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Preprocessing of leaf images using brightness preserving dynamic fuzzy histogram equalization technique

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ABSTRACT

Agriculture serves as the backbone of many countries. It provides food and other essential materials as per our requirement. Various kinds of diseases are affecting the agricultural crops which in turn reduce the quantity and quality of the agricultural sector. This can also lead to the decrease in food production thereby affecting the economic growth and development. Even though the symptoms and other impacts of the diseases are outwardly visible, manual identification of diseases and rectification is a tedious and time-consuming process. Therefore, detecting the diseases using an automatic computer-based model will be an effective solution. Image processing methods in conjunction with machine learning algorithms provide greater assistance in the field of plant disease detection. In the proposed work, plant leaf images of 10 crops are collected as the dataset. The images after acquisition are preprocessed using brightness preserving dynamic fuzzy histogram equalization (BPDFHE), an advanced version of histogram equalization and Gaussian filtering. The results are calculated and compared using the parameters such as peak signal to noise ratio (PSNR), structural similarity index (SSIM) and mean square error (MSE). This method performs more accurately than the existing preprocessing approaches.

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1. INTRODUCTION

Agriculture is a very important sector as it helps us in various forms. There are many nations that depend upon agriculture for their daily needs. From food substances to energy products, agriculture has many roles in our lives. Still there are many obstacles encountered by the agricultural sector which affects the production, quantity and quality of the crops. The frequent problems are the diseases caused by the pests and other insects, and climatic changes. The traditional method that is followed to identify and eradicate the diseases is the naked eye observation technique. But this method cannot be relayed when it comes to large scale farming. The naked eye observation technique is a time consuming process and the accuracy of the disease detection made through this process cannot be trusted. Also the farmers must be educated and expertise in order to detect the diseases through this naked eye test.

An alternative to this is a computer based automatic disease detection system which can be achieved through the collection of respective datasets and then performing various techniques on them to classify according to the diseases. This has been a turning point in the history of disease detection and till date there are many studies going on based on automatic plant disease identification which has lead to many remarkable developments using technologies. The crop cultivation patterns changed drastically as a result of these studies. This also helped the farmers to gain knowledge and the experts to perform their work more easily and accurately. All these progresses had improved the overall agricultural production and thereby expanding the economic gain. But still there are many areas that couldn't make much improvement such as disease detection, pest detection, and effects of climatic changes, because the variety of diseases and pests affecting the plants are evolving alongside us. Completely eliminating them is an impossible mission; instead we can only control them to a certain level and this can be accomplished using the automated systems. Performance and accuracy of the systems are the areas which should be focused so as to get better outputs.

The given Figure 1 shows the general setup of an automated system. This is a step by step process and it starts with data acquisition. Based on the requirement the dataset has to be collected and cleaned to free from noise and other distortions. This process is known as preprocessing and there are various methods to preprocess the dataset. Here we have used brightness preserving dynamic fuzzy histogram equalization (BPDFHE), an advanced histogram equalization technique and Gaussian filtering to preprocess the image dataset. Next, some features or properties of the preprocessed image are extracted to train the system. The output can be obtained using classifiers such as support vector machine (SVM), k-nearest neighbors (kNN), neural networks, and convolutional neural networks (CNN). In this work an advanced version of the conventional histogram equalization, BPDFHE is followed and also we have compared it with the traditional histogram equalization technique.

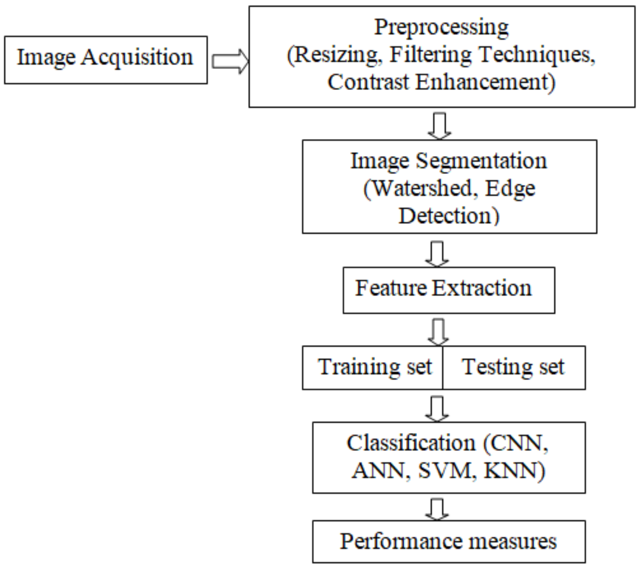

Figure 1. General block diagram of an automated plant disease detection system

2. LITERATURE REVIEW

Large varieties of automated crop disease detection models have been developed and are available in the market. In this section we can see some commonly used pre processing techniques and their merits over the others. Alessandrini *et al*. [1] have collected the images of healthy and unhealthy grapevine leaves under real conditions to detect and classify Esca disease in vineyards. Also they have discussed in detail about the devices that were used to collect the datasets. The initial stages that includes dataset acquisition and preprocessing has to be carefully handled as it is provides the base to further processing. A large amount of data is lost due to the noise and blur of the devices. In order to rectify this issue Latif *et al*. [2] has proposed a non- blurring technique to improve the efficiency of the input images. They have also discussed a hybrid method to remove all kinds of noises in the preprocessing stage. In this paper, they have used an openCL parallel programming language and a heterogeneous XU4 system. Kumar and Kumar [3], they have taken tomato leaves and the various types of diseases affecting it. As a part of preprocessing they have removed noises, de-blurred, compressed and resized the image. CNN architecture is used in the classification section.

A hybrid algorithm is proposed to enhance the contrast, preprocess and segment the image for accurate classification [4]. They have also used a low pass filter, Gaussian filter to remove the noise by blurring the image so as to identify the rice varieties. Karuppusamy [5] suggests CNN architecture with 2 additional novel layers for the development of any detection system. Here two kinds of modifications are done to the CNN. Firstly they have used Euler methodology for feature vector transformation and secondly they have combined both the raw and normalized features for the better performance of the system. There are many fungal diseases that affect the plants [6]. One such fungal disease that is commonly observed on vegetative crops is *Fusarium*wilt. In this paper they have taken the tomato leaves as input data and followed a 2-factor identification method for better accuracy. Tripathi [7] classifies the fruits using the latest architectures from the features with which they have trained the system. They have used resizing and data augmentation techniques for preprocessing. With the help of convolutional and pooling layers they have extracted the features and classified using many classifiers. The performance analysis shows that DenseNet outperforms all the other classifiers with better performance and accuracy. Ferentinos [8] has taken a variety of 38 classes of vegetative crops and have trained using many classifiers. Out of all visual geometry group (VGG) classifier gave the best result with an accuracy of 99.53%. Hamdani *et al.* [9] discusses the diseases affecting the oil palm leaves and built a model with the neural networks. The features to test and train the system were extracted using the principal component analysis (PCA). Here they have taken 300 leaf images and the model gives a higher performance than the existing systems.

Dayang and Meli [10] proposed a method to test and compare the segmentation techniques such as k-nearest, Canny edge detection, k-mean clustering. As a region of study they have taken corn, tomato and potato leaves. The experimental results show that k-nearest algorithm performs well when compared to the other two algorithms. A detection system to identify three commonly occurring rice leaf diseases is developed by [11]. After processing the images it is fed to four classifiers and the results are computed accordingly. Decision tree algorithm showed the best performance with an accuracy of 97.91% when compared to the other algorithms. Madhavan *et al.* [12] have used matlab for preprocessing the pomegranate leaf images and classified using SVM algorithm. Chen *et al.* [13] proposes a modification to the existing transfer learning algorithm. They have combined the MobileNet and Squeeze and excitation block which forms a new network. They also performed transfer learning separately to obtain the expected result. Zhao *et al.* [14] discusses the difficulty in classifying unbalanced image datasets. In order to solve this they have used DoubleGAN network. It is also compared with many other networks. Hua *et al.* [15] proposes a novel approach to identify the diseases affecting the agricultural crops using a multi feature fusion algorithm known as pest detecting region-based CNN (PD R-CNN). Experimental results show that this technique performs more accurately than other algorithms. A detection technique to identify the three commonly occurring diseases: leaf smut, brown spot and bacterial leaf blight that affects the rice leaf is proposed in paper [16]. They have followed the hue and saturation technique for preprocessing and extreme gradient boosting decision tree ensemble for classification.

A histogram equalization technique based on the fuzzy logic is recommended to improve the contrast of the input images [17]. This method is assessed using the metrices namely, mean square error (MSE) and peak signal to noise ratio (PSNR). By taking average value of initial image and fuzzy logic of histogram is divided into two subparts, and later they are equalized to preserve the brightness of image. Archana and Sahayadhas [18] discusses a comparison study based on the image quality by considering the four types of filtering techniques: Gaussian filter, median filter, mean filter and Weiner filter with the help of a common data set. And it is observed that Weiner filter has the better PSNR and signal to noise ratio (SNR) values among all the filtering processes. Temiatse *et al.* [19] utilizes the conventional histogram equalization method to enhance and improve the lemon grass images. Mat lab is used to calculate the efficiency of the system. From the simulation it was comprehensible that even though Histogram Equalization is a traditional approach, it has the capacity to effectively enhance the images and bring out the hidden details present in each image.

Sudeep and Pal [20] discusses the importance of preprocessing the image data for a classification algorithm using CNN. Here they have used CIFAR10 Dataset. Their accuracy is higher for zero component analysis (ZCA) when tested with both mean normalization and standardization techniques. Vishnoi *et al.* [21] reviews a variety of feature extraction techniques used in the development of automatic plant disease identification and classification models. The comparative study shows that many features together give more accurate values than features taken as single types. Chethan *et al.* [22] uses the advanced histogram equalization technique to preprocess the images and then using k-means clustering the images are segmented. Features are extracted with the help of a grey-level co-occurrence matrix. Later, SVM and CNN were used to classify the diseases based on the features extracted, and the results were compared. As a part of preprocessing, here researchers have resized and then enhanced the contrast of the images using a histogram equalization technique known as contrast limited adaptive histogram equalization (CLAHE) [23]. Also in the final algorithm they have combined five CNN architectures to produce the output. The result obtained stated that ensemble model gave more accuracy when compared to individual architectures. For the computer vision models to achieve better results in low resolution and comparatively poor contrast [24], Sambasivam and Opiyo [25] have included CLAHE algorithm in their work. Kaur [26] proposed a preprocessing technique BPDFHE that enhances the contrast of input image data. A comparative evaluation is done with the existing preprocessing techniques such as CLAHE and contrast stretching. The quality of the image data is calculated using the PSNR, structural similarity index(SSIM), MSE metrics and the output obtained shows an improvement with the proposed algorithm. Sheet *et al.* [27] suggested a novel modification to the existing preprocessing technique BPDHE so as to surmount the limitations of the system. The advanced method BPDFHE, BPDFHEuses fuzzy domain to represent and process digital image. Experimental results show that BPDFHE gives more accurate results when compared to that of BPDHE. The computational time for each method are also discussed in this paper. Kuber *et al.* [28] compares the conventional histogram equalization techniques such as CLAHE, uniform histogram equalization (UHE), global histogram equalization (GHE), and brightness preserving dynamic histogram equalization (BPDHE) with BPDFHE. The result shows that BPDFHE can proficiently conserve mean image brightness and provide better PSNR values than the other histogram models.

3. PROPOSED METHODOLOGY

Preprocessing of the input data is a significant stage as it provides noise free, high contrast images for accurate segmentation and feature extraction. It also improves the input data by eliminating the unwanted elements from the image and intensifies some features that are important in the further stages. There are various preprocessing techniques and here we follow BPDFHE, an advanced version of conventional histogram equalization along with Gaussian Filtering to preprocess the image. Histogram equalization is a commonly used preprocessing technique that uses the image histogram to evaluate the frequency distribution. It is similar to a bar graph and this graphical representation shows the areas of the image with low contrast. The equalization is done here by taking the frequently occurred pixel intensity values as the threshold and spreading out the values based on them. A major drawback of this process is when some intensity values of the pixels are inexact. Such inexact or vague gray values cannot be considered in the conventional histogram equalization, and this can produce variations in the expected image histogram. In these situations, it is always better to go for BPDFHE technique which utilizes fuzzy domain to represent the pixel values. This fuzzy domain has the ability to manage inexactness or vagueness of the gray level values. It also shows good contrast enhancement capabilities with reduced computational complexity. It also performs well when compared with the other histogram equalization techniques. Figure 2 is the pictorial representation of the preprocessing stage performed in this work.

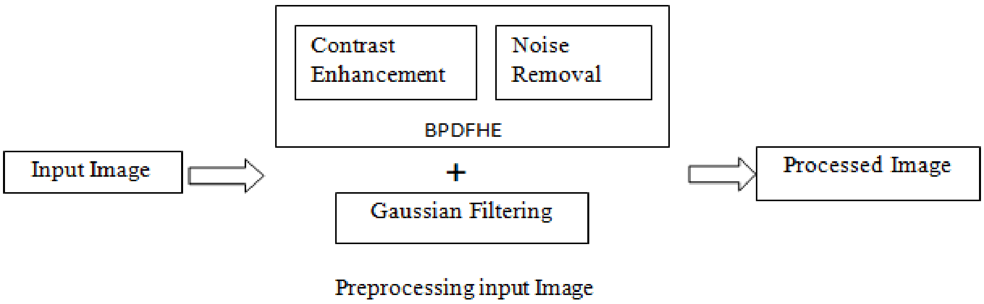

Figure 2. Block diagram of the proposed model

3.1. Image dataset

Here a plant village dataset of 38 different classes of plant varieties is taken and we selected 10 classes of crops (tomato, bell pepper, potato, cucumber, bitter gourd, brinjal, pumpkin, peas, paprika, cluster beans) as the input dataset from the entire set. All together there are 54,303 images of diseased and healthy leaves present in plant village dataset and we took 10,505 images of diseased and healthy images leaf images corresponding to the 10 classes of crops which we have chosen. It is an international image dataset mainly used for the detection of plant diseases using machine learning algorithms and these open access repositories of images are provided by the Kaggle website. There are various preprocessing techniques available and can be followed as per our need. In this paper we have taken the advanced version of histogram equalization, BPDFHE to preprocess input data. Histogram equalization is an approach to intensify the contrast of an image. This enhancement of the image equalizes the histogram of the resultant image and changes the overall shape of the histogram. BPDFHE technique is a modified alteration to the standard method where there is no repetition of the peaks from input to output histogram while performing the mapping action. The main advantages are the low computation time and better contrast improvement. Gaussian blur is another preprocessing technique followed in this paper.

3.2. Histogram equalization

Histogram Equalization is one of the oldest and frequently used preprocessing techniques. This technique is mainly used for improving brightness of input image. As we have to improve the image quality for the further processes, enhancing the contrast of the input image is an essential step in preprocessing.

i. Import the required libraries
ii. Read the input image
iii. Generate the histogram for the input image
iv. Calculate the probability mass function (PMF) either using a histogram or a matrix
v. Evaluate the cumulative distributive function (CDF) by taking the cumulative sums of all the values which are calculated using PMF
vi. A new set of grey level values are obtained which can be mapped onto the histogram to produce an equalized image

3.3. Brightness preserving dynamic fuzzy histogram equalization (BPDFHE)

It is an advanced form of histogram equalization that has better contrast enhancement capabilities with reduced computational complexity. Histogram equalization is a commonly used preprocessing technique that uses the image histogram to evaluate the frequency distribution. It is similar to a bar graph and this graphical representation shows the areas of the image with low contrast. The equalization is done here by taking the frequently occurred pixel intensity values as the threshold and spreading out the values based on them. A major drawback of this process is when some intensity values of the pixels are inexact. Such inexact or vague gray values cannot be considered in the conventional histogram equalization, and this can produce variations in the expected image histogram. In BPDFHE technique the image values are represented in fuzzy domain which helps the histogram equalization approach to handle vagueness of gray level of the pixel values in a finer way so that it can provide good performance. The following are the functioning stages in BPDFHE technique: i) fuzzy histogram calculation, ii) splitting up of histogram, iii) dynamic histogram equalization (DHE) of partitions, and iv) normalization of image brightness.

3.3.1. Fuzzy histogram calculation

In BPDFHE, the inexactness of the gray level values of the pixels are handled using the fuzzy domain and by considering all the values including the vague ones, a smooth histogram is produced. The fuzzy histogram which is a sequence of real numbers is denoted using $h(i)$, where$i\epsilon$ $\{0,1,\ldots,L-1\}$ and $h(i)$ represents the frequency of the gray values. Let's consider,$I(x,y)$ the gray value as a fuzzy number $I^{\sim}(x,y)$. So here the fuzzy histogram calculated will be in the form:

$$h(i) \leftarrow h(i) + \sum_x \sum_y \mu_{I^{\sim}(x,y)i}\,, k \in [a,b] \tag{1}$$

where, $\mu_{I^{\sim}(x,y)i}$is triangular fuzzy membership function and it is defined as,

$$\mu_{I^{\sim}(x,y)i} = \max\left(0,1 - \frac{|I(x,y)-i|}{4}\right) \tag{2}$$

here, [a, b] is defined as the membership function support.

3.3.2. Splitting up of histogram

The process of partitioning histogram is known as DHE. This is done by calculating two consecutive local maxima. Local maxima are nothing but the brightest pixels. After getting the two consecutive local maxima the partitioning is done at its valley. That is, dividing the original histogram into two sub or secondary histograms takes place in the valley of two consecutive local maxima. Local maxima detection: central differential operator to calculate the discrete operator.

$$h^{'}(i) = \frac{dh(i)}{di} \triangleq \frac{h(i+1)-h(i-1)}{2} \tag{3}$$

The second order derivative can be calculated as,

$$h^{''}(i) = \frac{d^2h(i)}{di^2} \triangleq h(i+1) - 2h(i) + h(i-1) \tag{4}$$

$$i_{max} = i\nabla\{h^{'}(i+1)h^{'}(i-1) < 0, h^{''} < 0\} \quad (5)$$

Among the neighboring maxima pair, this is of the highest count. It is calculated to eliminate the issue of ambiguity. If there are (n+1) local maxima intensity levels, then it is indicated as $\{m_0, m_1, \ldots, m_n\}$. (n+1) sub- histograms will be generated after the partition if the fuzzy histogram is in range of $[I_{min}, I_{max}]$ and the expansion range will be $\{[I_{min}, m_0], [m_0+1, m_1], \ldots [m_n+1, I_{max}]\}$.

3.3.3. Dynamic histogram equalization of partitions

Here we are equalizing the sub histograms which we received from the previous steps. A spanning is done to equalize each sub histograms and here the spanning is based on the total number of pixels present in the partition. Usually, this process involves two operations. Firstly, we have to plot or map the partitions to a dynamic range and then we have to equalize the histogram. Dynamic equalization process consists of many parameters and is provided by the given equations:

$$span_i = high_i - low_i \quad (6)$$

where the $high_i$ and low_i are the highest and lowest intensities from the i^th input sub histogram, respectively.

$$factor = span_i \times log_{10} M_i \quad (7)$$

Here, M_i is the total pixel number and $span_i$ is nothing but dynamic range of input sub histogram. If we have $range_i$ instead of $span_i$, then it is given as,

$$range_i = \frac{(L-1) \times factor_i}{\sum_{k=1}^{n+1} \ factor_i} \quad (8)$$

Now the i^{th} output sub histogram can be calculated as,

$$start_i = \sum_{k=1}^{n-1} range_k + 1 \quad (9)$$

and,

$$stop_i = \sum_{k=1}^{n} range_k \quad (10)$$

exceptions or anomalies are close by at the two extremities where $[start_1, stop_1] = [0, range_1]$ and $[start_{n+1}, stop_{n+1}] = [\sum_{k=1}^{n+1} range_k, L-1]$. In order to equalize each sub histogram, it is essential to obtain remapped values. These values are obtained in (11) for the i^{th} sub histogram. It can be calculated as,

$$y(j) = start_i + range_i \sum_{k=start_i}^{i} \frac{h(k)}{M_i} \quad (11)$$

here y(j) is new intensity level and M_i is the total number of pixels.

3.3.4. Normalization of image brightness

Mean brightness obtained after the DHE of each sub histogram have slight difference from that of the input image. The output image is normalized to overcome this issue. Here g represents the output of the BPDFHE technique, and then grey level value at pixel location (x, y) for image g is given by,

$$g(x,y) = \frac{m_i}{m_0} f(x,y) \quad (12)$$

4. RESULTS ANDDISCUSSION

The figures and tables are the results after applying the preprocessing techniques. Here we have taken conventional histogram equalization technique and its advanced version BPDFHE. Both techniques are applied to the input images and compared using the image quantity evaluating parameters such as PSNR, SSIM, and MSE. Figure 3 is the image after applying histogram equalization. The proposed preprocessing technique here is BPDFHE and Gaussian filtering combined. Figure 4 show the image after performing Gaussian blur. The combined result is shown in Figure 5. The quality assessment computation is done using the three metrics: PSNR, SSIM, and MSE. The values are given in the form of a tabular column Table 1.

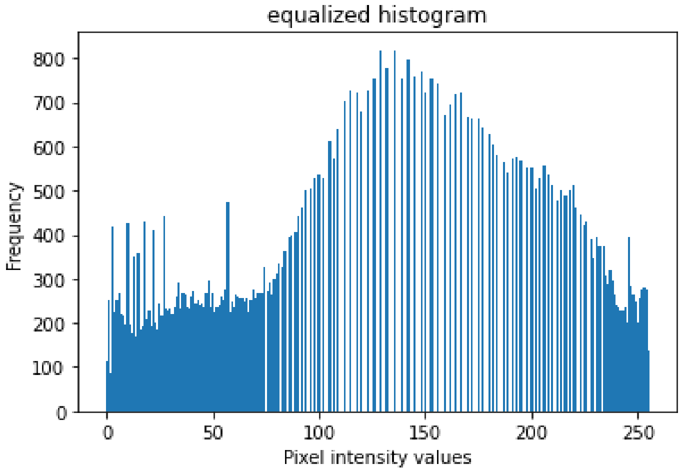

Figure 3. Histogram equalized image and its corresponding graph

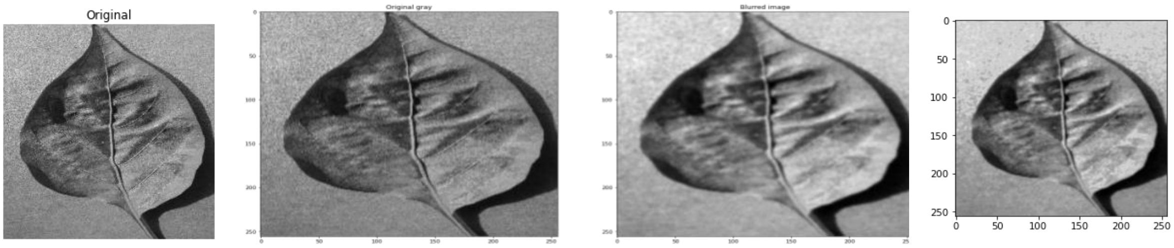

Figure 4. Gaussian blurred image

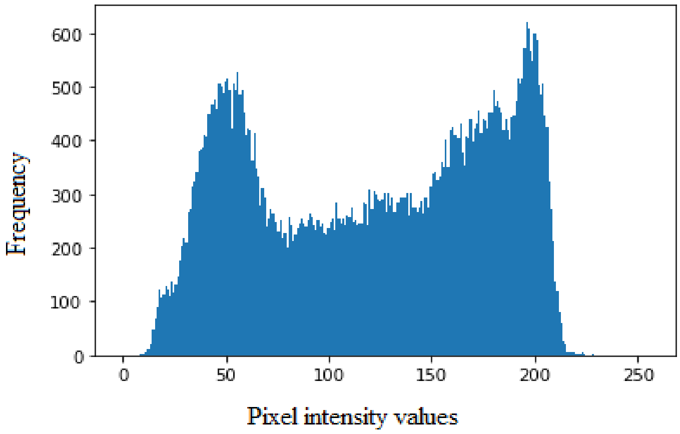

Figure 5. Image after preprocessing

Table 1. Quality evaluation done for leaf image 1 and 2

Image ID	Quality metrics	Histogram equalized image	BPDFHE iImage	Existing system	Proposed system
Image 1	PSNR	27.96	27.9979	26.04	31.509
Image 1	SSIM	0.756	0.9219	0.9652	0.978
Image 1	MSE	231.16	230.90	239.87	304.21
Image 2	PSNR	27.92	27.80	26.04	34.10
Image 2	SSIM	0.2356	0.2665	0.9652	0.9653
Image 2	MSE	187.02	204.04	239.87	134.90

5. CONCLUSION

Pre-processing is an obligatory procedure to improve the input image data for further evaluation and development to achieve the appropriate results. The cropping or resizing of the image is a significant technique to eliminate the unwanted elements in order to reduce both the memory space and computation time. Various filtering methods are used as a part of preprocessing for the removal of noises and other distortions. Application of the enhancement techniques are purely based on the contrast of the images. Images that are preprocessed and ready give more accurate results. In this work we have used BPDFHE and Gaussian filtering to preprocess the images. Experimental outcomes obtained prove that the proposed system provides more accurate values than the existing system.

REFERENCES

[1] M. Alessandrini, R. Calero Fuentes Rivera, L. Falaschetti, D. Pau, V. Tomaselli, and C. Turchetti, "A grapevine leaves dataset for early detection and classification of esca disease in vineyards through machine learning," *Data in Brief*, vol. 35, 2021, doi: 10.1016/j.dib.2021.106809.

[2] R. Latif, L. Jamad, and A. Saddik, "Implementation of hybrid algorithm for the UAV images preprocessing based on embedded heterogeneous system: The case of precision agriculture," pp. 151–164, 2021, doi: 10.1007/978-981-33-6129-4_11.

[3] N. A. Kumar and S. Sathish Kumar, "Deep learning-based image preprocessing techniques for crop disease identification," *Lecture Notes in Electrical Engineering*, vol. 792, pp. 1–10, 2022, doi: 10.1007/978-981-16-4625-6_1.

[4] Komal, G. K. Sethi, and R. K. Bawa, "A hybrid approach of preprocessing and segmentation techniques in automatic rice variety identification system," *Journal of Scientific Research*, vol. 14, no. 1, pp. 205–213, 2022, doi: 10.3329/jsr.v14i1.54811.

[5] P. Karuppusamy, "Building detection using two-layered novel convolutional neural networks," *Journal of Soft Computing Paradigm*, vol. 3, no. 1, pp. 29–37, 2021, doi: 10.36548/jscp.2021.1.004.

[6] R. Dhaya, "Flawless identification of Fusarium Oxysporum in tomato plant leaves by machine learning algorithm," *Journal of Innovative Image Processing*, vol. 2, no. 4, pp. 194–201, 2021, doi: 10.36548/jiip.2020.4.004.

[7] M. Tripathi, "Analysis of convolutional neural network based image classification techniques," *Journal of Innovative Image Processing*, vol. 3, no. 2, pp. 100–117, 2021, doi: 10.36548/jiip.2021.2.003.

[8] K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," *Computers and Electronics in Agriculture*, vol. 145, pp. 311–318, 2018, doi: 10.1016/j.compag.2018.01.009.

[9] H. Hamdani, A. Septiarini, A. Sunyoto, S. Suyanto, and F. Utaminingrum, "Detection of oil palm leaf disease based on color histogram and supervised classifier," *Optik*, vol. 245, 2021, doi: 10.1016/j.ijleo.2021.167753.

[10] P. Dayang and A. S. K. Meli, "Evaluation of image segmentation algorithms for plant disease detection," *International Journal of Image, Graphics and Signal Processing*, vol. 13, no. 5, pp. 14–26, 2021, doi: 10.5815/ijigsp.2021.05.02.

[11] K. Ahmed, T. R. Shahidi, S. M. Irfanul Alam, and S. Momen, "Rice leaf disease detection using machine learning techniques," *2019 International Conference on Sustainable Technologies for Industry 4.0, STI 2019*, 2019, doi: 10.1109/STI47673.2019.9068096.

[12] M. V. Madhavan, D. N. H. Thanh, A. Khamparia, S. Pande, R. Malik, and D. Gupta, "Recognition and classification of pomegranate leaves diseases by image processing and machine learning techniques," *Computers, Materials and Continua*, vol. 66, no. 3, pp. 2939–2955, 2021, doi: 10.32604/cmc.2021.012466.

[13] J. Chen, D. Zhang, M. Suzauddola, Y. A. Nanehkaran, and Y. Sun, "Identification of plant disease images via a squeeze-and-excitation MobileNet model and twice transfer learning," *IET Image Processing*, vol. 15, no. 5, pp. 1115–1127, 2021, doi: 10.1049/ipr2.12090.

[14] Y. Zhao *et al.*, "Plant disease detection using generated leaves based on doubleGAN," *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 19, no. 3, pp. 1817–1826, 2022, doi: 10.1109/TCBB.2021.3056683.

[15] S. Hua, M. Xu, Z. Xu, H. Ye, and C. Zhou, "Multi-feature decision fusion algorithm for disease detection on crop surface based on machine vision," *Neural Computing and Applications*, vol. 34, no. 12, pp. 9471–9484, 2022, doi: 10.1007/s00521-021-06388-7.

[16] M. A. Azim, M. K. Islam, M. M. Rahman, and F. Jahan, "An effective feature extraction method for rice leaf disease classification," *Telkomnika (Telecommunication Computing Electronics and Control)*, vol. 19, no. 2, pp. 463–470, 2021, doi: 10.12928/TELKOMNIKA.v19i2.16488.

[17] F. I. Abbas, N. M. Mirza, A. H. Abbas, and L. H. Abbas, "Enhancement of wheat leaf images using fuzzy-Logic based histogram equalization to recognize diseases," *Iraqi Journal of Science*, vol. 61, no. 9, pp. 2408–2417, 2020, doi: 10.24996/ijs.2020.61.9.27.

[18] K. S. Archana and A. Sahayadhas, "Comparison of various filters for noise removal in paddy leaf images," *International Journal of Engineering and Technology(UAE)*, vol. 7, no. 2, pp. 372–374, 2018, doi: 10.14419/ijet.v7i2.21.12444.

[19] O. S. Temiatse, S. Misra, C. Dhawale, R. Ahuja, and V. Matthews, "Image enhancement of lemon grasses using image processing techniques (Histogram equalization)," *Communications in Computer and Information Science*, vol. 799, pp. 298–308, 2018, doi: 10.1007/978-981-10-8527-7_24.

[20] K. S. Sudeep and K. K. Pal, "Preprocessing for image classification by convolutional neural networks," *2016 IEEE International Conference on Recent Trends in Electronics, Information and Communication Technology, RTEICT 2016 - Proceedings*, pp. 1778–1781, 2017, doi: 10.1109/RTEICT.2016.7808140.

[21] V. K. Vishnoi, K. Kumar, and B. Kumar, "A comprehensive study of feature extraction techniques for plant leaf disease detection," *Multimedia Tools and Applications*, vol. 81, no. 1, pp. 367–419, 2022, doi: 10.1007/s11042-021-11375-0.

[22] K. S. Chethan, S. Donepudi, H. V. Supreeth, and V. D. Maani, "Mobile application for classification of plant leaf diseases using image processing and neural networks," pp. 287–306, 2021, doi: 10.1007/978-981-15-8530-2_22.

[23] A. Acharya, A. Muvvala, S. Gawali, R. Dhopavkar, R. Kadam, and A. Harsola, "Plant disease detection for paddy crop using ensemble of CNNs," *2020 IEEE International Conference for Innovation in Technology, INOCON 2020*, 2020, doi: 10.1109/INOCON50539.2020.9298295.

[24] Sonali, S. Sahu, A. K. Singh, S. P. Ghrera, and M. Elhoseny, "An approach for de-noising and contrast enhancement of retinal fundus image using CLAHE," *Optics and Laser Technology*, vol. 110, pp. 87–98, 2019, doi: 10.1016/j.optlastec.2018.06.061.

[25] G. Sambasivam and G. D. Opiyo, "A predictive machine learning application in agriculture: Cassava disease detection and classification with imbalanced dataset using convolutional neural networks," *Egyptian Informatics Journal*, vol. 22, no. 1, pp. 27–34, 2021, doi: 10.1016/j.eij.2020.02.007.
[26] B. Kaur, "BPDFHE based hybrid pre-processing methodology of leaf images for efficient disease detection," *Proceedings - 2nd International Conference on Smart Electronics and Communication, ICOSEC 2021*, pp. 1704–1708, 2021, doi: 10.1109/ICOSEC51865.2021.9591766.
[27] D. Sheet, H. Garud, A. Suveer, M. Mahadevappa, and J. Chatterjee, "Brightness preserving dynamic fuzzy histogram equalization," *IEEE Transactions on Consumer Electronics*, vol. 56, no. 4, pp. 2475–2480, 2010, doi: 10.1109/TCE.2010.5681130.
[28] M. P. S. Kuber, M. Dixit, and S. Silakari, "Improving brightness using dynamic fuzzy histogram equalization," *International Journal of Signal Processing, Image Processing and Pattern Recognition*, vol. 8, no. 2, pp. 303–312, 2015, doi: 10.14257/ijsip.2015.8.2.29.

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