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Efficient Identification of Cucumber Leaf Pathogenic Spores Using K-Means Segmentation and Mobile Net Classification

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ABSTRACT: Cucumber leaf pathogenic spores identification is an significant stage in achieving quick disease analysis for cultivation. Image processing techniques primarily rely on manually created characteristics that are challenging to handle when it comes to pathogen spore detection. In this paper, a Mobile Net classification is suggested to quickly recognise harmful spores in cucumbers leaf. Firstly, grayscale conversion is applied to the cucumber leaf disease dataset to change the color image in to gray and the unwanted noises are removed using the median filter to get high quality image. Next, the processed image is given to the K-Means clustering for the separation of relevant regions. After that cucumber leaf image is featured by Gray-Level Co-occurrence Matrix (GLCM) textured is designed for further analysis. Finally, a Mobile Net framework is processed to enhance the classification of cucumber leaf pathogenic spores. Using python software proposed framework have accuracy of 94.12% is accomplished when compared to other techniques.

Keywords: Mobile Net, Gray-Level Co-occurrence Matrix (GLCM), Median Filtering, Grayscale conversion, K-Means Clustering, Cucumber leaf pathogenic spores.

1. Introduction

Nowadays, one of the most significant research areas worldwide is agriculture [1] One of the top ten vegetable in the world is cucumber, cucumbers are well-known for their great nutritional, food, and therapeutic qualities. However, the humidity and temperature in the greenhouse through cucumber farming remain ideal for the growth then distribution of fungi that cause illnesses like downy mildew and cucumber gray mold. The areas under agriculture have grown even more in recent years, and the prevalence of disease has increased. In extreme circumstances, this result in a yield loss of 20% to 50% or no harvesting in the area [2]. Here, biological stressors such as bacterial and fungal illnesses are predictable during the growing phase of cucumbers. The greenhouse environment's temperature and humidity levels are more favourable to the occurrence and spread of airborne fungal diseases [3]. However, the disease like Pseudoperonospora is the cause of cucumber downy mildew [4]. After the disease occurs, the disease mostly damages the cucumber plant's leaves, stems, and inflorescences. Most cucumber plant leaves die within a week or two due to the illness, which affect cucumbers since the sprout period to the growing period, particularly during the harvest stage. The field of cucumbers is yellow when the disease is affected [5-6]. Moreover for the identification purpose, molecular biology, microscopic image processing, and microscopic observation are examples of traditional spore identification techniques. The drawbacks of the conventional microscopic observation approach include a heavy workload, poor efficiency, and decreased accuracy over extended working hours [7]. By distinguishing the target spores from the background image, the semantic segmentation-based approach generates predictions at the pixel level. This technique identify disease spores in natural locations, however it will be less accurate if there is spore adherence present in the image. Additionally, this method's practicability needs to be enhanced because pixel-by-pixel classification of the spore images is a time-consuming. It is a hard operation when the pixel value changes its data [8]. Moreover, a number of techniques are employed, including the Sharif Saliency-Based (SHSB) method, which is based on color characteristics, Harmonic Mean (HM), Chi-Square distance, Mean Deviation (MD), and fusion of active contour segmentation to segment the cucumber leaf disease. Decreasing its ability to adjust the objects with distinguished shape alterations outside of the training data range [9]. In order to detect cucumber powdery mildew, a fine Gaussian support vector machines system is developed and corroborated to distinguish between well and diseased pixels with high accuracy. It is difficult to handle unbalanced data and inadequate performance when dealing with noisy data [10]. The spectral response of powdery mildew-affected leaves is characterized using hyper spectral image analysis, and the machine-learning technique called Random Forest model and XG boost distinguish between healthy and diseased leaves. Because of its ensemble character, the model is difficult to inferring [11]. Conversely, using machine learning techniques the cucumber pathogenic spores from greenhouse crops is performed with high accuracy. Low performance in high-dimensional areas and a high computational cost [12].Furthermore, using SVM and high gradient boosting algorithms, cucumber plants with varying degrees of anthracnose and brown spot disease are successfully classified under chlorophyll fluorescence imaging locations. SVM takes more periods to process the classification of cucumber leaf disease [13]. Moreover, a Convolutional Neural Network (CNN) with ResNET-50 to classify healthy and diseased cucumber leaves and enhances the early and precise detection of diseases in cucumbers. CNN with ResNET-50 have high processing difficulties, lacking a portion of labeled data [14–15]. To overcome these limitations the developed work introduces MOBILENET.

2. Related work

Ghen *et al* [16] (2024) have developed a Convolutional Neural Network (CNN) technique for the cucumber downy mildew in early detection. Using fluorescence imageries the cucumber downy mildew is predicted and increases the accuracy of classification. High processing difficulties and problems with interpretability.

Wang *et al* [17] (2024) have proposed a Convolutional Neural Network with Long Short Term Memory (CNN with LSTM) system is to predict cucumber downy mildew with high accuracy. CNN-LSTM model is reliable enough to accurately and efficiently identify and classify cucumber leaf disease. It takes more intervals to access the process when identifying the disease.

Liu *et al* [18] (2022) have invented a Long Short Term Memory (LSTM) Neural Network structure to predict the model with time-series environmental factors. A prediction for cucumber downy mildew is by debugging the parameters and combining the data from manual analysis and statistics with the downy mildew occurrence. Low accuracy in complex issues, particularly when functioning with high-dimensional search places.

Liu *et al* [19] (2022) have suggested a model called Convolutional Neural Network-Light (CNN Light) to predict the cucumber leaf disease. CNN Light uses less energy to calculate and have comparatively good classification accuracy for cucumber leaf disease. Due to its complexity CNN Light is over fitting.

Agarwal *et al* [20] (2021) have proposed a Conv2D model with Modified ReLU activation function for cucumber disease classification. The Conv2D model with Modified ReLU activation function model is reliable enough to accurately and efficiently identify and classify cucumber leaf disease. When identifying cucumber leaf diseases, several issues are increased, such is poor identification speed, high computation costs, and inadequate precision.

The contribution of this study is summarized as follows:

- Introduces grayscale conversion to change the color image to gray and median filtering is used to remove the unwanted noises enhance the image quality for cucumber leaf disease.
- Improved segmentation and feature selection using K-means clustering and Gray Scale Co-occurrence Matrix (GLCM) for classification
- Advances a Mobile Net model to enhance cucumber leaf disease accuracy and efficiency.

3. Proposed work

The proposed block diagram in figure 1 is for cucumber leaf disease classification. The Deep Learning technique is applied to cucumber leaf disease datasets. Initially using gray scale conversion the cucumber leaf disease is changed as color image into gray. After that unwanted noise is reduced using median filtering. Then the processed cucumber leaf disease image is given as input to K-Means clustering here it separates the relevant region to segment the cucumber leaf disease.

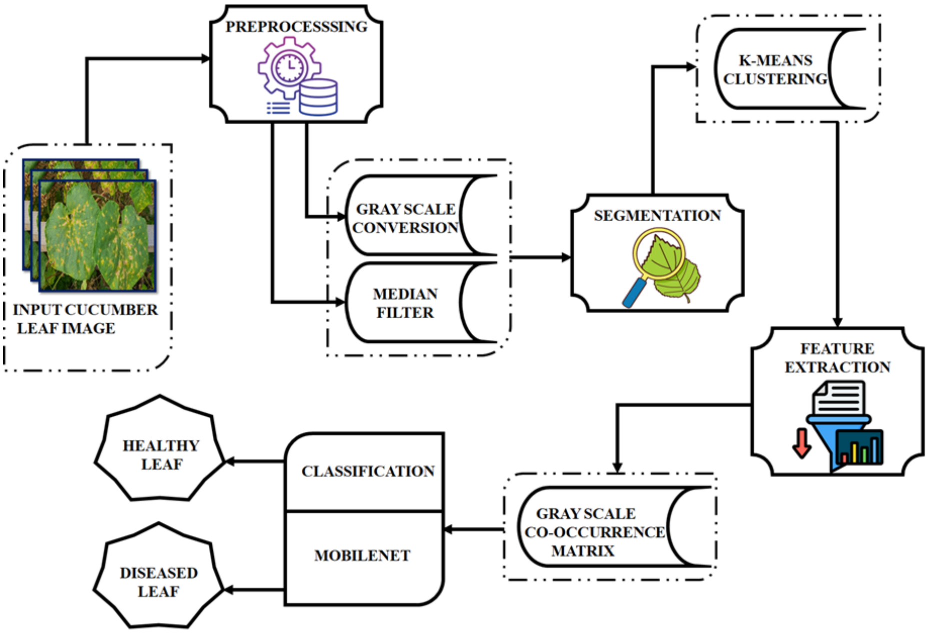

Figure 1: *Block diagram of proposed Mobile Net*

Feature extraction by GLCM features here the segmented cucumber leaf images are featured by its properties. At last, model training is classified using the extracted image for classification. A proposed Mobile Net is utilized to increase the accuracy and efficiency for cucumber leaf image. To improve model accuracy, of cucumber leaf disease the deep learning technique is used.

3. 1 Pre-processing for cucumber leaf image:

In the cucumber leaf disease identification pre-processing have two methods grayscale conversion and median filtering.

i) Grayscale conversion

In order to make it simpler to see the distribution and evolution of diseased areas on cucumber leaves, pre-processing aims to display a color image by mapping the grayscale image of the one-dimensional fluorescence value to the three-dimensional RGB value using a false color system.

ii) Median Filter

A median filter is a statistical nonlinear technique. Instead of using the noisy value of the digital image or sequence, the median value of the neighbourhood (mask) is utilized. The noisy value is replaced with the group median value once the mask's pixels are arranged according to their gray levels. Then to lower the noise, the average filter is applied and the image resolution is adjusted to 80 × 80 pixels.

$$q(x,y) = med\,\{r(x-i, y-j), i,j \in W\} \quad (1)$$

Where W denotes two-dimensional mask, and $q(x,y)$and $r(x,y)$are the original besides output images, respectively.
The median filter's ability is to reduce noise. The median filtering's noise variance for an image with zero mean noise under a normal distribution is unevenly then

$$\sigma_{med}^2 = \frac{1}{4n\,f^2\overline{(n)}} \approx \frac{\sigma_i^2}{n+\frac{\pi}{2}-1}\cdot\frac{\pi}{2} \quad (2)$$

Where σ_i^2 is the input noise power (the variance), $f\,\overline{(n)}$is the function of the noise density, as well as n denotes dimension of the median filter mask. Furthermore, the noise variance of the average filtering is $\sigma_o^2 = \frac{1}{n}\sigma_i^2$ (3)
The dimension of the mask and the noise scattering are the two factors that determine the median filtering effects when comparing equation (1) and (2). Following to this the pre-processed image is given to the segmentation.

3.2 Segmentation using K-Means clustering

K-Means Clustering is an unsupervised learning algorithm it is used to segment the clustering center. First, randomly initialize k points in the cucumber leaf called cluster centroids. The main objective of k-means clustering has three points one is grouping similar data points; other is minimizing within cluster distance and maximizing between cluster distances. Basically, to identify a cluster in a data point a distance measurement is created as $D(x,y) = \|x-y\|^2$. Figure 2 shows the basic K-means clustering.

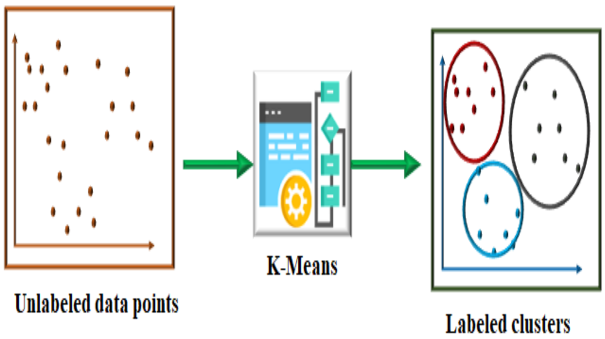

Figure 2: *Basic K-means clustering*

A data point's distance from these cluster centres is compared, and it is part of the closest cluster.

$$l_k(x_k) = argmin_i D(x_k - C_i)\; argmin_i \|x_k - C_i\|^2 \quad (4)$$

Where l_k is the data pointx_k label. The K-Means algorithm looks for a collection of these cluster centers in order to minimize the overall distortion. In this case, the cumulative sum of the data points' separations from the cluster centre defines the distortion as:

$$\emptyset(X,C) = \sum i \in C \sum j \;\; ith\ cluster\; \left\|x_j - C_i\right\|^2 \quad (5)$$

To minimize $\emptyset$, Labeling and Re-centering are the two processes that the K-Means method iterates. Figure3 shows the flow of K-means clustering.

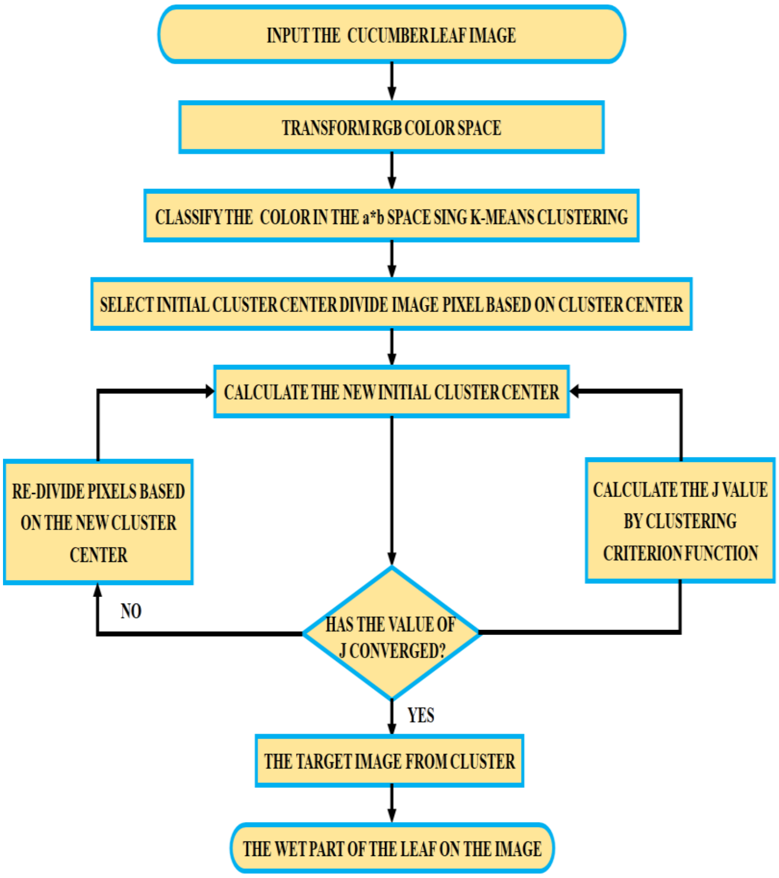

Figure 3: *Flow of K-means clustering*

Following by segmentation the cucumber leaf disease is given to the feature extraction.

3. 3 Feature extraction using GLCM

The Grey-Level Co-occurrence Matrix (GLCM) feature, a statistical technique that examines the relationship between pixels to analyze an image's texture. In order to extract the texture features, first the grayscale image that had additional image information, following their extraction from grayscale images, the texture indices were chosen as texture characteristics based on their strong correlations with cucumber pathogenic spores. Due of their large dimensions, the GLCMs are very sensitive to the size of the texture images in figure 4. As a result, the number of gray levels frequently declines.

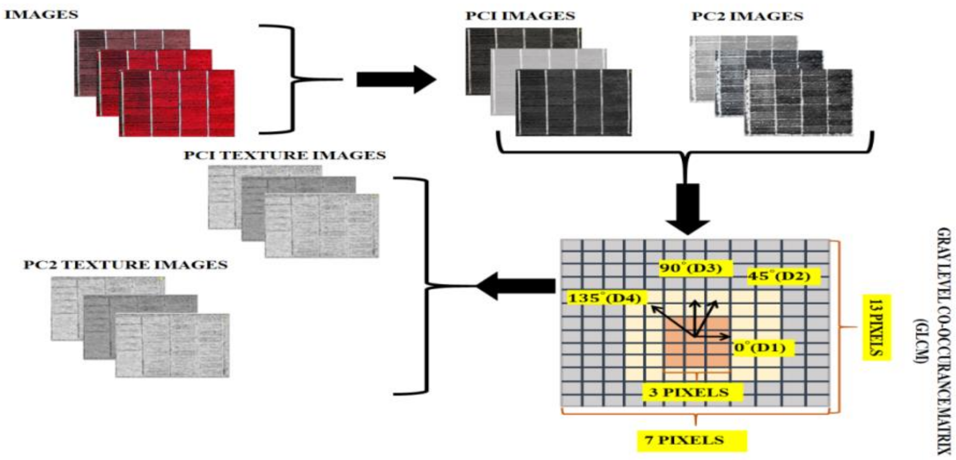

Figure 4: *GLCM feature*

Statistical features in the GLCM experimentally determined four essential features: the correlation, entropy, contrasts, and Angular Second Moment (ASM) features. Prior to computation, the GLCM needs to be normalized. An equation expressed as follows

$$P_{\varphi,d} = \frac{G_{GLCM}(i,j)}{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} G_{CLCM}(i,j)} \qquad (6)$$

$$Contrast = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(|i-j|)^2 P_{\varphi,d}(i,j) \qquad (7)$$

$$Asm = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} P_{\varphi,d}^2(i,j) \qquad (8)$$

$$Entropy \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} P_{\varphi,d}(i,j) log_2 P_{\varphi,d}(i,j) \qquad (9)$$

$$Correlation = \frac{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}[(i,j)P_{\varphi,d}(i,j)-\mu_x\mu_y]}{\sigma_x\sigma_y} \qquad (10)$$

Where in equation,

$$\mu_x = \sum_{i=0}^{N-1} i \sum_{j=0}^{N-1} P_{\varphi,d}(i,j) \qquad (11)$$

$$\mu_y = \sum_{i=0}^{N-1} j \sum_{j=0}^{N-1} P_{\varphi,d}(i,j) \qquad (12)$$

$$\sigma_x^2 = \sum_{i=0}^{N-1}(i-\mu_x)^2 \sum_{j=0}^{N-1} P_{\varphi,d}(i,j) \qquad (13)$$

$$\sigma_y^2 = \sum_{i=0}^{N-1}(i-\mu_y)^2 \sum_{j=0}^{N-1} P_{\varphi,d}(i,j) \qquad (14)$$

Where, $\mathrm{P(i,j)}$ are the features i,j of the standardised regular GLCM, Ndenotes the sum of gray levels, μ is the mean of GLCM and σ^2 denotes the variance of the intensities.

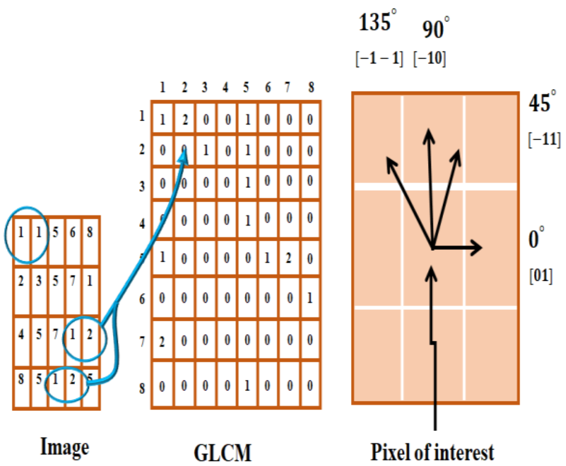

Figure 5: *Four directions of GLCM feature*

The 16 feature values were obtained by converting the pre-processed images hooked on 16 gray levels then calculating the four main GLCM features in the following four directions: 0°, 45°, 90°, and 135° in figure 5. At last, by feature extraction the extracted cucumber leaf image is given to the proposed Mobile Net.

4. Classification by Mobile Net

In this proposed work Deep Learning method called Mobile Net is utilized for effective classification of cucumber leaf disease.

4.1 Mobile Net Architecture

The basis of Mobile Net is depth wise separable convolutions, which are made up of two central layers: a depth wise and point wise convolution used to classify the cucumber leaf disease. The process of filtering data without producing new features is called depth wise convolution. As a result, point wise convolution is a technique for constructing extra features which is integrated. Eventually, the two-layer combination is dubbed depth wise separable convolution. This method functional a single filter to every input channel by depth wise convolutions, and formerly it created a linear combination of outputs from the depth wise layer using 1x1 convolution (point wise). Figure 6 shows the Mobile Net architecture.

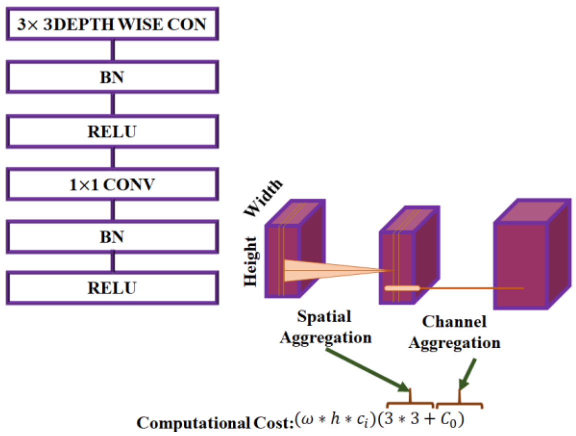

Figure 6: *Mobile Net architecture*

Following each convolution, the Rectified Linear Unit (ReLU) and Batch Normalization (BN) Approximately four million parameters make up this model, which is incredibly minimal in comparison to other models.

4.2 Implementation of Mobile Net

In this study, for cucumber leaf disease image a deep neural network architecture called Mobile

Net, which built the lightweight networks using depth-wise separable convolutions. Despite using fewer parameters than other efficiency models for the same depth, Google's Mobile Net architecture demonstrated remarkable performance and designed to balance accuracy and latency. Mobile Net that effectively categorize the pathogenic spores of cucumbers.

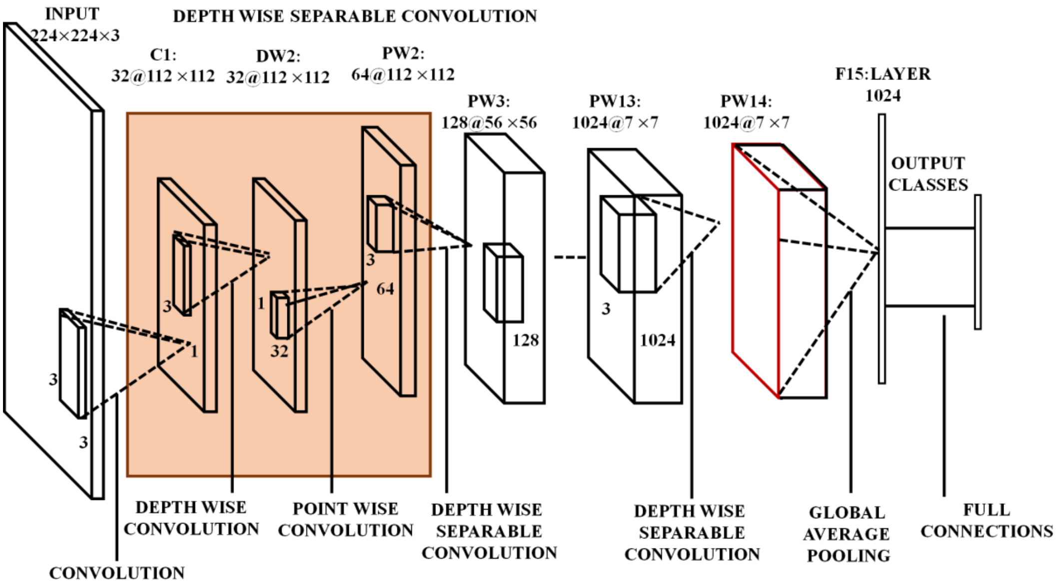

Figure 7: *Mobile Net network layer*

The Mobile Net network layer in figure 7 served as the model for design, which flinches with the first convolutional layer then evolutions over thirteen depth wise convolution layers, each which is prospered by point wise convolution layers. Following each depth wise and point wise convolution layer, the Rectified Linear Unit (ReLU) activation function and batch normalization (BN) are used.

5. Result and discussion

The aim of this work is improve the efficiency of various prospective DL algorithms and Mobile Net classifier is used. Using Python software the proposed work is illustrated. To assess the algorithms' performance, the cucumber leaf disease dataset is utilized. Here the number of images in train classes and image counts are downy mildew have 1284 images, healthy leaves have 1229 images and powdery mildew have 1190 images whereas for test classes downy mildew have 23 images, healthy leaves have 17 images and powdery mildew have 11 images.

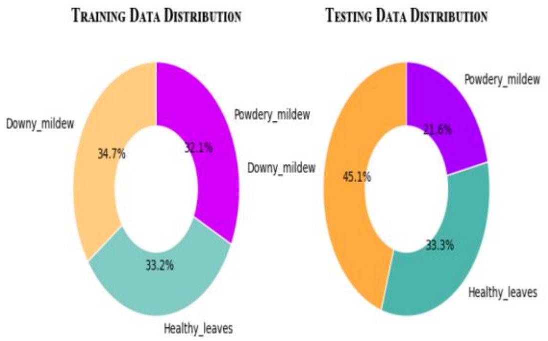

Figure 8: *Test and train data is distribution*

In figure 8 the test and train data is distribution is plotted. Here for the training distribution the downy mildew have the percentage of 34.7%, healthy leaves have the percentage of 33.2% and powdery mildew have the percentage of 32.1%. Whereas for testing data distribution the downy mildew have the percentage of 45.1%, healthy leaves have the percentage of 33.3% and powdery mildew have the percentage of 21.6%.

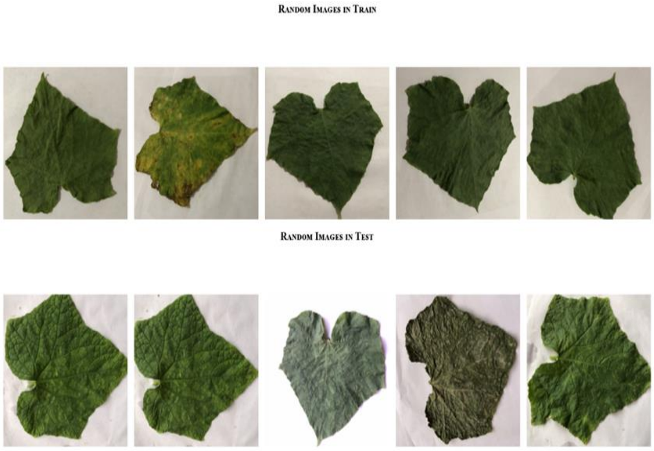

Figure 9: *Random images in test and train*

In figure 9 random images in test and train are shown. Here five cucumber leaf disease image is for both test and train random images. The random images in test and train are taken from the cucumber leaf disease dataset. Here the three different classes of downy mildew, healthy leaves and powdery mildew are present.

Figure 10: *Input cucumber leaf disease image*

Figure 10 shows the input cucumber leaf disease image. Here the input image is taken from the cucumber leaf disease dataset. Using the image processing techniques the input image is processed.

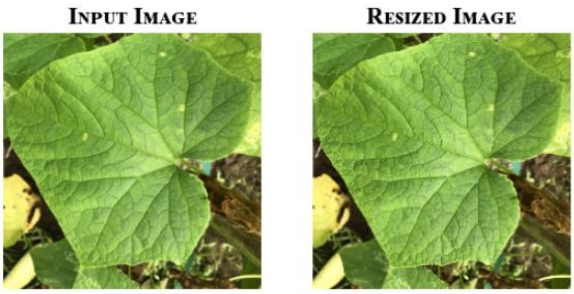

Figure 11: *Resized image*

Figure 11 shows the resized image cucumber leaf disease image. Here the input cucumber leaf disease image is resized for processing. Using image resizing technique the input image is captured as a perfect vision.

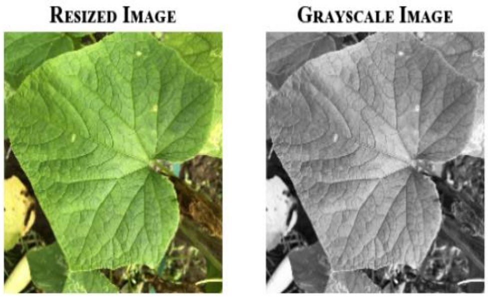

Figure 12: *Grayscale image*

Two steps of pre-processing for cucumber leaf disease images are depicted in the provided image in Figure 12. Converting resized image in to grayscale image using grayscale conversion technique.

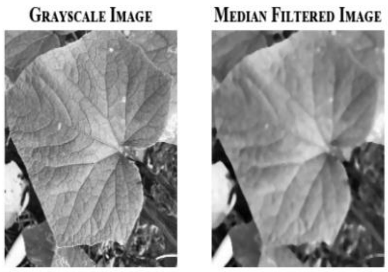

Figure 13: *Median filter image*

After conversion of gray scale image, median filter is utilized; the cucumber leaf disease appearance to eliminate the unwanted noise which shows the flawless of the cucumber leaf pathogenic spores image is shown in figure 13.

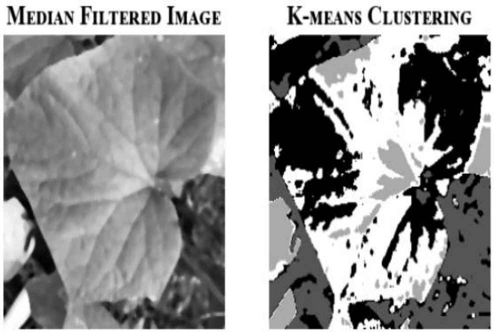

Figure 14: *K-Means clustering image*

Figure 14 illustrates K-Means clustering. The median filtered image is given as input to segmentation stage. Here the clustered distance is minimized within the cluster and maximized between the clusters. Clustered region are calculated from the centroid of the cucumber leaf disease image.

Table 1: *GLCM properties*

GLCM properties	Values
Contrast	0.411095
Dissimilarity	0.161895
Correlation	0.877089
Energy	0.505035
Homogeneity	0.943972

The GLCM features for the cucumber leaf disease image are calculated with their properties that are contrast, homogeneity, energy, dissimilarity and correlation is in table 2.

Figure 15: *Healthy leaves*

Figure 15 shows the predicted healthy leaves. The healthy leaves are identified successfully. The healthy cucumber leaves are analyzed and predicted using Mobile Net.

Performance metrics

By examining accuracy, precision, sensitivity, specificity, Area under the Curve (AUC), classification with "positive" and "negative" labels, the performance of each classification model in this study explained in table 3.

Table 3: *Performance metrics*

Performance metrics	Formula
Accuracy	$\frac{(TN+TP)}{TS}$
Precision	$\frac{(TP)}{TP+FP}$
Recall	$\frac{(TP)}{(TP+FN)}$
$F1-score$	$\frac{(2 * \text{Precision} * \text{Recall})}{(Precision + Recall)}$

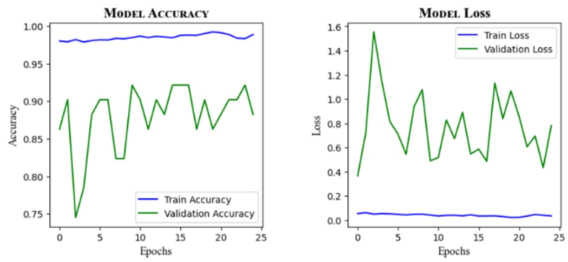

Figure 16 : *Model accuracy and model loss*

The Model Loss graph figure 16 shows a reliable decline in training and validation loss, representing improved learning and reduced error. The X-axis denotes the epochs and y-axis is accuracy for model accuracy simultaneously for model loss X-axis for epochs and Y-axis for loss. The Model Accuracy graph illustrates increasing accuracy of 94.12%, with the model achieving high performance and minimal over fitting.

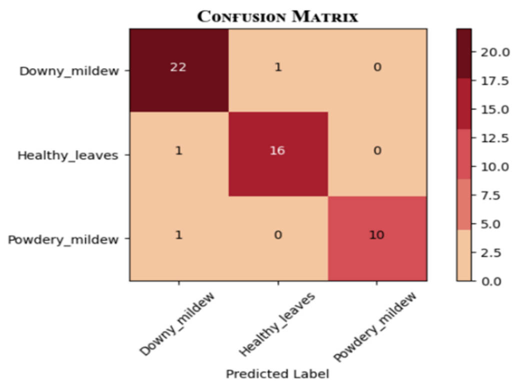

Figure 17: *Confusion matrix for Mobile Net*

Based on a collection of experimental data with known true values, the confusion matrix is a table that assesses well a classification model performs in figure 17. For this investigation, the following definitions are given: False Negative (FN), False Positive (FP), True Positive (TP), and True Negative (TN) are calculated for downy mildew, healthy leaves and powdery mildew.

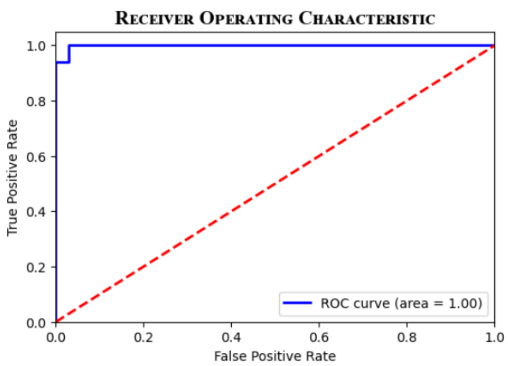

Figure 18: *ROC curve for cucumber leaf disease*

In figure 18 the ROC curve shows the true positive rate and false positive rate. The ROC curve for cucumber leaf disease is about 100%.

Comparison for the proposed method

The comparison of the proposed method with existing method is presented in table 4. The SVM and extreme gradient boosting algorithms have the classification accuracy of 90% [13], CNN with ResNet-50 have the accuracy of 93.45% [15] and Conv2D model with Modified ReLU activation have the accuracy of 93.75%. The proposed Mobile Net have the higher accuracy of 94.12% compared to the existing method in table 4. The proposed Mobile Net have better performance.

Table 4: *Comparison for the proposed method*

Study	Method	Accuracy
Sun *et al.* [13]	SVM and extreme gradient boosting algorithms	90%
Omer *et al.*[15]	CNN with ResNet-50	93.45%
Agarwal *et al.* [20]	Conv2D model with Modified ReLU activation	93.75%
Proposed approach	Mobile Net	94.12%

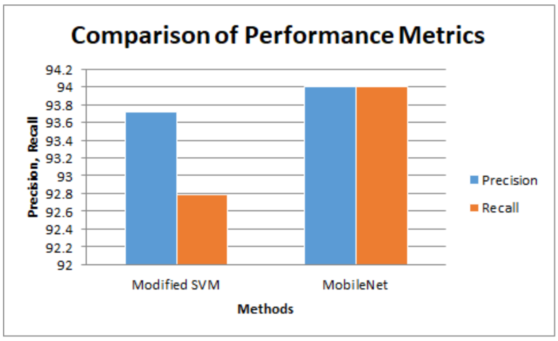

Figure 19: Performance metrics for Mobile Net

The Precision and recall value for classifiers modified SVM and the proposed is presented in Figure 19. The modified SVM have the value of 93.72% and 92.78% [9] and proposed Mobile Net method have the precision value of 94% and recall of 94% for healthy leaf.

6. Conclusion

In this study, Mobile Net is proposed for the classification of cucumber leaf disease. The integration of advanced preprocessing techniques, such as resizing, grayscale conversion, median 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 GLCM feature analyzed the properties. The performance evaluation, conducted on the cucumber leaf disease dataset, demonstrates the superior abilities of the Mobile Net related to existing methods. The improved accuracy of 94.12% is achieved as a higher accuracy when compared to the existing techniques.

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