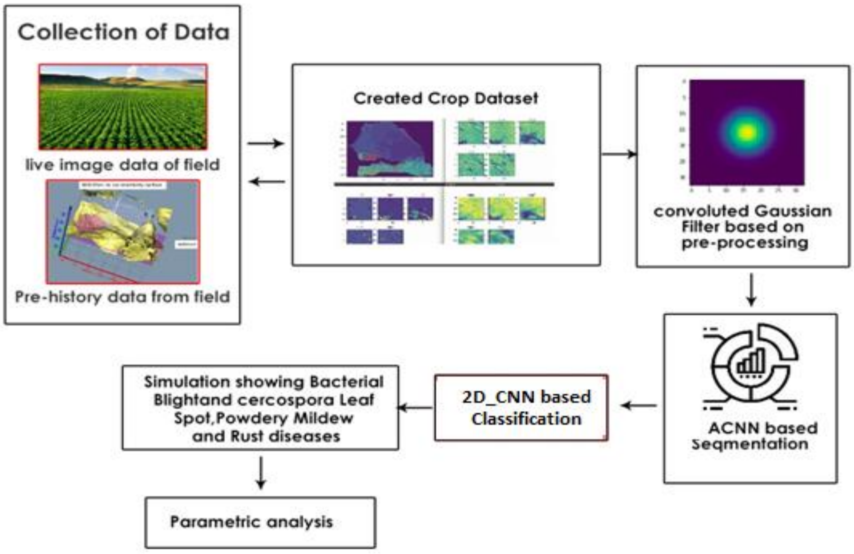


Fig.-1 Architecture for crop disease detection using 2D CNN

Pre-processing using convoluted Gaussian filtering:

Noise in the image is removed in the primary stage. Grayscale conversion of leaf input picture is performed and the filtering method in the preprocessing stage used for removing noises. Here proposed model uses convoluted Gaussian filtering.

Gaussian filters are a class of convolution filters having the weights selected based on the Gaussian function shape. The best filter to remove noise from the Gaussian distribution is Gaussian smoothing. The 1D zero-mean Gaussian function is follows

$$g(x) = e^{-\frac{x^2}{2\sigma^2}} \quad (1)$$

In 3-D an isotropic Gaussian (i.e. circularly symmetric) with the expression:

$$G(x,y,z) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2+z^2}{2\sigma^2}} \quad (2)$$

The Gaussian filtering utilizes this convolution used to achieve this. Image storage is performed by a group of discrete pixels so it is needed to generate a discrete approximation to Gaussian function previously performing convolution. Theoretically, non-zero Gaussian distribution is adopted, which needs an infinite practically 0 and higher than 3 standard deviation and mean, and at this point kernel is truncated. Gaussian with σ of 1.0 is approximated by an appropriate integer-valued convolution kernel. Gaussian is approximated by selecting the obvious mask values. In this mask, a pixel centre with a Gaussian value is used, and it is inaccurate due to the Gaussian value non-linear variation across the pixel. Over the entire pixel (summation of Gaussian at 0.001 increments), the Gaussian value is integrated. Integrals are not in the form of integers: A corner value of 1 is obtained from array rescaling. At last, all the values summed in the mask are 273.

Noise is added and filtered by utilizing the add noise built-in function, Gaussian Blur, and built-in function from Image J. The "Gaussian Blur" includes the kernel convolution, defined by a Gaussian function, with the image pixels. The discrete case convolution is expressed as

$$\mathrm{f} * \mathrm{g}[\mathrm{n}] \overset{\mathrm{def}}{=} \sum_{m=-\infty}^{\infty} \mathrm{f}[\mathrm{m}] \cdot \mathrm{g}[\mathrm{n}-\mathrm{m}] \quad (3)$$

The 2D Gaussian function is generates the kernel. In the following function, the amplitude is defined by A, the centre is (x0, y0), the standard deviations in the x and y directions are σx, σy:

$$f(x,y) = A \cdot e^{-\left(\frac{(x-x_0)^2}{2\sigma x^2} + \frac{(x-y_0)^2}{2\sigma y^2}\right)} \quad (4)$$

In image processing, the Convolution kernel is used to approximate the Gaussian distribution. Therefore, the Convolutional matrix is constructed by values from the distribution and then put into the original image. So, the heaviest weight having the highest Gaussian value) is received by the value of the original pixel and smaller weights are received by neighboring pixels when increasing the original pixel distance.

Image borders are smoothened by a low pass filter known as Gaussian kernel having convolution. Gaussian distribution's variation is the filter defined by parameter, Filtering results are dramatically affected. This work is mainly focused on Gaussian blur effects. Results are obtained based on the filtered image comparison with the original image by the quality factor and expressed as

$$Q(f,g) = \frac{\sigma_{f,g}}{\sigma_g^2 \sigma_f^2} \cdot 2 \cdot \frac{Tg}{f^2+g^2} \cdot 2 \cdot \frac{\sigma_g^2 \cdot \sigma_f^2}{\sigma_f^2+\sigma_g^2} \quad (5)$$

Where gold standard (original image with no noise) is represented as g and the filtered image is represented by f. $\sigma_{f,g}$ is the covariance among the two images, σ_f^2 is the image f 's variance, σ_g^2 is the image g's variance and image f mean is represented by $\overline{f}$ and image g mean is represented by $\overline{g}$. Covariance among the two images are compared by this quality factor, the luminance distortion (the mean values) and the contrast distortion (the variance values).

The indicator we used to evaluate the noise level in the images is the SNR, evaluating image's noise level and represented as:

$$SNR = 20.\log\left(\frac{\sigma_{signal}}{\sigma_{noise}}\right) \quad (6)$$

Signal intensity and noise intensity is compared by basic SNR. Quality of the image is better by increasing SNR

By this filtering method, Noise background is removed, so that image data is improved and unlike distortion are also suppressed. Examination and processing features of images are enhances. In the RGB format images are stored and standard size is resized.

Segmentation using active contour neural network (ACNN):

A technique for standard image examination is the Active Contour Model (ACM) in which several variants were concerned on a massive quantity of research across numerous fields. The Eulerian functional energy of ACM with single-pixel parameter maps detected by ACM is initialized by it. Importantly, Tensor Flow is used to fully implement both the components of CNN and ACM, and the whole architecture of ACNN is differentiable automatically and with no user intervention back propagation trainable.

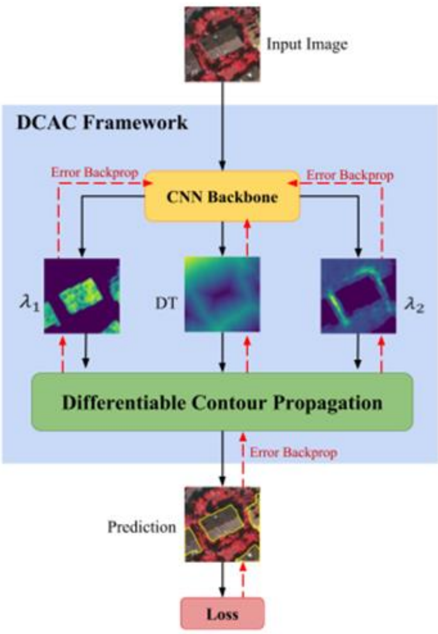


Fig.2: ACNN is a framework training of an ACM which is automatically differentiable

Level Set Active Contours:

Let a closed time-varying contour is $C(t) = \{(x,y) \mid \phi(x,y,t) = 0\}$ denoted in Ω ∈ R2 by the signed distance map's zero level set φ(x, y, t).

φ(x, y, t) is evaluated on the basis of

$$\begin{cases} \frac{\partial \phi}{\partial t} = |\nabla \phi| \operatorname{div}\left(\frac{\nabla \phi}{|\nabla \phi|}\right) \\ \phi(x,y,0) = \phi_0(x,y) \end{cases} \quad (7)$$

The initial level set is represented by φ(x, y, 0).

Active contour models (ACMs), as well denoted as snakes, which is initially used for the evolution of contours by finding a solution for the problem of energy minimization. As compared to the snake's parameter, contours are defined by level set-based ACMs indirectly. In recent years, different types of ACMs were established to enhance the image segmentation performance, amongst the region-based Chan-Vese model that is used widely. The Chan-Vase model's energy function is expressed as

$$F(c_1, c_2, C) = \mu \cdot \text{Length } (C) + \nu \cdot \text{Area (inside } (C)) \\ +\lambda_1 \int_{\text{inside } (C)} |u_0(x,y) - c_1|^2 dxdy \\ +\lambda_2 \int_{\text{outside } (C)} |u_0(x,y) - c_2|^2 dxdy \quad (8)$$

The raw image u0(x, y), a closed curve is C, C's length is represented by the first term Length (C) , the area inside C is denoted by the second term, and regulated scalar parameters are μ,ν,λ1,λ2. Furthermore, the image u0(x, y)'s mean values inside and outside the curve C is represented by c1,c2 respectively.

I(x, y), image interest assumed model, comprises 2 regions of different intensities. The smoothed Heaviside function represents C's interior

$$H_e(\phi) = \frac{1}{2} + \frac{1}{\pi} \arctan\left(\frac{\phi}{\epsilon}\right) \quad (9)$$

And exterior is represented by $1 - H_\epsilon$. The smoothed Dirac delta function's derivative is,

$$\delta_e(\phi) = \frac{\partial H_e(\phi)}{\partial \phi} = \frac{1}{\pi} \frac{\epsilon}{\epsilon^2 + \phi^2} \quad (10)$$

The functional energy related to C is given by

$$E(\phi(x,y,t)) = \\ \int_\Omega \mu \delta_e(\phi(x,y,t)) |\nabla \phi(x,y,t)| + \nu H_e(\phi(x,y,t)) dxdy \\ + \int_\Omega \lambda_1(x,y)(I(x,y) - m_1)^2 H_\varepsilon(\phi(x,y,t)) dxdy \\ + \int_\Omega \lambda_2(x,y)(I(x,y) - m_2)^2 (1 - H_e(\phi(x,y,t))) dxdy \quad (11)$$

C's length is penalized by μ and enclosed area is penalized by ν (ν = 0 and (μ = 0.2 are set), and the inside and outside mean intensities of image are C m1 and m2.

Superior control over C is afforded, and λ2 and λ1 are the generalized constants utilized in [3] to λ2(x, y) and λ1(x, y) which are parameter functions in (4). The expansion and shrinkage of contour definite location (x, y) if λ2(x, y) > λ1(x, y) or λ2(x, y) < λ1(x, y) are the location where the contour shrinks or expands. These functions of parameter are trainable and learned straight through CNN backbone in DCACNN.

Given φ(x, y, 0) and λ2(x, y) and λ1(x, y) are the parameter maps, the Active Contour Model is progressed by numerical time-integration, inside a narrow band from place to place C for increasing the efficiency of computation.

2D CNN Based Disease Classification:

A two dimensional CNN design consists a series of convolutions that are utilized to extract feature from pictures. To forecast a specific class label or a group of class probabilities, this type of design frequently finishes with completely linked layers. Convolutional layers add filters to all pixels of the input picture to produce a set of high abstract features; pooling layers limit the no., of features to prevent over-fitting; and completely layers restructure the outcome in to vectors of the same size as the no., of classes. A 2D-CNN uses two activation functions for classification: softmax for such output nodes and Rectified Linear Unit (ReLu) for the remainder of the layers. Softmax seeks to scale the outcomes among zero and one, indicating the likelihood of coverage belonging to a certain class. If the input is positive, ReLu is a linear function which will produce it immediately. Otherwise, it will return a value of zero. In addition, 2D-CNN 1 is made up of three convolutional layers that are preceded by a max-pooling layer. The filter size (fs) for this sequence was picked from among fs = [2 2, 4 4, 8 8,] as the first no., that provided for the best performance. Fig., 4 shows a graphical representation of the 2D-CNN architecture.

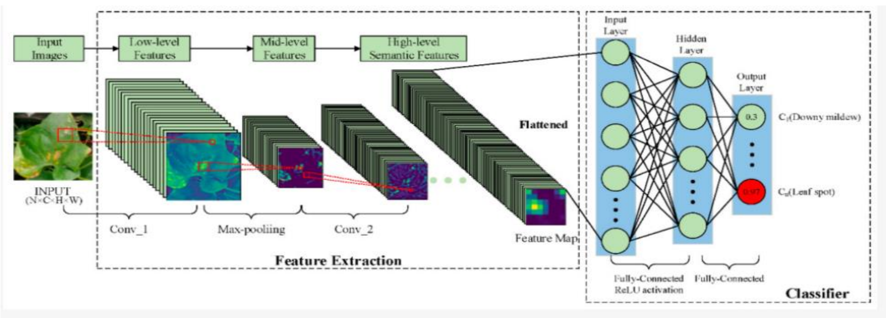


Fig. 4. A schematic view of the proposed 2D-CNN

The 2D-CNN 2, on the other hand, is made up of 3 convolution layers, which are preceded by a 2 2 max-pooling. A one-to-one convolution layer is used in this design to extract more characteristics from the pictures without sacrificing information. Then, to prevent overfitting, dropout layers are used to disable a fraction of the neurons.

There are seven levels in the CNN model. Certain information is handled in each layer. The following are the 7 layers. The data is stored in the case of images in the input layer. The image's height, breadth, and depth, as well as its colour information, are among the characteristics (RGB). The picture input size is set to 224 X 224 RGB.

Convolution Layer: The feature extraction layer is also known as the convolution layer. Utilizing dot products of the picture dimensions, this layer extracts the main characteristics from the provided collection of photographs.

Pooling Layer: By lowering (or) altering the shape of the featured matrix created by utilising dot products, the pooling layer aims to limit the processing resources required to analyse the data.

Layer that is fully connected: Loads, neurons, and biases are all part of it. It links neurons in different convolution layers.

Multi-classification is carried out via the Softmax Layer/Logistic Layer. The binary classification is carried out by the logistic layer. It determines the likelihood of a certain object being present in the picture. The probability is '1' if the object is visible in the image; else, it is '0'.

ReLU's Activation Function: It activates the node by transforming the whole weighted input thru the node and putting it into the operation. The Rectified Linear Unit (ReLU) is a convolution algorithm utilized in neural networks.

4. Result and Discussion

Plant disorder detection is focused in this work and this is detected by using the method of ensemble classification. By using convoluted Gaussian filtering and deep convoluted active contour neural network (DCACNN), this approach's performances are evaluated. The performance metrics are precision, recall, and accuracy

Accuracy: The no., of patterns that are properly segmented to the entire no., of samples is defined as accuracy and this accuracy is calculated :

$$A = \frac{TP+TN}{TP+TN+FP+FN} \tag{11}$$

Precision: The ratio of positive no., of samples to the total no., of samples is known as precision.

$$P = \frac{TP}{TP+FP} \tag{12}$$

Recall: The ratio of true positive no., of patterns to the total positive declared no., of patterns is known as recall.

$$R = \frac{TP}{TP+FN} \tag{13}$$

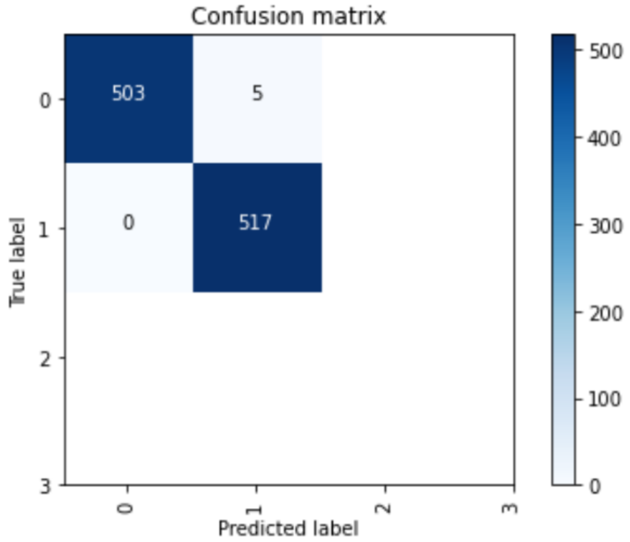


Fig.-4 Confusion matrix of crop disease predicted class

The testing accuracy of the model will be generated after every epoch while deploying the model. The confusion matrix for crop disease predicted class has been shown in fig.,-4. The below fig.,-5 shows healthy and unhealthy leaves of input dataset.

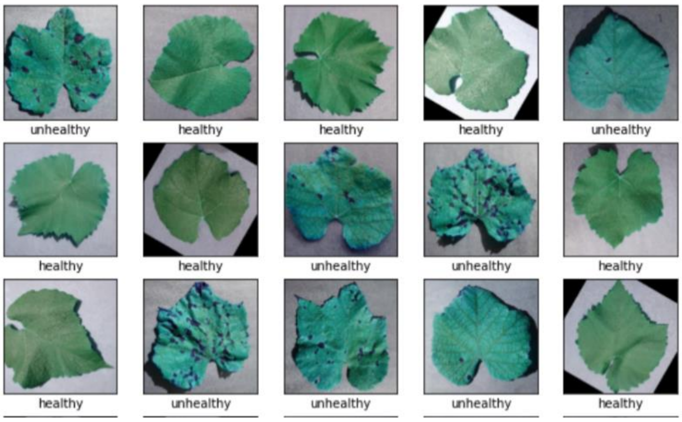


Fig.-5 detection of healthy and unhealthy leaves

The below fig.,-7 shows proportion of healthy and unhealthy leaves detected using proposed classification technique.

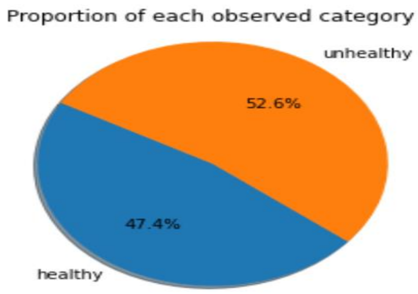


Fig.-7 proportion of healthy and unhealthy leaves detected using proposed classification technique

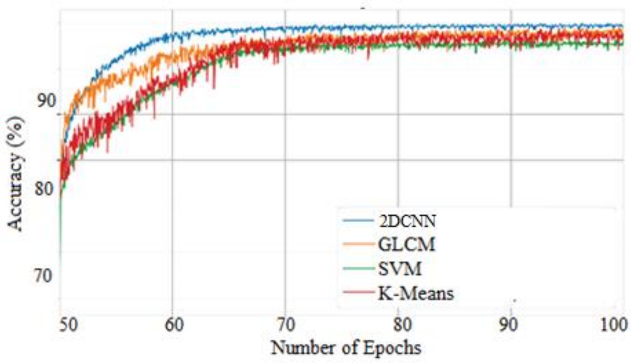


Fig.-8 Examination of accuracy for existing and proposed technique

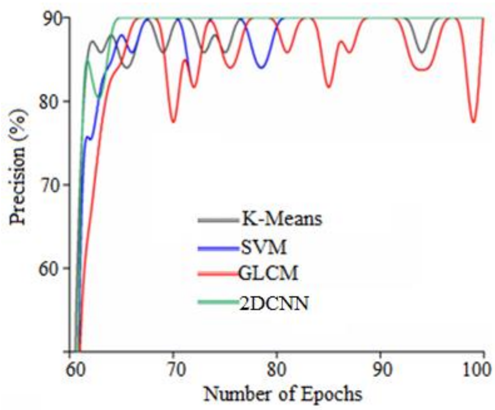


Fig.-9 Precision examination for existing and proposed technique

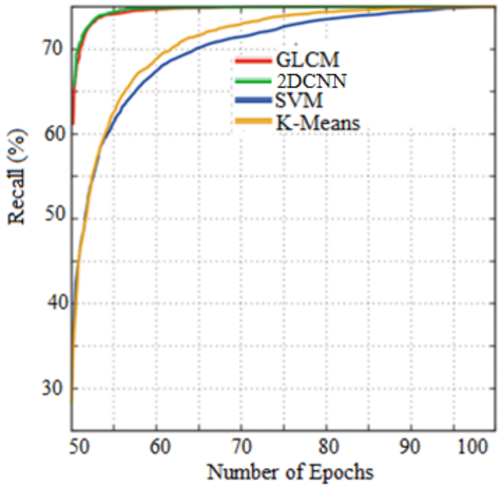


Fig.-10 Recall examination for existing and proposed technique

The above fig., 8,9 and 10 shows the parametric examination of accuracy and re-call between existing and proposed technique. The comparative examination in crop disease detection has been shown in table-1, and its representation is shown in below fig., 11

Table-1 Comparative Examination in crop disease detection

Crop	Parameter	k-means	SVM	GLCM	Pro_2DCNN
Tomato	Accuracy	95	96	97	98
	Precision	89	90	92	93
	Recall	74	75	76	78
	f1-score	73	75	76	77
Grapes	Accuracy	94	95	96	98
	Precision	86	87	89	90
	Recall	71	72	74	75
	f1-score	71	73	75	76

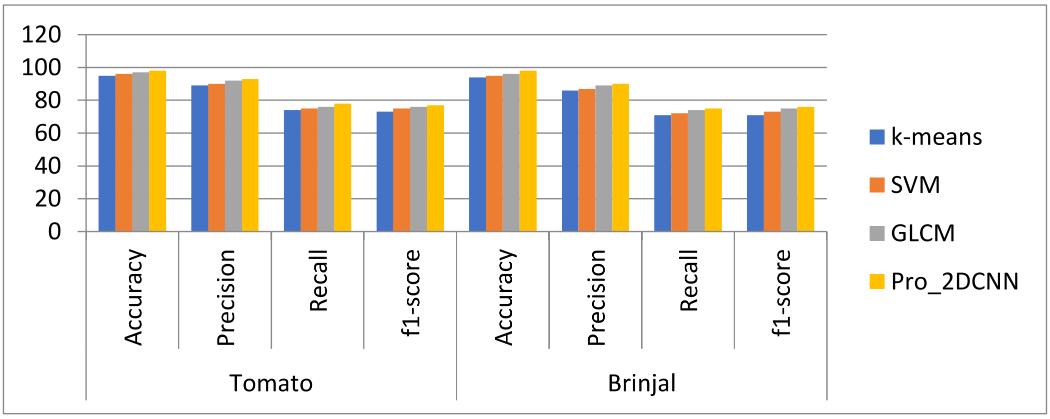
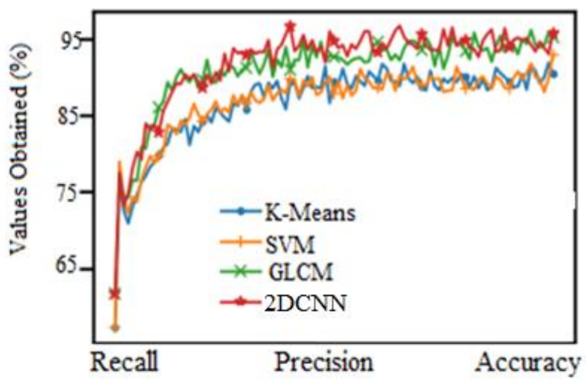


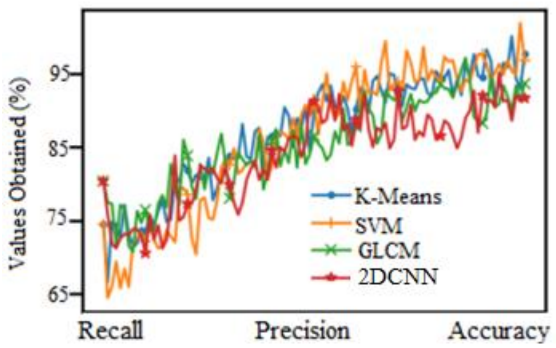
Fig. 11: Accuracy of Tomato and Bingil in terms of (Precision, Recall, and f1-score)

Table- 3 Parametric Comparison examination for crop disease detection

Tomato



Brinjal



5. Conclusion and Future Work

Plant disease detection is the main challenge for deep learning and image processing. So this paper proposed crop disease detection based on preprocessing and segmentation process using filtering and neural network technique. We presented the processing and filtering procedure by pre-processing using convoluted Gaussian filtering and then based on neural network the image has been segmented using active contour neural network (ACNN) and classified using 2DCNN. Plant Disease Image's benchmark dataset is used for performing experiments. Healthy Leave's1000 images and crop diseases are present in this dataset. Automatic detection of crop disease is an improvement is the major motivation of this system. 98% of accuracy is obtained in the classification through experimental results by the proposed system. Database for identification of diseases in plants are expanded in the future research and also used in classification purpose. Training increment increase the system's accuracy so the training data is needed to be improved in future research.

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