OPEN ACCESS JOURNALS
Indiana Journal of Multidisciplinary Research
Abbreviated Tittle- Ind J Multi Res
ISSN *(Online)*- 2583-3820
Journal Homepage Link- https://indianapublications.com/Journals/IJMR
DOI: https://doi.org/10.5281/zenodo.21623319

INDIANA PUBLICATIONS
PRODUCTIVE AND QUALITY RESEARCH

Research Articles

Volume-06|Issue-04|2026

EKSTRAP Clustering and SVC for Fruit Health Screening

Rao Ashlesha Padmananda[1], Sudheeksha K[2], Terence Johnson[3], Deekshith P[4], Rathan[5]

[1,2,3]UG Student, Mangalore Institute of Technology & Engineering, Moodabidre, Mangalore, Karnataka, India.
[4]Kadubeesanahalli, Sarjapur, Bengaluru, Karnataka 560087, India.
[5]Langoor Digital Agency, Doresanipalya, Arekere Bannerghatta Main Road, Bengaluru 560076, India.

Article History
Received: 05.05.2026
Accepted: 22.06.2026
Published: 25.07.2026

Citation
Padmananda, R. A., Sudheeksha, K ., Johnson, T., Deekshith, P., Rathan (2026) EKSTRAP Clustering and SVC for Fruit Health Screening. *Indiana Journal of Multidisciplinary Research, 6*(4), 481-487.

Abstract: This work integrates the Enhanced K-STRAnge Points (EKSTRAP) Clustering Algorithm for precise image segmentation with Support Vector Classification (SVC) for classification for fruit health screening. The system is designed to achieve higher accuracy and efficiency, especially in identifying early-stage diseases. The approach entails collecting high-resolution images of fruits, pre-processing them to enhance quality, and segmenting areas of interest in order to detect any unhealthy regions in fruits. These areas of interest are used to extract features including color, texture, and form, which are then used to train an SVM classifier that is optimized using different kernel functions. The goal of the research is to develop an intuitive system that can analyze pictures of fruits in a variety of lighting scenarios and produce accurate results with little or no human assistance. This application reduces crop losses and provides farmers with valuable disease management information.

Keywords: Enhanced K-STR Ange Points Clustering, Fruit Disease Detection, Machine Learning, Support Vector Classification (SVC)

INTRODUCTION

Identifying fruits ripeness and lack of infections is paramount to delivering high quality produce to consumers. Fruits are graded and assessed during harvest utilizing image processing combined with machine learning methodologies as the screening of fruit for diseases is essential in order to improve the quality and marketability of fruits [1]. Many-a-times, orthodox methods like manually inspecting the fruit is imprecise leading to the incorrect categorization of contaminated fruits from the healthy ones. By distinguishing the infected fruits from healthy ones, the methodology used in this research can minimize post-harvest losses and assure a quality produce [2] [3]. Early fruit disease identification is vital to reducing financial losses brought about by infections that diminish the quality of fruits. Conventional inspection methodologies that need manual observation and scrutiny are tedious and prone to shortfalls. This paper deals with screening fruit diseases using features such as color, size, and shape to identify fruits that are not healthy with greater accuracy. The automated system discussed in the research facilitates the efficient selection of nutrient-rich fruits, thus improving quality control for both the farmer and the consumer [4]. Automating tasks involved in farming including identifying fruits, detecting infections and assessment of quality are eased by image processing. Detecting diseases in fruits is a chasm due to the variations in shape, size and color, specifically under light-filled environments or partly hidden by vegetation [5]. It is less cumbersome to detect fruits like oranges and apples due to methods like texture analysis, shape recognition and circular Hough transformations. Early disease diagnosis helps increase fruit productivity, and reduces the need for deep analysis, all of which helps farmers maintain fruit quality [6].

MOTIVATION

For agriculturists throughout the world, fruit disease poses a serious problem. It might lead to reduced food production, agricultural losses and challenges for farmers to earn their livelihood. The usual approach of examining fruits visually to check for diseases takes a long time, is prone to mistakes, specifically for large farms and the assessment of its health is subjective and varies from one person to another. Proliferation of fruit diseases and excessive use of pesticides may take place due to dearth of reliable and automated methods for promptly diagnosing them. This paper is driven by the potential of image processing and machine learning to screen these issues [7]. By using Enhanced K-STRAnge Points (EKSTRAP) Clustering for segmenting images and Support Vector Machine (SVM) for classifying fruit diseases, farmers can gain access to a precise, quick, and cost-effective method of detecting diseases. The objective is to minimize losses of crops, minimize the application of pesticides, and provide adequate produce, and also make the process low-cost and simple to implement on a large scale. Through the integration of advanced image processing with real-time analysis, the work in this paper aims to bring modernization to agriculture [8].

LITERATURE REVIEW

The Support Vector Machine (SVM) integrated with Enhanced K-STRAnge Points (EKSTRAP) Clustering Algorithm is an advanced method of the field of automatic fruit disease identification, taking advantage of modern image processing and machine learning technology [9]. Research work in this area identifies the criticality of sound segmentation algorithms for precise separation of disease areas in images. Classical clustering algorithms such as K- Means [10], tend to have difficulty with sophisticated image data containing fine color and texture variations. By contrast, Enhanced K-STRAnge Points (EKSTRAP) Clustering Algorithm, enhances sensitivity through the use of sophisticated distance measures and adaptive clustering mechanisms, providing accurate segmentation even in adverse conditions such as uneven lighting or noisy backgrounds. Once the diseased regions are effectively segmented, feature extraction processes generate key attributes such as color histograms, texture gradients, and shape descriptors. These features serve as inputs to SVM, a supervised learning algorithm widely recognized for its efficiency in classification tasks [11]. SVM employs optimized kernel functions to separate data points belonging to healthy and diseased classes with high accuracy. By combining EKSTRAP clustering for segmentation with SVM for classification, this methodology achieves superior performance metrics in terms of accuracy, recall, F1-score, confusion matrix, and precision. This model provides better quantitative performance measures than in the previous segmentation and classification procedures. It provides a solution that is efficient, scalable, and user-friendly to apply in real-world applications, including precision farming. With the application of EKSTRAP clustering and SVC, this method can work with various datasets and environments, and thus it is a powerful method to use for the early detection of fruit diseases. R. Ramya, P. Kumar K. Sivanandam, and M. Babykala [12] tried the experiments on the different machine learning techniques for diagnosis of diseases in fruit [13]. Their work involved using image processing approaches to diagnose diseases in fruit by virtue of visual data analysis. On the contrary, our enhanced project on disease screening employs the Enhanced K-STRAnge Points (EKSTRAP) Clustering Algorithm to achieve more sensitive and effective image segmentation. The method does capture minute color and texture changes so that it can even help to reveal very initial symptoms of diseases. Meanwhile, we also have Support Vector Machine (SVM) as the classifier that ensures the improvement of performance by delivering greater accuracy and enhanced generalization across various datasets, thus improving real-world scenario instances than those aforementioned approaches in their study. S. Malathy, R. R. Karthiga, K. Swetha, and G. Preethi highlight the importance of machine learning algorithms for fruit disease detection with a major thrust on image processing applications [14]. Their methodology combines the evolving classification models with traditional segmentation methods along with feature extraction in diseased fruits' trace and identification. This work can be viewed along with the above as the use of the Enhanced K-STRAnge Points(EKSTRAP) Clustering Algorithm for precise image segmentation, early detection and diagnostic segmentation of subtle diseases, and so on. The incorporation of Support Vector Machine (SVM) into our system ensures improvements in accuracy achieved compared to their work, generalization, and processing time, thus making it more practical in diverse real-world agricultural environments. M. A. Matboli and A. Atia base their investigation on deep learning techniques related to Convolutional Neural Networks (CNNs) for identifying diseases in fruits [15] [16]. They discuss how CNNs could identify and recognize different types of fruit diseases with great accuracy by analyzing images of fruits. Our work based on this study would include the application of the Enhanced K-STRAnge Points (EKSTRAP) Clustering Algorithm to reduce processing dependencies on large datasets, and subsequently SVM classifiers, thus making our system achieve high accuracy more scalably and accessibly, especially to small-scale farmers or low-resource environments. Awate, D. Deshmankar, G. Amrutkar, U. Bagul, and S. Sonavane worked on the application of machine learning techniques, particularly K-Nearest Neighbors (KNN) and decision trees, for the categorization of fruit diseases [17]. The idea in this research, employs the Enhanced K-Strange Points Clustering Algorithm to identify more subtle color and texture variations, thereby improving segmentation. The SVM, was utilized for classification improving the precision of infection diagnosis. Their amalgamation results in a fruit disease detection system that is more dependable and scalable. Even though there have been advancements in fruit disease detection, yet there a number of issues with the methods in practice. The considerable computation costs in training data CNN-based techniques coupled with the requirement of large datasets, makes them impractical for online agricultural applications. Segmentation techniques such as K-Means clustering with Decision Trees are process-intensive, brittle to noise, and perform poorly in practical clinical settings despite underlying disease structure being complex. Conventional image processing methodologies offer low adaptability and tend not to identify early-stage diseases. Hand-crafted techniques for feature extraction, used with Random Forest and KNN classifiers as an example, necessitate manual involvement that can lead to the possibility of missing important disease features at times. Remote sensing techniques are also expensive and not available for a large number of farmers.

PROPOSED SYSTEM & METHODOLOGY

The system uses clustering and classification along with

***Corresponding Author:** Rao Ashlesha Padmananda

image processing techniques and can overcome the issues related to classical fruit disease detection methods [18]. The methodology proposed in this work combines Support Vector Machine (SVM) for dependable classification with the Enhanced K-STRAnge Points Clustering Algorithm (EKSTRAP) for precise fruit region segmentation. Based on minute variations of symptoms that are frequently missed in human assessments, this method uses low-power, cost-effective technology to identify and reduce the frequency of specific diseases and promote early disease identification. In a variety of conditions, the automated process yields results that are reliable, accurate, and scalable. High-resolution fruit picture segmentation relies on the Enhanced K-STRAnge Points (EKSTRAP) Clustering Algorithm to identify areas of interest (ROIs) that may be indicative of disease. The algorithm is especially effective in detecting diseases in their early stages because it is extremely sensitive to even little changes in color and texture. Important characteristics including color, texture, and form descriptors are automatically extracted following segmentation. The features are then fed into the SVM classifier optimized with different kernel functions to classify the fruits correctly into healthy or diseased categories. The design remains simple and user-friendly such that farmers and agriculturists do not need special training or high-end equipment to use the system. The designed system is capable of operating under variable environmental conditions, including lighting, which enhances its ability to operate in real-life agricultural scenarios. To enhance robustness, the system was trained and tested on richly populated datasets of fruits such as apples, oranges, and bananas, representing a very wide range of both healthy and diseased conditions. Validation was carried out on hold-out test datasets, where performance was bench-marked against existing methods which exhibited improvements with respect to accuracy and efficiency. As the application's design can be scaled, it facilitates expansion to accommodate other fruit types and diseases in future upgrades.

The fruit images are pre-processed before the clustering process.

Step 1: Image Pre-processing
Pre-processing includes:

- Resizing the image to a fixed size.
- Switching to the CIELAB color space, where the differences in color are more consistent with how humans perceive them than in RGB.
- A Gaussian filter is applied to reduce the noise present in the image.
- Transfer learning is performed to apply contrast stretching through histogram equalization, adding emphasis to the portions affected by the disease.

Once pre-processing is complete, the Enhanced K-STRAnge Points Clustering (EKSTRAP) algorithm is applied to segment the image into clusters, identifying healthy and diseased regions.

Step 2: Choosing Initial Strange Points
1. Find Minimum Point (Xmin):
a) Locate the pixel in the image that has the lowest intensity value, **Xmin**, which corresponds to the least dominant color in the fruit image.

2. Find Maximum Point (Xmax):
a) Compute the Euclidean distance of every pixel from **Xmin**.
b) The pixel that is farthest from **Xmin** is selected as **Xmax**.

3. Find the Third Strange Point (D):
a) Identify the pixel farthest from both **Xmin** and **Xmax** as **D**.

Step 3: Adjusting X-Strange Points
a) With the aid of the three selected points, the algorithm computes the most suitable third clustering center, **Xstr**.

b) If **d(Xmin, D) = d(Xmax, D)**, then:
Xstr = D

c) If **d(Xmin, D) < d(Xmax, D)**, the coordinate **Xstr** will be adjusted by:
$$\mathbf{Xstr = Xstr_{(prev)} + Xm \times |Xmax - Xstr_{(prev)}| / (X - 1)}$$

d) If **d(Xmin, D) > d(Xmax, D)**, the coordinate **Xstr** will be adjusted by:
$$\mathbf{Xstr = Xmin + Xm \times |Xstr_{(prev)} - Xmin| / (X - 1)}$$

e) Repeat these steps until all **X-strange points** (cluster centers) are located.

Step 4: Assigning Clusters
From all the three X-strange points, find the distance of any other pixel using the Euclidean distance formula:
$$d(a,b) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

Group each pixel into the nearest X-strange point cluster.

The result is **X** clusters representing distinct zones of the fruit.

Step 5: Feature Extraction from Clusters
Relevant features are extracted from these segmented regions to train the classification model. The extracted features are:

- **Color Features:** RGB and LAB histograms to assess color variations that may be caused by diseases.
- **Texture Features:** Gray Level Co-occurrence Matrix (GLCM) for detecting roughness and surface irregularities.
- **Shape Features:** Aspect ratio and boundary irregularity to recognize deformations in the fruit.

***Corresponding Author:** Rao Ashlesha Padmananda

Step 6: SVM Model Training

I. Preparation of Data

a) Assign labels **"Healthy"** or **"Diseased"** to the feature vectors extracted from the training dataset.

b) Partition the dataset into training (70%) and testing (30%) sets for model evaluation.

II. Defining the SVM Classifier

a) Initialize an SVM model with different kernel functions.

b) **Linear Kernel:** Used when features are linearly separable.

c) **Polynomial Kernel:** Helps capture complex decision boundaries.

d) **Radial Basis Function (RBF) Kernel:** Performs well when disease classes are non-linearly separable.

III. Training the SVM Model

a) Train the SVM model using the labeled feature vectors.

b) The model finds the optimal hyperplane that separates healthy and diseased samples by maximizing the margin.

c) The margin is calculated as:

$$\mathbf{1 / \|w\| = Margin}$$

d) The optimization problem is to minimize $\|w\|^2$ subject to the constraint:

$$\mathbf{y_i(w \cdot x_i + b) \geq 1}$$

where $\mathbf{y_i}$ is the class label (+1 for healthy and −1 for diseased), $\mathbf{x_i}$ is the feature vector, $\mathbf{w}$ is the weight vector, and $\mathbf{b}$ is the bias.

IMPLEMENTATION AND RESULTS

On running our model on 200 odd fruit samples, it was observed that our model exhibited exemplary recall (0.928), proving that it is very proficient at classifying positive cases with a robust AUC that exhibits extremely good discriminatory strength as seen in the ROC curve in Fig. 1.

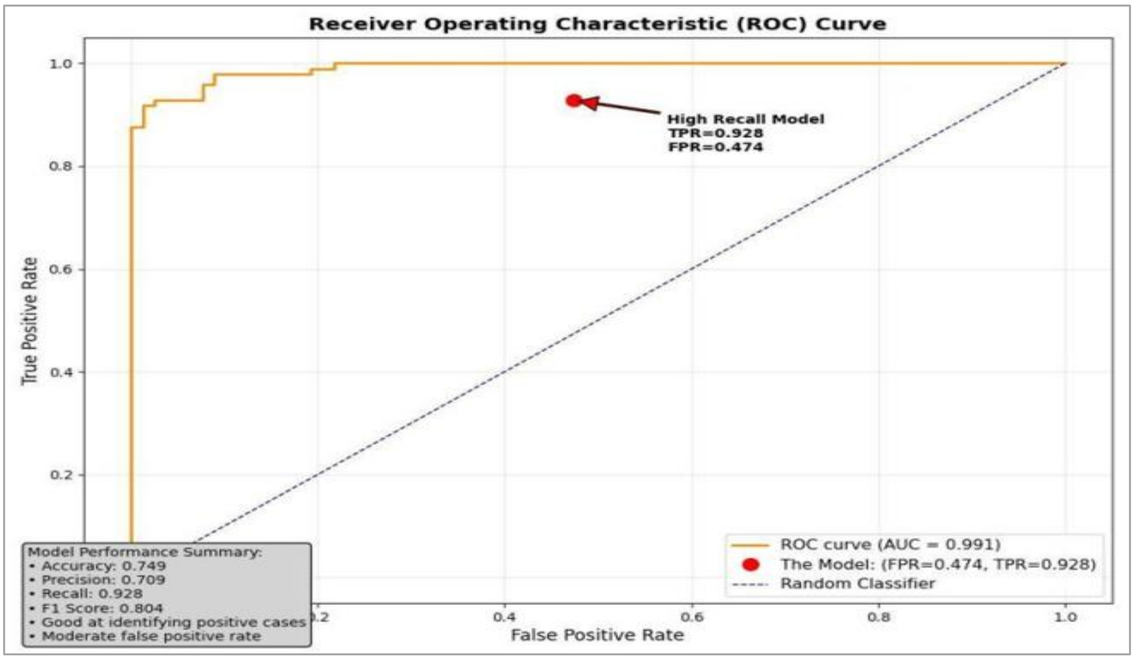

Fig 1: ROC curve

The Table 1. below shows the comparison of the average running times of four clustering strategies employed, which accentuates the fact that our model (EKSTRAP) outperforms the other clustering methods. It undoubtedly exhibits that EKSTRAP Clustering is the fastest taking the least amount of time for execution, whereas the K-Medoids Clustering requires the longest duration for completion of its execution as seen in Fig. 2. This fact is also corroborated in Table 2. and Fig. 3. which shows the percentage ratio in the normalized evaluation table and corresponding graph which depicts the normalized times relative to the fastest algorithm where we set the fastest clustering method to 100% efficiency.

Table 1: Comparison of the Average Execution Times of Four Clustering Methods

Clustering Method	Average Execution Time (s)
K-Means Clustering	0.0038
EKSTRAP Clustering	0.0007
K-Medoids Clustering	0.5116
Bisecting K-Means Clustering	0.0064

***Corresponding Author:** Rao Ashlesha Padmananda

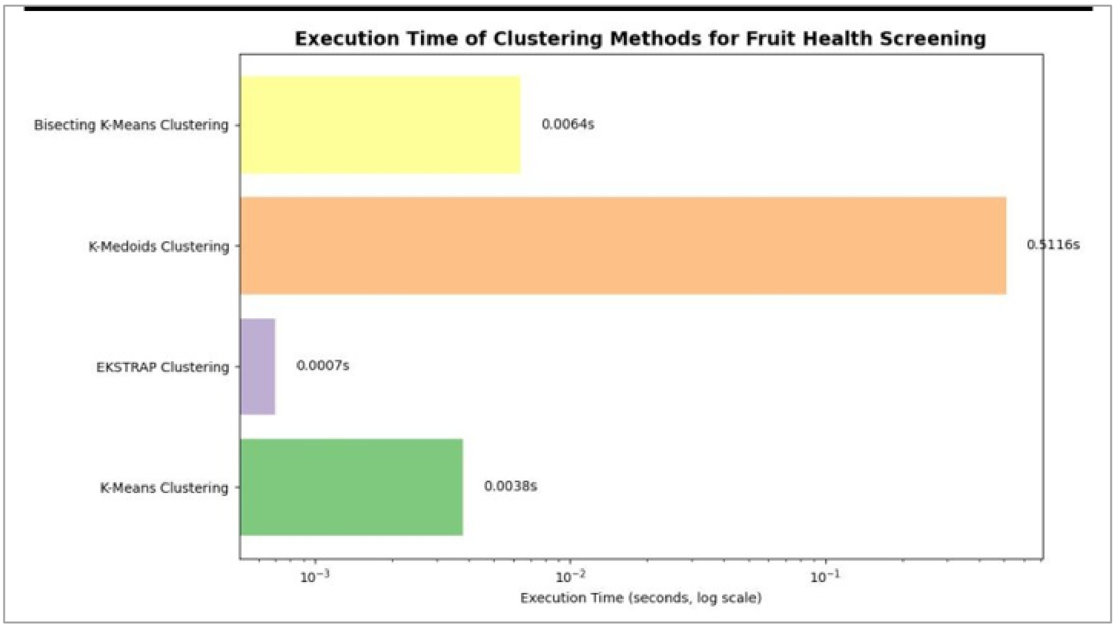

Fig 2: Execution time of clustering method for fruit health screening

Table 2: Normalized Evaluation Scale

Clustering Method	Time (s)	Normalized Efficiency (%)
EKSTRAP	0.0007	**100% (Fastest)**
K-Means	0.0038	18.4%
Bisecting K-Means	0.0064	10.9%
K-Medoids	0.5116	0.14%

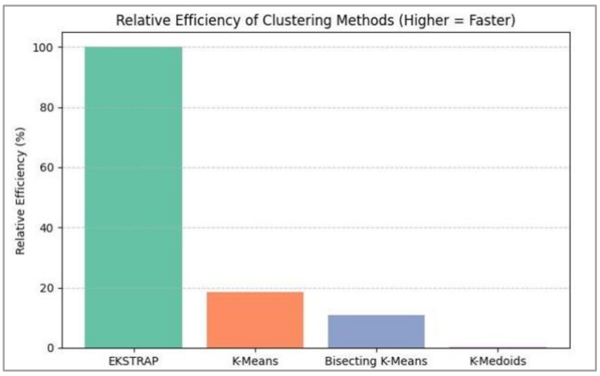

Fig. 3: Relative Efficiency of Clustering Methods

The performance of the trained SVM classifier on new fruit images is assessed using the following evaluation metrics:

- **Accuracy:** Measures the overall correctness of the classification.
- **Precision:** Evaluates the number of predicted diseased fruits that are actually diseased.
- **Recall:** Measures the ability of the model to detect all diseased fruits.
- **F1-Score:** Provides a balanced evaluation metric by considering both precision and recall.
- **ROC:** Measures the model's ability to distinguish between healthy and diseased fruits at different thresholds by plotting the True Positive Rate against the False Positive Rate.

Deployment and Real-Time Prediction

- The user uploads a fruit image through the web interface.
- The system preprocesses the image and performs EKSPC clustering.
- Features are extracted from the segmented regions and fed to the SVM classifier.
- The SVM model classifies the fruit as **Healthy** or **Diseased**.
- The output is displayed on the screen, showing the fruit's health status along with the visual segmentation output and comparative results of both methods, as shown in **Fig. 4**.

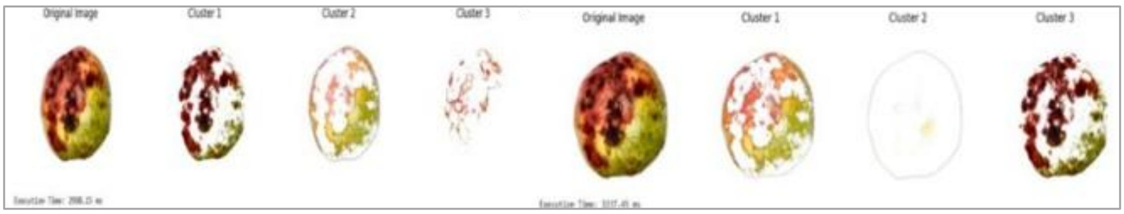

Fig. 4: Results with EKSTRAP Clustering (left image) and K-Means Clustering (right image)

***Corresponding Author:** Rao Ashlesha Padmananda

The user interface (UI) of the fruit disease detection application allows users to smoothly upload fruit images and inspect the classification results. The home page enables users to select and upload an image using color-coded buttons labeled **"Choose an Image"** and **"Upload and Classify."**

Fig. 5: Diseased Fruit (left image) and Healthy Fruit (right image)

Upon successful image processing, the classification result is displayed (e.g., **"Healthy"** or **"Diseased"**), as shown in **Fig. 5**. On the results page, the processing times for both the EKSTRAP and K-Means algorithms are presented to provide transparency regarding the system's internal operation. The user can compare the output images generated by the two algorithms alongside the original image. To illustrate how the system segments the fruit under analysis, different fruit regions are highlighted in both the EKSTRAP and K-Means processed images. Finally, an **"Upload Another Image"** button allows users to conveniently perform additional classifications.

CONCLUSION

One of the main issues facing modern agriculture is the early and precise detection of fruit illnesses, which is effectively addressed by this project. Traditional disease detection techniques, which rely on manual inspections and expert observation, are laborious, prone to human error, and subjective. To address these issues, the project uses image processing and machine learning to automatically detect illnesses, which improves speed, accuracy, and scalability. The combination of Support Vector Classification (SVC) for effective classification and the Enhanced K-STRAnge Points Clustering Algorithm (EKSTRAP) for accurate region segmentation proved to be highly successful. The system successfully processes pictures, detects subtle color and texture differences, and identifies diseases in their early stages. When compared to traditional approaches, validation findings show excellent accuracy, shorter processing times, and improved usability, making the system a useful tool for farmers and farming professionals. In addition to generating immediate financial gains, the project contributes to agricultural expansion by reducing crop damage losses, promoting sustainable agriculture, and improving pesticide misuse. With more data and training, the system's solid foundation which focuses on common fruits like apples, oranges, guavas, and mangoes can be extended to other fruits and illnesses. Notwithstanding its advancements, the initiative acknowledges many shortcomings, such as its failure to account for internal defects and post-harvest illnesses. Future research will concentrate on combining state-of-the-art deep learning architectures, covering a wider range of fruit diseases, and investigating mobile and Internet of Things-based real-time disease monitoring systems in order to expand its capabilities. All things considered, this research is a significant step toward the automation of agricultural disease control using Image Processing and Machine Learning to increase food security, economic stability, and environmental sustainability.

FUTURE SCOPE

This system can also be implemented by changing the clustering methods to include different categories of clustering like soft computing-based clustering, hierarchical based clustering, genetic algorithms-based clustering and more. The fuzzy C Strange Points Clustering [19] and the redesigned fuzzy C Strange Points Clustering algorithms [20] can be good candidates for replacing the clustering method used in this paper. Both these methods use the membership function as distance metric for computing the closeness of points to each other. These methods also provide a marginally higher purity of clustering. The divisive hierarchical bisecting min max clustering algorithm is another candidate for replacing the clustering method used in this work. In that the cluster space is bisected in each iteration using the min max concept which groups points into two clusters based on the values which are farthest from each other [21]. Another candidate for replacing the clustering method used in this paper is the genetic algorithms-based Enhanced K-Strange Points Clustering which uses optimization methods steered by the principles of evolution and genetics [22].

REFERENCES

1. Momeny, M. M., Jahanbakhshi, A., Neshat, A. A., Hadipour-Rokni, R., Zhang, Y.-D., & Ampatzidis, Y. (2022). Detection of citrus black spot disease and ripeness level in orange fruit using learning-to-augment incorporated deep networks. *Ecological Informatics, 71*, Article 101829.
2. Naziya, S., & Sivaraj, C. (2022). Fruit disease detection and classification using artificial intelligence. *International Research Journal of Engineering and Technology (IRJET), 9*(8), 1916–1921.
3. Mahendrakumar, S., Neelam, K., Chandrasekaran, G., Vanitha, K., Neeraj, P., Mahajan, T., & Kumar, N. (2022). Fruit disease and freshness identification by image processing method using Raspberry Pi. In *2022 International Conference on Smart Generation Computing, Communication and Networking* (pp. 1–5). IEEE.

***Corresponding Author:** Rao Ashlesha Padmananda

4. Marandi, S., & Chakravorty, C. (2021). Apple fruit disease detection using image processing. *Journal of Emerging Technologies and Innovative Research (JETIR), 8*(6).
5. Nikhitha, M., Roopa Sri, S., & Uma Maheswari, B. (2019). Fruit recognition and grade of disease detection using Inception V3 model. In *2019 3rd International Conference on Electronics, Communication and Aerospace Technology (ICECA)* (pp. 1–6). IEEE.
6. Keresztes, B., et al. (2018). Real-time fruit detection using deep neural networks. In *Proceedings of the 14th International Conference on Precision Agriculture*.
7. Ayyub, S. R. N. M., & Manjramkar, A. (2019). Fruit disease classification and identification using image processing. In *2019 3rd International Conference on Computing Methodologies and Communication (ICCMC)* (pp. 1–6). IEEE.
8. Dharmasiri, S. B. D. H., & Jayalal, S. (2019). Passion fruit disease detection using image processing. In *2019 International Research Conference on Smart Computing and Systems Engineering (SCSE)* (pp. 1–6). IEEE.
9. Johnson, T., & Singh, S. K. (2015). Enhanced K Strange Points clustering algorithm. In *2015 International Conference on Emerging Information Technology and Engineering Solutions* (pp. 32–37). IEEE.
10. Sinaga, K. P., & Yang, M.-S. (2020). Unsupervised K-means clustering algorithm. *IEEE Access, 8*, 80716–80727.
11. Hearst, M. A., Dumais, S. T., Osuna, E., Platt, J., & Schölkopf, B. (1998). Support vector machines. *IEEE Intelligent Systems and Their Applications, 13*(4), 18–28.
12. Ramya, R., Kumar, P., Sivanandam, K., & Babykala, M. (2020). Detection and classification of fruit diseases using image processing and cloud computing. In *2020 International Conference on Computer Communication and Informatics (ICCCI)* (pp. 1–6). IEEE.
13. T. K., Sharafath, M. M., Abimanyu, S., & Naveen, K. (2023). Disease detection in orange fruit using machine learning techniques. In *2023 2nd International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA)* (pp. 1–6). IEEE.
14. Malathy, S., Karthiga, R. R., Swetha, K., & Preethi, G. (2021). Disease detection in fruits using image processing. In *2021 6th International Conference on Inventive Computation Technologies (ICICT)* (pp. 747–752). IEEE.
15. Matboli, M. A., & Atia, A. (2022). Fruit disease identification and classification using deep learning model. In *2022 2nd International Mobile, Intelligent, and Ubiquitous Computing Conference (MIUCC)* (pp. 432–437). IEEE.
16. Patel, H. B., & Patil, N. J. (2024). Enhanced CNN for fruit disease detection and grading classification using SSDAE-SVM for postharvest fruits. *IEEE Sensors Journal, 24*(5), 6719–6732.
17. Awate, A., Deshmankar, D., Amrutkar, G., Bagul, U., & Sonavane, S. (2015). Fruit disease detection using color, texture analysis and ANN. In *2015 International Conference on Green Computing and Internet of Things (ICGCIoT)* (pp. 970–975). IEEE.
18. Agarwal, A., Sarkar, A., & Dubey, A. K. (2019). Computer vision-based fruit disease detection and classification. In S. Tiwari, M. Trivedi, K. Mishra, A. Misra, & K. Kumar (Eds.), *Smart Innovations in Communication and Computational Sciences* (Advances in Intelligent Systems and Computing, Vol. 851, pp. 105–115). Springer.
19. Johnson, T., & Singh, S. K. (2016). Fuzzy C Strange Points clustering algorithm. In *2016 International Conference on Information Communication and Embedded Systems (ICICES)* (pp. 1–5). IEEE.
20. Johnson, T., Singh, S. K., & Sharma, A. (2016). The redesigned Fuzzy C Strange Points clustering algorithm. In *2016 2nd International Conference on Contemporary Computing and Informatics (IC3I)* (pp. 789–793). IEEE.
21. Johnson, T., & Singh, S. K. (2017). Divisive hierarchical bisecting min–max clustering algorithm. In S. Satapathy, V. Bhateja, & A. Joshi (Eds.), *Proceedings of the International Conference on Data Engineering and Communication Technology* (Advances in Intelligent Systems and Computing, Vol. 468, pp. 579–592). Springer.
22. Johnson, T., & Singh, S. K. (2015). Genetic algorithms based enhanced K Strange Points clustering algorithm. In *International Conference on Computing and Network Communications (CoCoNet)* (pp. 737–741). IEEE.

***Corresponding Author:** Rao Ashlesha Padmananda