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Image segmentation in Diagnosing the Ground Bud Necrosis Virus in Tomatoes using K-Means Clustering

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ABSTRACT- Early-stage fruit disease detection will ensure the natural product quality for the organic agriculture business. The potential of using K-Means segmentation for diagnosing tomatoes fruit disease was intended to be explored by this proposed method. The main goal of paper is to increase classification accuracy by locating tomatoes with Ground Bud Necrosis Virus in Tomatoes disease using an image segmentation approach. The K-means clustering algorithm is intended to boost segmentation effectiveness. In the end product, the images are divided into three classes: Grade 0—00-15%; Grade 1—16-35%; Grade 2—36-65%; Grade 3—66-85%; and Class 4—86-100%. Moreover, the tested results of the proposed approach explore a variety of unhealthy images and disease Tomatoes and demonstrate that, when compared to existing methods, the proposed method has the highest accuracy.

Keywords: Ground Bud Necrosis Virus, fruit disease, K-means clustering, Image Segmentation.

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1. INTRODUCTION

One of the most extensively farmed vegetables in the world and a crucial component of the human diet is the tomato. Toxic infections like the Ground Bud Necrosis Virus (GBNV) frequently harm tomato crops, which can result in large financial losses. Therefore, for disease management and control, timely and accurate GBNV detection is crucial [1]. The ability to recognize and categories sick areas in plant images make image segmentation a valuable tool for studying plant diseases. A well-liked unsupervised machine learning approach called K-means clustering separates a picture into groups or segments depending on how similar the pixel intensity values are [2].

However, there is a possible production failure due to various diseases because of the high area under tomato cultivation and low efficiency (20 tonnes per hectare). It impacts a vast range of viral disorders in addition to fungal and bacterial illnesses [3]. The tomato Alfamo, Luteo, Carla, Cucumo, Gemini, Poty, Illar, Nepo, Tombus, Tobamo, and Tospovirus families are linked to more than 40 viruses [4]. Tospovirus and tomato leaf curls are crucial in a number of viral illnesses. Every year, there are more cases of Tospovirus in vegetable crops, and they are particularly prevalent in tomatoes [5]. The only genus of the Bunyaviridae family that may infect plants is Tospovirus [6]. Tospovirus is closed, semicircular, and contains three linear ssRNA genes, which are denoted by the letters small (S), medium (M), and large (L). A number of vegetable illnesses, including those that affect tomatoes, potatoes, peppers, and watermelons, are brought on by the Groundnut bud necrosis tospovirus (GBNV), Peanut Yellow Spot Virus, and Watermelon Bud Necrosis Virus in India. The prevalence of tospovirus on tomatoes is currently on the rise, particularly in areas like Tamil Nadu, Karnataka, Maharashtra, and Andhra Pradesh [7].

The Indian financial system is heavily dependent on the agricultural manufacturer, for example. One of the major problems in farming is identifying plant diseases because they are so common in plants. If proper precautions are not taken in this region, the facility could suffer serious consequences that would affect the production, quality, or quantity of the specific product. An important plant power source has been affected, and fixing the issue is crucial to addressing the problem of global warming [8][9].

Manual disease detection of plants is quite difficult. It requires a significant amount of work, expertise in plant diseases, and lengthy processing times. Because of this, image processing (IP) is used to identify plant diseases (IPD) [10]. The benefits of IPD through an automatic method include a reduction in the labor-intensive task of crop supervision in large farms and the early detection of disease symptoms on plant leaves. This subchapter does a literature review to examine the various IP system techniques that make it easier to detect plant diseases via IP. Image segmentation techniques are used to scan and analyses the area of the plant that is impacted. There is numerous Image segmentation that can separate the aberrant area in a plant picture. Furthermore, it's thought that a lot of feature extraction techniques separate the specific characteristics of the segmented image [11]. A feature extraction technique is a technique that locates comparable patterns in the segmented image and transfers them to the IPD classifier section later on. Different users provide clarification for distinct classifiers during the machine learning algorithm's prediction of the plant disease. The most crucial tenet of the literature review outlined the benefits of applying different IP techniques at every stage of the IPD [12].

The fundamental computer-based technique employed in IP is image segmentation. The word Image segmentation refers to a technique for segmenting a digital image into various parts depending on a set of pixel values. The image segmentation takes part in the important responsibility depicted in the graphic, assisting the tester in classifying the various components. Highly developed ISTs employed for PDI have been demonstrated [13]. The aforementioned research provides an example of system strategies that analyses the provided image and separate the diseased area, which can help the classifier provide the desired outcome. In order to fulfill the higher accuracy level for segmentation, both Otsu's method and a color-based segmentation algorithm (i.e., the green plane) are evaluated. The method designer came to the conclusion that the designed module produces a satisfactory output based on experimental findings [14].

The segmenting of the plant's diseased area using various techniques was detailed in [15]. The EM algorithm is utilized for segmentation of the image segmentation, which is the boundary with spot detection, and Otsu thresholding [16]. The outcomes of the experiments and the comparisons with similar methodologies demonstrate the effectiveness and high practical usefulness of the suggested technology for plant disease detection [17]. Particle swarm optimization is used to segment sunflower leaf images, which is an important feature for disease classification. The tests performed on images of leaves have defined acceptable outcomes [18]. The survey on Segmentation Algorithm is given in *table 1*.

In this work, K-means clustering-based image segmentation technique (KCIST) for GBNV (Ground Bud Necrosis Virus) diagnosis in tomatoes is proposed. According to the severity of the sickness, the suggested approach was designed to grade photos of diseased tomatoes into several categories. The grades were separated into Grade 0 (00-15%), Grade 1, Grade 2, Grade 3, and Class 4 (86-100%), respectively. The suggested technique includes noise removal and feature enhancement on tomato picture pre-processing. The preprocessed pictures were then subjected to K-means clustering to divide them into several clusters according to their pixel intensity levels. The segmented pictures were then categorized using a decision tree-based classification technique into the respective grades.

2. METHODOLOGY

Clustering is a useful technique for processing fruit image. Clustering techniques are used to more precisely set clusters and classify things into various categories based on their shared qualities. In a variety of fields, such as machine learning, image analysis, pattern recognition, bioinformatics-data mining and data segmentation is the standard method for assessing statistical data. Using an Unsupervised Learning approach, the computer segments the data set into K-subsets. K-means clustering is an example of a common clustering method. Many clustering approaches are created for various objectives. Due to its simplicity, clarity, and speed in other areas, the K-Means Clustering (K-MC) is appealing in practical. Therefore, a K-MC is employed to ascertain the natural pixel grouping that exists in an image.

The K-MC approach is depicted in *figure 1*. The clustering inputs, sometimes referred to as the input data points, have a K-value. To divide the input dataset into a K cluster in K-MC, each cluster's optimization is represented by a shifting center. The Cluster Centre is another name for that facility. From this moment calculations start with some starting values called Seed-Points. The K-MC method is a UL clustering technique that divides the input data objects into various classes according to how far apart they naturally are from one another. There are other ways to measure distance, but Euclidean distance is the most common. The clustering method looks for natural clustering in the vector space that the data features generate.

Table 1: Survey on Segmentation Algorithms

Title	Advantage	Improvement
Crop leaf disease detection and classification using machine learning and deep learning algorithms by visual symptoms: a review[19]	Detecting the Diseases in planes presents a better precision level	Accuracy of 99%
Plant disease leaf image segmentation based on super-pixel clustering and EM algorithm. [20]	The K-means clustering is used for classification of the object based on a set of features into K number of classes. Thresholding creates binary images from grey-level images	helps to find the infected part of the leaf
Sunflower leaf diseases detection using Image Segmentation based on Particle swarm optimization. [21]	With very less computational efforts, the optimum results were obtained. It effectively shows the efficiency of proposed algorithm in recognition and classification sunflower leaf diseases.	The average accuracy of classification of proposed algorithm is 98.0 %.

Utilizing Convolutional Neural Networks for Image Recognition of Tea Leaf Diseases. [22]	The image of tea leaf illnesses is recognized using the CNN model. To hasten the convergence of the network, neurons are activated using the ReLU linear function.	In contrast to other machine learning, CNN has an accuracy rate of 93.75%.

The categorization of objects and backgrounds without compromising the image's quality is one of the key aims of image segmentation. Partitioning the GBNV disease-infected area is a nice illustration of separating the good tomatoes from the bad tomatoes. Information that is helpful concerning the location where the infected are found. When employing the K-Means technique for image analysis, picture segmentation can be quite helpful. The fruit is the default component since K-means does not always produce the same cluster index value. Therefore, determine the index of each cluster in the programme programmatically. However, we may achieve this by using the cluster's center value, which is the average value of all features taken into account across all clusters. After the aforementioned procedures have been completed, it is critical to locate the damaged area. The grade is based on the sick area. The five categories of affected regions by this work are listed below. These sections are shown in *table 2*.

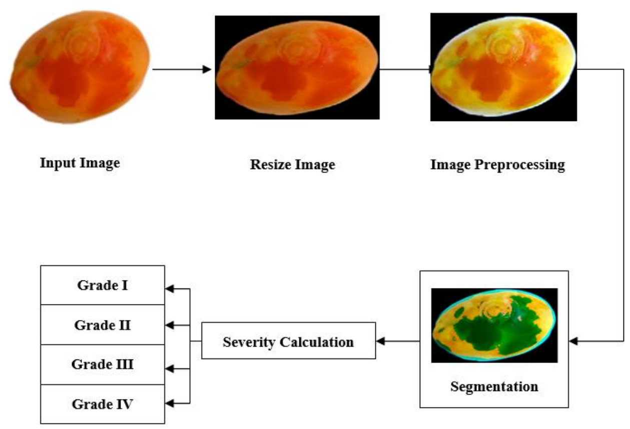


Figure 1: Machine Learning based GNBV Disease Diagnosis Method

Table 2: Grading as per infected area

Grades	Infected area in (%)
G-0	Up to 20
G-1	21-40
G-2	41-60
G-3	61-75
G-4	76-100

When processing food images, the clustering technique is a fantastic tool for correctly sorting objects into groups based on shared characteristics. The most common method for analyzing statistical data is data segmentation, where K-subsets are set in using unsupervised learning. The image is divided using the simple and quick K-means method by grouping the image's pixels. There are numerous clustering techniques that use aesthetically pleasing K-means. Utilizing every cluster's optimization's focus of change, the cluster center divides the input dataset into K-clusters. The nearby cluster is expanded by calculating the separation between the clustering input and the center. In this work, used a repetitive K-means algorithm implementation to divide the tomato image into two sections, representing both the diseased and the healthy parts. Below is the steps of the image segmentation algorithm.

Step 1: Converting an Image in the CIELAB color space from RGB.

Normalize the RGB values to the range [0, 1] using *eq. 1 to eq. 3.*

$$R_{Normalized} = {}^{R}/_{255} \tag{1}$$

$$G_{Normalized} = {}^{G}/_{255} \tag{2}$$

$$B_{Normalized} = {}^{B}/_{255} \tag{3}$$

Convert the normalized RGB values to linear RGB values by applying the inverse gamma correction. For most standard RGB spaces, the gamma correction value is approximately 2.2. So, using *equation 4 to equation 6.*

$$R_{Linear} = R_{Normalized} * 2.2 \tag{4}$$

$$G_{Linear} = G_{Normalized} * 2.2 \tag{5}$$

$$B_{Linear} = B_{Normalized} * 2.2 \tag{6}$$

Compute the XYZ values from the linear RGB values using the *equation 7 to equation 9.*

$$X = R_{Linear} * 0.4124564 + G_{Linear} * 0.3575761 + B_{Linear} * 0.1804375 \tag{7}$$

$$Y = R_{Linear} * 0.2126729 + G_{Linear} * 0.7151522 + B_{Linear} * 0.0721750 \tag{8}$$

$$Z = R_{Linear} * 0.0193339 + G_{Linear} * 0.1191920 + B_{Linear} * 0.9503041 \tag{9}$$

Normalize the XYZ values relative to the reference white point (Xr, Yr, Zr). For the standard illuminant D65, the reference white point values are given by *equation 10 to equation 12.*

$$X_{normalized} = {}^{X}/_{0.95047} \tag{10}$$

$$Y_{normalized} = {}^{Y}/_{1.00000} \tag{11}$$

$$Z_{normalized} = {}^{Z}/_{1.08883} \tag{12}$$

Apply non-linear transformations to obtain the LAB values as given in *eq. 13 to eq. 16.*

$$f = \lambda(t): t^{**}({}^{1}/_{3})\ if\ t > (6/29)^{**}3\ else \frac{(2969)^{**}2^{*}t}{3} + \frac{4}{29} \tag{13}$$

$$L = 116 * (f(Y_{normalized}) - 16) \tag{14}$$

$$a = 500 * (f(X_{normalized}) - f(Y_{normalized})) \tag{15}$$

$$b = 200 * (f(Y_{normalized}) - f(Z_{normalized})) \tag{16}$$

The resulting LAB values (L, a, b) represent the color in the CIELAB color space. This formula can be applied to each individual color or pixel in an image to convert the entire image from RGB to CIELAB.

Step 2: Euclidean used distance metrics to evaluate the differences in the two colors and K-means clustering to divide them into 'a * b *' spaces.

Step 3: Drawing conclusions from the K-mean clustering results. Applying the name, or labeling each tomato image pixel as an infected or good pixel, is the first step. Determine the number of pixels in each segment after naming.

Step 4: The pixels in the image must be divided using the name provided in order to produce various images dependent on the quantity of clusters. Use color to display visuals with two positive and contagious colors.

Finding the affected area is crucial after the aforementioned processes have been finished. The diseased area determines the grade. In just this study, the contaminated area is determined using the method below.

Step 0: Coordination of the run-length position of the initial image reference frame is step zero.

Step 1: By comparing these coordinates, you may identify the image's extreme points to the left, right, top, and bottom.

Step 2: Transform the image's X and Y axes by a degree of 50 degrees in the reference frame.

Step 3: The extreme characteristics of this new image co-ordinate scheme should be determined as well as stored.

Step 4: E = 10 °, 15 °, 20 ° and so on again process (2), and (3), and for 16 different angles.

Step 5: Regarding the area depicted by n polygon vertices (Xb Yk), and (Xo, Yo) = (Xn, Yn).

Step 6: To determine the severity of the GBNV disease, evaluate the affected region to the threshold levels previously established.

Depending on the particular methodology applied, the extended dataset produced by these procedures might change. An enlarged dataset could include modifications of the original photos or data points in data augmentation, for instance. The increased dataset for synthetic data production will include freshly created synthetic data points. The original dataset as well as the pre-trained characteristics that were taken from a bigger dataset will make up the enlarged dataset in transfer learning. Whatever the technique, the objective of expanding the dataset is to increase its size and diversity in order to enhance the model's performance.

3. RESULTS AND DISCUSSION

After sorting the tomatoes correctly, the next stage is to determine whether they are GBNV-infected, and the following step in establishing their grade is to determine what the affected region is. To determine the size of the contaminated area, the clustering method has been used. There are various clustering techniques. K-Means clustering is the approach that is most frequently utilized. Create a color conversion composition that defines the color space conversion given by type in order to calculate the infected area first. Then, "Replicates" refers to the number of times to repeat clustering using a fresh beginning cluster centroid point. There has been no change in the infected area determined by K-Means clustering even if the number of replicates has been increased from 1 to 20 using a measure of Euclidean distance.

They are located using a variety of techniques, including Square Euclidean distance, Cityblock, and Cosine. Each centroid of the Square Euclidean distance system represents the mean of the points that make up that cluster. In the Cityblock, the total of the absolute differences is determined. Each centroid represents the middle point in that cluster, component-wise.

In this procedure, the angle between the points is inserted in the cosine, minus the cosine. Each centroid represents the midway of the points within that cluster when those units of Euclid's unit length are adjusted. Results of the comparison of the various distance measurement techniques are provided in *table 3*.

The values of the centers that were extracted using various techniques are shown in *table 3*. Square Euclidean distance, Cityblock, and Cosine, in that order, provided forecasts for an infected area of 80.62%, 79.59%, and 75.32%, respectively. Also marked is the area of interest. Square Euclidean distance was discovered to be an effective strategy in this extracted percentage and in the self-extracted diseased area. The Squared Euclidean distance approach was used to evaluate various photographs, and it was discovered that they produce excellent results in this work. Different grades of tomatoes were used to test for the GNBV disease, and very good accuracy was obtained. *Table 4* displays the outcomes of the photos examined using this technique. 17.17%, 32.86%, 38.92, 48.41, 73.90, and 78.70% of infected images were examined. These Infected Images were broken down into G-0, G-I, G-II, G-III, and G-IV, accordingly.

K-means clustering lacks the conventional network structure because it is not a neural network. Instead, it employs an unsupervised machine learning technique to combine comparable data points into clusters.

In this work, we suggested a K-means clustering-based image segmentation technique for GBNV (Ground Bud Necrosis Virus) diagnosis in tomatoes. According to the severity of the sickness, the suggested approach was designed to grade photos of diseased tomatoes into several categories. The grades were separated into Grade 0 (00-15%), Grade 1, Grade 2, Grade 3, and Class 4 (86-100%), respectively. The suggested technique includes noise removal and feature enhancement on tomato picture preprocessing. The preprocessed pictures were then subjected to K-means clustering to divide them into several clusters according to their pixel intensity levels. The segmented pictures were then categorized using a decision tree-based classification technique into the respective grades.

Table 3: Analysis of different clustering methods

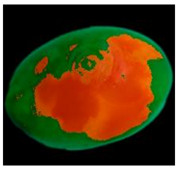
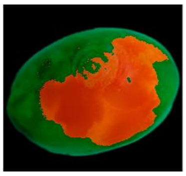
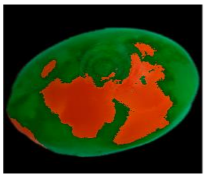
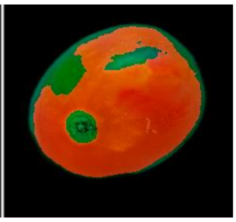
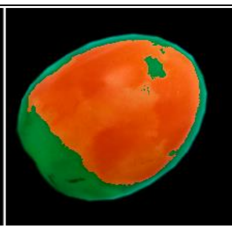
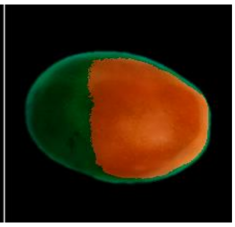
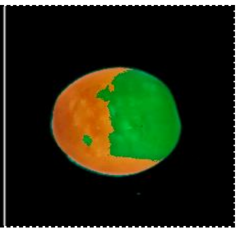
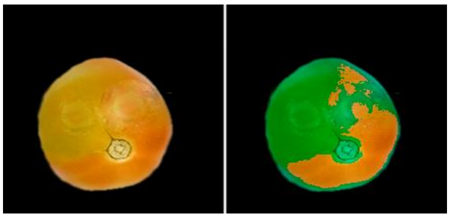
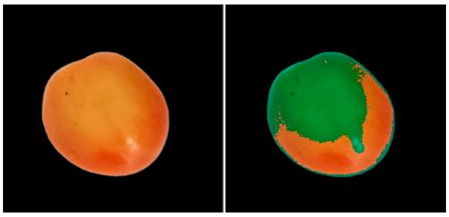
Distance Metric	Centers	Region of Interest	Affected Area (%)
Squared Euclidean distance:	162.80, 182.83		80.62
Cityblock:	184.00, 188.00		79.59
Cosine:	0.7064, 0.7078		75.32

Table 4: Results of infected area detection

Input Image	Distance Metric	Input Image	Region of Interest	Infected area (%)	Grade
125.png	Squared Euclidean distance			17.17	Grade-0
156.png	Squared Euclidean distance			32.86	Grade-I
68.png	Squared Euclidean distance			38.92	Grade-I
140.png	Squared Euclidean distance			48.41	Grade-II

171.png	Squared Euclidean distance		73.90	Grade-III
77.png	Squared Euclidean distance		78.70	Grade-IV

The Squared Euclidean distance method was used to examine a variety of photographs, and it was discovered that the results it produces are excellent for this purpose. In *table 4*, the outcomes of the photos examined using this technique are displayed. 17.17%, 32.86%, 38.92, 48.41, 73.90, and 76.70% of images had diseased areas, according to the analysis. G-0, G-I, G-II, G-III, and G-IV were separated into those Infected Images, correspondingly. This study analyses huge mixed sets of tomato photos and presents the results, which include group registration and image segmentation and clustering into subgroups. The framework is a compilation of various complex methods for particular elements. To show effectiveness and determine effectiveness, this approach analyses a wide range of data sets, including healthy and GBNV-infected tomatoes. The Squared Euclidean distance approach was used to examine a variety of images, and it was discovered that they produce excellent results in this job. Different grades of tomatoes were used to test for the GNBV disease, and the results were quite accurate. Images with contaminated areas 17.17%, 32.86%, 38.92, 48.41, 73.90, and 78.70% were examined. These Infected Images were categorized into G-0, G-I, Grade-II, G-III, and G-IV, accordingly. Comparison with existing methods is given in *table 5*.

Table 5: Comparison with Existing Methods

Title	Improvement
Super-pixel clustering and EM algorithm. [20]	helps to find the infected part of the leaf
Particle swarm optimization. [21]	The average accuracy of classification of proposed algorithm is 98.0 %.
Convolutional Neural Networks [22]	In contrast to other machine learning, CNN has an accuracy rate of 93.75%.
KCIST (Proposed)	Improve segmentation's effectiveness. KCIST has accuracy 99.00 %

4. CONCLUSION

The Indian economy has grown significantly as a result of the agriculture sector. Early detection of fruit diseases would ensure the natural product quality for the organic agricultural sector. The goal of the suggested approach was to look into the diagnostic value of K-Means segmentation for tomato fruit illness. The paper's main goal is to increase classification accuracy by locating tomatoes that are infected with the illness known as Ground Bud Necrosis Virus in Tomatoes. The K-means clustering method tries to boost segmentation's effectiveness. On the images of the finished product, three categories—G-0: 00-15%, G-1:16-35%, G-2:36-65%, G-3: 66-85 % and G-4: 86-100%—are applied. While K-Means Clustering is a popular and reliable method for segmenting images, investigating and creating more sophisticated segmentation algorithms can increase the precision and robustness of GBNV diagnosis. To increase the precision of GBNV identification, methods like Convolutional Neural Networks (CNNs), U-Net, or Mask R-CNN, which has demonstrated promising results in a variety of picture segmentation applications, can be researched and used.

Conflict of Interest Statement
We declare that there is no conflict of interest in the study.

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