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DEVELOPMENT OF NEW MACHINE LEARNING ALGORITHM FOR CUCUMBER AND GRAPE LEAF DISEASE DETECTION USING MULTI SVM WITH CUSTOM KERNELS

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ABSTRACT

In Agricultural production crop disease is a wide spread problem, it effects the productivity and quality of crops. Cucumbers are high water content vegetables and many minerals and vitamins, But Cucumbers are susceptible to several diseases. In wine production grapes are main ingredient, but these are severely attack by brown spot, mites, Anthracnose, downy mildew, black rot, and leaf blight. Identification and detection of crop diseases are at most care for reducing economic loss for the formers also improve productivity. But manual detection takes huge amount of time, sometimes it gives inaccurate results. To overcome these challenges by using advanced artificial intelligence techniques including Alex net, VGG-16,U-Net,ResNet,VGG-19,Fine KNN, Random forest Algorithms, YOLO v5.But these algorithms struggle with irrelevant features, noise and poor performance. To handle these we proposed novel approach using Multi SVM with Custom SVM kernels along with the GLCM features. The primary objective of the new algorithm is to enhance the model's performance and increase the efficiency of disease detection. Our datasets cucumber and grapes collected from Kaggle and directly from cucumber farms, it contains four different categories: Healthy, Powdery mildew, Downy mildew and Target Leaf Spot. First phase is to apply image augmentation technique for enhancing the image. Second affected area is calculated using K-Means Algorithm. Next from the images GLCM features are extracted. Subsequently classification is performed using Multi SVM algorithm with Custom SVM kernels. Our Novel Approach achieved best identification result with mAP is 90.62% compare with YOLO v5M mAP is 84.6.
Keywords- *Random Forest Algorithms, YOLO v5, GLCM, mAP, MultiSVM.*

1. INTRODUCTION

The population of industrialized world is increased by 56 million. Now 5300 million is our world population, is increasing 250000 every day.[1]Around the world for billions of people, agriculture is the primary source of food production, providing the necessary sustenance of their lives. As the global population increases, the demand for food also rises, making agriculture indispensable for ensuring food security. Adequate nutrition is essential for the health and well-being of individuals, especially for the physical and cognitive development of children. Sustainable agricultural practices are essential for preserving natural resources and maintaining environmental balance. Agriculture is significantly affected by plant leaf diseases, as these diseases can lead to reduced crop yields, economic losses for farmers, and challenges in maintaining food security. Efforts to develop disease-resistant crop varieties, environmentally friendly control methods, and early detection technologies are essential for addressing the challenges posed by plant leaf diseases.

Traditional methods for leaf disease detection often involve visual inspection and manual observation by farmers or agricultural experts regularly conduct visual inspections of crops by closely examining plant leaves for abnormalities. Symptoms such as discoloration, wilting, lesions, spots, or deformities may indicate the presence of diseases. [2] Agricultural extension officers or experts may conduct field surveys to assess the overall health of crops in a specific area. Common symptoms include rusts, powdery mildew, blights, and leaf spots, each with distinct visual indicators.[3]While traditional methods may have limitations in terms of accuracy and early detection. Integrating modern technologies, such as digital imaging, remote sensing, and molecular diagnostics, can enhance the efficiency and precision of disease detection in agriculture. Combining traditional knowledge with innovative technologies provides a comprehensive approach to managing plant diseases effectively.

Cucumbers are an important and versatile vegetable. Used in traditional dishes, salads, and snacks, contributing to the culinary diversity of different regions . They are composed of about 95% water and are a popular choice for salads, snacks, and beverages, providing hydration along with a crisp, refreshing taste. Other vegetables with similar properties include lettuce, celery, and zucchini. These are low in calories and high in water content, making them a hydrating and refreshing vegetable. They also provide essential nutrients, including vitamin K and vitamin C, minerals like potassium and magnesium and antioxidants. Good source of dietary fiber, particularly in the skin. Potassium to supports heart health by helping regulate blood pressure, also contain various antioxidants. These helps to reducing the risk of chronic diseases and inflammation. Vitamin K plays a role in bone health by contributing to proper blood clotting and bone mineralization. Grapes are often eaten fresh as a healthy and convenient snack. These are a primary ingredient in the production of wine. These are used to make a variety of grape-based products, including juice, jelly, and grape jam. But these are suffering with various diseases, which cause severe economic losses to the grape industry.

Traditional methods, often time-consuming and prone to inaccuracies, towards the adoption of advanced techniques .[4] Machine learning algorithms are emerging as transformative tools in this domain. As research in computer vision technology progresses, addressing these challenges becomes pivotal for ensuring the seamless integration of AI in cucumber production and agriculture at large.

In response to the challenges posed by traditional methods and acknowledging the potential of artificial intelligence, our research endeavors to introduce a robust and efficient machine learning algorithm. This algorithm is specifically designed for calculating affected area of cucumber leaves using segmentation which is a critical step in early disease detection. Our dataset collected from a cucumber field located in Regalapalli village of Proddatur along with data sourced from Kaggle.

The study makes significant contributions to the field of cucumber disease detection and classification. The main contributions are outlined as follows:

1.1 *Novel Machine Learning Algorithm for Disease Detection:*

The power of the Multi SVM with Custom SVM Kernels, to significantly improve the accuracy of disease detection in cucumber plants and grapes is to introduce in this research. Achieving an impressive Mean Average Precision rate of 90.62%, this algorithm represents a substantial improvement in agricultural of disease identification. The innovative application of machine learning techniques enhances the precision and reliability of cucumber plant disease diagnosis.

It emphasizes the importance of a comprehensive and realistic dataset, distinguishing itself by combining information from a specific cucumber field with data from Kaggle. The richness of the dataset enhances the accuracy and reliability of the algorithm's analysis, leading to improved diagnosis and more effective management strategies for plant diseases in agriculture.

2. LITERATURE REVIEW

Muhammad Attique Khan [5] used pretrained models-VGG-M and VGG-19 for feature extraction. Saman Muhammad Omer proposing new CNN algorithm with parameter tuning for improving model performance and YOLO v5 network .[6]

Jaweria Kainat, Syed Sajid Ullah and colleagues [7] used Fine KNN, Tan Triggers and Otsu's methods used for best accuracy result. Muhammad Attique Khan using Multi level Deep Entropy-ELM techniques fused features and classification of diseases various cucumber diseases. [8]

DICNN network was used for identification of diseased cucumber leaves from healthy ones .This paper shows the comparison between SVM, KNN and CNN of eight different leaf diseases . Isha Agrawal, Prada Hedge, Pooja Shetty, and Priyanka Shingane used CNN used to detect the cucurbitaceous family plant diseases.[9] Whale Optimization Algorithm is used to classify five diseases of cucumber.This paper focus on combination of SVM,Logistic Regression along

with GLCM,SIFT,LBP and Hybrid feature Law mask are used to classify bell pepper , tomato and potato has been observed by Navneet Kaur , Dr. V. Devendran [10].Authors proposed YOLO V5 network for classification of different cucumber .
Javidan used k-means algorithm to identify diseases on grape leaves [11].Prasad proposed DICNN to detect diseases of various grape diseases in different conditions .Authors used machine learning algorithms to evaluate performance while identifying diseases in grapes .[12]
Ghost convolution, mobile net V3 and CNN-SVM models are used to evaluate the disease detection in grape leaves. [13]

Table 1. Performance Of Different Algorithms For Cucumber, Grape Leaf Disease Detection.

First Author, Year	Name of Classification Algorithms	Classification of Diseases	Limitations
Muhammad Attique Khan·2020.	VGG-19 & VGG-M	Angular leaf, Powdery Mildew, Anthracnose ,Downy Mildew ,Corynespora,IHealthy	Huge time for training process, complex structure, add more features for improvement
Saman Muhammad Omer, 2023.	YOLOv5	spider, Leaf Miner ,Downy mildew ,Powdery mildew, CYSDV,Healthy	Enhancement of detection capabilities. Improvement of YOLO v5 network.
Jaweria Kainat, 2021.	Fine KNN	Angular leaf spot, Anthracnose, Blight, Corynespora, Downy mildew, Powdery mildew.	Improvement of feature selection and future fusion.
Muhammad Attique Khan, 2022.	Entropy-ELM	Cucumber Mosaic, Angular leaf, Powdery Mildew, Anthracnose ,Downy Mildew, Blight	Use of Butterfly meta heuristic algorithm f refinement features.
Jingyao Zhang, 2021.	AR-GAN + DICNN	anthracnose, downy mildew, and spot target	Identifying more diseas and this wo is extended more plants
B.V. Nikitha, 2023.	CNN	Bacterial Blight, Brown Spot, Downy Mildew, Powdery Mildew, Southern Blight, Soybean Mosaic Virus	Many additional machine learning algorithms are used for improvement of precision and accuracy.
Isha Agrawal, 2021	CNN	Cucurbitaceous family	increased dataset to improve accuracy, usability is increased by converting web app to android app.
Nazar Hussain, 2021.	VGG (Visual Geometry Group) and Inception V3	Angular leaf spot, Anthracnose, Blight, Downy mildew, Powdery mildew.	Because of Jeff augmentation process repetition of image dataset is need to eliminate.
Navneet Kaur, 2021.	LBP, GLCM, SIFT and Gabor	SVM, ANN, KNN, logistic regression, and Naïve Bayes	Need to improve the performance of the model.
Yiming Lou,2021	YOLO v5	Healthy, Target spot ,Powdery Mildew, Downy Mildew	classification of more cucumber diseases
Bin Liu, 2020.	DICNN	Anthracnose, Brown spot, Mites, Black rot, Downy mildew, Leaf blight, Healthy leaves.	Classification of more diseases, reduce processing time.
Moh. Arie Hasan, 2020.	CNN	Black Rot , Esca Leaf Blight , and Health	Recognition of more grape leaf diseases.
This Proposed Work	MultiSVM with Custom kernels	Healthy, ,Powdery Mildew, Downy Mildew, Target leaf spot	------

3. PROPOSED WORK

Machine learning significantly enhances the capabilities of image processing by providing sophisticated, efficient, and scalable solutions .[14] Its impact is evident across various industries, leading to more accurate analysis, real-time processing, and innovative applications that were previously unattainable with traditional image processing methods. As ML technologies continue to advance, their integration with image processing will likely yield even more ground breaking results.[15]

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Dataset 1:

The required dataset is gathered from Kaggle. Image augmentation is applied for enhancing the image by using Strechlim () function. Then affected area is calculated using k-means. From the enhanced images texture information is extracted. Last phase classification is performed with MultiSVM along with custom kernels-Anova, Sigmoid and RBF kernels which better performance compare with YOLO v5 network with mAP is 90.12%.“Fig.1”,shows methodology of Block Diagram.

3.1 Image Acquisition:

Gathered images of cucumber from Kaggle are Target Leaf Spot, Powdery Mildew, Downy Mildew and Healthy for better evaluation of model. “Fig.2”, shows Sample images are:

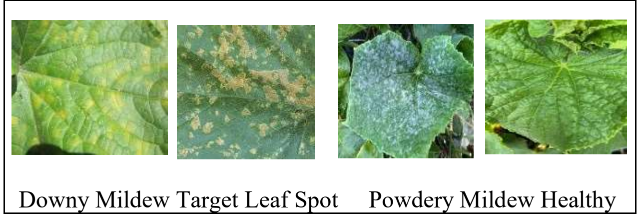

Figure 2: Various Cucumbers leaves

3.2 Contrast Enhancement:

Adjusting the Contrast of image pixels by stretchlim () for better evaluation of images. It is used to increase the intensity values of image. “Fig.3”, shows the Contrast Enhancement image.

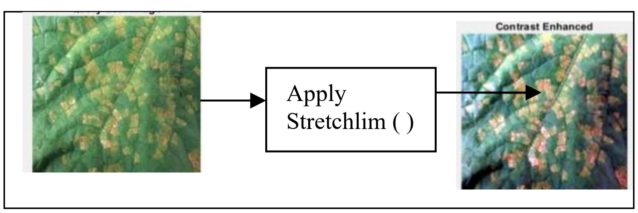

Figure 3: Contrast Enhancement image

ALGORITHM FOR CONTRAST ENHANCEMENT OF IMAGE
Input: Cucumber leave image
Output: Enhancement of contrast for image

1. Read the image from image dataset.
2. Apply Stretchlim () to image.
3. Convert RGB to gray scale image.
4. Repeat above procedure for all images.

3.2.1 Segmentation (K-Means)

Collected images are contain noise, is difficult to do segmentation. Clustering is used to divide dataset into different clusters by similar points assigned as a cluster using K-Means. It is an unsupervised machine algorithm and affected area of image is also calculated using clustering algorithm. “Fig.4”, shows the clustered images.

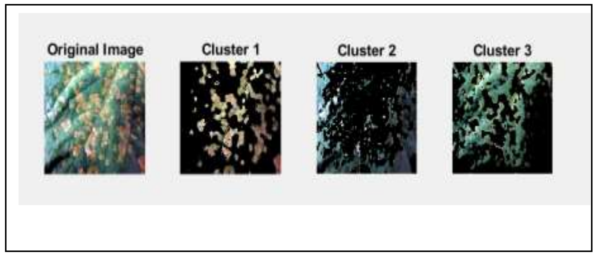

Figure 4: The clustered images.

3.2.2 GLCM Feature Extraction

Texture features are extracted from images using GLCM.It captures spatial distribution of pixel intensity values from images. [16] To identify the disease spot of image based on texture information. Total 13 features are extracted from segmented images.

- Contrast: To measure local intensity variation is to use texture features, such as the contrast or energy derived from Co-occurrence Matrix.
- Correlation: This shows the texture similarity between the image's horizontal and vertical directions.
- Energy: Texture homogeneity is represented by energy, which is the total of squared components in the GLCM.
- Homogeneity: This feature quantifies how near the GLCM diagonal the distribution of elements in the GLCM is.
- Entropy: Entropy analyzes the erratic nature an image is, and this can reveal complexity.
- RMS: For contrast values it measures the average magnitude.
- Variance: The spatial distribution of the image's grayscale value range has been defined by variance.

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- Standard Deviation: For set of values it calculates the amount of variation between the pixels.
- Mean: The mean represents the average pixel value, serving as an indicator of the central or typical gray-level value in the distribution.
- Smoothness: Measures the regularity or uniformity of the pixel intensity changes in an image.
- Kurtosis: It can be used to analyze the distribution of pixel intensities in an image.
- Skewness: The asymmetry of the probability distribution of a real-valued random variable is quantified.
- IDM: It quatifies the local homogeneity of the image.

In Image analysis these GLCM features are useful to shows difference between healthy and defected regions in plant leaves shown in "Table 1".

Table 2. GLCM Features Of 30 Images:

	1	2	3	4	5	6	7	8	9	10	11	12	13
1	0.5509	0.8701	0.8126	0.9699	14.9243	51.0841	1.5029	4.5726	2.3771e+...	1.0000	14.5309	3.5620	255
2	0.1481	0.9665	0.8090	0.9853	17.7531	52.9980	2.3830	6.5808	2.7131e+...	1.0000	14.2956	3.4809	255
3	0.3453	0.9264	0.6371	0.9639	21.3386	49.4201	2.1165	5.3631	1.6501e+...	1.0000	7.4506	2.3410	255
4	1.2669	0.8717	0.5141	0.9260	44.4921	77.8639	2.8959	8.0598	5.5050e+...	1.0000	3.1564	1.3544	255
5	0.4213	0.9613	0.3586	0.9034	58.9048	80.6157	4.5496	9.8408	4.8559e+...	1.0000	2.4195	0.9715	255
6	0.4602	0.9485	0.4986	0.9364	43.4950	74.6903	3.1021	8.0004	4.8863e+...	1.0000	3.3658	1.3890	255
7	0.3059	0.8759	0.7851	0.9778	10.9148	36.6080	1.3268	4.0169	1.1909e+...	1.0000	16.6448	3.6895	255
8	1.6733	0.8210	0.2832	0.8760	54.4575	73.1056	4.3587	10.5174	5.0179e+...	1.0000	2.4123	0.9588	255
9	0.2712	0.9452	0.5431	0.9659	22.9971	53.3562	2.5383	6.1773	2.1771e+...	1.0000	6.7822	2.2854	255
10	1.3008	0.7779	0.3173	0.8723	46.1151	59.9722	3.7582	10.1447	3.4564e+...	1.0000	2.2413	0.8132	255
11	0.8423	0.7985	0.2585	0.9078	34.8255	50.7441	4.7580	10.5133	2.0397e+...	1.0000	4.9589	1.5721	255
12	0.6084	0.8997	0.6463	0.9444	22.5596	55.8659	2.0834	5.8379	2.5084e+...	1.0000	8.1324	2.4975	255
13	1.2451	0.8086	0.2717	0.8649	44.3016	60.5642	4.4437	10.4370	3.3011e+...	1.0000	3.1101	1.1287	255
14	0.9439	0.8801	0.5932	0.9588	35.4005	70.1298	2.6717	7.2805	4.1853e+...	1.0000	4.3786	1.7105	255
15	0.4536	0.8974	0.5564	0.9372	26.8971	54.7254	2.9519	7.7846	2.2669e+...	1.0000	7.6304	2.2738	255
16	0.1718	0.9695	0.4067	0.9538	41.6692	63.0459	4.3160	9.8942	3.4876e+...	1.0000	4.2194	1.4780	255
17	0.4025	0.9448	0.5342	0.9607	31.4579	61.5122	2.9286	5.7261	1.7438e+...	1.0000	5.0010	1.8191	255
18	0.2731	0.8542	0.5883	0.9442	14.8026	33.5393	2.2134	6.5188	983.1916	1.0000	6.7767	2.2179	255
19	0.0963	0.6413	0.9709	0.9924	1.6615	16.1267	0.1847	1.2839	257.6394	1.0000	112.3940	10.3197	0
20	0.2442	0.8214	0.7799	0.9737	8.3630	27.8714	1.2632	4.1061	701.9165	1.0000	20.9982	3.9554	255
21	0.4730	0.8773	0.4437	0.9356	27.7462	46.6421	3.3066	8.7428	1.9240e+...	1.0000	4.0578	1.5009	255
22	0.6241	0.9000	0.7059	0.9524	21.3432	58.5066	1.9064	5.7065	2.9383e+...	1.0000	9.0299	2.7285	255
23	0.2660	0.9474	0.3911	0.9216	41.3289	61.2785	3.8320	8.5757	2.4335e+...	1.0000	3.7001	1.3114	255
24	0.3839	0.9564	0.3031	0.8925	52.9076	74.8689	4.7310	10.5094	1.8304e+...	1.0000	4.3571	1.5187	255
25	0.0533	0.9446	0.9531	0.9938	3.0036	23.6000	0.3116	0.9764	490.7499	1.0000	74.5848	8.4025	255
26	1.4589	0.7044	0.6009	0.9181	19.5621	53.2487	2.1402	6.5267	2.7606e+...	1.0000	12.3312	3.1632	255
27	0.3445	0.9224	0.6452	0.9619	20.3639	48.1179	2.0612	5.2630	1.5885e+...	1.0000	7.7907	2.4045	255
28	0.0322	0.9946	0.8352	0.9903	18.4360	61.9160	1.4450	5.2578	3.8436e+...	1.0000	12.2523	3.3165	255
29	0.1075	0.9316	0.8364	0.9885	7.7926	28.8352	1.0151	3.0632	707.4477	1.0000	18.2130	3.9488	255
30	0.6593	0.8332	0.3674	0.9279	33.6184	49.5887	3.9400	9.6349	2.0834e+...	1.0000	4.0206	1.3480	255

K-MEANS CLUSTERING ALGORITHM

Input: Gray Scale image.

Output: Segmented Image

1. K is chosen to decide number of clusters.

2. Select K number of centroids.

3. Assign each data point to nearest centroid.

4. Measure the variance for new centroid for each cluster.

5. Repeat above procedure.

6. Apply GLCM function to calculate features of input image.

3.2.3 Classification

To separate two or more than two classes by creating best decision boundary by SVM . So it is used to locate new data points in particular class.

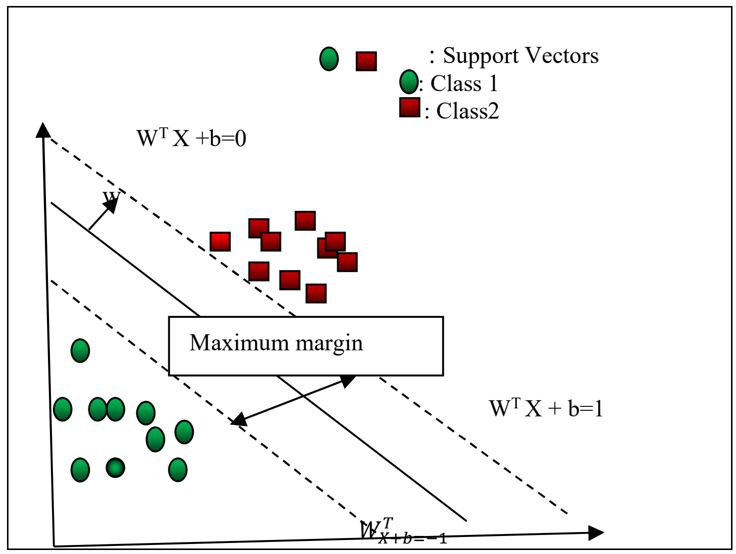

Figure 5: SVM Algorithm

Multi SVM: This is used to handle more than two classes. There are two types: one-one and one-all . [17]

One-One (OvO):

- Classifier Count: For N classes need to train N (N−1)/2 binary classifiers, each of which is capable of distinguishing between two classes.
- Training: To differentiate between two classes, each binary classifier undergoes training.
- Prediction: the class with the greatest number of votes becomes the final prediction.

One-All (OvA):

- N binary classifiers, specifies the number of classifiers .
- Training: To differentiate between one class and the remainder (all other classes grouped together), each binary classifier is trained.
- Prediction: Among all binary classifiers, the class with the highest decision function output is selected as the final prediction.
- Computational Cost: SVM is computationally more efficient than OvO since it is trained N times.

ALGORITHM FOR DISEASE CLASSIFICATION
Input: Segmented image
Output: Disease Type
Dataset(Train: Test=80:20)

1. Select query image from image dataset.
2.Apply Stertchlim function
3. Convert RGB to grayscale image.
4. Apply K-means for enhanced image.
5. Calculate GLCM features from segmented image.
6. Apply these to Multisvm algorithm.
7. Divide data into train and test.
8. Classify the disease type.
7. Evaluate performance model by calculating Map, Accuarcy, Recall and Precision.

Kernel Function K: SVMs are able to identify a hyper plane that successfully divides several classes using dot product between the data points.

K is defined as follows given a pair of data points, xi and xj: K(xi,xj)=ϕ(xi)·ϕ(xj)

Here:

- The input data points in the original feature space are xi and xj.
- The function of feature mapping, represented by ϕ, is responsible for converting the input data points into a space of higher dimensions.

In proposed work we combine RBF, Sigmoid and ANOVA kernel for making better prediction model.

1. RBF Kernel: Based on Euclidean distance it measures the similarity between x_i, xj.

$K(xi,xj) = e^{2}\sigma^{2}\|xi - xj\|2$
(1)

K is the RBF kernel function.

xi and xj are input data points in the original feature space.

∥xi−xj∥ denotes the Euclidean distance between the two data points.

σ (sigma) is a width of the Gaussian function.

2. Sigmoid Kernel: The sigmoid (logistic) function tanh(x), which transfers input values to a range between -1 and 1, served as the model for the sigmoid kernel. The SVM decision function is made non-linear by utilizing the hyperbolic tangent function.

$K(xi,xj) = tanh(\alpha xi.xj + c)$
(2)

Here

K is the sigmoid kernel function.

xiand xj are input data points in the original feature space.

α is a scaling parameter.

c is an additional parameter that can be used to shift the kernel function.

3. ANOVA kernel: For multidimensional regression problems this kernel performs well.

$K(xi,xj) = e^{-\alpha * \|xi-xj\|}2$
(3)

K is the sigmoid kernel function

Xi and xj are input data points in the original space.

α is a scaling parameter

ALGORITHM FOR MULTISVM
Inputs:
X, Y: Input data matrices (each row is a data point)
alpha_sigmoid: Sigmoid kernel parameter (alpha)
sigma: RBF kernel parameter
c_sigmoid: Sigmoid kernel parameter (c)
alpha: Weight parameter to balance RBF with other kernels
Output:
K: Combined kernel matrix

```
Function K = customRBFsigmoid1(X, Y, alpha_sigmoid, sigma, c_sigmoid, alpha)
  1.Compute the ANOVA Kernel
    anova_kernel = exp(-alpha * pdist2(X, Y, 'city block'))
  2. Compute the RBF Kernel
    rbf_kernel = exp(-pdist2(X, Y, 'squaredeuclidean') / (2 * sigma^2))
  3.Compute the Sigmoid Kernel
    sigmoid_kernel = tanh (alpha_sigmoid * (X * Y') + c_sigmoid)
  4. Combine the kernels using the weight parameter alpha
    K = alpha * rbf_kernel + (1 - alpha) * (anova_kernel + sigmoid_kernel)
  return K
end
```

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4. EXPERIMENT RESULTS

4.1. Dataset 1: Cucumber:

For segmentation of cucumber images experiments are performed.Reserch is continued based on images gathered from Kaggle. Segmentation and classification of cucumber images and grape images are simulated using mat lab software. [18] First phase images are resized then contrast of image is enhanced using stretchlim () for better classification results. Second affected area of image is calculated using segmentation. Third GCLM features are extracted. Using Multi SVM with custom kernels are used to classify diseases of cucumber and grapes . Here custom kernels are RBF, ANOVA and Sigmoid kernels for improving prediction results.

4.2. Confusion Matrix:

Overall summery of machine learning models are shows in confusion matrix. [19]

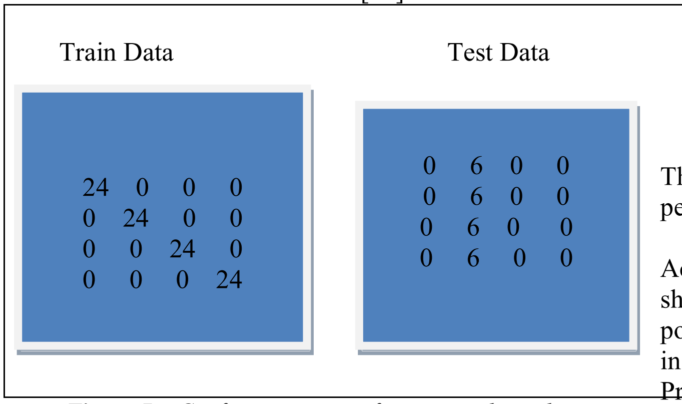

Figure 7: *Confusion matrices for train and test data*

4.3 Heat Map:

In graphical representation of co-occurrence values of GLCM matrix in two dimensional forms with color values along with the labels.

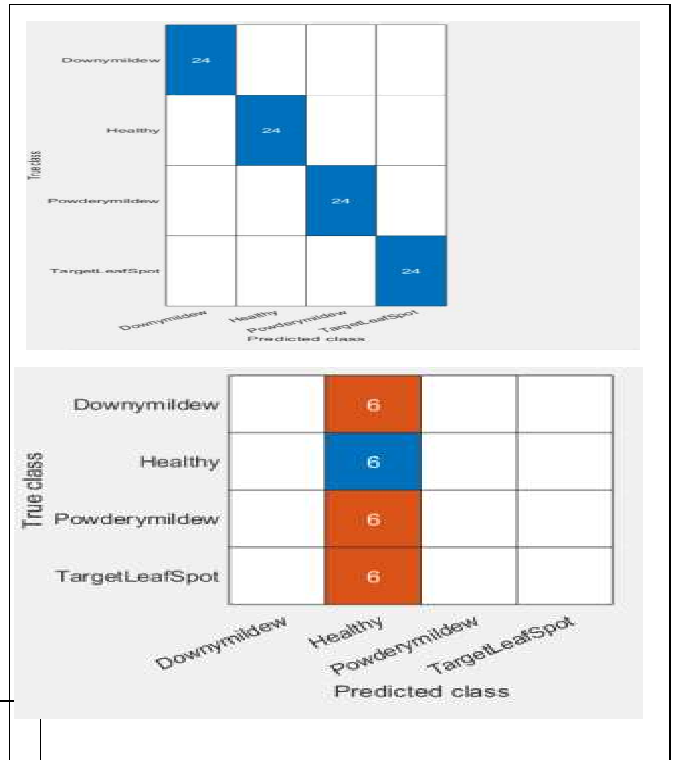

Fig. 8 Heat map of train and test data

The model's performance is evaluated using various performance metrics. [20]

Accuracy: It quantifies the model's accuracy. It shows the percentage of actual results—true positives and true negatives—among all the instances considered .

Precision: The precision of positive predictions can be determined. It shows the percentage of accepted identifications that were in fact accurate .

Recall: It measures the percentage of appropriately identified as real positives.

F1Score: which strikes a balance between the two measures such as recall and precision?

Mean Average Precision: It combines each class average precision then divides by the number of classes.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k \quad (4)$$

Here n= Total classes, AP_k=Average precision per each class k

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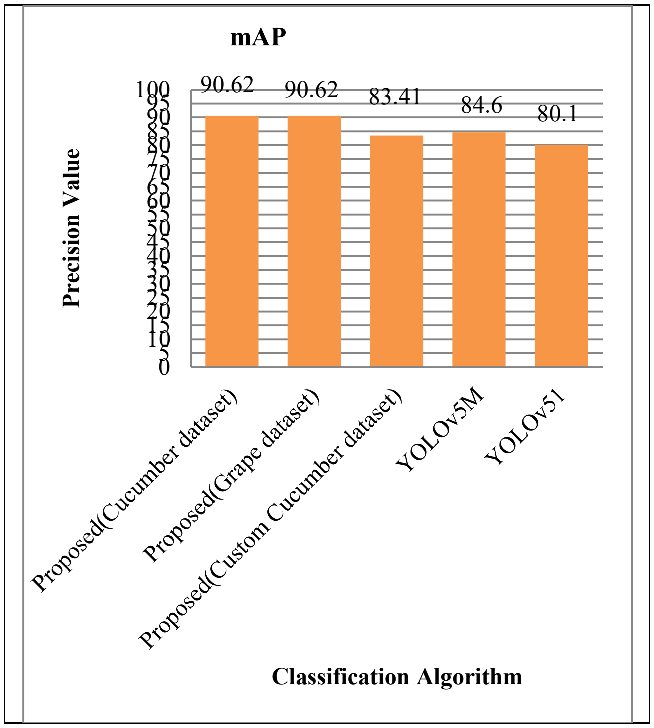


Figure 9: Model Comparison

In proposed model along with mAP, we calculate Accuracy,F1,Recall,FPR for cucumber dataset.

Table 3. Evaluation Metrics For Cucumber Dataset1.

Evaluation Metrics	80: 20	70: 30	60: 40
mAP	**90.63%**	**90.63%**	**90.76%**
Recall	62.50%	62.50%	64.59%
f1	69.12%	69.12%	71.48%
FPR	12.50%	12.50%	11.81%
Accuracy	62.50%	62.50%	64.58%

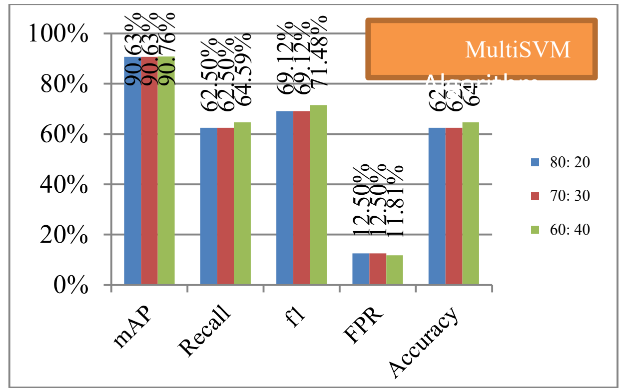
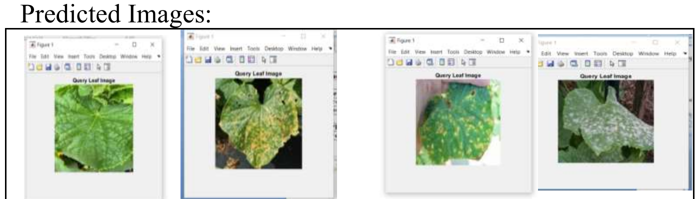


Figure 10. Performance Evaluation of dataset1 with 4 classes

Predicted Images:



Healthy Downy mildew Powdery mildew Target Leaf Spot

Figure 11: Predicted images

Dataset 2:

Table 4. Performance Evaluation Table For Cucumber Dataset2.

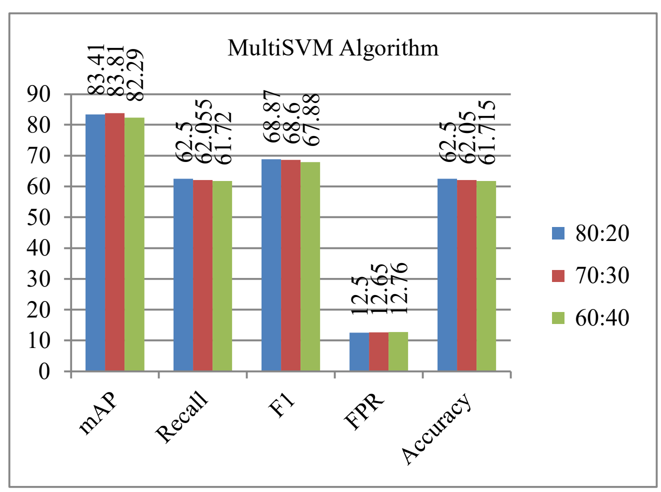
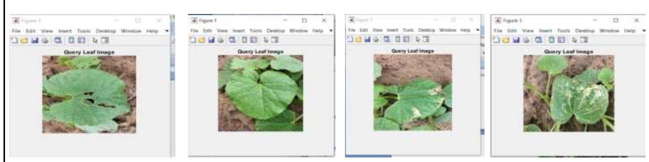


Figure 12: Dataset 2 Performance Evaluation of 4

classes

Predicted images:



Anthracnose Healthy Angular Leaf Spot Downy mildew

Figure 13: Predicted images of Custom Cucumber Dataset

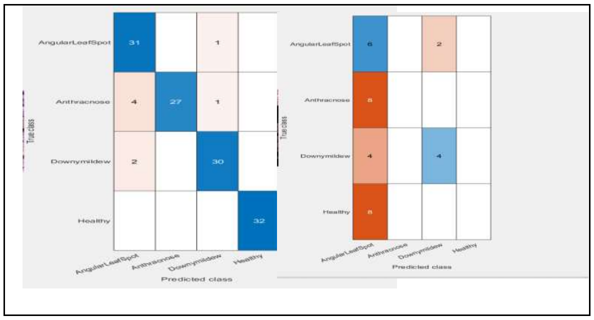


Figure 14: Heat Map Representation of Cucumber dataset

Grapes:

Grapes are often eaten fresh as a healthy and convenient snack. These are a primary ingredient in the production of wine

Table 5. Grape Dataset Evaluation Measurement Table.

Evaluation Metrics	80:20	70:30	60:40
mAP	90.625	90.625	90.625
Recall	62.5	62.5	62.5
F1	69.12	69.12	69.12
FPR	12.5	12.5	12.5
Accuracy	62.5	62.5	62.5

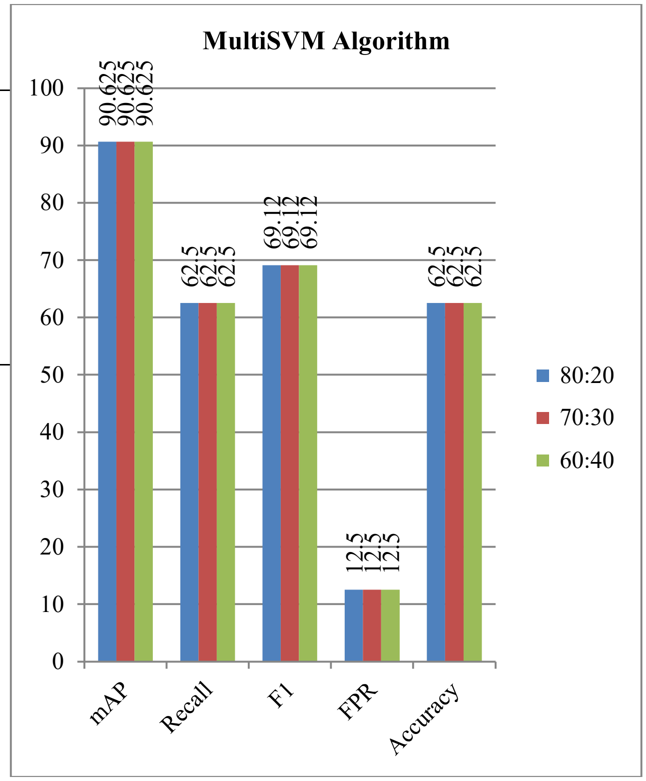
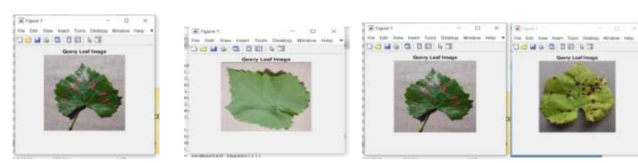


Figure 15: Grape Dataset Performance Evaluation of 4 classes

Predicted images:



Black Measules Healthy Black Rot Leaf Blight

Figure 16: Predicted Images of Grape Dataset

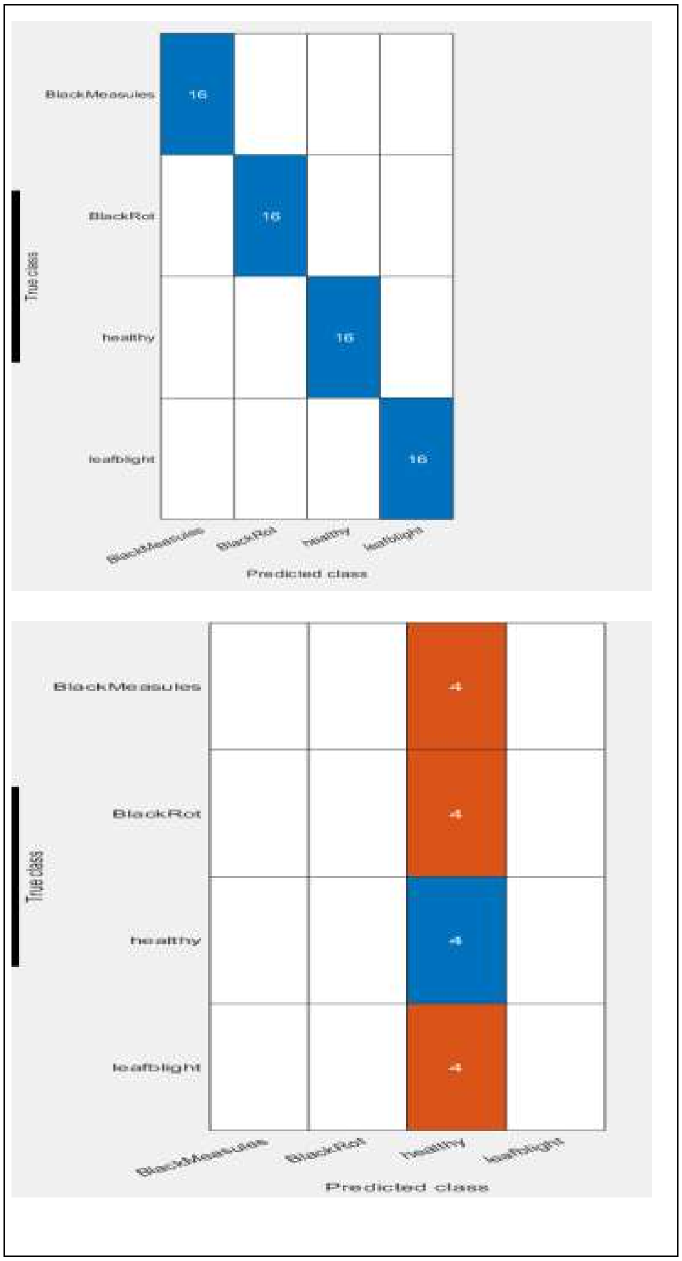


Figure 17: Heat map representation of grape dataset

5. CONCLUSION

The proposed methodology stands out as a highly effective and optimal approach for classification of cucumber and grape leaf diseases. In the first phase, images are resized, and contrast is enhanced using the stretchlim() function for better classification results. Second calculates the affected area of image by performing segmentation on the image. Third required features are gathered from texture information. Then classification is performed using MultiSVM with custom kernels. Here custom kernels are RBF, ANOVA and Sigmoid kernels for improving prediction results. This algorithm classifies four classes of Cucumber and Grape with highest mAP of existing YOLO v51 and YOLOv5M network of 90.62% of cucumber and Grape. In the future, there is a targeted effort to design an embedded machine dedicated to plant disease identification, emphasizing the incorporation of an extensive dataset encompassing a greater number of distinct classes.

Conflicts of interest

The authors proclaim that there is no conflict of interests concerning the publication of this paper.

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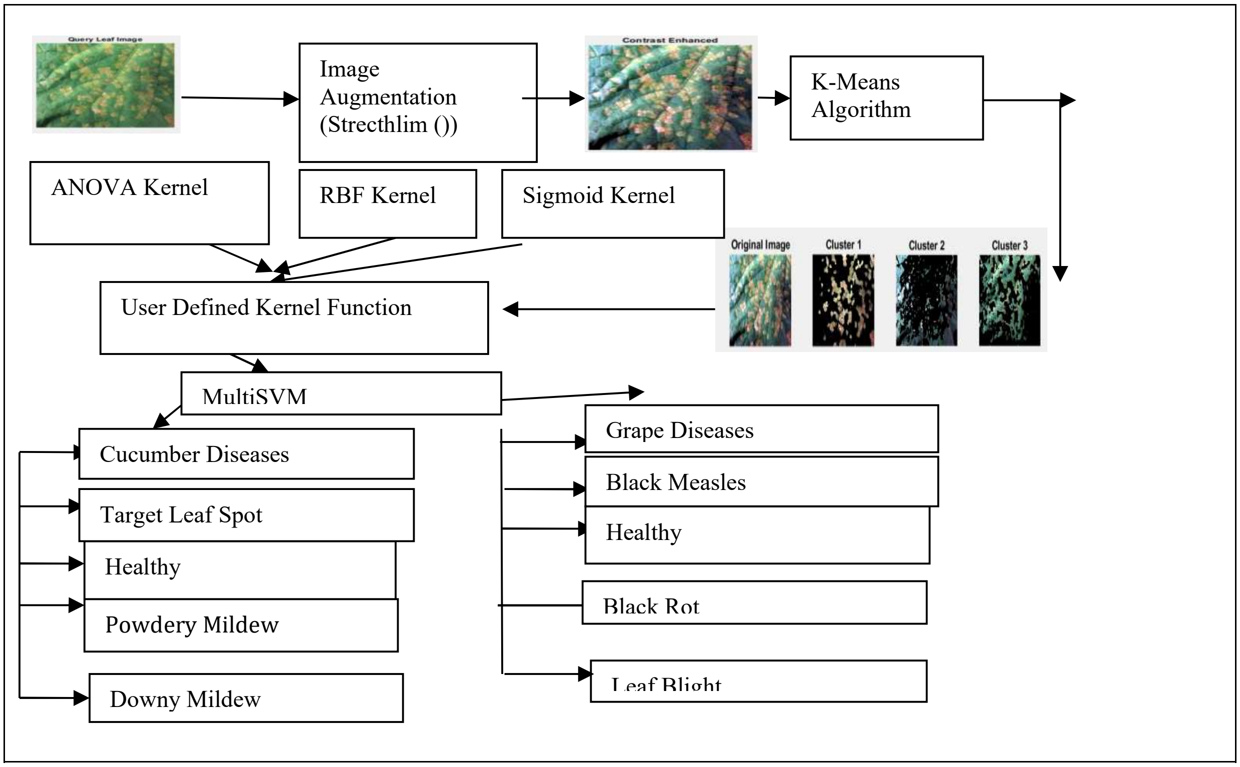

Figure 1: Methodology of Block diagram

Flowchart of proposed Algorithm:

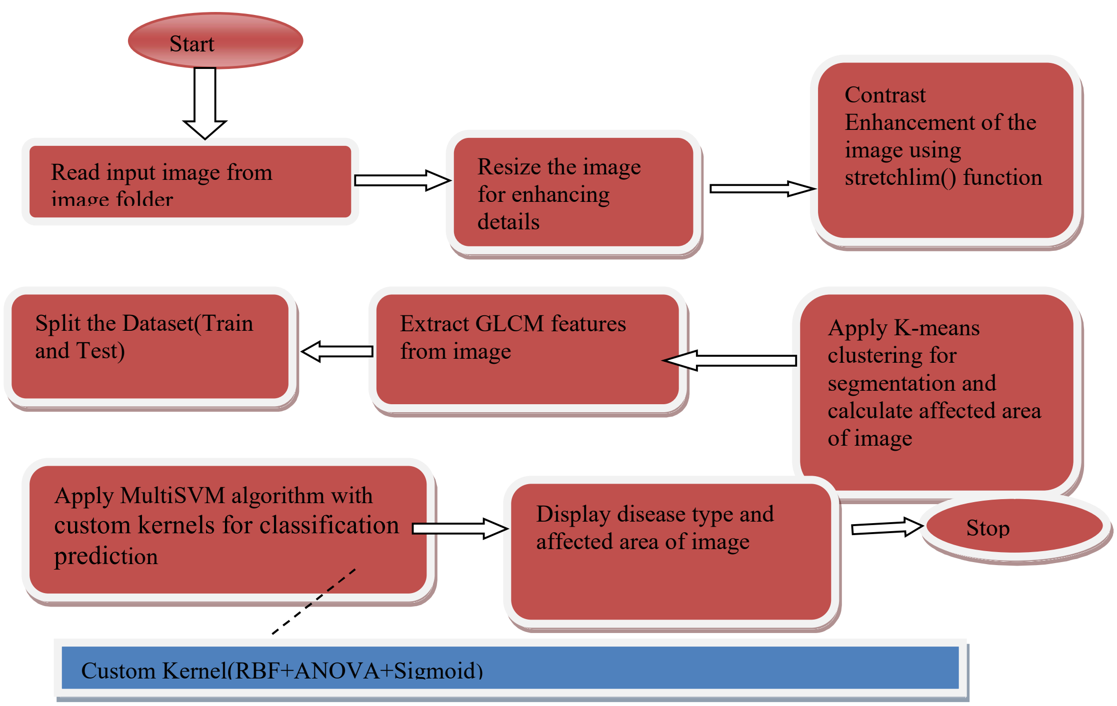

Figure 6: Flowchart of proposed Algorithm