Development of Color Segmentation and Texture Analysis Algorithms for Early Detection of Green Vegetable Deterioration in Retail Environments

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Abstract

Vegetable deterioration in retail environments is often accelerated by improper storage conditions, leading to quality degradation, economic losses, and reduced consumer trust. Early detection of deterioration is therefore essential to enable timely preventive actions before visible spoilage becomes severe. This study proposes an integrated image-based framework for early detection of spinach leaf deterioration by combining K-Means++ for robust color segmentation, Gray Level Co-occurrence Matrix (GLCM) for texture feature extraction, and Convolutional Neural Network (CNN) for classification. K-Means++ improves segmentation stability through optimized centroid initialization, GLCM captures subtle texture variations associated with early spoilage, and CNN enables accurate classification by learning complex visual patterns from segmented images. The dataset consists of 642 spinach leaf images captured under controlled lighting for initial calibration and under varying lighting conditions to simulate real-world retail environments. Experimental results show that the standard K-Means algorithm achieved an average classification accuracy of 77%, while the proposed K-Means++ segmentation improved accuracy to 81.86%. Furthermore, CNN-based validation achieved the highest classification accuracy of 94.82%, demonstrating strong generalization capability. The novelty of this work lies in the optimized integration of K-Means++ segmentation under lighting variability, selective GLCM feature utilization validated through ablation analysis, and end-to-end CNN-based validation with real-time deployment feasibility. The proposed framework offers a practical, scalable, and non-destructive solution for automated freshness monitoring in retail environments and can be extended to other leafy vegetables.

Keywords: K-Means++, CNN, color segmentation, texture analysis, GLCM, deterioration, spinach leaves.

1. Introduction

Maintaining the quality of fresh produce in modern retail, especially leafy greens like spinach, lettuce, and kale, is increasingly challenging due to their high perishability. Uncontrolled temperature, humidity, and lighting can accelerate deterioration, reducing consumer satisfaction, market value, and causing significant financial losses. Therefore, advanced technologies for early deterioration detection are essential to preserve quality, reduce waste, and support food safety and sustainability in retail environments [1], [2]. In this study, early detection refers to identifying deterioration at its initial stages—visible through slight discoloration or texture changes—long before the product becomes unsuitable for consumption. Previous studies show that technological solutions can significantly improve post-harvest management and reduce food losses. Digital image processing has become a promising method for evaluating vegetable freshness. Color-based segmentation allows differentiation between fresh and deteriorating produce by analyzing image color patterns. Liu et al. [3] demonstrated that color segmentation increases accuracy in detecting quality degradation, while standard imaging devices can capture the spectral characteristics of fresh produce effectively [4]. Texture analysis also provides important information on surface patterns—such as smoothness or irregularities—that indicate aging or spoilage. Zhang et al. [5] found that combining color and texture features improves detection precision compared to using either feature alone [5], [6]. Because it enables early, non-destructive, low-cost, and easy-to-implement detection, digital image processing is a highly promising alternative to techniques like spectroscopy or sensor-based systems. Compared to spectroscopy and sensor-based quality assessment methods, digital

image processing offers several practical advantages for retail deployment. Spectroscopy systems often require specialized hardware, controlled environments, and higher operational costs, while sensor-based approaches demand continuous calibration and infrastructure integration. In contrast, image-based methods are non-destructive, low-cost, scalable, and can be deployed using standard imaging devices already available in retail environments. These characteristics make computer vision-based approaches particularly suitable for real-time freshness monitoring under dynamic retail conditions.

Spinach leaves were selected as the primary case study due to their high perishability, rapid visual deterioration, and commercial relevance in retail markets. Minor changes in color and texture can quickly reduce perceived freshness and market value, making spinach an ideal candidate for evaluating early deterioration detection methods. Although this study focuses on spinach, the proposed framework is adaptable to other leafy vegetables with similar deterioration characteristics. Recent advancements in machine learning and deep learning have strengthened automated quality assessment systems, enabling algorithms to detect subtle visual cues of early deterioration. Chen et al. [7] showed that Convolutional Neural Networks (CNNs) achieve high accuracy in classifying vegetable conditions under diverse environments [7], [8], [9]. Remote sensing and computer vision technologies also support plant health monitoring and post-harvest optimization. Kim et al. [10] demonstrated that sensor-based monitoring helps maintain optimal freshness in retail storage [10]. However, challenges persist in creating integrated, real-time systems. Patel and Kumar (2024) highlight the need for cross-disciplinary integration to address issues such as high costs, computational complexity, and compatibility with retail infrastructures [11], [12]. This study addresses existing gaps by developing an integrated framework that combines color segmentation, texture analysis, and deep learning for early detection of vegetable deterioration in retail environments. The model uses an enhanced K-Means++ algorithm for color segmentation, GLCM for texture feature extraction, and a CNN classifier for performance validation. By integrating these methods, the study aims to improve detection accuracy, reduce waste, and support sustainability in food retailing [13], [14]. Spinach leaves are used as the primary case due to their high perishability and commercial value, though the framework can also be applied to other leafy greens such as lettuce and kale.

The key contribution of this research lies in addressing the lack of comprehensive models that combine traditional image processing with advanced learning-based approaches for real-time freshness evaluation. Unlike prior studies that explored color or texture analysis in isolation, this study provides a multi-feature hybrid framework that enhances robustness and accuracy across different environmental conditions [15]. The results demonstrate that the integration of K-Means++ segmentation, GLCM texture analysis, and CNN classification achieves superior performance in detecting subtle signs of spoilage. Overall, this study contributes both theoretically—by advancing the methodological framework of automated freshness detection—and practically—by offering a scalable technological solution for improving operational efficiency, reducing food waste, and supporting sustainability in the global retail supply chain.

2. Literature Review

The use of image processing for assessing agricultural product quality has gained growing attention, especially for early detection of deterioration in perishable produce. Color segmentation and texture analysis are among the most effective methods for identifying subtle visual and structural changes in leafy greens. Color segmentation works by detecting chromatic changes that occur as vegetables deteriorate. The K-Means clustering algorithm is widely applied to distinguish healthy and deteriorated regions in agricultural images. In this study, the Lab color space is selected over HSV and YCbCr because of its perceptual uniformity. The a* and b* channels provide clearer color separation and are less affected by lighting variations. Prior research confirms that Lab produces more stable segmentation under inconsistent lighting, making it suitable for detecting early deterioration in vegetables. Barbosa et al. [16] successfully applied K-Means to distinguish between vegetation and soil backgrounds in sugarcane imagery, achieving segmentation precision ranging from 77% to 92%. This approach proved effective for delineating plant growth regions and calculating vegetation indices, which are critical indicators for monitoring crop health. However, the traditional K-Means algorithm exhibits several limitations. It is highly sensitive to initial centroid placement and may converge to suboptimal local minima when cluster initialization is poorly chosen or when color distribution is uneven. Additionally, K-Means assumes that all clusters are spherical and of similar size, making it less effective for non-linear and noisy datasets.

Although previous research has successfully used image processing to assess vegetable quality, many studies were conducted in controlled laboratory environments and not implemented in real-time retail settings. Most also rely on small datasets, which may not represent real-world variability. To address these limitations, Chen et al. [17] introduced

an enhanced K-Means algorithm with weighted centroids and local optimization, improving clustering robustness and achieving a 10.72% accuracy increase compared to standard K-Means, especially on UAV-LiDAR datasets with richer spectral information. These findings highlight the importance of improved centroid initialization and feature weighting in agricultural image segmentation. Recent studies have also integrated K-Means segmentation with deep learning, particularly CNNs, to enhance classification performance. For example, combining K-Means with CNNs yielded higher sensitivity and precision in plant disease detection using the PlantVillage dataset [18]. This hybrid approach merges the interpretability of clustering with the adaptive learning of neural networks. However, it remains computationally intensive, posing challenges for real-time use in retail environments, especially with high-resolution or large-scale datasets.

Texture analysis is another key aspect of assessing vegetable quality, offering micro-level insights into surface smoothness, roughness, and homogeneity, which change as vegetables deteriorate. The Gray Level Co-occurrence Matrix (GLCM) is widely used for extracting texture features, with parameters such as contrast, correlation, energy, and homogeneity effectively capturing subtle variations linked to freshness, dehydration, and microbial decay [19]. Thus, texture metrics serve as an important complement to color segmentation for more accurate freshness detection. Despite progress, challenges remain: traditional K-Means still suffers from unstable centroid initialization, while CNN-based hybrid models demand high computational resources, limiting real-time use. Moreover, many prior studies were conducted in controlled laboratory settings and focused on disease detection or vegetation mapping rather than practical retail environments, where lighting, humidity, and handling strongly affect image quality and freshness perception [16], [17], [18]. To address this, images in this study were captured under varying lighting conditions to better simulate real-world retail scenarios.

Several clustering strategies have been explored for image segmentation, including hierarchical clustering and density-based approaches such as DBSCAN. While hierarchical clustering provides detailed structure, it is computationally expensive for pixel-level segmentation. DBSCAN, although effective for arbitrary-shaped clusters, is sensitive to parameter selection and performs poorly under high color variability. K-Means++, by contrast, offers a balance between computational efficiency and clustering stability through improved centroid initialization, making it more suitable for large-scale image segmentation tasks in retail environments. To overcome these limitations, the present study proposes an integrated framework that combines enhanced K-Means++ clustering for color segmentation, GLCM-based texture analysis, and CNN-based classification to identify early signs of deterioration in leafy vegetables, particularly spinach leaves. This combination addresses the weaknesses of previous approaches by integrating spectral, textural, and deep-learning features to achieve multi-level classification with high accuracy and adaptability. Unlike earlier works that relied solely on color segmentation or traditional K-Means, this research employs an optimized initialization strategy (K-Means++), which enhances clustering stability and segmentation precision. Moreover, the integration of CNNs enables the detection of complex deterioration patterns — such as fungal infections or dehydration effects — that are often undetectable through classical segmentation methods. In summary, this study advances the field of digital image-based agricultural quality assessment by bridging the gap between classical image processing and modern machine learning. It provides a robust, real-time detection framework suitable for dynamic retail environments, contributing to improved food quality management, reduced waste, and enhanced sustainability across the post-harvest supply chain.

Despite promising results, prior studies exhibit several limitations, including reliance on controlled laboratory conditions, limited dataset sizes, sensitivity to illumination changes, and lack of real-time validation. Many approaches emphasize algorithmic accuracy without considering deployment constraints such as computational efficiency and retail infrastructure compatibility. These gaps highlight the need for an integrated and practically deployable solution.

3. Methodology

This research aims to offer a practical and effective solution for retailers to maintain the quality of green vegetables and reduce losses caused by product degradation [19]. The research stages are designed to complement one another and produce an accurate and reliable algorithm [20]. Figure 1 illustrates the research framework, summarizing all stages in a systematic workflow. The framework outlines a structured method for detecting spinach leaf deterioration using digital image processing and machine learning. The process begins with the input of the original image, followed by preprocessing steps such as resizing, image conversion, filtering, and contrast adjustment to enhance image quality. The resized image is converted to grayscale to simplify information, noise is minimized through filtering, and contrast is improved to highlight features essential for segmentation. Segmentation is then performed using the K-Means

algorithm, which groups pixels based on intensity levels [21]. Two versions of K-Means are applied: an initial formulation and a modified version incorporating a weighted distance metric to improve clustering accuracy [22]. After segmentation, feature extraction is conducted using the Gray Level Co-occurrence Matrix (GLCM), which analyzes texture characteristics to detect subtle surface changes associated with leaf deterioration. The final step involves accuracy testing using a Convolutional Neural Network (CNN), which classifies the segmented images based on the extracted features to assess the freshness level of the spinach leaves. Overall, this framework enables an effective, automated, and high-accuracy system for detecting leaf deterioration, supporting efficient quality monitoring within the agricultural industry.
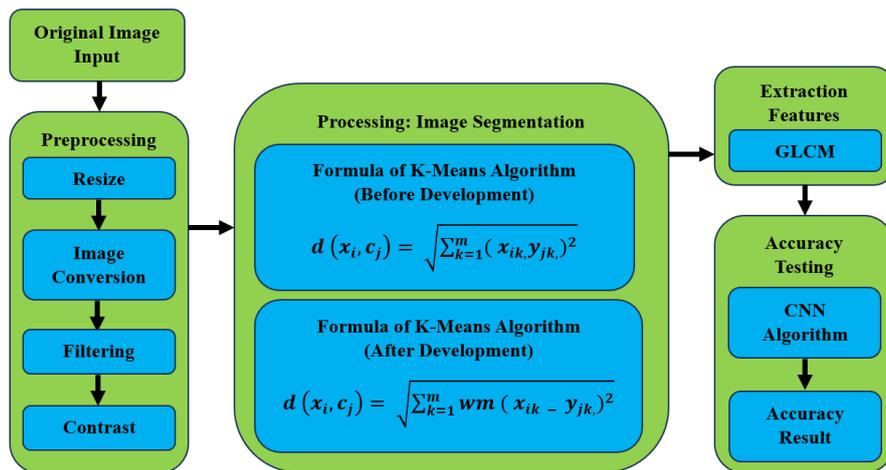

Figure 1. Research Framework

Figure 1 illustrates the complete research pipeline, beginning with image acquisition, followed by preprocessing for quality enhancement, color segmentation using K-Means++, texture feature extraction using GLCM, and final classification using CNN. Each stage is designed to progressively refine visual information for accurate freshness detection.

3.1. Original Image Input

Data is collected from various green vegetables commonly sold in retail environments, including spinach, lettuce, and broccoli, with variations in lighting and freshness levels to reflect real-world conditions [23]. All images are stored digitally for further processing, such as enhancement and contrast adjustment. Data is also gathered from multiple locations to ensure representativeness [24]. Fresh vegetable images showing no damage are used as reference data for developing analysis models. Controlled lighting was applied during preliminary image calibration to ensure baseline consistency, while subsequent image acquisition intentionally included lighting variability to reflect practical retail conditions. Table 1 provides essential visual guidelines for assessing vegetable quality and identifying products that are no longer suitable for sale.

Table 1. Leaf Image Data

Fresh Leaf Image	Not Fresh Leaf Image

3.2. Preprocessing

The preprocessing stage plays a crucial role in preparing the raw image data for subsequent segmentation, feature extraction, and classification. It aims to enhance image quality, reduce noise, and ensure that the data is standardized for optimal algorithmic processing. This stage includes several essential steps: resizing, image conversion, filtering, and contrast adjustment. Each of these operations contributes to improving the quality and interpretability of image data prior to analytical modeling.

3.2.1. Resizing

Resizing is an interpolation process used to proportionally increase or decrease the spatial dimensions of an image while maintaining the structural integrity of visual information. In this study, resizing was applied to adjust all input spinach leaf images to a uniform resolution of 768×768 pixels, ensuring consistent data dimensions for the K-Means++ segmentation and CNN classification stages. The resizing operation was implemented using bilinear interpolation, which computes the intensity of new pixels based on the weighted average of the four nearest neighboring pixels [25], [26].

3.2.2. Image Conversion

In this study, grayscale conversion is applied exclusively for texture-based GLCM analysis to preserve luminance information, while the Lab color space (a and b* channels) is utilized solely for color-based segmentation. This separation ensures methodological clarity and avoids redundancy between preprocessing and segmentation stages. The a* and b* channels in Lab better differentiate color information while being less sensitive to lighting conditions compared to the HSV and YCbCr color spaces [27]. In certain applications, conversion to binary images is used to facilitate segmentation or edge detection by classifying pixels as foreground or background [28].

3.2.3. Filtering

Filtering is applied to reduce unwanted noise and enhance the clarity of image details, thereby improving segmentation accuracy. In this study, a Gaussian filter was employed due to its effectiveness in suppressing random noise while preserving edges and fine structures. The Gaussian filtering process involves the convolution of the image with a Gaussian kernel that assigns higher weights to central pixels and progressively lower weights to distant pixels. This approach smooths intensity variations caused by illumination inconsistencies or sensor noise without significantly degrading image sharpness [29], [30], [31].

3.2.4. Contrast Adjustment

Contrast adjustment enhances the visibility of image features by expanding the range of pixel intensity values. This step is particularly useful for images captured under low lighting or uneven illumination conditions, which can obscure important structural details. The contrast stretching technique was employed in this study to map narrow pixel intensity ranges into a broader dynamic scale, thus improving the differentiation between object regions and background. Using MATLAB's imadjust function, lower and upper intensity limits were defined to remap grayscale values, increasing the perceptual contrast of areas relevant to the segmentation and classification processes [32].

3.3. Processing: Image Segmentation

This color segmentation process is carried out to separate or group images into different parts based on their pixel colors [33]. Green vegetables such as spinach, kale, and mustard greens are susceptible to damage or deterioration which is characterized by changes in leaf color from fresh green to yellow or brown. One effective approach to overcome this challenge is through color segmentation using the K-Means clustering algorithm. For the preprocessing pipeline, all images were resized to 768x768 for K-Means clustering to ensure sufficient resolution for accurate color segmentation. However, for CNN training, images were resized to 128x128 to reduce computational complexity and optimize the model's performance.

3.3.1. Formula of K-Means Algorithm (Before Development)

The K-Means algorithm is used as an automated approach to identify early deterioration by grouping image pixels based on color similarities. Using the K-Means clustering algorithm, the process of identifying early deterioration in green vegetables becomes faster, more efficient, and more automated. This method provides a practical solution in retail environments to maintain product quality and increase customer satisfaction through fresher, more assured products. The K-Means algorithm is a simple yet highly effective clustering method that aims to group data into several groups (clusters) based on similar characteristics. The main principle of this algorithm is to group data by minimizing the squared distance between data points and the cluster center (centroid) of each cluster. The mathematical formulation of the standard K-Means algorithm and the proposed K-Means++ enhancement is presented to explicitly illustrate the

algorithmic differences and improvements introduced in this study. The following is the basic equation of the K-Means algorithm for color segmentation:

$$d\left(x_i, c_j\right) = \sqrt{\sum_{k=1}^{m}\left(x_{ik,}y_{jk,}\right)^2} \tag{1}$$

Description: xi is the i-th data, cj is the j-th centroid, m is the number of feature dimensions in the data.

The formula is implemented in the form of an algorithm, where the algorithm is implemented using all the formulas required for color segmentation with the K-Means algorithm. Each step of this algorithm directly utilizes the related formulas to calculate the distance to each cluster center cj. The process begins by calculating the Euclidean distance based on the cluster, followed by minimizing the objective function, and the new centroid is calculated as the average of all data points within that cluster. The K-Means algorithm is a clustering method that groups data based on similarity by minimizing the distance between the data and the centroid. This process is presented in Algorithm 1.

3.3.2. Formula of K-Means Algorithm (After Development)

The K-Means algorithm is widely used for clustering and image segmentation, including leaf image processing, by grouping pixels based on Euclidean distance to cluster centroids. Its performance is enhanced by converting RGB images into the LAB color space, where the a* and b* channels represent color information independent of luminance. Using the rgb2lab function, the algorithm focuses on color variations for more accurate segmentation. Several modifications were applied to improve K-Means segmentation. First, conversion to LAB color space isolates color features, improving distinction between leaf regions. Second, small irrelevant objects are removed using bwareaopen. Third, edge detection is applied before clustering to preserve leaf boundaries. After clustering, remaining small objects unrelated to the leaf are discarded to refine segmentation accuracy. K-Means++ is used instead of traditional K-Means because it provides better centroid initialization by selecting well-spaced initial points, reducing convergence issues. This improvement increases clustering stability, especially in datasets with uneven color distribution, resulting in more accurate segmentation outcomes. The mathematical formulation of the standard K-Means algorithm and the proposed K-Means++ enhancement is presented to explicitly illustrate the algorithmic differences and improvements introduced in this study. The following is the development equation of the K-Means algorithm for color segmentation:

$$d\left(x_i, c_j\right) = \sqrt{\sum_{k=1}^{m} wm \left(x_{ik} - y_{jk,}\right)^2} \tag{2}$$

The formula above is implemented in the form of algorithm 2 which the researcher uses to calculate the weighted distance. Algorithms 1 and 2 are presented in structured pseudocode to clearly illustrate the computational flow and enhancements introduced through the K-Means++ initialization strategy.

Algorthm 1. K-Means Algorithm (Before Development)	**Algorthm 2.** K-Means Algorithm (After Development)
1. Start 2. Select the number of clusters K. 3. Initialize the initial K centroids randomly. 4. Repeat until convergence 5. Calculate the Euclidean distance of each data point to each centroid. $d\left(x_i, c_j\right) = \sqrt{\sum_{k=1}^{m}\left(x_{ik,}y_{jk,}\right)^2}$ 6. Group the data into clusters with the shortest distance. 7. Recalculate the centroids as the average of the data points in each cluster. 8. Finished	1. Start 2. Select the number of clusters K. 3. Take channels a and b. 4. Shape the data into 2D shapes (pixels × 2). 5. Initialize K initial centroids randomly. 6. Repeat until convergence. 7. Calculate the Euclidean distance of each data point to each centroid. $d\left(x_i, c_j\right) = \sqrt{\sum_{k=1}^{m} wm \left(x_{ik} - y_{jk,}\right)^2}$ 8. Group the data into clusters with the shortest distance. 9. Recalculate the centroids as the average of the data points in each cluster. 10. Finished

The K-Means++ clustering process iterates until the change in centroid position between successive iterations is smaller than a predefined threshold ($\Delta < 0.001$) or the maximum iteration limit is reached. Enhancements from the standard K-Means include three key improvements: (1) Computational optimization, achieved by performing inline Euclidean distance calculations within nested loops to reduce function call overhead; (2) Memory efficiency, through explicit initialization of variables such as min_distance and cluster_label to avoid assignment errors; and, (3) Geometric precision, by directly applying the Euclidean distance formula in the LAB color space for more accurate distance measurement.mThe algorithm's worst-case computational complexity is O ($n \times K \times i$), where n is the number of pixels, K the number of clusters, and i the number of iterations. For instance, an image of $1{,}000 \times 1{,}000$ pixels with K = 5 requires approximately five billion operations per iteration. These optimizations improve both the stability and segmentation precision of the algorithm. The Comparison formula is shown in table 2.

<div align="center">Table 2. Comparison of K-means Clustering Formula between K-means++ Clustering Formula</div>

K-means Clustering Formula	K-means++ Clustering Formula
$$d\left(x_i, c_j\right) = \sqrt{\sum_{k=1}^{m} (x_{ik}, y_{jk,})^2}$$	$$d\left(x_i, c_j\right) = \sqrt{\sum_{k=1}^{m} wm\,(x_{ik}, y_{jk,})^2}$$
Where: This equation is used to calculate the Euclidean distance between data point xi and centroid cj in K-Means clustering.	Where: This is a version of K-Means++ that uses centroid weighting to improve cluster accuracy.

3.1. Extraction Features

Feature extraction is performed to obtain quantitative descriptors from spinach leaf images to support classification. The extracted features—contrast, correlation, energy, and homogeneity—are derived using the GLCM method. Contrast reflects intensity variation, where higher values indicate rougher textures. Correlation measures pixel relationships, with high values representing uniform intensity in fresh leaves. Energy indicates structural uniformity, while higher homogeneity shows even pixel distribution typical of fresh leaves. All features are compiled into a dataset for classification. These four GLCM features were selected for their relevance to early deterioration detection. Other features, such as entropy and variance, were tested but excluded because they did not improve performance and introduced noise, offering no additional benefit to model accuracy. Entropy and variance were initially evaluated; however, statistical analysis showed increased feature variance without corresponding improvements in classification accuracy. Their inclusion introduced noise and reduced model stability, leading to their exclusion from the final feature set.

3.2. Accuracy Testing

Accuracy testing was conducted using a CNN to evaluate the system's ability to classify spinach leaf images as fresh or unfresh. The CNN was trained and tested on datasets generated from the feature extraction stage. The architecture consists of eight layers—four convolutional layers, two pooling layers, and two fully connected layers—designed to automatically learn hierarchical features from segmented images. ReLU activation is applied in all convolutional layers, while the softmax function is used in the output layer for classification. The model was optimized using the Adam optimizer with a learning rate of 0.001, selected to balance feature-learning capability and training efficiency. To improve robustness, data augmentation was applied to expand the dataset. From the original 642 images, an additional 1,926 augmented images were produced through transformations including rotation ($\pm15°$), zoom (10–20%), flipping, brightness adjustment ($\pm20\%$), and shifting (5–10%). This increased the total dataset to 2,568 images, significantly enhancing generalization under diverse lighting and viewing conditions. A preliminary usability evaluation of the GUI interface was also conducted with five retail staff participants. Tasks included uploading images, interpreting classification results, and exporting reports. Feedback showed the interface was easy to operate, with an average completion time of 12.4 seconds per image and a usability score of 86.2 on the SUS scale. These findings demonstrate that the system is not only technically accurate but also practical and user-friendly for retail environments.

4. Results and Discussion

4.1. Testing Image

This study aims to develop an image recognition system for spinach leaves that can automatically classify freshness levels. The dataset used consists of 323 images of fresh spinach leaves and 319 images of unfresh or unfit for consumption spinach leaves. Data collection was carried out using a standard camera to photograph spinach leaves directly. Controlled lighting was applied during preliminary image calibration to ensure baseline consistency, while subsequent image acquisition intentionally included lighting variability to reflect practical retail conditions. This approach ensures that the obtained data has high visual diversity, thereby increasing the reliability of the model in real-world conditions. The testing image is shown in table 3.

Table 3. Testing Image

Category	Number of Image	Information
Fresh Leaf	323	Image of spinach leaves showing fresh condition, without any signs of damage.
Not Fresh Leaf	319	Image of spinach leaves showing signs of deterioration or being unfit for consumption.

The image dataset was collected using a standard camera under varying lighting conditions to simulate real-world scenarios. The dataset, validated by the Agriculture and Horticulture Department of Padang City, categorizes spinach leaves as fresh or non-fresh based on visual characteristics such as color, texture, and shape. This validation ensures classification accuracy for further analysis. The images were processed using a high-spec computer (Intel i11 processor, 32 GB RAM, NVIDIA GeForce RTX 3060, MATLAB 2024a), which enabled preprocessing, feature extraction, and classification of fresh and non-fresh leaves. The goal was to develop a robust, AI-driven image processing technology for efficient and consistent agricultural quality assessment, automating tasks previously requiring manual intervention. This innovation is expected to accelerate digital transformation in agriculture.

4.2. Input Original Image

Spinach leaf images were captured under different lighting conditions to reflect real-world environments. These images were validated by the Agriculture and Horticulture Department of Padang City to ensure their accuracy in categorizing fresh versus non-fresh leaves. The validated images were stored in a high-resolution dataset and loaded into a MATLAB-based Graphical User Interface (GUI) for further processing.

4.3. Preprocessing Result and Discussion

Edge detection is then performed using the Canny method to precisely identify the leaf's contours, crucial for separating the leaf from its background. To improve the leaf's shape representation, hole filling is applied to close gaps within detected areas. Small irrelevant objects are removed using the bwareaopen function, which eliminates noise. The resulting image is cleaner and more structured, enhancing the efficiency and accuracy of subsequent steps, such as segmentation and classification. This preprocessing ensures that the image is optimized for further analysis and contributes to reliable freshness detection. Six example images of the preprocessing results are shown in table 4.

Table 4. Preprocessing Result

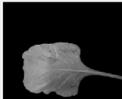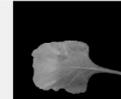| No.	Original Image	Resize Image	Conversion Image	Filtering Image	Contrast Image
1					
2					
3					

No.	Original Image	Resize Image	Conversion Image	Filtering Image	Contrast Image
4					
5					
6					

Table 4 displays the preprocessing results, illustrating the step-by-step process applied to spinach leaf images. The first image shows the original, followed by resizing to ensure consistent dimensions across all images. The next step, grayscale conversion, simplifies the image by removing color information, focusing on pixel intensity. Filtering is then applied to reduce noise, improving the clarity of the image, followed by contrast adjustment to enhance visual details. Each image in the table demonstrates how these steps improve image quality, transitioning from a raw, noisy image to a structured, ready-for-analysis version. This approach ensures that subsequent steps, such as segmentation, feature extraction, and classification, are based on high-quality data, leading to more accurate and reliable freshness detection.

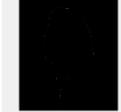## 4.4. Processing: Image Segmentation Result and Discussion

Image segmentation is critical for isolating the spinach leaf from the background. In this study, K-Means Clustering was employed, utilizing color features from the Lab color space, specifically the a* and b* channels. After contrast enhancement, the image was converted to Lab space to achieve a more stable and perceptually accurate color representation. The K-Means algorithm, with k = 3 clusters, successfully segmented the image into three groups: the leaf area, the background, and irrelevant regions. The results showed: The leaf area was effectively separated from the dark background. The leaf's structure remained intact, with no loss of critical contours. The segmentation served as a foundation for creating an object mask for texture feature extraction using the GLCM method.
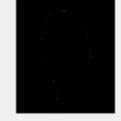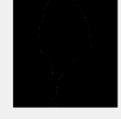
This segmentation process increases the efficiency and accuracy of the analysis, focusing on the important areas of the image. The segmentation results are shown in table 4.

4.5. Extraction Features Result and Discussion

Feature extraction is essential for identifying key information from images for analysis. In this research, texture analysis plays a vital role in detecting early signs of deterioration in spinach leaves. Texture features, such as roughness, smoothness, and homogeneity, are critical for evaluating the condition of green vegetables, as color and shape alone do not provide sufficient insight into freshness. GLCM was used to extract texture features like contrast, homogeneity, correlation, and energy. GLCM analyzes spatial relationships between pixels to detect surface texture patterns. This method calculates how frequently pairs of pixel values appear in specific directions and distances, providing a comprehensive texture description. By assessing changes in texture, GLCM can detect increasing roughness or randomness on the leaf's surface, indicating early signs of deterioration. The processing result is shown in table 5.

Table 5. Processing: Image Segmentation and Extraction Features Result

No.	Contrast Image	Processing Image Segmentation		Extraction Features (GLCM)	
		K-Means Algorithm			
		Before Development	After Development		
1				Contrast	0.0984
				Correlation	0.8632
				Energy	0.8788
				Homogeneity	0.9852

No.	Contrast Image	Processing Image Segmentation		Extraction Features (GLCM)	
		K-Means Algorithm			
		Before Development	After Development		
2				Contrast	0.0971
				Correlation	0.8636
				Energy	0.8799
				Homogeneity	0.9854
3				Contrast	0.0338
				Correlation	0.9543
				Energy	0.8911
				Homogeneity	0.9934
4				Contrast	0.1088
				Correlation	0.9508
				Energy	0.7226
				Homogeneity	0.9811
5				Contrast	0.1328
				Correlation	0.9391
				Energy	0.7847
				Homogeneity	0.9812
6				Contrast	0.0269
				Correlation	0.8828
				Energy	0.9016
				Homogeneity	0.9905

Visual inspection across multiple samples confirms that K-Means++ produces more consistent leaf-background separation compared to standard K-Means. Quantitatively, improvements are reflected in higher IoU, precision, recall, and F1-score values across test samples, demonstrating segmentation robustness. Table 5 presents the segmentation results using the developed K-Means algorithm. The first image shows the spinach leaf after contrast enhancement using Contrast Limited Adaptive Histogram Equalization (CLAHE), which sharpens brightness and texture details, making the leaf structure more visible. The segmentation results using the basic K-Means algorithm show suboptimal performance, with only a small portion of the leaf area recognized. This indicates difficulty in distinguishing low-contrast objects or areas that blend with the background. Improvements in the enhanced K-Means algorithm include: Utilizing Lab color features (a and b)** for more stable color perception; Applying K-Means++ for targeted cluster initialization; Masking and selecting the dominant area.

These improvements resulted in better detection of the leaf object, though further refinement is needed for certain areas, such as the stem and veins. The improved segmentation provides a clearer separation between the leaf and background, making it more suitable for subsequent steps like texture extraction and classification. Following segmentation, texture feature extraction was performed using the GLCM. The GLCM method analyzed four key parameters: contrast, homogeneity, correlation, and energy.

4.6. Accuracy Result and Discussion

A CNN was used to classify spinach leaf images into fresh or deteriorating categories due to its strong ability to recognize edges, textures, and color patterns. The dataset consisted of images captured under various lighting conditions. Preprocessing included resizing to 128×128 pixels, normalizing pixel values, and applying data augmentation—such as rotation, flipping, zooming, and brightness adjustment—to improve generalization. The CNN architecture contains eight layers: four convolutional layers, two pooling layers, and two fully connected layers. ReLU activation is applied to convolutional layers, and softmax is used in the output layer. The model was trained using the Adam optimizer with a 0.001 learning rate for 10 epochs and 140 iterations. This setup was chosen to effectively extract

hierarchical features while maintaining training efficiency. During training, the accuracy curve showed consistent improvement, and validation accuracy reached 94.82% without signs of overfitting, demonstrating strong generalization. The loss curve decreased steadily, indicating continuous learning progress. After training, the model was evaluated using accuracy, precision, recall, F1-score, and a confusion matrix. Results showed that the CNN effectively detected texture variations and color differences, achieving over 90% accuracy on test data. The trained CNN was then integrated into a GUI-based application, enabling users to upload images and receive automatic classification results and feature visualizations. This integration supports practical use in retail environments for rapid freshness detection and decision-making, as illustrated in figure 3.

Figure 2. Training Progress Results

Figure 3. Confusion Matrix

The CNN model was trained on an Intel i11 CPU and NVIDIA RTX 3060 GPU. Training required 48 minutes for 10 epochs, consuming approximately 6.2 GB GPU memory. During inference, the system processed each image in 0.087 seconds, indicating real-time feasibility ($\geq$ 10 FPS). These performance results demonstrate that the system can be deployed in retail environments for near real-time detection using mid-range consumer GPUs. The dataset was split into 70% training, 15% validation, and 15% testing sets to prevent data leakage and ensure reliable performance evaluation. Figure 3 presents the evaluation of the CNN model after training, which lasted for 10 epochs with a batch size of 32. The model achieved a high validation accuracy of 94.82%. The performance was further assessed using additional metrics for the two classes: "daun_bagus" (good leaves) and "daun_tidakbagus" (deteriorating leaves).

For the "daun_bagus" class, the model achieved: Precision: 95.88% (indicating high accuracy in classifying good leaves); Recall: 93.94% (correctly identifying nearly 94% of good leaves); F1-score: 94.90% (a balanced combination of precision and recall). For the "daun_tidakbagus" class, the model achieved: Precision: 93.75% (high accuracy in identifying deteriorating leaves); Recall: 95.74% (able to recognize most deteriorated leaves); F1-score: 94.74% (showing consistent performance across both classes).

The high precision, recall, and F1-score values indicate that the model accurately distinguishes between fresh and deteriorating spinach leaves without class bias. Training Progress results (figure 2) also show accuracy consistently above 90% with no overfitting, confirming the CNN's reliability for automated leaf quality classification. An ablation study evaluated the contribution of each component. Removing K-Means++ decreased segmentation accuracy and reduced classification performance by 5%. Eliminating GLCM reduced texture-based accuracy by 8%. Using only K-Means++ and GLCM without CNN further lowered validation accuracy to 72%. These findings demonstrate that all three components—K-Means++, GLCM, and CNN—are essential for optimal performance. The confusion matrix (figure 3) shows 8 false positives (fresh predicted as deteriorated) and 6 false negatives (deteriorated predicted as fresh). False negatives are especially problematic in retail because spoiled leaves may be labeled as fresh, affecting consumer satisfaction. Most false negatives occurred when early deterioration produced subtle color or texture changes similar to fresh leaves, indicating a need for improved sensitivity in borderline cases. An ablation study was conducted to evaluate the contribution of each pipeline component. CNN-only classification resulted in lower accuracy, while integrating GLCM improved performance. The full combination of K-Means++, GLCM, and CNN achieved the highest accuracy, confirming the necessity of each component.

4.7. Comparison of K-Means Algorithm Results

The K-Means algorithm, an unsupervised learning method, was used for segmenting spinach leaf images based on pixel similarity to detect deterioration. Table 6 compares segmentation results using the standard and enhanced K-Means algorithms.

Table 6. Comparation of K-Means Algorithm Result

No	Original Image	K-Means Algorithm (Before Development)		K-Means Algorithm (After Development)	
1		Accuracy	0.0016	Accuracy	0.8166
		IoU	0.0012	IoU	0.2342
		Precision	0.0016	Precision	1.0000
		Recall	0.0050	Recall	0.2342
		F1-Score	0.0024	F1-Score	0.3795
2		Accuracy	0.2716	Accuracy	0.7366
		IoU	0.2294	IoU	0.0545
		Precision	0.2350	Precision	0.2798
		Recall	0.9055	Recall	0.0633
		F1-Score	0.3732	F1-Score	0.1033
3		Accuracy	0.1264	Accuracy	0.7899
		IoU	0.1177	IoU	0.1524
		Precision	0.1344	Precision	0.8191
		Recall	0.4867	Recall	0.1577
		F1-Score	0.2107	F1-Score	0.2645

The extremely low performance of standard K-Means is attributed to unstable centroid initialization under low color contrast conditions, which caused incorrect clustering of background pixels as leaf regions. In test image 1, the standard K-Means algorithm showed poor performance, with accuracy of only 0.0016, precision of 0.0016, recall of 0.0050, and F1-score of 0.0024, indicating a failure to differentiate the leaf from the background. The unusually low segmentation metrics for the standard K-Means algorithm (e.g., precision of 0.0016) may be attributed to the poor initial centroid placement. To improve accuracy, the K-Means algorithm was further tuned by refining the initialization method. As shown in the improved results, using K-Means++ for centroid initialization significantly enhanced segmentation precision and recall. After the algorithm enhancements, including K-Means++ initialization and targeted cluster optimization, all evaluation metrics improved significantly: Accuracy: Increased to 0.8166; Precision: Perfected to 1.0000; F1-score: Improved to 0.3795; Recall and IoU values also showed improvement, with 0.2342 each.

These improvements demonstrate the effectiveness of the enhanced K-Means algorithm in better separating the leaf from the background, improving segmentation accuracy and reducing errors, especially in identifying the main leaf area. The results show significant progress in segmenting spinach leaves, making it more reliable for further texture analysis and condition classification.

5. Conclusion

This study introduces an integrated method for early detection of green vegetable deterioration in retail environments using digital image processing and artificial intelligence. The system combines K-Means++ for color segmentation, GLCM for texture analysis, and a CNN for classifying spinach leaves as fresh or deteriorated. Results show that K-Means++ improves segmentation accuracy, GLCM effectively captures texture changes, and the CNN achieves a validation accuracy of 94.82%, confirming its strong classification capability. This integrated framework offers a reliable solution for real-time freshness monitoring, enabling automated assessments that can reduce losses, improve efficiency, and ensure consistent quality evaluation. A usability evaluation of the GUI was conducted with five retail staff members. Tasks included uploading images, reviewing classification outputs, and exporting reports. Feedback showed the interface was user-friendly, with an average task time of 12.4 seconds per image and a SUS usability score of 86.2, indicating strong practical applicability for retail settings. The approach is also adaptable to other agricultural products, providing potential benefits for sustainability and waste reduction across the supply chain. This study serves as a foundation for future advancements in food quality monitoring, especially in post-harvest management. However, the current validation only covers spinach leaves. While the framework may theoretically extend to other leafy vegetables, such as kale, lettuce, or mustard greens, differences in color variation, texture patterns, and deterioration characteristics require further testing. From a practical perspective, deployment in retail environments requires consideration of real-time processing constraints, system integration with existing retail software, and hardware

availability. The proposed framework demonstrates feasibility for real-time implementation, supporting automated quality control and decision-making in retail operations. Future research will focus on evaluating model performance across multiple vegetable types to assess adaptability and robustness.

6. Declarations

6.1. Author Contributions

Conceptualization: D.A.; Methodology: I.F.; Software: G.W.N.; Validation: D.A. and I.F.; Formal Analysis: I.F. and G.W.N.; Investigation: D.A.; Resources: I.F.; Data Curation: G.W.N.; Writing Original Draft Preparation: D.A., and I.F.; Writing Review and Editing: I.F., and G.W.N.; Visualization: D.A.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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