CNN BASED METHOD FOR MULTI-TYPE DISEASED ARECANUT IMAGE CLASSIFICATION

S. B. Mallikarjuna[1*], Palaiahnakote Shivakumara[2], Vijeta Khare[3], N. VinayKumar[4], M.Basavanna[5], Umapada Pal[6], B.Poornima[7]

[1,7]Department of Computer Science and Engineering, Bapuji Institute of Engineering and Technology, Davanagere, Affiliated to Visvesvaraya Theological University, Belagavi, Karnataka, India

[2]Faculty of Computer Science and Information Technology, University of Malaya, Kuala Lumpur, Malaysia

[3]Adani Institute of Infrastructure Engineering, India

[4]Freelance Researcher, Bangalore, India

[5]Department of Computer Science, Davanagere University, Karnataka, India

[6]Computer Vision and Pattern Recognition Unit, Indian Statistical Institute, Kolkata, India

Email: malliksbm@gmail.com[1*](corresponding author), shiva@um.edu.my[2], vijeta.khare@aii.ac.in[3], vinaykumar.natraj@gmail.com[4], basavanna_m@yahoo.com[5], umapada@isical.ac.in[6], poornimateju@gmail.com[7]

ABSTRACT

Arecanut image classification is a challenging task to the researchers and in this paper a new combined approach of multi-gradient images and deep convolutional neural networks for multi-type arecanut image classification is presented. To enhance the fine details in arecanut images affected by different diseases, namely, rot, split and rot-split, we propose to explore multiple-Sobel masks for convolving with the input image. Although, the images suffer from distortion due to disease infection, this masking operation helps to enhance the fine details. We believe that the fine details provide vital clues for classification of normal, rot, split and rot-split images. To extract such clues, we explore the combination of multi-gradient and AlexNet by feeding enhanced images as input. Implementation results on the four-class dataset indicate that the approach proposed is superior in terms of classification rate, recall, precision and F-measures. The same conclusion can be drawn from the results of comparative study of proposed method with the existing methods.

Keywords: *Multi-Sobel, CNN, Arecanut, Rot Disease, Split Disease, Rot-Split Disease*

1.0   INTRODUCTION

Arecanut is the seed of the areca palm tree that grows in most of the tropical Pacific, Southeast and South Asia, and parts of eastern Africa [1]. It is also known as the betel nut. It is a practice, custom, or ritual that dates back thousands of years in most of the geographical areas from South Asia east to the Pacific to chew the mixture of arecanut and betel leaves. In most of the Asian and Oceanic countries, including India, Bangladesh, Malaysia, Myanmar, Maldives, Nepal, Sri Lanka, Bhutan, China, Thailand, Indonesia, etc., it is a significant and common cultural activity.

As the demand is huge for this nut, it is important to provide the high-quality nuts for consumption. At the same time, production of arecanut should be increased to meet the requirement of high demand. The arecanut is useful not only for chewing, it can also be used as one of the ingredients for making diabetes formulations, Ayurveda medicine, soaps, areca tea, tooth powder, and wines [2, 3]. However, the main cause for not yielding expected productions and maintaining quality of the nut is that the common disease, namely, rot, split and rot-split. These diseases make the nut inferior in quality and affect production. This results in huge loss for the farmers. Therefore, to estimate production, prevent spreading of disease and grading, there is a need for classifying the arecanut images affected by diseases. This is because classifying manually is troublesome task and it is cost expensive due to a large number of labors required. Also, if we separate the

infected nuts, the market price of the good nuts increase. Therefore, classification of the diseased images from normal images is necessary and it is an urgent need. In this work, we consider the following four classes, namely Healthy Nuts, Rot Disease, and Split Disease and combined Rot-Split Disease. The reason to consider these diseases is that these are very common and dangerous diseases compared to other diseases. Sample arecanut images of the four classes shown in Fig.1, where one can see classifying the images of rot-split is not easy compared to other classes.

Rot Disease: Extensive shedding of the undeveloped nuts that lie scattered at the base of the tree is a distinctive sign of rotting. Dark green/yellowish water-soaked lesions on the nut surface near the perianth occur as initial signs. The infected nuts lose their natural, high quality green luster and therefore have low market value.

Split Disease: Improper drainage will cause nut split and fall. Areca palms of 10-25 years old are more prone to this disorder. This is common in paddy converted fields as well as high water table gardens. It's severe in rainy season. Sudden flush of water after a prolonged period of drought leads to this disorder. Initial visual symptom appears when nuts are half to three-fourth mature, as premature yellowing. This is accompanied by the splitting of nuts from either side or tips that stretch longitudinally to reveal the kernel to the calyx.

Rot Split Disease: This occurs mainly during rainy seasons. The drainage causes nut splitting while lack of sunlight causes rotting. All these diseases cause huge difference in the quality of nuts and their market price.

There are methods for classifying different type of arecanut images including affected by disease in the literature [4, 5, 6] but most of the methods use geometrical features, shape based features, texture based features of the images and conventional classifier, such as SVM for classification. As a result, these methods are not robust for variation in the image affected by multiple diseases. Thus, the proposed work introduces the combination of multi-gradient and convolutional neural network. The motivation to explore gradient information is that the gradient suppresses distortion by sharpening edge information in the images [7]. In the same way, the deep learning architectures have strong ability to classify complex images [8].
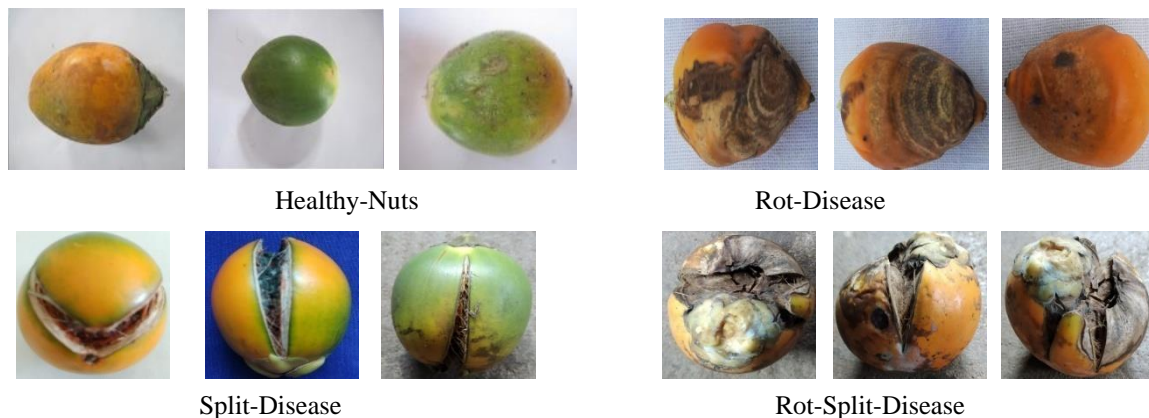

Healthy-Nuts   Rot-Disease

Split-Disease   Rot-Split-Disease

Fig.1: Sample arecanut images for classification

2.0   RELATED WORK

Some methods are developed for arecanut image segmentation and classification in the images in the past. We review both segmentation and classification methods. Dhanesha et al. [2] have used YCR color model technique for segmentation of arecanut bunches. The method uses volumetric overlap error and dice similarity coefficient for estimating the similarity between the input image and ground truth for segmenting bunches. The focus of this method is segmenting branches of arecanut but not arecanut. For the intent of segmentation of bunches, the same technique is extended using HSV color model [3]. The similar idea has been explored in this work. Gowda et al. [9] suggested a method for arecanut plucking using robot from the trees. In this work, the robot is designed to cut the branches of arecanut. The scope of the method is developing system but not the method to segment the arecanut. The system is not fully automatic for cutting the branches as it requires human intervention to separate arecanut branches from other branches in the tree. In summary, the segmentation methods use color and similarity measures for segmenting branches of arecanut from the tree. But it is not clear what is the input and how the methods separate the branches of arecanut when there is a partial occlusion and

256

arecanuts are degraded due to disease and open environment. Therefore, these features cannot be used for classification of different types of arecanuts.

For classification, a few methods are proposed in the literature. This shows that different types of arecanut image classification are at infant stage. Siddesh et al. [10] proposed a method for classification of arecanut images using color features and KNN classifier. The method proposes the combination of color features and color moments and use histogram operation for feature extraction. The feature matrix is fed to KNN classifier for classification. This technique works well for images of high quality, but not for images suffering from distortion, low quality and color bleeding due to diseases. A technique for betel nut classification is based on transfer learning was proposed by Cai et al. [11]. The method uses AlexNet architecture for classification. However, since the method considers arecanut after removing the skin and therefore, the shape of this nut is different from the raw images. The focus of this method is limited to peeled arecanut images. In addition, the performance of the method heavily depends on the number of samples and parameter tuning. Suresha et al. [6] proposed a method for classification diseased arecanut images using texture features. The method proposes the combination of several features, such as local binary pattern based, Haar wavelet based, color based GLCM texture based features. The feature matrix is an input to KNN classifier for classification. The scope of the method is limited to two-class classification and it requires peeled arecanut images but not raw arecanut images considered in the proposed work. Danti et al. [12] suggested a method based on three sigma control limits for the segmentation and classification of peeled Arecanut images. This method also uses the combination of color and three sigma control limits for classification. To segment the arecanut effectively, the upper and lower limits of the color components are used. However, the method does not consider the images affected by diseases. Therefore, the proposed feature may not be robust for the classification considered in our work.

From the literature survey it is observed that the existing methods focus either on two class classification or classification of peeled arecanut images. None of the methods consider the classification of healthy arecanut image from the images affected by disease, namely, rot, spit and rot-split. Hence, classification of such images remains unsolved and open issue for the researchers. Thus, this work proposes a new method for classification of four types of arecanut images by exploring multi-gradient images and convolutional neural network. When we look at arecanut images of different classes, the shape of nut supposed to be same. But it is not true for the nuts affected by diseases, where one can expect different deformed shapes arecanut of each class. In addition, the shape feature is invariant to geometrical transformations, namely, rotation and scaling [13]. This is the cue and motivation to propose a method for classification of arecanut images of different diseases from the images of healthy nuts. It is noted that convolving Multi-Sobel kernels with the input images enhances fine details in the images irrespective distortion caused by different diseases [7]. Therefore, it is expected unique edge representation for each class. Motivated by this observation, the proposed method obtains four multi-gradient images for each input image of different classes. In the same way, inspired by special property of the CNN model that has a very strong discriminating power [8,14,–15], the proposed method adapts AlexNet for classification by considering multi-gradient images as input. The main contribution of the proposed work is follows. This is the first attempt to classify four types of arecanut images of different disease. The combination of multi-gradient and CNN model is a new approach for the classification of various types of healthy and diseased arecanut images.

3.0   PROPOSED METHODOLOGY

In this work, we consider the four classes, namely, Healthy, which contains arecanut images without affecting any disease; rot, which contains images affected by immature nuts with color bleeding; Split, which contains the images affected by cracks on the images and Rot-Split, which contains the images affected by both Rot and Split diseases for classification. It is noted that images of each class have unique edge representation because of the effect of different diseases. However, due to disease effect, there are high chances of losing such unique edge pattern in the images. To restore those details in the images, the proposed work introduces multi-gradient images obtained by Multi-Sobel kernels. This is because gradient in different direction facilitates us to enhance the fine details by suppressing distortion effect [7]. Therefore, this step results in unique edge pattern for images of each class. To extract such observations, we propose the combination of AlexNet as it has ability to extract deep features for classification [8]. The Fig.2 shown is the block diagram of the proposed method, it has two stages namely training and testing. Before passing the multi-gradient images, the proposed method transforms the input image size to the standard size and use augmentation techniques to maximize the number of samples, which can prevent the causes of overfitting and under fitting. Next, the structure of the architecture is modified according to the problem complexity.
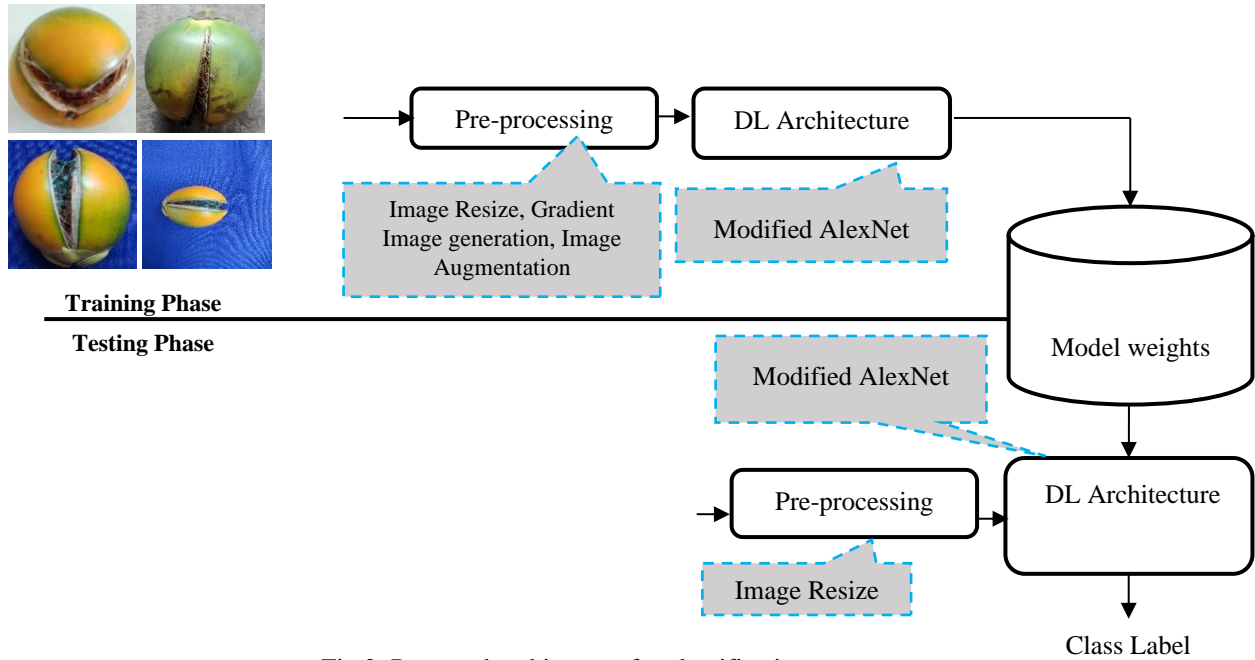
Fig.2: Proposed architecture for classification

3.1 Generating Multi-Gradient Images

To obtain multi-gradient images the proposed method uses the Multi-Sobel kernels for each input images as shown in Fig.3. Instead of using fixed values, we consider calculating automatic values for the kernels in order to deal with the variations caused by different diseases. The value of the S can be calculated as defined in Equation (1) and Equation (2), which uses neighbor information for calculating kernel values automatically. It is shown in [7] that multi-gradient images can withstand variations of handwriting for classification of gender using handwriting analysis. It is motivated us to explore the same for generating multi-gradient images for arecanut images in this work. The Equation (2) can be used to obtain Sum of Absolute Difference (SAD) for eight adjacent pixels. This helps to analyze the variation in visual content of the images. By using Equation (1) the weight value of the T scale can be computed dynamically. The Fig.4 shows the effectiveness of the multi-gradient operation, where it can be seen that each directional kernel operation highlights prominent information of respective direction of the kernels. The advantage of obtaining multi-gradient images is that it gives rich information about the content of the images in different directions.
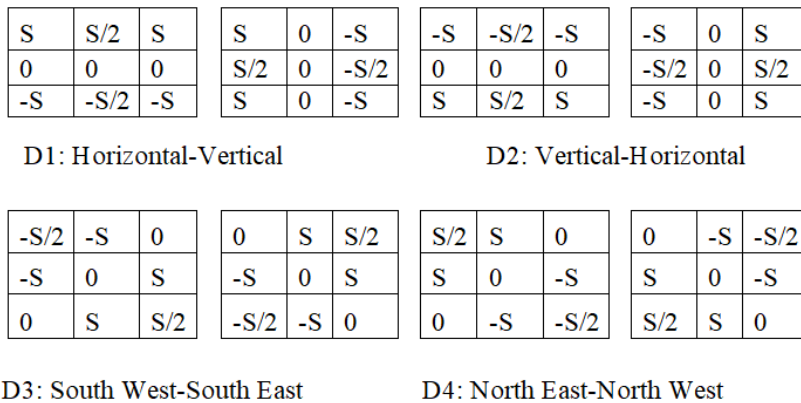

D1: Horizontal-Vertical D2: Vertical-Horizontal

D3: South West-South East D4: North East-North West

Fig. 3 Adaptive Multi-Sobel Kernels for multi-gradient image generation

$$S = \frac{T_{scale}S_{local}}{S_{max}} \qquad (1)$$

Where S_{local} signifies the Sum of Absolute Difference (SAD), and S_{max} signifies the maximum SAD value.

$$S_{local} = SAD = \frac{1}{9} \sum_{K=-1}^{1} \sum_{L=-1}^{1} |f(i,j) - f(i+K, j+L)| \tag{2}$$

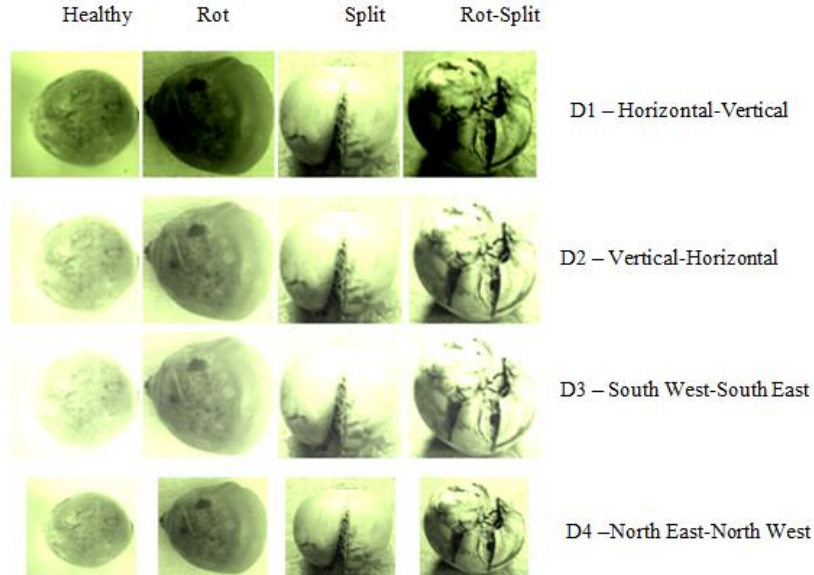Where $f(i, j)$ is the middle pixel 3×3 window in the gray image

Fig.4: The effects of multi-gradient images for four classes of arecanut

3.2 Diseased Arecanut Images Classification using CNN Model

The multi-gradient images obtained in the preceding section are fed to the deep learning architecture for classification. In this work, we propose to explore the basic AlexNet architecture [8] as shown in Fig.5 for classification, though there exists many deep learning architectures available in the literature for classification [16]. As an initial attempt towards the classification of arecanut images, we made use of the AlexNet, which is basically a traditional deep learning network architecture to startup by any naïve researchers [16]. There are eight layers in the architecture: 5-Convolution layers and 3-Fully connected layers, as shown in Fig. 5. The advantage of AlexNet is as follows. By placing half of the model's neurons on one GPU and the other half on another GPU, AlexNet allows for multi-GPU training. This not only guarantees that it is possible to train a larger model, but also cuts down on training time.

Traditionally, CNN's "pool" the outputs of adjacent neuron groups without overlap. However, when overlapping is introduced, an error reduction of about 0.5 per cent can be seen and overlapping pooling models are generally found to be more difficult to overfit.
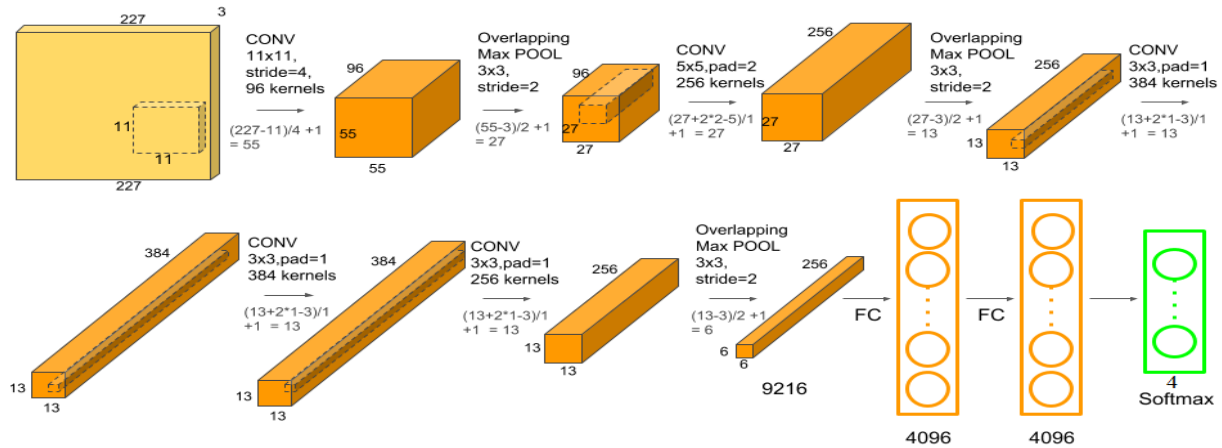
Fig.5: AlexNet architecture for classification of arecanut images

The architecture is comprised of the following components:

(i) 1-Convolution layer with kernel size 11×11 (1CONV), (ii) Rectified Linear Unit Layer Activation (ReLU), (iii) Response Normalization Layer, (iv) 1-Max Pooling (3×3 kernel), (v) 2-Convolution layer with kernel size 5×5 (2CONV), (vi) Rectified Linear Unit Layer (ReLU), (vii) Response Normalization Layer,(viii) 2-Max Pooling (3×3), (ix)3-Convolution layer with kernel size 3×3 (3CONV), (x) Rectified Linear Unit Layer Activation (ReLU), (xi) 4-Convolution layer with kernel size 3×3(4CONV), (xii) Rectified Linear Unit Layer Activation (ReLU), (xiii) 3-Max Pooling (3×3 kernel), (xiv) Fully Connected Layer (4096 nodes), (xv) Rectified Linear Unit Layer Activation (ReLU), (xvi) Fully Connected Layer (4096 nodes), (xvii) Rectified Linear Unit Layer (ReLU), (xviii)Soft-Max out.

The input images are down-sampled from 256 x 256 to 227 x 227 in terms of spatial resolution to lower the computational complexity of our deep learning architecture.5-Convolutional (CONV) layers followed by 3-Pooling layers (POOL) and rectified linear unit layers (ReLU) are used in the proposed system. 96 kernels of a relatively large size $11 \times 11 \times 3$ are used for the 1st-convolution layer and 256 kernels of size 5×5 are used for the 2nd -Convolution layer. In the 3rd, 4th and 5th layers, 384 kernels of size 3×3 are used. A feature map is created by each convolutional layer. The 1st, 2nd and 5th Convolution layer feature maps are used in combination with 3×3 pooling layers and 2×2 strides. There are eight layered architectures with 4096 nodes in the framework. It is possible to characterize their work as:

Convolution network Layer: 5-Convolution layers with the ReLU layer and response normalization layer in the proposed architecture are used to extract more number of feature maps from the input images in order to train the dataset with high accuracy.

Rectified Linear Unit Layer: We applied the ReLU activation function to all the trainable layers in order to strengthen our network by making it non-linear in the next phase, and this layer accounts for the non-linearity in an appropriate manner. It is applied over the output feature map which is generated from the convolutional layer. Because deep convolution neural networks train at a much faster pace when intact with the ReLU layer, we included the ReLU layer in our proposed framework.

Max Pooling Layer: In the proposed architecture, after the 1st and 2nd Convolution layer, and then after the 5th Convolution layer, a max pooling layer is used to minimize the spatial size of each frame to minimize the computational complexity of the proposed deep learning framework. The pooling operation normally averages or simply picks the maximum value for every slice of the image. As we have achieved better results in this setting, we apply pooling in the proposed work by using the maximum value against each slice. This creates trainable feature maps, i.e. feature extraction phenomena are performed in these layers. In order to evaluate the classification probabilities used by the final output classification layer, the feature maps are subjected to fully connected layers (FC) and Soft-Max activation is performed. In the Soft-Max layer, these classification probabilities can build categories of up to 1000 different classes, but we have four classes in our dataset.

4.0 EXPERIMENTAL RESULTS

There is no standard dataset available for evaluation as this is the first work on the classification of arecanut images of various diseases. Therefore, we have created our own dataset which includes images of different shapes, color, degradations. In addition, our dataset includes arecanut of different seasons and time. The number of images chosen for each class is reported in Table 1 before augmentation. Our plan is to explore deep learning to achieve better classification rate. The size of the dataset mentioned in Table 1 may not be sufficient for training the model. In order to maximize the number of samples for each class, we use augmentation techniques like flip, blur and rotation, as stated in Table 1 after augmentation, which provides10,116 images. To make implementation easy and save processing time the input images size are converted to standard size of 256×256 dimension in the proposed work

Table 1: Number of samples to learn the proposed architecture before and after augmentation (Rotation, flip, blur)

Class	Before Augmentation	After Augmentation
	Samples	Samples
Healthy	192	6912
Rot	29	1044
Split	32	1152
Rot-Split	28	1008

To study the effectiveness of the proportion of the number of training and testing samples on classification, we consider different proportion as mentioned in Table 2, where we have used 30-70, 50-50 and 70-30 of training and testing samples, respectively. It is expected that the accuracy of the technique can improve as the number of training samples increases.

Table 2: Dataset distribution for different training and testing proportions (30:70; 50:50 and 70:30)

Classes	30-70		50-50		70-30	
	Training	Testing	Training	Testing	Training	Testing
Healthy	2074	4838	3456	3456	4838	2074
Rot	313	731	522	522	731	313
Split	346	806	576	576	806	346
Rot-Split	302	706	504	504	706	302

We consider the following most recently proposed approaches for comparative analysis to illustrate the robustness of the suggested method. Siddesh et al. [10], which proposes color features and KNN classifier for classification of raw arecanut images. Suresh et al. [6], which uses texture, features for classification of diseased arecanut images. Cai & Liu [11] proposes transfer learning for classification different type of betel nut images. The reason for choosing the above-mentioned methods for comparative analysis is that Siddesh et al., which is developed for the classification of raw arecanut images, which is the same as the proposed work. Suresha et al., which is developed for diseased arecanut image

classification as the proposed work. Cai & Liu proposed a method for classification of betel nut images using deep learning techniques.

In order to demonstrate that the existing techniques are inadequate to distinguish the four classes of arecanut images affected by different diseases, the combined multi-Sobel and CNN approach is therefore applied to compare with the existing methods in this work.

Standard measures [17] are used to determine the efficiency of the proposed and existing methods, i.e. recall (R), precision (P) and F-measure (F) can be described in Equation (3), (4) and (5).

$$P = \frac{T_p}{T_p + F_p} \tag{3}$$

$$R = \frac{T_p}{T_p + F_n} \tag{4}$$

$$F - \text{Measure} = \frac{P}{P + R} \tag{5}$$

Here, T_p implies the total number of correctly classified images, F_p implies the total number of the original images mistakenly classified as others, and F_n is the total number of images.

4.1   Experiment on Multi-Type Arecanut Image Classification

Table 3 describes the quantitative results of the proposed approach in terms of the confusion matrix and the average classification rate (ACR) for four classes of datasets and also shows that the performance of the proposed classification improves in terms of ACR as the training samples numbers increases. This shows that dividing data into the number of training and testing samples play a vital role in achieving better results. The same conclusions can be made from the results reported in Table 4, where the recall, precision and F-measure for each class for the different training and testing sample ratios have been reported. When we look at F-measure of each class, it increases as the ratio increases. Overall, the proposed method achieves promising results for classification of four classes of arecanut images of different diseases. Sample images of the suggested approach for successful and unsuccessful classifications are shown in Fig. 6, where one can see sometimes, the extracted features fail to classify the images correctly. This indicates that there is a scope for enhancement to make the proposed approach more robust.

Split	Rot & Split
Healthy	Rot

(a) Successful Classification

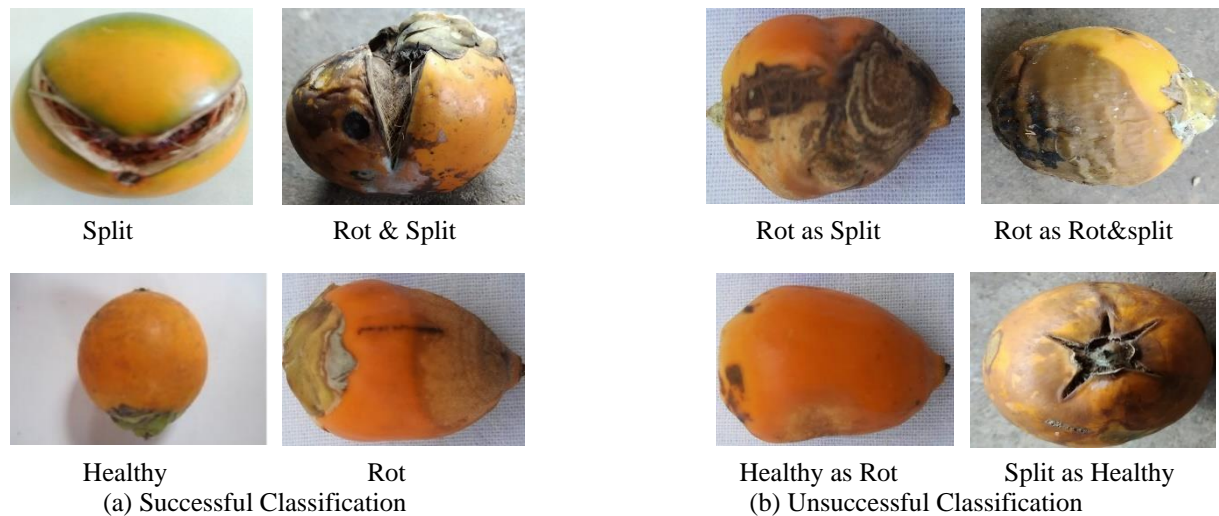| Rot as Split	Rot as Rot&split
Healthy as Rot	Split as Healthy

(b) Unsuccessful Classification

Fig. 6: Some examples of successful and unsuccessful classifications.

Table 3: Confusion matrix of proposed method for classification of arecanut images on different distribution of data

Ratio	30-70				50-50				70-30			
Classes	Healthy	Rot	Split	Rot-Split	Healthy	Rot	Split	Rot-Split	Healthy	Rot	Split	Rot-Split
Healthy	2815	203	1030	790	2360	98	765	233	1501	92	301	180
Rot	4	635	19	73	10	478	4	30	0	290	0	23
Split	16	36	684	70	19	57	460	40	16	8	310	12
Rot-Split	3	51	19	633	6	21	11	466	2	8	0	292
ACR	67.3%				74.4%				78.8%			

Table 4: Class-Wise Precision, Recall, and F-Measure for classification of arecanut images on different distribution of data

Ratio	30-70			50-50			70-30		
Classes	Precision	Recall	F-Measure	Precision	Recall	F-Measure	Precision	Recall	F-Measure
Healthy	0.99	0.58	0.73	0.98	0.68	0.80	0.98	0.72	0.83
Rot	0.68	0.86	0.76	0.73	0.91	0.81	0.72	0.92	0.81
Split	0.39	0.84	0.53	0.37	0.79	0.50	0.50	0.89	0.64
Rot-Split	0.40	0.89	0.55	0.60	0.92	0.73	0.57	0.96	0.72

In Fig.7 and Fig.8, classification rate, recall, precision and F-measures of the suggested and the existing methods are presented. For both the experiments, the proposed method achieves the best classification rate, recall, precision and F-measure compared to the existing methods. Siddesha et al.[10] (color characteristics) reported the lowest results relative to the methods proposed and other existing ones. The main reason for the poor result is that the method is not robust because the method is developed for different types of arecanut images but not diseased images. Therefore, the features used in the method are sensitive to degradations caused by different diseases. In the same way, Suresh et al. [6] (LBP, HAAR, GLCM, GABOR, Texture features) and Cai & Liu [11] (Transfer learning) methods are developed for arecanut after removing skin (seeds) but not for raw arecanut images. Therefore, the shape and pattern of the content of the images are different from the raw arecanut image considered in this work. The features and model used in the methods [6, 11] may not work well for our dataset. On the other hand, the combination of multi-gradient image and deep learning model has strong discriminative ability and hence the proposed method outperforms existing methods.
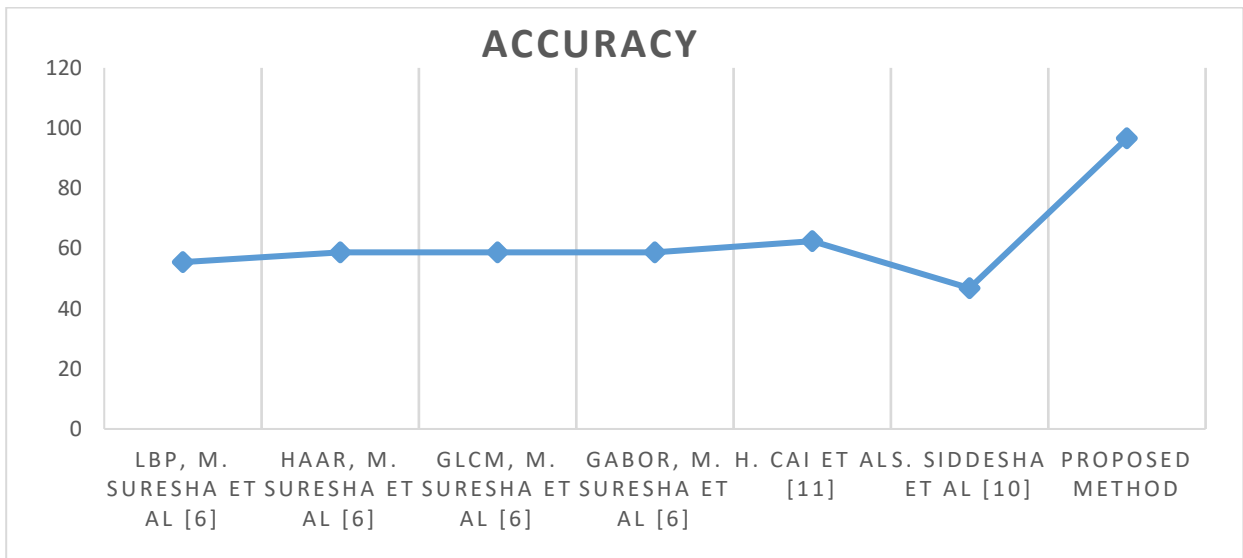
Fig. 7: Performances of the suggested and existing methods for classification in terms of classification rate
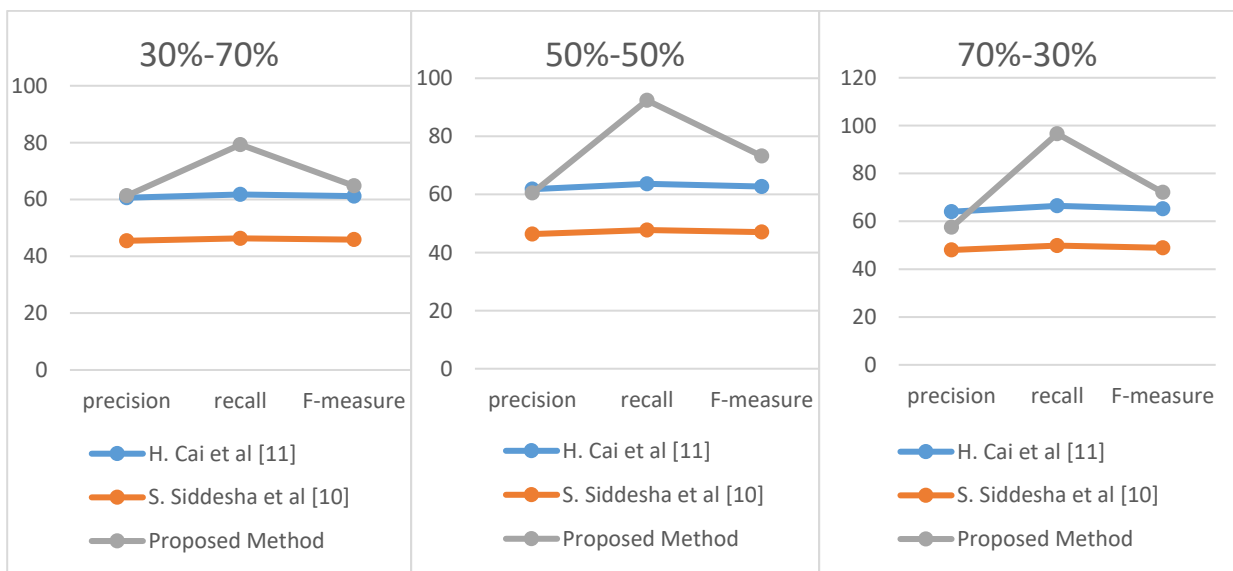

Fig. 8: Performances of the suggested and existing methods for classification in terms of Recall, Precision and F-Measures

5.0 CONCLUSION AND FUTURE WORK

In this work, we have proposed a new method for classification of arecanut images of different diseases. We have considered four classes, namely, images of Healthy, Rot, Split and Rot-Split for classification. To overcome the effect of different diseases on images, the proposed method exploits multi-gradient concept to generate four gradient images, which enhances the fine details in the images irrespective of disease effect. For classification, we have explored AlexNet deep learning architecture by adapting according to complexity of the problem. The implementation results of the proposed and existing methods show that in terms of classification rate, recall, precision and F-measure, the proposed method outperforms. Since the scope of the proposed work is limited to four classes, our future target is to extend the same idea for more number of classes. In addition, after classification, the next work should be identification of disease by analyzing the content of the images.

REFERENCES

[1]   Bhat, A. G. (2019). Arecanut tree-climbing and pesticide spraying robot using servo controlled nozzle. In Proc. GCAT, pp 1-4.

[2]   Dhanesha, R., Naika, C. L. S and Kantharaj, Y. (2019). Segmentation of arecanut bunches using YCgCr color model. In Proc. ICAIT, pp 50-53.

[3]   Dhanesha, R. and Naika, C. L. S. (2018). Segmentation of arecanut bunches using HSV color model. In Proc. ICEECCOT, pp 37-41.

[4]   Manjunatha, M. and Parkavi, A. (2018). Estimation of arecanut yield in various climatic zones of Karnataka using datamining technique: A survey. In Proc. ICCTCT, pp 1-4.

[5]   Swamy, H. M. M., Ramasamy, A., Kalleshwaraswamy, C. M. and Adarsgh, S. K. (2019). Arecanut white gubs leucopholis species (Melonthinae: Scarabaeidae: Coleoptera) morphological, molecular identification and phylogenetic. Journal of Asia-Pacific Entomology, pp 880-8888.

[6]   Suresha, M., Danti, A., & Narasimhamurthy, S. K. (2014). Classification of Diseased Arecanut based on Texture Features. International Journal of Computer Applications, pp 1-6, 2014.

[7]   Navya, B. J., Shivakumara, P., Shwetha, G. C., Roy, S., Guru, D. S., Pal, U., & Lu, T. (2018), Adaptive multi-gradient kernels for handwritting based gender identification. In Proc. ICFHR, pp 392-397.

[8]   Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2017). Imagenet classification with deep convolutional neural networks. Communications of the ACM, pp84-90.

[9]   Gowda, S. K., Prathima, K. R., Yashaswini, L., Rakesh, M. D. and Kumar, T. R. S. (2019). Pneumatic controlled smart arecanut plucking robot with raspberry Pi. In Proc. ICCES, pp 527-532.

[10]   Siddesha, S., Niranjan, S. K., & Aradhya, V. M. (2018). Color Features and KNN in Classification of Raw Arecanut images. In Proc. ICGCIoT, pp 504-509.

[11]   Cai, H., & Liu, S. (2019). Betel Nut Classification Method Based on Transfer Learning. In Proc. DDCLS, pp 1039-1043.

[12]   Danti, A. and Suresha, Segmentation and classification of raw arecanut based on three sigma control limits. Procedia Technology, pp 215-219.

[13]   Mahesh, V. G. V., Raj, A. N. J and Fan, Z. (2017). Invariant moments based convolution neural network for image analysis. International Journal of Computational Intelligence Systems, Vol.10, pp. 936-950.

[14]   Raj, A. N. J and Mahesh, V. G.V. (2017). Zernike-Moments-Based Shape Descriptors for Pattern Recognition and Classification Applications. Advanced Image Processing Techniques and Applications. DOI: 10.4018/978-1-5225-2053-5.ch004.

[15]   Zunic, J., Hirota, K and Rosin, P. L. (2010). A Hu moment invariant as a shape circularity measure. Pattern Recognition, Vol. 43, Issue 1, pp. 47-57.

[16]   Liu, W., Wang, Z., Liu, X., Zeng, N., Liu, Y and Alsaadid, F. E. (2017). A survey of deep neural network architectures and their applications, Neurocomputing, pp. 11-26.

[17]   Powers, David, M.W. Evaluation (2011). From Precision, Recall and F-Measure to ROC, In-formedness, Markedness & Correlation, Journal of Machine Learning and Technology, pp.37–63.