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Mango Plant Disease Detection System Using Hybrid BBHE and CNN Approach

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ABSTRACT

Detection of plant diseases plays a crucial role in taking disease control measures to increase the quality and quantity of crops produced. Plant disease automation is beneficial because it eliminates surveillance work at significant farms. As plants are a food source, diagnosing leaf conditions early and accurately is essential. This work involves a detailed learning approach that automates leaf disease detection in mango plant species. This paper presents a detection system using Brightness Preserving Bi-Histogram Equalization (BBHE) and Convolutional Neural Network (CNN). The photographs of mango leaves were first flattened, then resized and translated to their threshold value, followed by feature extraction. CNN and BBHE have extensively been used for pattern recognition. The test images of affected leaves were subsequently uploaded to the system and then matched to the ailments being trained. Training data and test data were cross-validated to balance over-adjustment and under-adjustment problems. The proposed method correctly detects the mango leaves disease at the early stage with 99.21% maximum accuracy.

1. INTRODUCTION

Fill Mango (Mangifera Indica) is a popular & delicious fruit variety of Indian agriculture. It is shipped in the form of fresh and mature mangoes to many countries, as well as refined consumables such as ripe mango and juice slices, raw Pickle mango, etc. Mango is plentiful in nutrients and vitamin A & C, just as having rich restorative characteristics in customary Indian Ayurvedic medication. Mango leaves are partly utilized for medicinal functions as they have antibacterial activity against gram-positive microbes. Recently, due to the unchecked use of pesticides, the export price of Indian mango has been decreasing; therefore, it is a good time for researchers to originate the ideas for the detection and control of toxic pesticides that are a threat to human health. Common mango diseases include black mildew hopper infest, pulp weevil attack, pulp-mineral attack, anthracnose attack, alternate leaf spots, etc., mango diseases, and other infections. The infestation of gall midges, an attack on black mildew hopper, mango fungus, seed mine, anthracnosis, alternative leaf spots, and many more are rare mango disorders. Leaf disease can disrupt photosynthesis which causes the plant to die in due time [1].

Mango Bacterial Canker is a fatal disease that causes a 10-100% loss to mango yield in the field and storage. It has been proven in the research done by Smith [2], Bark cracking is one of the major issues in some orchards, where around 93% of the mangoes suffered from the said problem. So, Mango diseases cause a crucial problem resulting in economic and agricultural industry loss. If those diseases are possible to identify rightly, then disease prevention would be easy. However, the identification of diseases is so difficult with the naked human eye, which makes it necessary to adopt machine learning to detect diseases at the early stage. Machine learning could be a feasible detection method of mango leaves disease with the advancement in technology, especially for the development of image processing techniques.

Pattern Recognition is a machine learning partner that focuses on pattern recognition and information training. Pattern Recognition system works on the supervised and unsupervised learning data. It is closely related to artificial intelligence and machine learning, organized with applications such as data mining, fruit/vegetable recognition, diagnostic systems, face recognition, biometrics, and image processing. The application of AI & ML aids in distinguishing galaxies by size, recognize signatures, show possible mammographic cancers, recognizing handwriting and recognizing diseases, etc. Since the revival of neural networks, techniques from statistical pattern recognition have obtained widespread use in digital image processing. The evaluation and development of leaf diseases have become more common nowadays, as environmental and climate conditions are more unstable than ever. In this changing environment, it is more important to identify relevant and timely diseases like early detection [3].

There are different forms of Neural Network named as convolution neural network (CNN), artificial neural network (ANN), and Feedforward Neural Network (FFNN). This research is carried out with the help of CNN. CNN is used to study the image in depth like how the pixels be agreed. The ratio of the training and testing phase will be 80:20. The training set should be large compared to testing to obtain maximum accuracy. CNN model works similarly to the human brain.

The Scientific name of the mango is Mangiferae Indica. India is the largest producer of the mangoes throughout the world. It reaches 50% of the global supply. In Tamil Nadu major mango growing districts are Dharmapuri, Krishnagiri, Vellore, and Theni. The window planting is prone to the wind; it reduces the effect and damage caused by the pest and disease. The planting is done from July to December. The important pests are hopper mealybug and fruit fly.

Strong infections lead to quick rotting, even light infections that mostly cause superficial harm can reduce fruit processing life. Various types of pooling are available. Overall losses are difficult to indicate, given the variability between seasons and locations, but crop losses in the different stages of the disease of up to 50% would be prevalent [4]. Mango grows without frost in a wide range of climates. The tree is the best producer for climates in which the flowering and fruit development with a high heat build-up is a well defined and rather cool dry season [5]. Super pooling and moderate pooling, for example. The flowering and fruiting season contributes to the growth of fungal diseases that cause flora and fruit to drop (High Moisture, Heavy Dew & Fog). The ideal mango temperature [6] is 24 to 27°C. During four summer months (June to September), the best mango weather has a rainfall of 750–2500 mm and a dry season of eight months [7]. Mango is now produced in tropics and subtropics as a vegetable tree and shade for the processing of commercial fruit [8, 9].

Most producers are unable to manufacture the goods as their success. This is the wrong way of preventing or treating your farm against plant disease. For certain regions, farmers use a chemical to tackle a question of plant diseases. Nevertheless, the remedy may not be suitable to address the issue due to the lack of knowledge and precision, or it may take a lot of time to overcome it. Today, farming is a dynamic activity that involves the collection and incorporation of information from a number of sources in order to encourage farmers to take decisions. This applies to a computer system concept based on agricultural precision. It consists of information and knowledge for decision-making. Therefore, the management of a farm requires knowledge and skills with experienced professionals [10].

In the field of agriculture, there are many technologies and applications developed to support them. Nearly these technologies and applications need a knowledge base for their operation. One of the most important components of an expert network is a knowledge base. An appropriate knowledge base is required to create an expert system to diagnose and classify high-level pests. This paper provides the basis for the identification of plant disease through data mining techniques in barracuda mango. The dataset was constructed using certain symptoms in the region of the mango leaf [11].

The invention of photo spectrometry led to a large number of researches works, which centered on the use of spectral data as well as spatial analysis. Spectroscopic and remote scanning techniques are used to image the object's optical characteristics with several spectral representations by Hyper Spectral Image (HSI) multi-variate imaging subset. Because of its advantages from the detection of many small spectral bands and a larger range of electromagnetic spectrums, research institutions and industries have become more interested in this new area [12].

1.1 The motivation of the study

There are many methods for automated or computer vision plant disease detection and classification, but the research on mango leaf is still lacking. In addition, there are still no commercial solutions on the market, except those dealing with plant species recognition based on the leaf's images. As far as current literature is considered in the field of plant disease recognition, there was no work with related results using the exact technique. So, this work motivates us to a detailed learning approach that automates leaf disease detection in plant (Mango) species.

1.2 Related works

In this section, the description of related papers is defined regarding deceases of mango leaves and applied methods. The learning approaches that automate leaf disease detection in mango plant species are defined.

A plant's contribution is of great importance to the environment as well as human life. Plants, like humans and animals, suffer from diseases. There are many diseases occurring in plants and affect a plant's normal growth. These diseases affect entire plants, including leaves, stems, fruits, roots, and flowers Usually the time is a plant's disease is not cared for, the plant dies or can cause leaves to fall, flowers & fruits to drop, etc. For the correct detection and treatment of plant diseases, proper diagnosis of such diseases is needed. Pathology of the Plants is researching the causes of plant diseases, their control and management procedures, as stated by Chouhan et al. [13].

The goal of Moriya et al. [14] work was to establish a technique involving the study of aerial photographs by a hyperspectral camera with the Unmanned Aerial System (UAS), resulting in identification and detection of mosaic-infected sugarcane plants. In order to establish an adequate working mode for a hyperspectral camera, which offers multiple imaging options for spectral bands but restricts each image to 25 spectral bands, spectral response is needed for healthy and contaminated sugarcane factories. The infected and healthy sugar cane was rendered using a spectral measuring system. A spectral library is developed. Once the most appropriate spectral band is selected, the camera could be configured and the aerial survey could be carried out. The analytical line method was followed to achieve hemispheric conical reflection variable values with a modification of the radiometric frame to create a mosaic suitable for the study.

Automatic identification & diagnostics of maize leaf diseases are very common in the field of agricultural information. In this study, Zhang et al. [15] proposed the enhanced GoogLeNet & Cifar10 models depended on deep learning to enhance precision of maize Detection of leaf disease & reduction in network parameters. Two modified models used to train & evaluate nine types of maize leaf images were obtained by modifying parameters, increasing configurations of pooling, adding dropout operations & rectified linear unit (Relu) functions, & reducing number of classifiers. Therefore, no. of variables of modified models is dramatically lower than that of the architectures of VGG and AlexNet.

Tumang [16] research helped mango farmers in Pampanga detecting pests & diseases with leaf & fruit marks, especially when applying pesticides to plants, to solve the major deterioration of mango production in the Philippines by pests and the farmers. This study helps mango farmers in Pampanga Anthracnotizing, fruit borer and sooty mold have been detected with 85 percent accuracy using image processing wiith multi-SVM & GLCM. Extracting contrast, kurtosis, skewness, & entropy determined it. This research project can be applied as a model for other fruit-bearing trees and a location-based foundation for plant leadership using data science.

Table 1. Research gaps: A literature gap of different methods and their parameters

S. No.	Author	Year	Method Used	Other Parameters
1	Moriya et al. [14]	2016	Aerial photographs by a hyperspectral camera with the unmanned aerial system (UAS)	The analytical line method was followed to achieve hemispheric conical reflection variable values with a modification of the radiometric frame
2	Chouhan et al. [13]	2017	Function Neural Network (BRBFNN).	Region growing method searching for seed points and grouping them having similar attributes
3	Zhang et al. [15]	2018	Enhanced GoogLeNet & Cifar10 models depended on deep learning	Maize Detection of leaf disease & reduction in network parameters
4	Singh et al. [17]	2019	Multilayer Convolutional Neural Network (MCNN)	Computer vision with machine learning methodologies has outperformed in solving a number of plants that leaves disease problems including pattern recognition, classification, object extraction etc. [13].

It has become a serious task with rapid population and urbanization growth in the cultivation and development of plants both important for sustaining nature needs and living creatures. In addition, economically and environmentally important plants need to be preserved. It is a time-consuming and expensive process to identify these animals Forest and shrubs including men. Kour and Arora [18] proposes, therefore, based on their leaf pictures, a unique approach for classifying and segmented the seven plant species, called Guava, Jamun, Mango, Grapes, Apple, Tomato and Arjun. To remove noise, resizing, and contrast enhancement, together with real-time images &images after crowd AI database will be collected and preprocessed in the first phase. Instead, in the second phase, various color and texture-based features are removed. The third phase includes object segmentation using an algorithm k-means. The fourth stage consists of help vector machine learning & eventually, the analysis is carried out in the last phase. PSO algo is applied to select a possible value in the segmentation and classification of the initialized parameter.

In precision agriculture, there is considerable research into the expansion of automatic systems for disease detection & classification. Researchers have been studying several cultures that exploit different parts of the plant over the past few decades. For Soji, photos of a plant are a small study. A rules-based semi-automatic system based on k-means concepts is designed to distinguish healthy leaves from diseased leaves. In addition, one of three classes is classified as a diseased leaf (down mildew, frog eye, and sectorial leaf blight). The trials take place on the basis of color, texture and their combinations by Kaur et al. [19], to train three models on the basis of vector support for the system classifier. Thousands of images from the data set of the Plant Village were produced. Acceptable, average precision values that have also been shown to be greater than current for all considered combinations. This research is intended to find the best method for the detection of soybean leaf disease. It is displayed that the process also measures the magnitude of the infection effectively. The appropriateness of the system proposed is demonstrated further by the visual examination of leaf samples for detection, classification, and calculation of severity.

Mishra et al. [20] in their research uses a wavelet transform image segmentation technique, they have employed this technique to automate the detection process and uses an approach based on WNN (Wavelet neural network) that performs the process of classification in mango leaf diseases in various species. Balasundram et al. [21] present survey conducted on various computer vision techniques employed on mango trees. In Sachdeva et. al. [22] introduce Bayesian process for efficient feature learning. Few papers [23, 24] discussed techniques based on an automatic web facilitated leave disease segmentation system for mango tree using a neural network (NN). They divide the work in four major steps. First, capture images, second, preprocessing of images done using scale invariant method. Third, Neural network is trained on dissimilar features. Finally, the radial basis function NN on the mango leave images to segment the diseased portion from image. Comparative analysis between the existing methodologies along with the research gaps is shown in Table 1.

2. METHODOLOGY USED

2.1 Histogram equalization

Histogram equalization is done to consider and differentiate the distribution of backdrop and foreground pixels. This also increases the picture contrast. This fine-tunes and uniformly distributes the picture intensities. This will boost the regions with lower regional comparisons. With this process, the global object contrast is improved. The equalization of the histogram divides the most common values of frequency. To maximize the image contrast, the image histogram is assigned a standardized pixel intensity value using the Eq. (1) histogram equalization process [25].

$$G(p_{(a,b)}) = round\left(\frac{f_{cde}\,(p_{(a,b)}) - f_{cde\,(min)}}{I \times A - f_{cde}} \times H - I\right) \tag{1}$$

where,

f_{cde} = gray level cumulative amplitude,

f_{cdemin} = cumulative distribution function minimum size, f_{cde} (p(a, b)) = up to date pixel strength,

I and A = service.

H.

where,

f_{cde} = gray level cumulative amplitude.

The improvement in the contrast of images done by Histogram equalization. This technique work by spreading the most frequency intensity value through the entire image. The Figure 1(A) and 1(B) shows the original image and histogram equalized image.

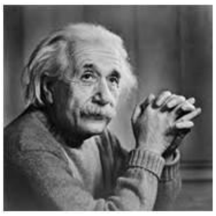

Figure 1(A). Original Image

Figure 1(B). Histogram equalize image

2.2 Convolutional neural network

Several CNN templates are available, such as AlexNet, VGG, Google Net and ResNet. The depth, parameters, non-linear shape, and unit-size are different for these models. Several variable variables are available, such as the drop-out frequency, the learning speed used in the dynamic analysis to solve identification problems and pattern recognition. The output size is cumbersome with volume weights. The input layer is extended or reduced depending on the padding and the phase. The width and height of the space are decreased in the convolution process, but the density increases. A model for each layer is added with the non-linear activation function, which does not vary linearly by specified input. RELU reduces the likelihood of gradient being lost. It leads to a sparse template as well. Pooling helps to reduce the software request and the activation function space. Because of less convergence and greater efficiency, Max pooling is more widely used. The frames have been sampled with a max-pooling surface. This also increases the risk of over-fitting. The final layer responsible for estimating the category of an object is thick and completely connected [26].

2.2.1 Convolution layer

The convolution layer in the Convolution Network will do most of the computation work. The image will be the input to the convolution layer; it will convert the image into a matrix form based on the pixel value of the leaves. In this layer there is a filter, at the top left corner move around the image, it will multiply the filter with the pixel value. After sliding the filter overall, we will obtain an activation map. The activation map is the input to the next layer of the Convolution Neural Network.

2.2.2 Pooling layer

The pooling layer will do the process called Dimensionality Reduction, which means reducing the size of the images can increase the computational complexity. It controls the overfitting. Different types such as max pooling and average pooling are available. The maximum value in the filter matrix will be selected by Max Pooling. Max pooling has the translational invariance. The term translational invariance means that it will work based on the feature extraction, the feature is presented exactly or rather. Average Pooling is known as subsampling. The sub-sampling helps with the overfitting of the data.

2.2.3 Fully linked layer

In a fully linked layer, the neuron in one level will connect to neurons in another layer. This layer will be the same as the traditional multi perception layer.

2.2.4 Brightness preserving bi-histogram equalization

The histogram of the initial image is divided in 2 sub-histograms with bi-histogram equalization, depended on the average histogram of the original image. Sub histograms are stable separately by a simplified histogram parallel that products flatter histograms. Such two histograms were separately equalized after this phase of separation. Thus, between the medium output and central gray point is the resulting mean illumination. The fundamental principles used during the BBHE method to distinguish original image in 2 sub-images & then translate separately histograms of sub-image-the so-called dualistic sub-image HE-into the similarly detailed type. DSIHE approach breaks down the image to maximize the entropy of Shannon's image, instead of breaking it down by means of its medium gray rate. The output object consists of two sub-images, one dark or one light, which preserve characteristics of the same area. The DSIHE Method does not have a substantial change in output luminosity, particularly in the large image area with the same gray levels. System Minimum Mean Brightness Error equalizer (MMBHE) divides the histogram of the original image into sub histograms, then equalizes every sub histogram separately to GHE. First, MMBEBHE calculates from the perspective of object illumination all possible individual points' values. Differences between the average value of the original image & average value of the sub histogram are determined for each separating point. The selection point reduces the difference between inputs and outputs means. Recursive histogram equalization (RSIHE) sub-image preferred to differentiate histograms with a maximum probability density of 0.5 based on a grayscale. This approach provides better protection against exposure and increases image quality. History Equalization assigns different clusters to every non-zero bin in a histogram of an image or determines the weight of each cluster. Instead, we combine neighboring cluster pairs using three parameters. Most sub-images according to their respective histograms are even in their mean and others away from the mean. Therefore, resulting in equalized subsets preserve a medium total brightness. The foremost problem is which situational contrast of the image is not improved [27].

Let I_M be image f say, assuming $I_M \in \{0, -1\}$. The photo split in 2 sub-images f_i and f_j based on I_M

$$f = f_i \cup f_j \#(2) \tag{2}$$

$$f_i = \{f(x,y)\}|f(x,y) \le I_{m,\forall f(x,y)\in f} \tag{3}$$

$$f_j = \{f(x,y)\}|f(x,y) \le I_{m,\forall f(x,y)\in f} \tag{4}$$

Sub-images f_i & f_j are distinct as the probability density function.

$$P_i(I_k) = \frac{n_j^k}{n_i} \tag{5}$$

$$P_j(I_k) = \frac{n_i^k}{n_j} \tag{6}$$

in which n_i^k and n_j^k represent the respective values of fI_k in the two sub-images f_i and f_j and n_i and n_j respectively the total values of f_i and f_j.

Here,

$$n_i = \sum_{k=I_0}^{I_m} n_i^k, n_j = \sum_{k=I_{m+1}}^{I_{m-1}} n_i^k \text{ and } n = n_i + n_j \tag{7}$$

Then the respective CDFs are defined as

$$P_i(I_k) = \sum_{k=0}^{I_m} p_i\,(I_k) \tag{8}$$

$$P_j(I_k) = \sum_{k=I_{m+1}}^{I_{m-1}} p_j\,(I_k) \tag{9}$$

Therefore (pi(jk)) =1 and (PJ(jk)) =1 by definition.
Conversion functions by CDFs

$$T_i(I_k) = I_0 + (I_m - I_0).\,P_i(I_k) \tag{10}$$

$$T_j(I_k) = I_{m+1} + (I_{L+1} - I_{m-1}).\,P_j(I_k) \tag{11}$$

The corresponding representation of histogram may then be represented as

$$G\,(x, y) = T\,(f\,(x, y)) \tag{12}$$

The mechanism described above is not very good, as max-pooling loses valuable information and does not encrypt relative spatial relationships between features. Because of this, Convolution Neural Network (CNN) is not actually invariant to large transformations of the input data. CNN does not encode the position and orientation of an object.

3. PROPOSED METHODOLOGY

3.1 Selective-retinex fusion algorithm

- Find the light sources in the image. Erode first to eliminate speckles, then dilate to recover the area. We can obtain the point light source Pn, $n = 1 \ldots N$.
- Reduce the halo. Compute the luminance-enhanced factor related to the distance.

$$f_T(i,j) = \text{minexp}\left[-\frac{c\sqrt{(i-i_{on})^2 + (j-j_{on})^2}}{M_n}\right], n = 1 \ldots N \tag{13}$$

- Deal with the two-part differently

$$f_L(i,j) = \min\exp\left\{\begin{matrix} 1, \\ \text{in the area of each point light source} \\ d.\,(p(i,j) - \text{Light})^2 \\ +1, \text{other parts in the image} \end{matrix}\right\} \tag{14}$$

- Enhance the luminance component of the whole image by using.

$$P_y(i,j) = w.\,P_m(i,j) + (1-w)P_k(i,j) \tag{15}$$

where, w is the weight. The fusion of the image is controlled by the value of w. As per the literature best range of w is from 0.1 to 0.3. $P_m(i,j)$ is the gray value for the faint image based on the modified Retinex algorithm and $P_k(i,j)$ is the gray value based on the selective and nonlinear gray mapping [28].

3.2 Canny edge detection

- Noise reduction edge detection is highly sensitive to image noise.
- Gradient calculation for detecting the edge intensity and direction by calculating the gradient of the image using edge detection operators.
- Non-maximum suppression to gradient intensity matrix and finds the pixels with the maximum value in the edge directions.
- The double threshold for strong, weak and non relevant pixels. Potential edges are determined by this thresholding. Edge pixels stronger than the high threshold are marked as strong; edge pixels weaker than the low threshold are suppressed and edge pixels between the two thresholds are marked as weak [29].
- Edge Tracking by Hysteresis for transforming weak pixels into strong ones

$$G(x,y,\sigma) = \frac{1}{2\pi\sigma^2} e^{\frac{-x^2y^2}{2\sigma^2}} \tag{16}$$

3.3 BBHE algorithm

1) Select the image.
2) Get the original picture histogram.
3) Calculate the histogram mean.
4) Divide the histogram into 2 parts based on the mean.
5) Equalize each part independently using PDF and CDF.
6) Combine both sub-images for final output.

Proposed Algorithm

Step 1 First, we browse the image of mango leaves from the dataset.

Step 2 Apply to preprocess on this original image by using the technique for the conservation of bi-histogram equalization (BBHE).

*Step 3 Resizing above BBHE image in a matrix of 256 * 256.*

Step 4 Assigning the class label to the training image and testing image by discriminate analysis classification model.

Step 5 CNN train model with the help of images training.

Step 6 Validate the model's performance and compare the other state-of-the-art approaches results.

Step 7 Performance evaluation of recognized image in the training step and testing step.

Step 8 Exit.

In the proposed method, mango leaf dataset considered which is publicly available at [30]. The dataset comprises of 265 diseased and 170 healthy images. The dataset has been divided into training and testing dataset. Training set comprises of 95% diseased images and 95% healthy images of overall dataset. Remaining 5% has been used for the testing purpose.

4. RESULT AND DISCUSSION

The BBHE technique is a merger of two techniques in this paper. In our proposed technique, we are using BBHE (Brightness Preserving Bi-Histogram Equalization). BBHE was suggested in 1997 by Kim. It divides a histogram of the image into two sections i.e., underexposed and overexposed on the basis of the average value. A histogram varies from 0 to M-1. The initial histogram has a set of values of 0 though the other has the value of M-1. These two histograms are automatically stable. It equalizes the sub-image histogram of the original image. The result of applying BBHE to the mango leaf image is shown in Figure 4. The value of bit-error-rate in BBHE is lower than the local HE technique. BBHE removes more error and enhances an image in comparison to Local HE. Mean square error is also less of the BBHE technique is also less than Local HE. Peak Signal to Noise Ratio is also more. Brightness Bi-Histogram Preservation Equalization reduces the change in mean intensity. It preserves the brightness and enhances contrast. The grayscale level is used for portioning the image. Figure 2 shows the images from the dataset. Figure 3 shows the layout of the implemented algorithm in MATLAB. Figure 5 shows the images after assigning class label step. Figure 6 and Figure 7 shows the images from the training and test set respectively.

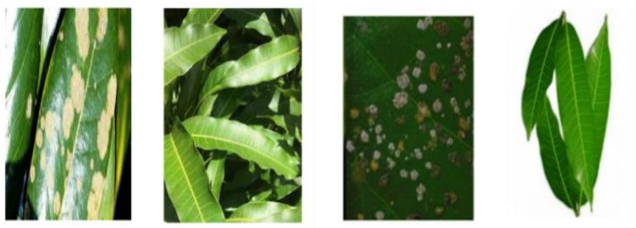

Figure 2. Image selected from dataset

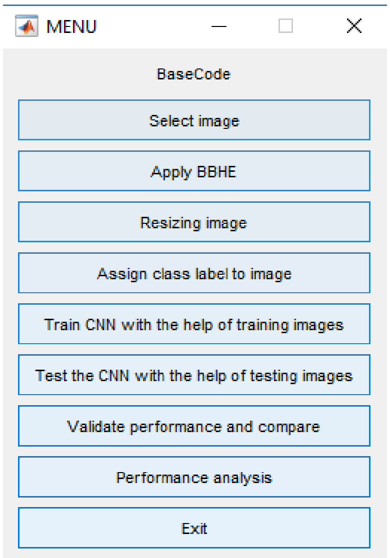

Figure 3. GUI for the proposed method

Figure 4. Mango leaf images after applying BBHE

Figure 5. Images after assigning the class level

Figure 6. Images from training set

Figure 7. Images from the testing set

Table 2. Base accuracy correlation and reliability in learning with various images

Trial name	BBHE training accuracy (%)	Selective-Retinex fusion training accuracy (%)	Canny Edge detection training accuracy (%)	(BBHE & CNN) training accuracy (%)
Trial 1	86.85	86.94	87.42	89.23
Trial 2	89.97	87.31	88.21	92.74
Trial 3	91.98	92.17	92.16	93.87
Trial 4	92.79	91.76	93.41	95.21

In the above Table 2, the training is applied to four images and the accuracy of the different algorithms is taking place.

Table 3. Base accuracy analysis or propose accuracy for various image analysis

Set name	BBHE testing accuracy (%)	Selective-Retinex fusion testing accuracy (%)	Canny Edge detection testing accuracy (%)	(BBHE & CNN) testing accuracy (%)
Set 1	91.43	91.94	97.46	95.65
Set 2	93.34	90.31	95.11	95.65
Set 3	95.00	93.17	92.66	91.30
Set 4	96.38	97.76	98.46	100.00

In the above table when the testing is applied on four images, the testing accuracy of different algorithms is examined.

The performance parameter of the proposed algorithm is shown in Table 4.

Table 4. The performance parameter of the proposed algorithm

Performance Parameter	Set 1 (%)	Set 2 (%)	Set 3 (%)	Set 4 (%)	Overall (%)
Accuracy (%)	95.65	95.65	91.30	100	95.65
Precision (%)	100	92.85	92.85	100	94.43
Recall (%)	93.33	100	92.85	100	96.55

The comparative analysis of accuracy is shown in bar chart in Figure 8 and Figure 9 for training and testing set respectively.

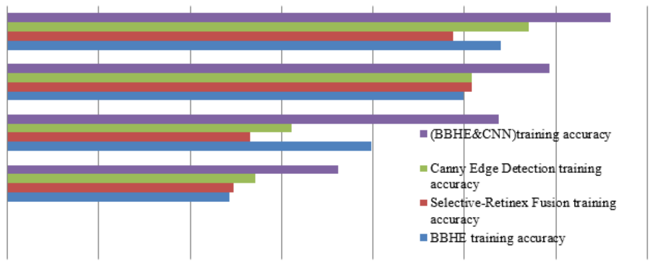

Figure 8. The bar graph of comparison of accuracy of training with different Image by using a different algorithm

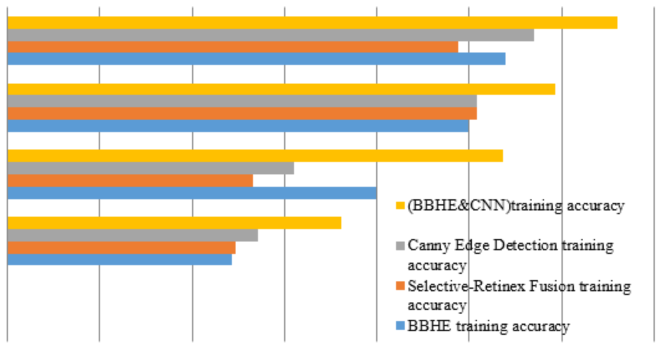

Figure 9. The bar graph of comparison of accuracy of testing with different image by using a different algorithm

5. CONCLUSION

In this, we have developed a Convolution Neural Network, applied for detection of plant disease identification using leaf images. The trained model required a low computational power to classify the images, making it feasible to integrate into the mobile application. The ML takes longer to train, but its testing is more efficient than traditional methods. The proposed model for the detection of CNN and BBHE-related leaf diseases is capable of classifying the stable mango leaves for four different diseases. Because CNN needs a tireless image and handcrafted functions, faster convergence and good training output inputs and handcrafted features, this is preferable to traditional algorithms for many applications. By providing more images in the dataset and tuning the parameters of a CNN system, classification accuracy can be further improved. So, in this study, we propose to identify Mango Leaves Infected as Anthracnose, a creative design called CNN & BBHE. Relative to other state-of-art methods for its precision, the better reliability of the proposed study is verified with an accuracy of 95.65%. Further, low-quality images of leaves are still a challenging issue that needs to be taken care for the detection of disease.

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