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A Deep Learning Approach for Automated Detection and Classification of Pomegranate Fruit Disease using EfficientNet

S. Komalavalli[1*], Dinesh Kumar Budagam[2], C. Jehan[3], P. Karputha Pandi[4]

[1]Assistant Professor, Department of Electronics and Communication Engineering, Einstein College of Engineering, Tirunelveli, 627012. komalavallimuralidharan@gmail.com
[2]Sr Cybersecurity Engineer at VISA, inc, Foster City, CA. getbdinesh@gmail.com
[3]Associate Professor, Computer Science and Engineering department, Vel Tech Multi Tech Dr. Rangarajan Dr. Sagunthala Engineering College, Avadi, Chennai-62. cjehan2001@gmail.com
[4]Assistant professor, Department of Electrical and Electronics Engineering, Erode Senguthar engineering College, Perundurai, karputhapandi15102@gmail.com

komalavallimuralidharan@gmail.com

ABSTRACT: Pomegranate is one of the most well-liked and nutritious fruits in the world. Pomegranates are now processed into a variety of food products and nutritional supplements due to the growing demand for them. Nowadays, pomegranate fruits are affected by diseases. In this paper, an Efficient Net classification is proposed to quickly identify diseases in pomegranate fruit. Firstly, histogram equalization is applied to the pomegranate fruit disease dataset to modify an image's pixel values based on its intensity and by using laplacian filtering edges are detected to get high quality image. Next, the processed image is given to the K-Means clustering for the separation of relevant regions. After that pomegranate fruit disease is featured using Scale-Invariant Feature Transform (SIFT) for further analysis. Finally, Efficient Net framework is processed to enhance the classification of pomegranate fruit disease. Using python software the proposed framework is examined and the developed classifier results with accuracy of 95% in detecting disease when compared to other techniques.

Keywords: Efficient Net, Scale-Invariant Feature Transform (SIFT), K-means clustering, Laplacian Filtering, Histogram Equalization, Pomegranate fruit disease.

1. Introduction

A pomegranate (Punica granatum) fruit is an important medicinal significance fruit. Pomegranates have been help to treat cardiac conditions and prevent cancer. It's an excellent antioxidant. Nevertheless, as the tree and fruit expand, these fruits also get a lot of diseases from different pests [1]. Conversely, India's economies have been negatively impacted by this disease since 2012, especially when it comes to the export of high-quality fruits. The disease's effects caused India's pomegranate production to decline by 60% after an epidemic in 2021 that caused the states of Karnataka and Maharashtra to lose 70% to 100% of their crop [2]. Pomegranate disease categorization using images of the fruits and leaves have lot of attention in both past and present agriculture as a means of boosting output and earnings [3-4]. Whereas, diseases that affect the pomegranate fruit disease are healthy, bacterial light, anthracnose, alternaria fruit spot and cercospora fruit spot. Healthy means a pomegranate with good skin should be bright and deep in color, usually between dark red and reddish-purple [5]. Pomegranate trees and their fruits are susceptible to a common disease called bacterial blight. On the fruit's surface, it is black, sunken lesions and lesions are spherical and they frequently have a dark or reddish-brown border around them. Cercospora fruit spot is present on the surface of the fruit, the first symptoms visible as tiny, irregular, or round dots. Usually it is brown or dark brown in color [6]. Moreover, alternaria generally happens in warm, humid weather. On the fruit's surface, the disease first shows as tiny, round, brown or black dots. These areas have a dark border and are slightly sunken [7]. Using the pre-processing technique as Finite Impulse Response (FIR) filter the image is filtered. It is possible to reduce the steady and round-off noise then produce high accuracy. [8]. Whereas, an adaptive histogram-based method is used for solving the pomegranate fruit disease problem. It effectively enhances the contrast of an image with good image quality. Drawback is low accuracy because over amplification of noise in constant area [9]. However, to increase the accuracy of pomegranate fruit disease an Artificial Neural Networks (ANN) is used. In order to enhance simplicity and avoid over-fitting of ANNs, a Support Vector Machine (SVM) have been trained. Long training period when using huge datasets are handled [10]. Moreover, to improve the performance of pomegranate fruit disease Principal Component Analysis (PCA) is used. Drawback is sensitive to data scaling when employed with non-linear data outliers [11]. Using Artificial Neural Network classifier the plant disease is detected and improves the classification accuracy. It takes more intervals to access the process when identifying the disease [12]. Furthermore, to identify and improve the accuracy of pomegranate fruit disease CNN is utilized which is good at automatically learning high-level and different level reflections from visual information when using CNN technique. CNNs need a lot of labeled training data [13-14]. Moreover, disease detection in pomegranates, utilizing a Pooling$_{mean/max}$ and Filtering$_{Median}$ technique based on the Convolutional Neural Network (PF-CNN) detects with high accuracy. It have high expenses of computation in layers [15]. To overcome this limitation an advanced Efficient Net is utilized.

2. Related work

Chakali *et al* [16] (2020) have proposed a Convolutional Neural Network (CNN) to identify the diseases of pomegranate fruit. According to the machine learning mechanism, the accuracy levels will always be higher when the input size is large. For large datasets, this lead to significant computation times and memory requirements. Substantial calculation times and memory needs for huge datasets.

Nouri *et al* [17] (2020) have proposed a Linear Discriminant Analysis (LDA), Back Propagation Neural Network (BPNN) and Support Vector Machine (SVM) to detect the pomegranate fruit disease. BPNN displayed higher accuracy and LDA detects the healthy and fruit samples. Slow convergence and local minima susceptibility are two drawbacks of conventional back-propagation neural networks.

Nirmal *et al* [18] (2023) have proposed a ResNet and Mobile Net to extract features and classify pomegranate fruit disease. ResNet and Mobile Net are reliable enough to accurately and efficiently identify and classify pomegranate conditions. It have high processing difficulties, lacking a portion of labeled data.

Yu *et al* [19] (2022) have proposed an improved F-Point net algorithm to accurately detect and locate individual pomegranate fruits in the orchard. Proficiently recognises disease subcategories with a significant divergent reaction to therapy. Because it is more difficult to describe the model's predictions, comprehending the process becomes difficult.

Kazi *et al* [20] (2023) have proposed a Convolutional Neural Network (CNN) to identify the pomegranate fruit disease. CNN effectively identifies, analyse fruit disease and predict a disease type accurately with high performance.

However, it takes more time to process the single image.

The contribution of this study is summarized as follows:

- The input image modifies its pixel values based on intensity using histogram equalization.
- The laplacian filtering is used to find edges and enhances the image quality of pomegranate fruit disease.
- Using K-means clustering it separates the relevant region and Scale-Invariant Feature Transform (SIFT) to analyze key points for better classification
- Advances an Efficient Net to enhance the accuracy and efficiency of pomegranate images.

3. Proposed work

The block diagram in figure1 shows the proposed Efficient Net classification for five classes of pomegranate fruit disease. Firstly, using histogram equalization the input image modifies its pixel values based on intensity. After that detects the edges using laplacian filter. Secondly, the processed pomegranate fruit disease image is given as input to K-Means clustering here it separates the relevant region to segment the fruit disease**.** Thirdly, by using feature extraction technique the Sift-Invariant Feature Transform (SIFT) analysis the key points.

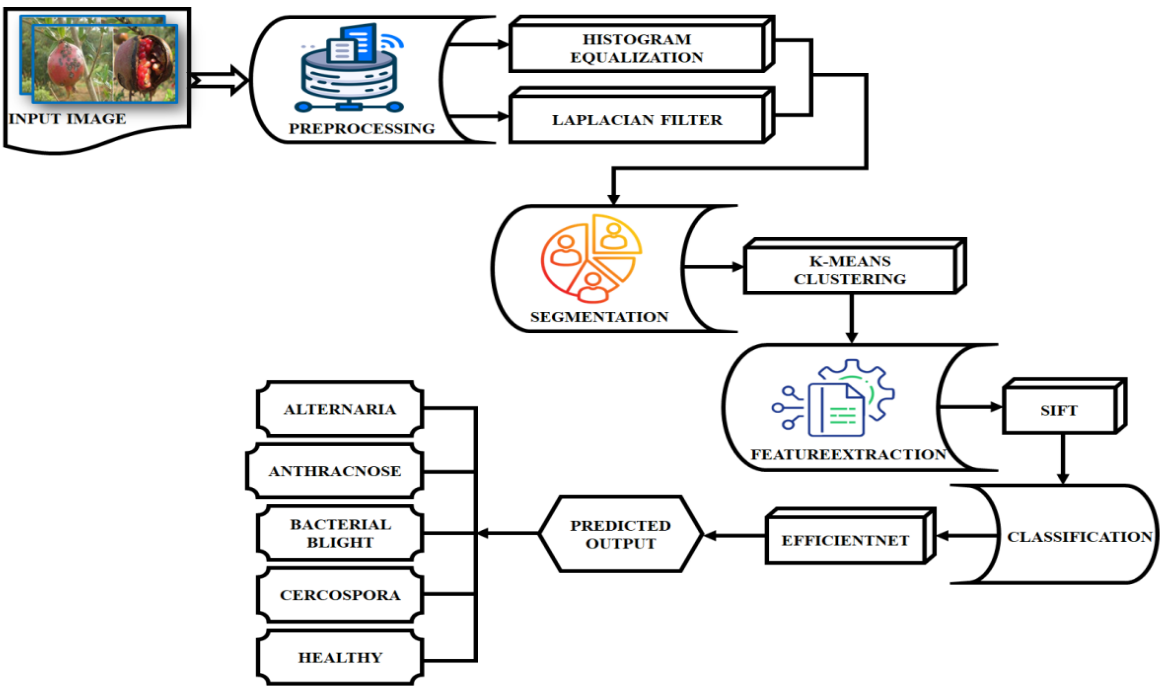

Figure 1: *Block diagram of proposed Efficient Net*

Finally, featured image is given to the classification process were Efficient Net is used for classifying the pomegranate fruit disease. The Efficient Net is used to classify the fruit image in depth for getting better accuracy when compared to the other techniques.

3.1 Pre-processing

In the pomegranate fruit disease detection the pre-processing have two method histogram equalization and laplacian filtering.

3.1.1 Histogram Equalization

A method called histogram equalization modifies an image's pixel values according on its intensity. The distribution of histograms varies in different color spaces for different disorders. By calculating the difference between the histogram of grayscale images and the histogram of color spaces are extracted.

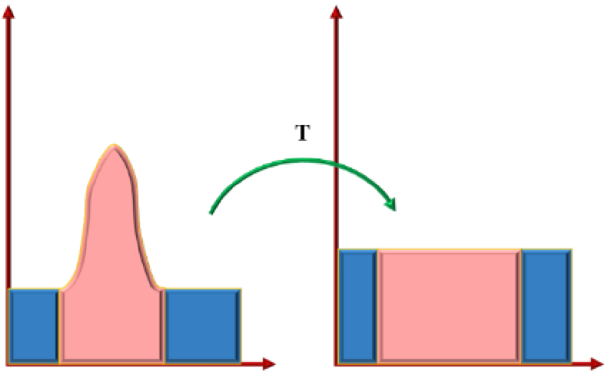

Figure 2: *Basic histogram equalization*

The gray image, which is the average of R, G, and B components and is regarded as a reference image as illustrated in Figures 2, is the rationale for taking it into account when evaluating distance features. Because the behavior of the histograms tolerates the effects of degradations and background fluctuations, the histogram technique is value examining.

$$S_k = T(r_k) = \sum_{j=0}^{k} \frac{n_j}{n}(L-1) \qquad (1)$$

Where, $k = 0,1, \ldots L-1$, L denotes number of grey levels in image, n_j denotes the sum of times j^{th} n is the total number of pixels in an image, and gray level appears in the image.

3.1.2 Laplacian filtering

Laplacian filtering is used because the original image contains background noise and unnecessary data. Additionally, the image must be sharpened in order to be processed further. In this a kernel is employed to sharpen the image using Laplacian filter. To obtain the appropriate sharpened output image, a $3 * 3$ matrix called a kernel is twisted with an image matrix. To obtain the Laplacian result, simply add the second derivative of the function with respect to x *and* y.

$$\nabla^2 x(t_1, t_2) = \frac{\partial^2 x(t_1,t_2)}{\partial^2 t_1} + \frac{\partial^2 x(t_1,t_2)}{\partial^2 t_2} \qquad (2)$$

Where, the second derivative of the function with respect to x and t is the number of intensity variables. Following to this the pre-processed image is given to the segmentation stage.

3. 2 Segmentation using K-means clustering

The k-means technique is used to categorize the image pixels into k clusters based on the future set. The image is divided into k-clusters in k-means clustering. First, choose the cluster centroid at random and reducing the sum of the squared distances between the image and the matching k cluster throughout the classification process. In Figure 3, the K-means clustering is displayed.

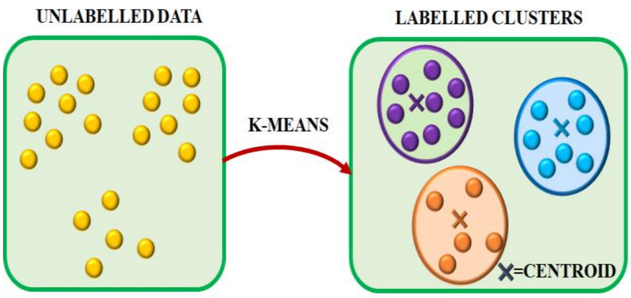

Figure 3: *K-Means clustering*

The distance between the observed value and the cluster centroid value is measured using the Euclidean distance. Evaluating a distance metric involves minimizing within-cluster distance. Furthermore, maximizing the distance between clusters is utilized to maximize the distance between them.

$$Euclidean\ Distance = \sqrt{(x1-x2)2+(y1-y2)2} \qquad (3)$$

$$Centroid = \frac{(x1+x2+x3)}{3}, \frac{(y1+y2+y3)}{3} \qquad (4)$$

This formula can be extended to encompass n points as follows:

$$Centroid = \frac{(x1+x2+\cdots+xn)}{n}, \frac{(y1+y2+\cdots+yn)}{n} \qquad (5)$$

K-means clustering operates on the basis of initialization, and centroids. Here, K points are selected from the image for initialization, and they also act as the initial cluster centroids in pomegranate fruit disease. Following to this the segmented image is given to feature extraction phase.

3. 3 Feature extraction by SIFT

For pomegranate fruit disease detection the feature is extracted using Scale-Invariant Feature Transform. SIFT is used to identify image that are tough to rotation, scale, and affine transformation changes. After identifying crucial points based on their local intensity extreme, descriptors are added to capture the local picture information surrounding key points in figure 4.

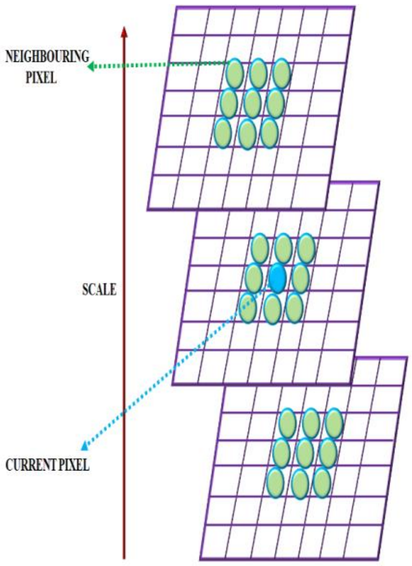

Figure 4: *Scale-Invariant Feature Transform*

SIFT algorithm is used to detect distinct feature called keypoints in images. The main steps in SIFT algorithm are

3.3.1 Scale-Space Extreme Detection

The pomegranate fruit disease images are detected using keypoints across different scales. In order to smooth the image to changing degrees, the method uses a Gaussian blur at different measurements. Image change from clear to blurry as a result and its equation is given as

$$L(x,y,\sigma) = G(x,y,\sigma) * I(x,y,) \qquad (6)$$

Wherever, $L(x,y,\sigma)$ denoted as blurry image at scale σ,$G(x,y,\sigma)$ denoted as Gaussian kernel and $I(x,y)$denoted as the original image

3.3.2 Keypoint Localization

To estimate a location near a given point a Taylor series expansion is used in pomegranate fruit disease image. Then to improve the location and scale a Difference of Gaussians (DoG) function is used. To remove the edges in pomegranate fruit disease image DoG function has higher response. The primary curvature is calculated using a 2x2 Hessian matrix (H).

3.3.3 Orientation Assignment

For each keypoint an orientation is assigned and to make the image rotation invariant. A region is drawn around the keypoint position based on the scale, gradient magnitude, and direction that are designed in the image.

3.3.4 Keypoint Descriptor

A vector is represented by a keypoint descriptor. Using pomegranate fruit disease image a keypoint is taken as a 16x16 neighbourhood around it. A total of 128 bin values are obtained by splitting the pomegranate fruit disease image into 16 as 4x4 sub-blocks and assigning an 8-bin orientation histogram to each sub-block. Key point descriptor in figure 5.

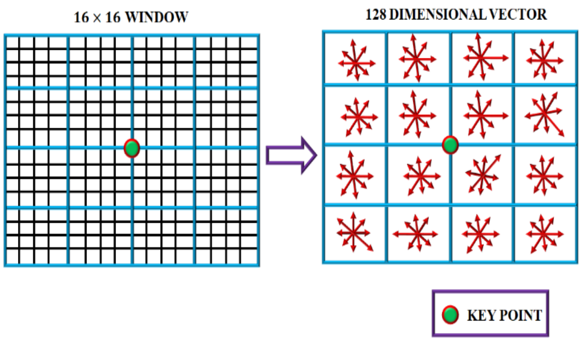

Figure 5: *Key point Descriptor*

Next by feature extraction he featured pomegranate fruit disease image is given as an input to proposed Efficient Net for better classification.

3.4 Classification by Efficient Net

The proposed Efficient Net is a baseline model, which is intended for effective image classification for pomegranate fruit disease. It uses less parameters and processing to attain high accuracy. The models have 37 layers and 5 stages, including Mobile Inverted Bottleneck Convolutions (MBConv), which employ squeeze-and-excitation blocks and depth wise separable convolutions for efficiency. Its compound scaling method balances computational cost and performance by consistently adjusting depth, width, and resolution.

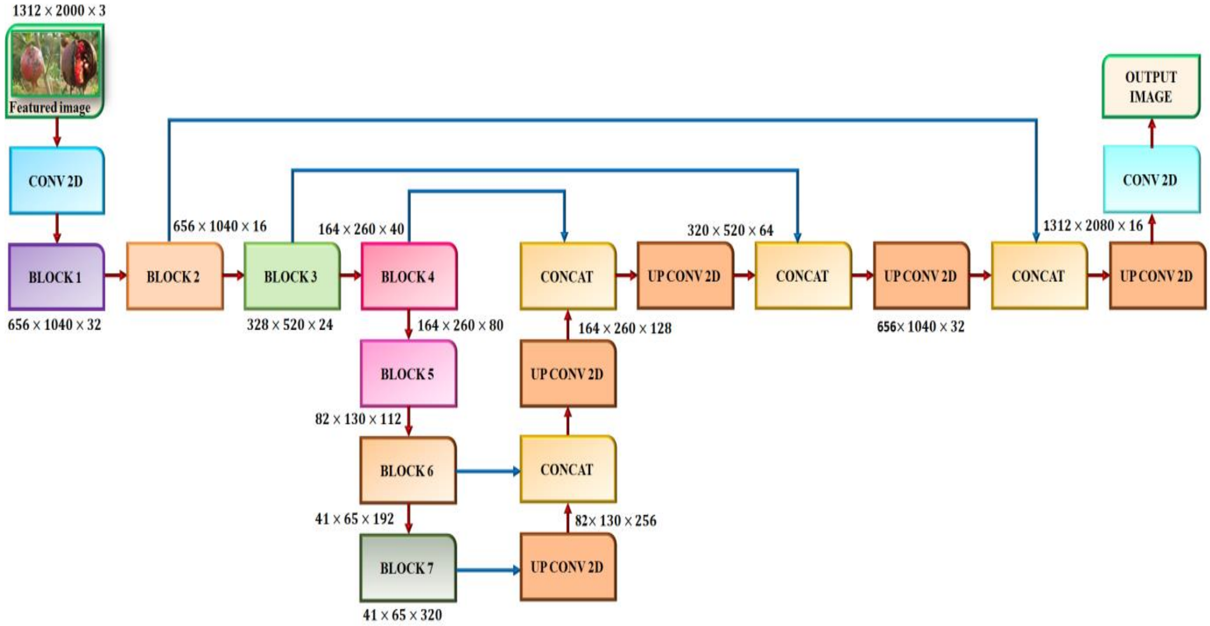

Figure 6: *Efficient Net architecture*

The Efficient Net architecture in figure 6 is trained using more than an image from the featured image. To increase speed and accuracy, the Efficient Net employs a compound scaling strategy with constant ratios in all three dimensions. To increase speed and accuracy, the Efficient Net employs a compound scaling strategy with constant ratios in all three dimensions.

Figure 7: *Blocks in Efficient Net*

There are 18 convolution layers in total, means that the depth is 18. Each layer contains a kernel that is either3×3 *or* 5×5. In order to minimize the size of the feature vector, the successive layers' resolution is decreased, but their width is increased to increase accuracy. In the event the breadth of the second convolution layer is 16 filters, the next convolution layer will have 24 filters. The maximum number of filters in the last layer and fully connected layer is 1,280. Typical kernels sizes are 3×3 *or* 5×5larger kernels improve the model and boost efficiency. Large kernels frequently help capture high-resolution patterns, whereas small kernels help extract low-resolution patterns

4. Result and discussion

The aim of this work is to classify the five classes of image. Dataset is taken from kaggle.com for disease analysis. Deep learning models are then applied to train pomegranate fruit disease dataset.

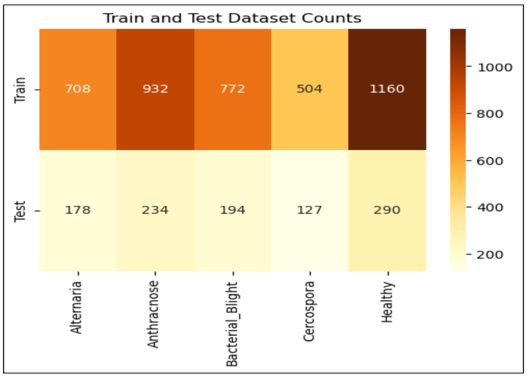

Figure 8: *Train and test dataset counts*

The figure 8 shows the train and test dataset counts. Here alternaria is represented by 708 trains and 178 tests; anthracnose is represented by 932 trains and 234 tests; bacterial blight is represented by 772 trains and 194 tests; cercospora is represented by 504 trains and 127 tests and healthy is represented by 1160 trains and 290 tests. These five types of pomegranate fruit disease are used in the proposed work.

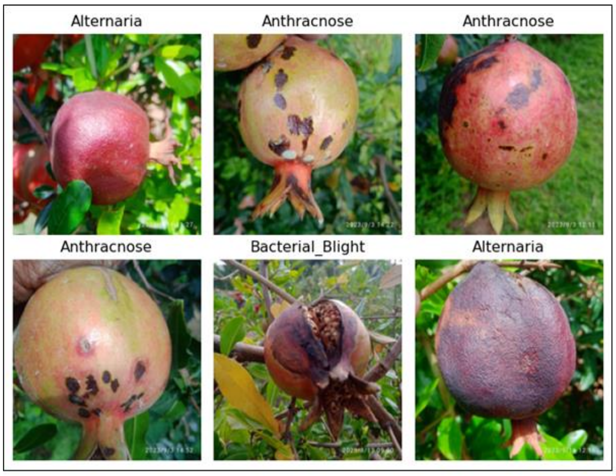

Figure 9: *Random images from train data*

In figure 9 random images in train are shown. Here pomegranate fruit disease image is for train random images. The random images in train are taken from the pomegranate fruit disease dataset. Here the three different classes of alternaria, anthracnose and bacterial blight with six images are present.

Figure 10: *Input images from all classes*

Figure 10 shows the input images from all classes. Here the input image is taken from the pomegranate fruit disease dataset. Using the pre-processing, segmentation, feature extraction and classification techniques the five classes of input pomegranate image are processed.

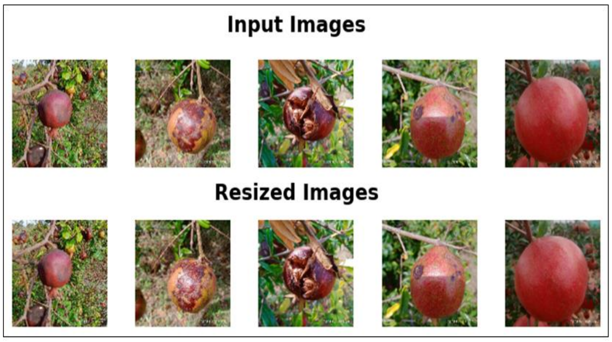

Figure 11: *Input image and resized images*

Figure 11 shows the input image and resized images of pomegranate fruit disease image. Here the input five classes of pomegranate image are resized for processing. Using image resizing technique the five classes of input pomegranate image is captured as a flawless image.

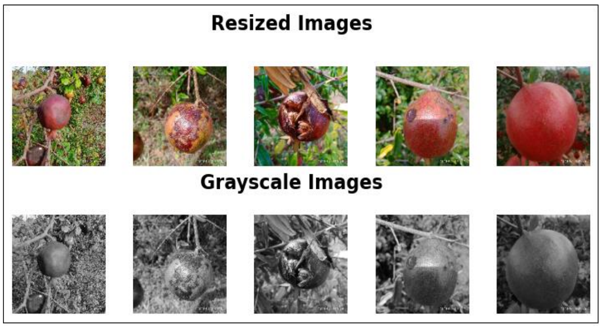

Figure 12: ***R****esized images into grayscale images*

Figure 12 shows the resized images into grayscale image. Resized images into grayscale conversion for five classes of pomegranate fruit disease is converted by using the grayscale conversion technique. Here R, G and B image is converted into gray.

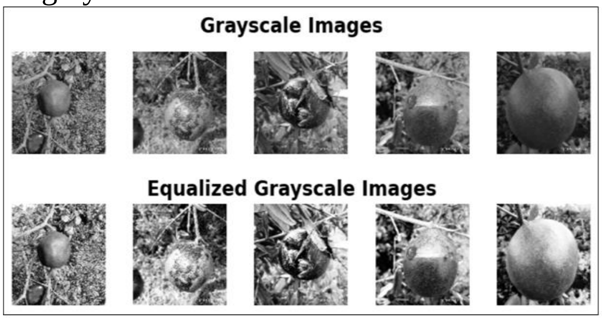

Figure 13: *Gray scale conversion to histogram equalization*

Figure 13 shows the gray scale conversion to histogram equalization. After conversion of gray scale image, histogram equalization is utilized to pre-process the five classes of pomegranate fruit disease image to modify an image's pixel values allowing on its intensity.

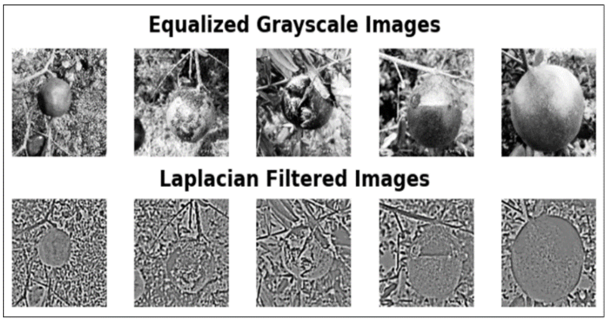

Figure 14: *Histogram equalized images into Laplacian filtered images*

Figure 14 shows the histogram equalized images into Laplacian filtered images. Here the five classes of images are detected by its edges and removes the background noise and unnecessary data.

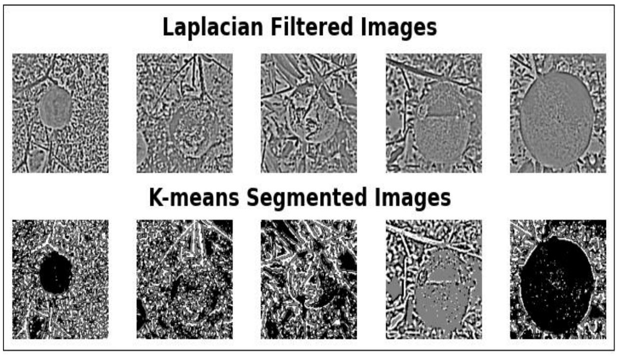

Figure 15 Laplacian filtered image into K-means clustering Figure 15 shows the laplacian filtered image into K-means clustering images. Here the five classes of pomegranate fruit disease image are clustered using K-Means clustering. The filtered image is given as input to segmentation stage the image by clustered based on their similarities. "Check the statement"

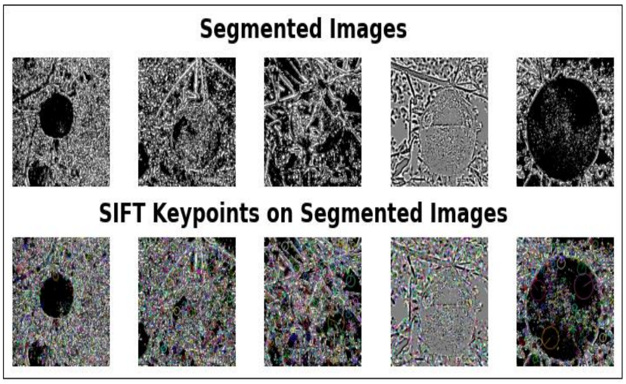

Figure 16: *SIFT keypoint*

Figure 16 shows the K-means segmented image into SIFT key point's images. Here the five classes of pomegranate fruit disease image is used for feature extraction. The segmented image is given as an input to SIFT. A key point is calculated from the scale of the pomegranate fruit disease image.

4.1 Performance metrics

Using various performance metrics the suggested method Efficient Net framework to training data is evaluated. And these metrics are accuracy, precision, recall, F1 score and AUC. Using the following equation each metrics are defined as

Accuracy:

$$Accuracy = \frac{(TN+TP)}{TS} \tag{7}$$

Precision:

$$Precision = \frac{(TP)}{(TP+FP)} \tag{8}$$

Recall:

$$recall = \frac{(TP)}{(TP+FN)} \tag{9}$$

F1 score:

$$F1 - score = \frac{(2*\mathrm{Prec}*\mathrm{Recal})}{(Precision + Recal)} \tag{10}$$

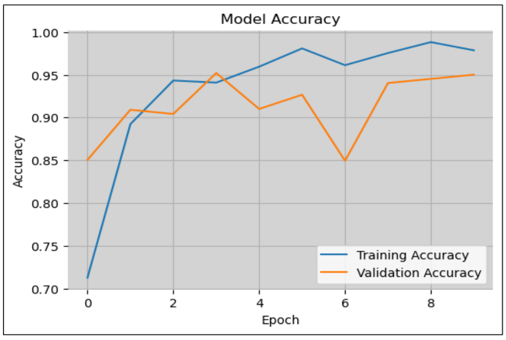

Figure 16: *Training vs validation accuracy*

In figure 17 training vs validation accuracy for pomegranate fruit disease is calculated. Model accuracy is the ratio of a model's accurate predictions to its total number of predictions. The accuracy for the proposed Efficient Net method is 95%.

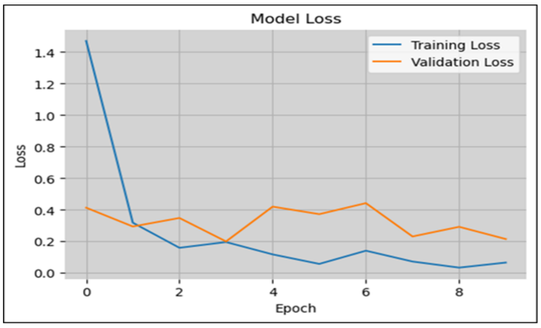

Figure 17: *Training vs validation loss for pomegranate fruit disease*

Figure 18 shows Training vs validation loss for pomegranate fruit disease is calculated. The X-axis denotes the epochs and y-axis is loss for training loss vs validation loss. Training loss value is going on decreasing from 1.5 to 0.2 after 0.2 also it is going on decreasing. Whereas, validation loss is the lower than the training loss for pomegranate fruit disease image.

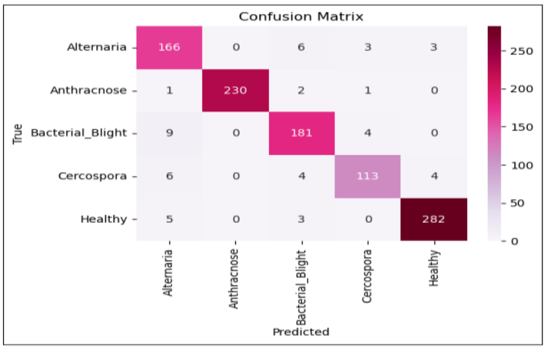

Figure 18: *Confusion matrix for Efficient Net*

Figure 19 illustrates the confusion matrix for Efficient Net. This matrix shows the values for true and predicted labels. Confusion matrices are commonly used to evaluate the performance of classification models, particularly those tasked with predicting categorical labels for input instances. Here the five classes of pomegranate fruit disease image for alternaria, anthracnose, bacterial blight, cercospora and healthy are matrixes.

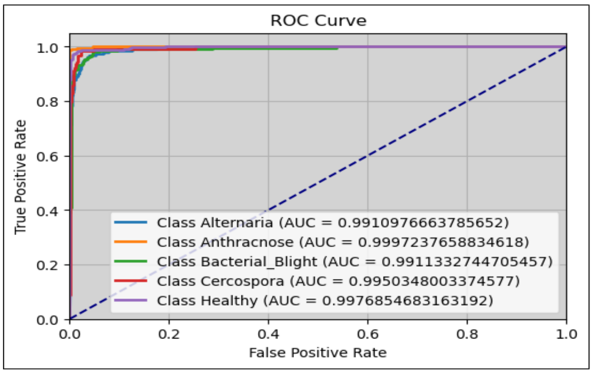

Figure 19: *ROC curve for five classes*

According to the AUC results shown in figure 20, the pomegranate fruit disease dataset significantly lowers the AUC value of Efficient Net, the sub-optimal model on datasets. The five classes are alternaria is 0.991, anthracnose is 0.991, bacterial blight is 0.99, cercospora is 0.995 and healthy is 0.997.

4.2 Comparison for the proposed method

The comparison of proposed method with existing method is presented in table 1. The CNN have the classification accuracy of 85.8% [20] and ANN-SVM have the accuracy of 90.8% [10]. The proposed Efficient Net have the higher accuracy of 95% compared to the existing method in table 1. The proposed Efficient Net have better performance.

Table 1: *Comparison for the proposed method*

Study	Method	Accuracy
Kazi *et al.* [20]	CNN	85.8%
Rezaei *et al.*[10]	ANN and SVM	90.8%

Proposed approach	Efficient Net	95%

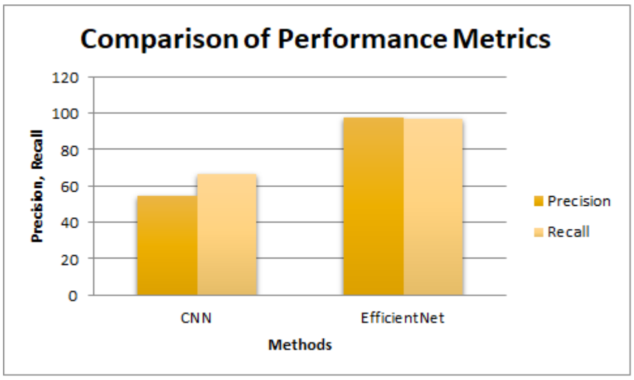

Figure 20: *Comparison of performance metrics*

The Precision and recall value for classifiers CNN and the proposed is presented in Figure 21. The CNN have the value of 55% and 67% [10] and proposed Efficient Net method have the precision value of 98% and recall of 97% for healthy pomegranate fruit.

5. Conclusion

In this study, Efficient Net is proposed for the classification of pomegranate fruit disease image. The integration of advanced preprocessing techniques, such as resizing, grayscale conversion, histogram equalization, laplacian filtering, ensures that the input images are optimized for segmentation. The use of approximate K-means clustering for segmentation further enhances the precision of identifying cluster data points in the images. Additionally, the SIFT feature analyzed the keypoints. The performance evaluation, conducted on the pomegranate fruit disease dataset, demonstrates the superior capabilities of the Efficient Net related to existing methods. The improved accuracy of 95% is achieved as a greater accuracy in contrast to the existing techniques.

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