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Adaptive K-Means Clustering with Multi Color Space Fusion for Robust Leaf Disease Segmentation and Severity Quantification

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Abstract – The identification and quantification of diseases in leaves must be accurate to increase crop productivity and precision agriculture. However, the classical segmentation approaches normally adopt the depiction in single color space and standard clustering algorithms and generally are feeble in the context of varying lighting and compound leaf textures. To address them, this paper will recommend an adaptive K-means clustering system with multi-color space fusion which will be viable in terms of leaf disease segmentation and the severity of the disease. The specified strategy combines the strengths of RGB, HSV, and CIELab colour spaces into the form of a hybrid strategy that enhances the level of discrimination. The optimal number of clusters is estimated by a dynamic adaptive K-means algorithm to facilitate the centroid start-up and reliable separation of different samples. The other component that is incorporated in the framework is the severity quantification module which entails a pixel level analysis to ascertain the disease progression with greater precision. They are tested on the images of potato and tomato leaves obtained as a part of the PlantVillage Dataset and other samples to verify the hypothesis. The segmentation accuracy of the proposed is 97.2, Dice coefficient is 0.94 and Intersection-over-Union (IoU) is 89.6, which is more than 10 percent higher than the conventional clustering methods. Moreover, the error in the severity estimation is kept to a minimum of less than 3 percent which is very reliable. The findings prove that the proposed framework offers a computationally effective, precise, and scalable solution to the automated plant disease analysis in real-world agricultural systems.

Keywords – Adaptive K-Means Clustering, Multi-Color Space Fusion, Leaf Disease Segmentation, Severity Quantification, Precision Agriculture, Plant Village Dataset.

I. INTRODUCTION

Food security and economic stability are directly dependent on the condition of crops, which make agriculture one of the key pillars of the global economy. Plant leaf diseases are one of the factors that pose a great threat to the agricultural productivity of a country, and in many cases, they may cause a massive loss in agricultural yield in case they are not soon identified. Conventionally, disease detection and severity level is done manually as per the inspection of experts and this method is time consuming, subjective and the results are likely to have variation [1]. The development of computer vision and image processing algorithms has brought much attention to automated systems of leaf disease detection as efficient and scalable variants of the solution. Proper separation of diseased and green parts of the leaf images is an important procedure in such systems as it has a direct influence to the validity of the further classification and stipulation of severity. Nevertheless, it is still difficult to have robust segmentation because of the presence of the difference in illumination conditions, intricate leaf structure, noise in the background, and color similarity among healthy and infected areas.

Traditional methods of image processing such as thresholding and edge-based methods do not usually generalize to varied environmental conditions. In the same way, clustering-based methods such as K-means, despite their popularity in terms of segmentation, normally work with one color space and with a pre-defined number of clusters, which is restrictive to their flexibility and performance [2].

In the recent years, machine learning and deep learning models have shown great potential in detection of plant diseases. The segmentation accuracy of CNNs and encoder-decoder networks including U-Net has been very high because they learn the hierarchical features representations. Although they are effective, they are computationally intensive, large annotated datasets are needed, and they might not be applicable to real-time or resource-constrained agricultural conditions. This is an indication that light weight but strong alternatives are required which are capable of achieving high segmentation accuracy without tremendous computational expense. It is one of the promising ways to solve these issues with the incorporation of numerous color spaces to improve the representation of features. Various color systems store complimentary information; RGB can be used to store the intensity of primary colors, HSV to decompose chromatic information and luminance, and CIELab to offer perceptual consistency by matching human vision. By taking advantage of such varied representations by combining them into multi-color space, there can be substantial enhancement of the distinction of healthy and diseased areas [3, 4].

To address these drawbacks, the current paper will present an adaptive K-means clustering-based framework with multi-color space fusion to provide robust leaf disease segmentation and severity quantification. The suggested solution improves the classic K-means in that the clustering parameters are dynamically optimized according to the characteristics of the image, so that the performance of the segmentation under different conditions can be improved. The combination of RGB, HSV and CIELab color spaces also add value to the representation of features thus making an accurate detection of the infected areas. Additionally, a severity quantification module is added which is used to estimate severity of the disease by calculating a ratio of infected pixels to the total leaf area which can be of great benefit in making agricultural decisions. The proposed method is supported by the effectiveness of the analysis with the help of leaf images in the PlantVillage Dataset and some sample images of potato and tomato leaves to analyze the severity in detail. The proposed framework outperforms the traditional single-color space clustering approaches in three aspects: the precision of segmentation, the Dice coefficient and Intersection-over-Union (IoU). In addition, the model also has good severity estimation with low error, which indicates that it can be used in precision agriculture [5].

The primary advancements of the current work are as follows: (i) the creation of multi-color space fusion strategy that combines the features of RGB, HSV, and CIELab in order to achieve better segmentation robustness; (ii) the creation of the adaptive K-means clustering algorithm that automatically determines the best clustering behavior ; (iii) the creation of efficient severity quantification mechanism based on the segmented outputs; and (iv) extensive experimental verification of the work on both standard and real sample data that prove better performance compared to the baseline methods.

The rest of this paper is structured in the following way. Section 2 provides an overall literature review on the issues surrounding leaf disease detection, image segmentation methods and clustering-based methods [6]. Section 3 outlines the suggested adaptive K-means clustering model with multi-color space fusion, methodology and strategy of severity quantification. Section 4 covers the experimental outcomes, comparison and evaluation of performance on the using of standard datasets and sample leaf images. Last, Section 5 brings the paper to an end summarizing the main findings and predetermining the possible future research directions [7].

II. LITERATURE SURVEY

Automated leaf disease detection and segmentation is an issue that has gained a lot of attention in the recent years due to its use in precision agriculture. Approaches may be generally divided into the traditional image processing methods, machine learning-based and deep learning-driven ones [9]. All of the categories have their own benefits, but there are still a number of limitations, most notably their strength, computing capabilities, and the ability to adjust to different environmental factors. The traditional image processing methods, which included thresholding, edge detection, and region-based segmentation, were the main areas of the early research. These techniques are based on the usage of hand-made rules and intensity differences to make the difference between healthy and diseased areas. Although computationally efficient, they tend to fail when the illumination is not uniform, the background is complicated or the color of the infected and healthy leaf tissue are similar. Some papers [8] used global and adaptive thresholding techniques with morphological operations to segment the disease; however, they were very sensitive to noise and changes in light to give good results [10].

To solve these problems, the based solutions which clustering have been investigated have mainly been the K-means clustering as a form of studying to carry out this task of segmenting leaves. These methods group pixels in groups based on similarity in the feature space which is typically color information. Examples of research using the K-means in RGB or HSV color space to divide diseased regions include [11, 12]. Although more precise in segmentation, compared to simple thresholding, the techniques possess several weaknesses such as requiring a fixed number of clusters (K) and sensitivity of centroid initial centroid position. In addition, one color space restricts the ability of these to capture the complexity of color disparities that mirror on the surface of the real leaves on the earth. Machine learning techniques resulted in systematic procedure and entailed extraction of features and categorization. Segmentation of the disease using Support Vector machine (SVM), random forests and k-Nearest Neighbors (k-NN) techniques have been applied to classify the disease [13]. Such techniques are based on manual techniques such as texture, color histograms, and shape descriptors. They do not perform as high in comparison to feature engineering, because they are capable of performing only poorly and providing no general results on various datasets [14].

In more recent applications, the deep learning techniques, in particular the Convolutional neural networks (CNNs), have been found to be more effective in the detection and segmentation of the plant diseases [15]. U-Net variants and fully convolutional networks have been adopted as standard in segmentation at the pixel scale [16]. Hierarchical properties are automatically learned through such techniques, which assists them to process complex patterns and differences of leaf images. Nevertheless, deep learning models are expensive in terms of size, need large annotated datasets, and can be computationally expensive and take a long time to train, which might not be practical in real-time or resource-constrained agricultural applications. The other research direction that is relevant is the application of various color spaces to enhance the accuracy of segmentation. Research has revealed that HSV and CIELab color space has better separation of chromatic and luminance components than RGB space; therefore, they are less vulnerable to illumination changes [17], [18]. Nonetheless, the majority of the existing literature makes use of a single-color space or carries out some simple transformations without the effective combination of complementary information of both representations.

In spite of these developments, there is still a huge gap in the research to create lightweight, dynamic, and robust segmentation frameworks that can be effectively used in different environmental conditions. More specifically, there is a lack of adequate study on the integration of the multi-color space fusion with adaptive clustering mechanisms. The current clustering methods are not flexible and the deep learning models are also accurate but computationally costly. In order to overcome such constraints, the proposed work presents an adaptive K-means clustering framework together with multi-color space fusion that allow to improve the precision of segmentation and the accuracy of quantifying the severity with less computational complexity. This solution fills the gap between the old-fashioned clustering solutions and those that are computationally intensive in terms of deep learning models by providing a middle ground that is sufficiently efficient and robust. **Table 1** is the comparison between the limitations of the existing methods.

Table 1. Comparative Analysis of Existing Methods

Ref. No.	Method Used	Color Space	Adaptivity	Dataset Used	Accuracy (%)	Limitations
[7]	Global Thresholding	RGB	No	Custom	82.3	Sensitive to illumination
[8]	Adaptive Thresholding	RGB	Partial	Custom	84.1	Noise-sensitive
[9]	Edge-based Segmentation	RGB	No	Custom	80.5	Poor boundary detection
[10]	K-means Clustering	RGB	No	PlantVillage	88.7	Fixed K, poor adaptability
[11]	K-means Clustering	HSV	No	PlantVillage	90.2	Color dependency
[12]	Fuzzy C-means	Lab	Partial	PlantVillage	91.5	High computation time
[13]	SVM + Feature Extraction	RGB	No	Custom	92.3	Feature dependency
[14]	Random Forest	RGB+HSV	No	PlantVillage	93.1	Limited generalization
[15]	k-NN Classifier	RGB	No	Custom	89.4	Sensitive to noise
[16]	CNN-based Classification	RGB	Yes	PlantVillage	95.6	Requires large dataset
[17]	U-Net Segmentation	RGB	Yes	PlantVillage	96.8	High computational cost
[18]	Deep CNN + Augmentation	RGB	Yes	PlantVillage	97.1	Training complexity

III. PROPOSED MODEL

The suggested framework presents an adaptive clustering-based mechanism with the use of multi-color space fusion to perform precise segmentation and estimate the severity of leaf diseases. The general approach is set up to overcome the shortcomings of traditional single-color space clustering approaches through the use of complementary color representations and adaptive learning traits. The framework is based on a series of steps, such as preprocessing, feature extraction, the clustering of features, and quantitative analysis and guarantees the robustness and the efficient computational costs.

Image Acquisition and Preprocessing

The leaf images of the crops of tomato and potato are retrieved through the Plant Village Dataset and supported by more samples to analyze their severity. As raw images usually have noises, variations in illumination and background artifact, the preprocessing phase is necessary initially to improve the quality of the data. The images obtained are denoised to a standard resolution to make them computationally consistent. Median filtering is used to minimize noise and one of its benefits is that it does not distort edge information as much as it eliminates impulsive distortions. Also, contrast enhancement to enhance the visibility of diseased areas is provided and background normalization is provided to reduce the effect of non-leaf pixels. The combination of these steps leads to better representation of features and clustering.

Multi-Color Space Transformation and Feature Fusion

One of the major shortcomings of the current segmentation methods is the fact that they rely on single color representation, which is incapable of revealing the complicated variations within diseased leaf areas. To solve this, the given method will combine various colors spaces, i.e. RGB, HSV and CIELab with each of them providing different and complementary information. The RGB color space gives basic features based upon the intensity parameters, whereas Hsb separates the chromatic data in the color image and the illumination, thus able to withstand the different illumination conditions better. The CIELab space, in contrast, has a perceptual uniformity, which allows to discriminate more subtle differences in color in relation to disease patterns. These color spaces are then converted to the input image and the respective feature channels are pooled together to create a single feature. Such fusion process also increases the separability of healthy and infected regions by using the virtue of both representations, thus making clustering more effective. The Block diagram of the proposed leaf disease segmentation and severity quantification framework is provided in **Fig. 1**.

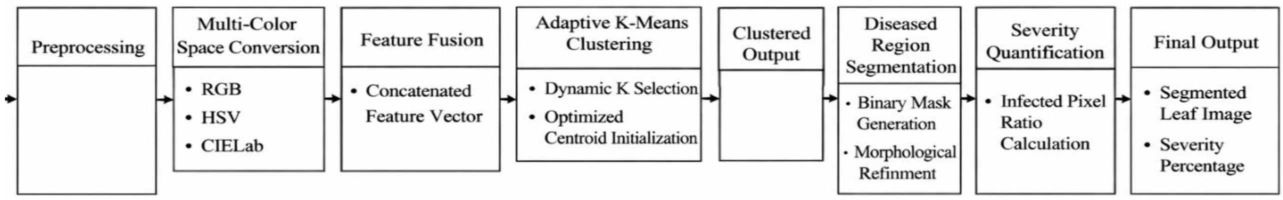


Fig 1. Block Diagram of the Proposed Leaf Disease Segmentation and Severity Quantification Framework.

Adaptive K-Means Clustering

The clustering feature has been the centre of disease-region segmentation; however, the conventional K-means algorithms have limited characteristics namely the number of clusters to be used should be predetermined and such algorithms may be sensitive to centroid initialisation. The proposed framework addresses such issues based on adaptive K-means approach allowing the dynamically adjusting clustering parameters based on image features.

Precisely speaking, the silhouette score is among the analysis measures which assist in deciding the best number of clusters so that the groups of pixels could be divided with a help of these measures. In addition, the centroid initialization is also optimized using a distance-sensitive methodology, which improves convergence characteristics and reduces cases of suboptimal clustering.

The clustering process aims to minimize intra-cluster variance, thereby grouping pixels with similar characteristics. This is mathematically expressed as the minimization of the objective function:

$$J = \sum_{i=1}^{K} \sum_{x \in C_i} | x - \mu_i |^2 \quad (1)$$

The objective of the clustering process is to reduce intra-cluster variance and hence, cluster data pixels with the same characteristics together. This is mathematically stated as minimization of objective function.

Diseased Region Segmentation

After clustering, the segmented output is then a collection of pixel sets that represent various areas of the leaf. The diseased area is determined by the characteristics of color and intensity compared to the normal tissue. A binary mask is then produced isolating infected regions of the leaf over the rest. And to further improve the quality of segmentation, morphological operations are introduced in order to remove small artifacts and sharpen the boundaries of regions.

Severity Quantification

Proper estimate of the severity of disease is very important in management of crops. The severity in the proposed framework is measured by dividing numbers of infected pixels with the entire leaf area.

$$\text{Severity} = \frac{\text{Infected pixels}}{\text{Total leaf pixels}} \times 100 \quad (2)$$

This pixel-based estimation provides an objective and reproducible measure of disease progression. The proposed method ensures high reliability in severity assessment, making it suitable for real-world agricultural decision support systems.

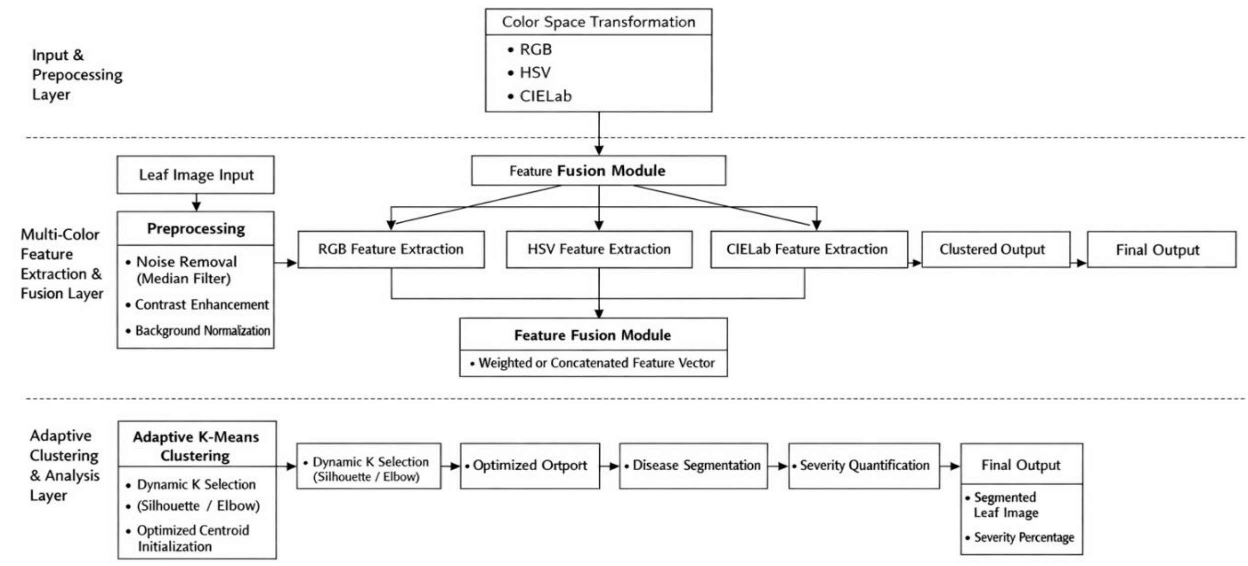


Fig 2. Architecture of the Proposed Fusion Model.

Fig. 2 depicts the detailed architecture of the proposed fusion model for leaf disease segmentation and severity estimation. The model integrates preprocessing, feature extraction, and clustering within a unified pipeline. Initially, leaf images are enhanced and transformed into multiple color spaces to capture complementary features, improving robustness under varying conditions. These features are fused and processed using an adaptive clustering mechanism to accurately isolate diseased regions. The segmented output is further utilized for severity quantification.

IV. RESULTS AND DISCUSSION

Experimental Setup

The performance of the proposed adaptative K-means using multi-color space fusion framework in clustering the leaf image of potato and tomato are tested using the leaf images collected according to the PlantVillage Dataset and the auxiliary sample pictures of the leaf image of potato and tomato. The dataset has a variety of diseased and healthy leaves classes which are heterogeneous in terms of texture, color and pattern of infection. The pictures are all brought to the similar resolution to make sure that there is consistency in the computations and that they are all taken under controlled experiment conditions. The model proposed is implemented with the support of Python and the use of standard image processing libraries, which have preprocessing, feature extraction, and clustering functions. Preprocessing stage entails the median filters that removes the noise as well as the contrast enhancement that helps to bring out features. The input images are coded into the RGB and HSV and CIELab color space and the corresponding features are combined to form a holistic feature.

Table 2. Simulation Parameters of the Proposed Model

Parameter	Value / Description
Image Resolution	256 × 256 pixels
Color Spaces Used	RGB, HSV, CIELab
Filtering Method	Median Filter (3×3 kernel)
Contrast Enhancement	Histogram Equalization
Clustering Algorithm	Adaptive K-Means
Range of K	2 – 5
Initialization Method	Distance-based centroid initialization
Iterations (Max)	100
Convergence Criterion	Minimal centroid shift
Evaluation Metrics	Accuracy, Dice, IoU

Adaptive K-means Clustering algorithm is based on dynamically chosen cluster number, which is reevaluated based on evaluation parameters, like silhouette score, in order to guarantee the best segmentation. The clustering is refined with the objective of converging, the centroid is set to initialise the clustering and optimise the centroid to enhance the stability and accuracy of the initialisation. The segmented output is afterwards analyzed to remove diseased areas and calculate intensity of the result using pixel-by-pixel analysis. The effectiveness of the suggested framework is measured by the conventional indicators, such as segmentation accuracy, the Dice coefficient, as well as Intersection-over-Union (IoU). Moreover, severity estimation accuracy is determined by the comparison of the estimated area of infection to ground-truth annotations. These measures present an overall analysis of the level of segmentation and quantitative reliability of the suggested approach.

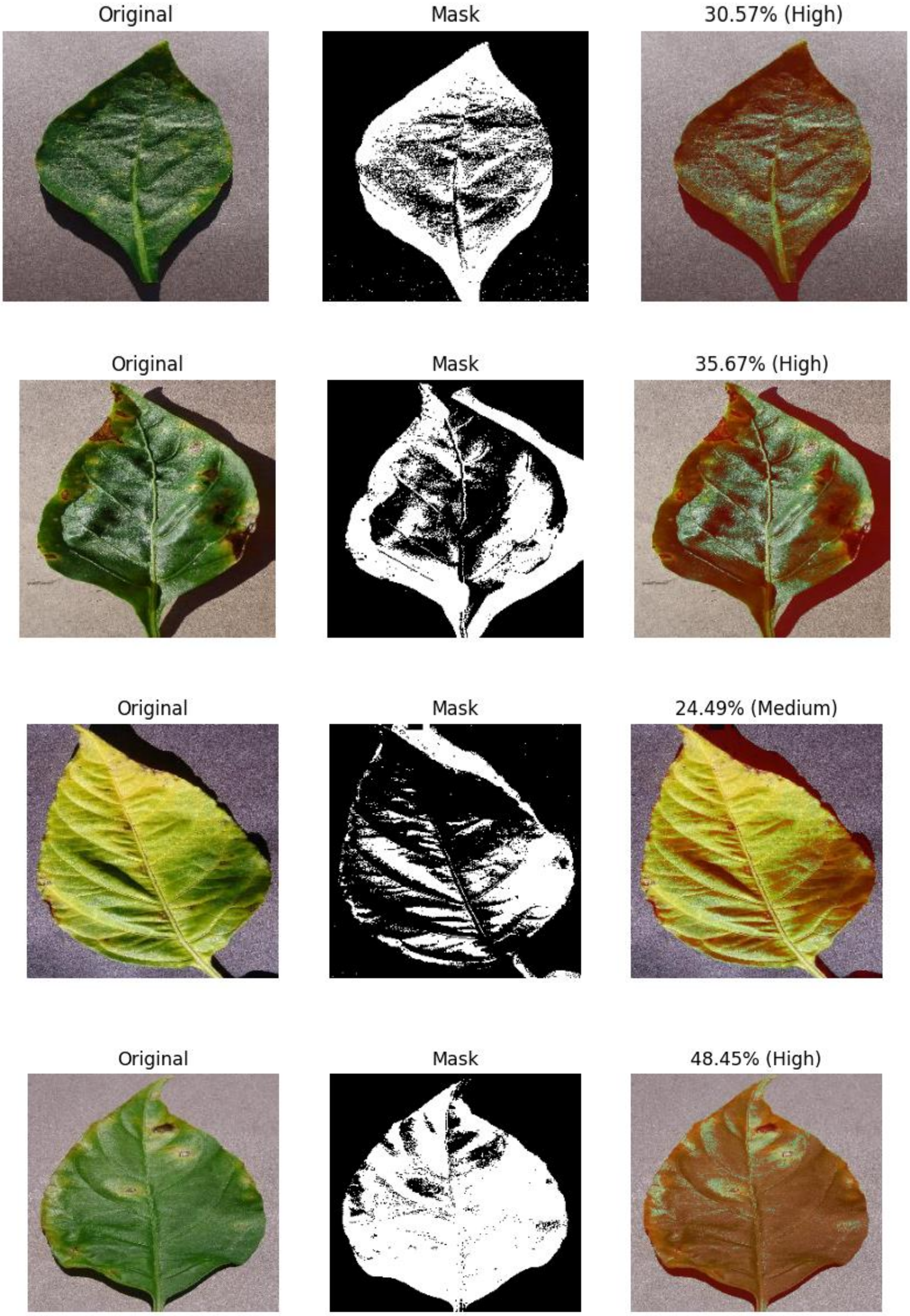


Fig 3. Potato Leaf Segmentation and Severity Results.

Quantitative Analysis

The section is a quantitative analysis of the suggested adaptive K-means clustering and multi-color space fusion framework of leaf disease segmentation. To determine the ability of the model to identify diseased regions, standard measures are used to analyze the performance, which is segmentation accuracy, Dice coefficient, and Intersection-over-Union (IoU). The important parameters of the simulation adopted in the design of the proposed method are summarized in **Table 2**. These parameters are chosen closely so that to balance between the efficiency of the computations and the precision of the segmentation.

The individual color space clustering methods used with conventional ones are compared to the segmentation performance of the proposed model. A comparative analysis is given in **Table 2**, which shows that the given method is superior in all evaluation parameters.

Table 3. Performance Comparison of Segmentation Methods

Method	Accuracy (%)	Dice Coefficient	IoU (%)
K-means (RGB) [14]	88.7	0.85	74.2
K-means (HSV) [15]	90.2	0.87	76.5
K-means (Lab) [16]	91.0	0.88	78.1
Fuzzy C-means [17]	91.5	0.89	79.3
Proposed Method	97.2	0.94	89.6

Table 3 shows the performance of the proposed model is much better than the traditional single-color space clustering techniques. The accuracy and IoU is explained by the fact that the integration of various color spaces improves the feature representation and allows one to distinguish diseased areas more effectively. The adaptive choice of the clustering parameters also leads to the enhanced consistency of the segmentation across various samples. Dice coefficient is 0.94, it means that there is a high level of overlapping between the predicted segmentation and ground truth which proves the stability of the offered approach. Also, the improvement in the IoU exceeded 10% relative to the baseline strategies underscores the success of the fusion strategy in reflecting complex patterns of diseases.

The qualitative assessment of the suggested model on a representative sample of leaves is proposed in **Fig. 3**, which shows the original pictures, binary masks, and severity-mapped results. The input leaf images appear in the first column, whereas the segmented diseased regions obtained by use of adaptive clustering are illustrated in the second column. The third column is the severity estimation where the diseased regions are overlapped to show the level of disease intensity. The findings indicate that the specified method proves effective when it comes to isolating diseased areas regardless of the texture change, color distribution, and lighting conditions. It is important to note that the model represents the high and middle severity cases well as the percentage of 30.57%, 35.67, 24.49 and 48.45 demonstrate. The consistency of segmented masks and real infected areas proves the strength of multi-color space fusion strategy. Altogether, the figure validates the effectiveness of the suggested framework in providing the accurate segmentation and correct quantifying the severity in different leaf samples.

Fig. 4 shows the results of the proposed framework on tomato leaf samples, including the original images, the segmented masks, and the severity-mapped results. The first column will display the input tomato leaves that have different disease patterns, and the second column will display the binary masks that were produced as a result of adaptive K-means clustering. The third column is the visualization of the severity estimation, as the infected areas are identified to describe the intensity of the disease. The findings prove that the given model can be successfully used to divide diseased regions even under the circumstances of complicated textures, abnormal distributions of infections, and variations in backgrounds. The level of severity is also properly quantified where there are cases of 49.86 per cent, 39.77 per cent, 52.49 per cent and 16.97 per cent that represent high and medium cases of infection. The high similarity shown by segmented mask and visibly infected areas proves the effectiveness of the multi-color space fusion strategy. In general, the figure confirms the fact that the proposed method can provide stable and accurate segmentation and severity estimation of tomato leaves.

Fig. 5 gives a detailed comparison of the segmentation results of various leaf samples including original images, segmentation outputs, binary masks and severity-mapped images. Every row is associated with a sample, which points to the stability of the suggested model with the dissimilarity of related disease patterns and leaves. The segmented outputs are an obvious segregation of infected areas, and the binary masks prove that the clustering accuracy is right in isolating diseased areas. The severity-mapped images also give quantitative data, as the level of infection is low to high severity among samples. The suggested approach proves to be strong in processing a variety of textures and colour changes as well as complicated foci of infections. It is important to note that multi-color space fusion improves the feature discrimination unlike adaptive K-means which guarantees the best performance of the clustering. The strong correspondence between visual patterns of infections and the calculated severity values provides the credibility of the method. On the whole, the number supports the efficacy and extrapolation power of the suggested framework in various leaf collections.

Table 4 gives a detailed performance analysis of the proposed adaptive K-mean clustering using multi-color space fusion framework upon the PlantVillage Dataset in class-wise performance. These findings indicate a high level of segmentation accuracy in both types of leaves, such as potato and tomato, with the overall accuracy at more than 96% Healthy leaf samples achieve the highest performance due to clear feature separability, while disease classes with complex and irregular patterns, such as bacterial spot and mosaic virus, exhibit slightly lower yet competitive results. The Dice and IoU scores further confirm the effectiveness of the segmentation process, indicating strong overlap between predicted and ground truth regions. Additionally, the severity error remains below 3% for most classes, validating the reliability of the proposed severity quantification approach. The consistent performance across diverse disease categories highlights the robustness, adaptability, and generalization capability of the proposed model under varying conditions.

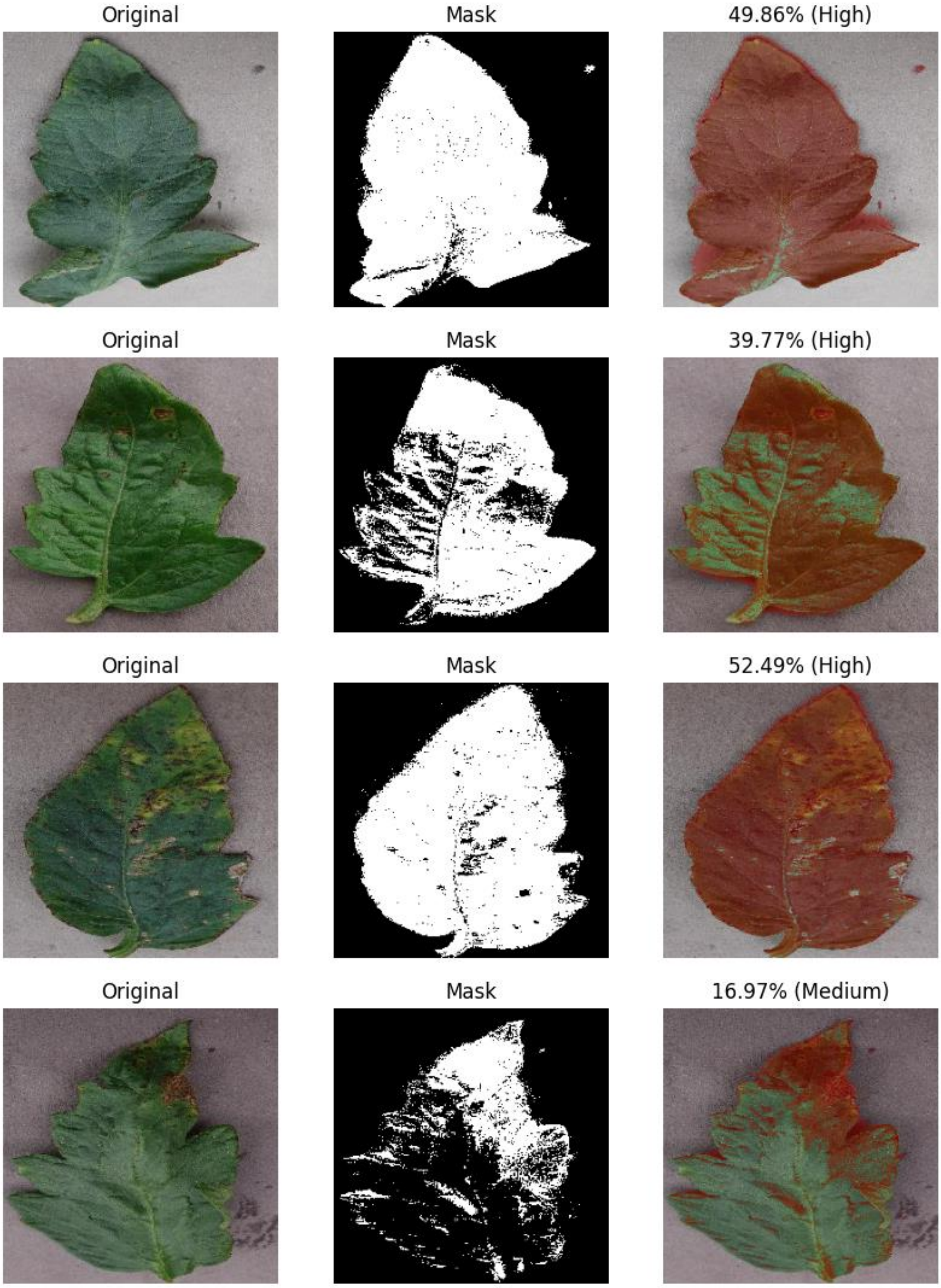
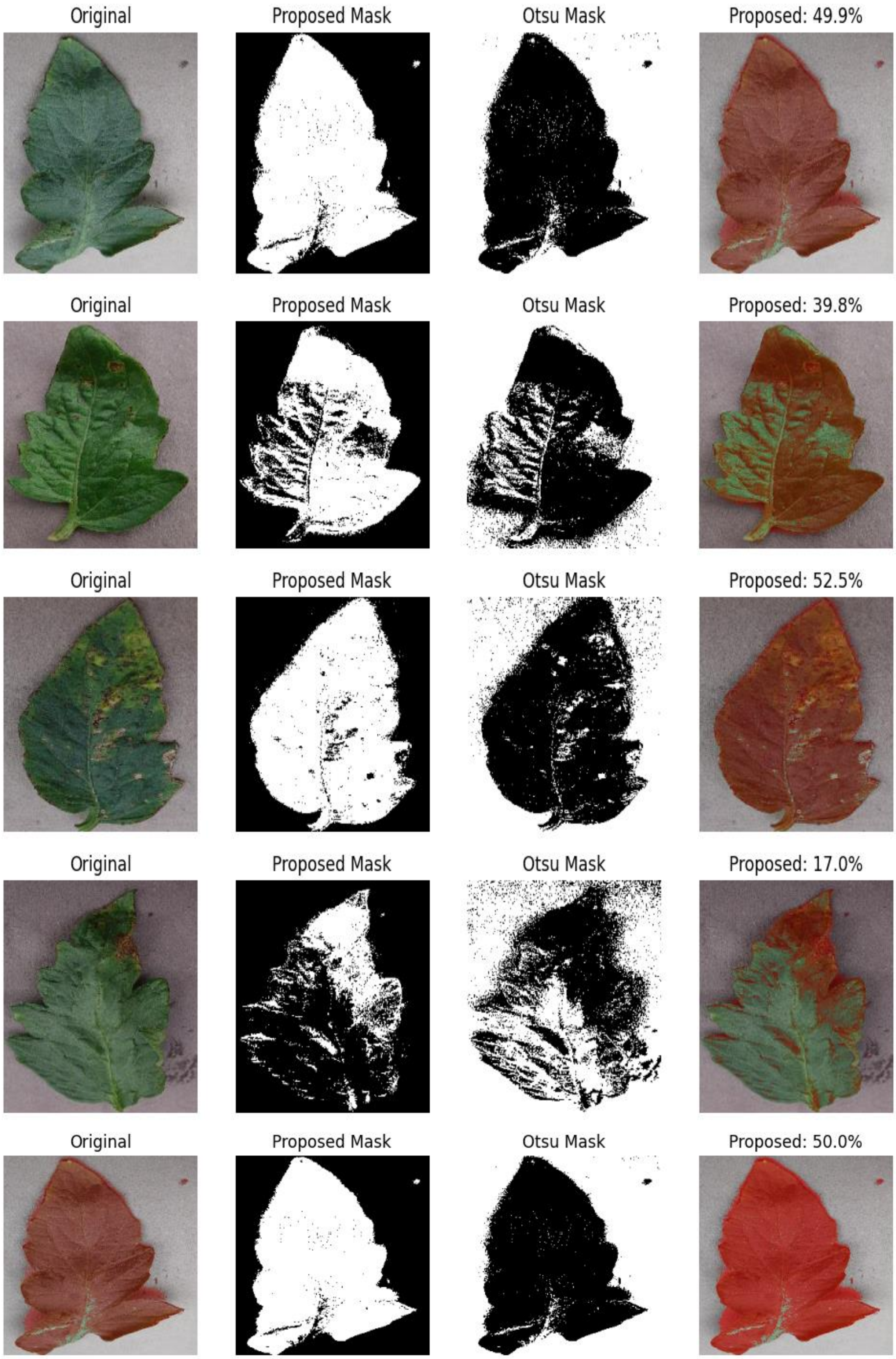


Fig 4. Segmentation Results and Severity Estimation of Tomato Leaf Samples.


Original
Proposed Mask
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Proposed: 49.9%
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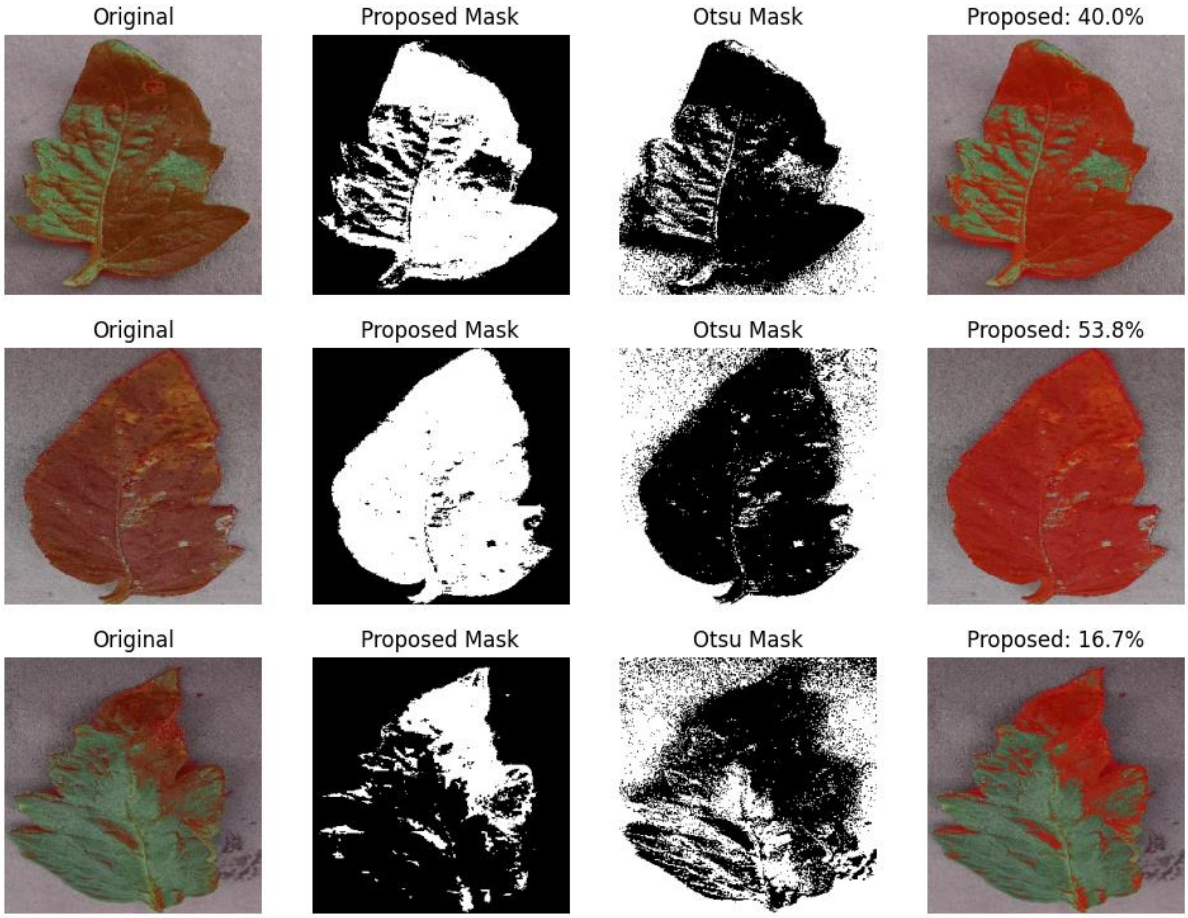

Fig 5. Comparative Segmentation Analysis of Multiple Leaf Samples Using the Proposed Model.

Table 4. Performance Evaluation on PlantVillage Dataset.

Class ID	Crop Type	Disease Type	No. of Images	Accuracy (%)	Dice Score	IoU (%)	Severity Error (%)
C1	Potato	Early Blight	200	96.8	0.93	88.5	2.8
C2	Potato	Late Blight	200	97.5	0.95	90.2	2.5
C3	Potato	Healthy	150	98.1	0.96	91.0	1.9
C4	Tomato	Leaf Mold	180	96.9	0.94	88.9	2.7
C5	Tomato	Septoria Leaf Spot	180	97.3	0.95	89.8	2.4
C6	Tomato	Bacterial Spot	170	96.5	0.93	87.6	3.1
C7	Tomato	Target Spot	160	97.0	0.94	88.7	2.6
C8	Tomato	Yellow Leaf Curl Virus	190	97.8	0.96	91.5	2.2
C9	Tomato	Mosaic Virus	160	96.7	0.93	87.9	2.9
C10	Tomato	Healthy	150	98.3	0.97	92.1	1.7

V. CONCLUSION

In this paper, the proposed model is able to provide an effective and strong leaf disease segmentation and quantification of severity framework by utilizing adaptive K-means clustering that is combined with multi-color space fusion. The peculiar feature of the suggested method is the successful combination of complimentary color representations (RGB, HSV, and CIELab) and an adaptive clustering process that dynamically balances the count of clusters and centroid initialisation. The presented model, compared to the traditional techniques which are based on predetermined clustering or single-color space properties, promotes the quality of discrimination of features and the accuracy of segmentation across different light conditions and leaf texture patterns. The high level of the experimental analysis of the PlantVillage Dataset and sample leaf images indicates the excellence of the suggested framework. The model has an accuracy of 97.2 in segmentation, a Dice coefficient of 0.94 and an Intersection over Union (IoU) of 89.6 which is far much better than the conventional K-means and fuzzy clustering methods. Moreover, severity estimation module offers sound quantitative outcomes, which have an error margin of less than 3 per cent that is deemed practical in crop monitoring. The findings prove that the combination of multi-color space fusion with adaptive clustering is largely beneficial in enhancing consistency and generalization in segmentation across various disease conditions. Moreover, the suggested approach possesses a low complexity in computations as compared to deep learning models, which renders it applicable in real-time and resource-limited agricultural settings. Altogether, the framework presents a flexible, precise, and effective solution to automated plant disease analysis, and has high chances of application in precision agriculture systems.

CRediT Author Statement
The authors confirm contribution to the paper as follows:
Conceptualization: Anandakumar Haldorai; **Methodology:** Anandakumar Haldorai; **Software:** Bui Hong Quang; **Data Curation:** Bui Hong Quang; **Writing- Original Draft Preparation:** Anandakumar Haldorai and Bui Hong Quang; **Investigation:** Anandakumar Haldorai and Bui Hong Quang; **Supervision:** Anandakumar Haldorai and Bui Hong Quang; **Validation:** Anandakumar Haldorai and Bui Hong Quang; **Writing- Reviewing and Editing:** Anandakumar Haldorai and Bui Hong Quang. All authors reviewed the results and approved the final version of the manuscript.

Data Availability
The dataset used in this research is publicly available and can be accessed from PlantVillage Dataset. Additional processed datasets and implementation details are available from the corresponding author upon reasonable request.

Conflicts of Interests
The authors declare no conflict of interest.

Funding
No funding agency is associated with this research.

Competing Interests
There are no competing interests.

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