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Leaf-Based Varietal Categorization of Sweetpotato (*Ipomoea batatas* L. Lam.), a Potentially Healthful Vegetable, Using Image Processing and K-Means Clustering

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ABSTRACT

Sweetpotato (*Ipomoea batatas* Lam) leaves contain higher concentrations of phenolic compounds, flavonoids, and carotenoids that are remarkable in health promotion. However, the nutrient content in sweetpotato leaves varies from variety to variety, and leaf shape and color are the key identifying factors for the varietal classification of sweetpotatoes. So, detecting sweetpotato leaves is essential for the in-situ identification of sweetpotato varieties and for developing intelligent agricultural systems. This study aimed to create a leaf-shape-based varietal classification technique for sweetpotato using image processing techniques coupled with a K-means clustering algorithm. 38 leaf images (RGB) of two sweetpotato cultivars were collected and pre-processed to extract relevant features. A distinct difference in leaf physical characteristics, i.e., leaf area, perimeter, circularity factor, breadth, and leaf ratio, between the two varieties was observed. K-means clustering algorithm identified two sweetpotato varieties as distinct clusters with centroid values (Cluster 0: Area 695627 and Cluster 1: Area 525895). Results revealed that sweet potato leaves in cluster 0 tend to have more prominent physical characteristics than in cluster 1. This result demonstrates the prospects of using machine learning and image processing techniques for in situ varietal classification of sweetpotato. The results bridge the visual characteristics and their quantitative assessment, fostering a deeper understanding of the plant's phenotype and supporting advancements in agriculture, research, and crop improvement.

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INTRODUCTION

Sweetpotato (*Ipomoea batatas* L.) is often referred to as a superfood and plays a pivotal role in ensuring food security worldwide. It is a potent source of essential nutrients such as vitamins A and C, dietary fiber, and minerals. Anthocyanins and carotenoids are potent antioxidants and offer several health advantages, including lowering the risk of cancer and heart disease, assisting blood sugar regulation, and reducing obesity. They are abundant in sweet potatoes (Islam, 2006; 2024). Sweetpotato is gaining popularity in the United States as a very healthy vegetable. The per capita intake of the sweetpotato increased by about 56% from 2000 to 2014 (Statista, 2016). Recent research on nutrients and phenolics has encouraged agriculturists and food scientists to investigate the beneficial characteristics of sweet potato leaves for human health. Several studies have reported that sweetpotato leaves offer remarkable health benefits, making them a valuable addition to any diet (Islam, 2008; Xu et al., 2010; Taira et al., 2013; Wang et al., 2016).

The increasing awareness of the health benefits of sweetpotatoes and their reputation as an alternative vegetable crop has been noticed by the food processors who have developed products that include sweetpotato fries, puffs, wedges, crisps, sticks, pie, and mashed sweetpotatoes that are now available in many local stores (Islam, 2006; Smith et al., 2009). Sweetpotato leaves contain high concentrations of polyphenolics compared with the major commercial vegetables such as spinach, broccoli, cabbage, and lettuce. Extensive reports have revealed that sweetpotato leaves can protect the human body from oxidative damage, inflammation, aging, and hypertension due to various antioxidant compounds, including phenolic compounds, flavonoids, vitamin C, and carotenoids (Gunathilake and Ranaweera, 2016; Rumbaoa et al., 2009). Several researchers claimed that sweetpotato leaves are superior in health-associated functionality compared to petioles, stems, tuberous roots, and many other commercial leafy vegetables (Lako et al., 2007; Xu et al., 2010; Huang et al., 2013).

Sweetpotato has a wide variability in phenotypic and botanical characteristics and is readily differentiated based on the shape of leaves and other agronomic characteristics (Zhang et al., 2000; Amankwaah, 2012). Sweetpotato leaves are medium to large and are cordate or heart-shaped with pointed tips. The leaves grow in an alternate pattern and may be palmate. Sweet potato leaves range in color from dark to yellow-green or purple and tend to be darker on the surface and lighter on the underside. According to the published report, the sweetpotato variety substantially affected antioxidant levels and the qualities of buds, leaves, petioles, and stems (Jia et al., 2022). Variety with pure green leaves had higher total phenolic content and antioxidant activity in buds, leaves, petioles, and stems. Still, the variety with green-purple leaves contained substantially more anthocyanins than green and yellow leaves (Chen et al., 2018; Jia et al., 2022). Also, the variation in nutritional quality among different sweetpotato varieties significantly impacts nutritional adequacy. Furthermore, other factors such as variety, environmental circumstances, and disease susceptibility influence sweetpotato plant productivity and quality (Ngailo et al., 2013). Therefore, sweet potato varietal categorization based on morphological features such as leaf size, shape, color, and texture are required for diversity evaluations for both plant genetic resource conservation and usage.

Conventional methods for the measurement and analysis of morphological characteristics in plant breeding are labor-intensive, costly, and time-consuming and increase the chance of generating errors in trait measurements (Kumar et al., 2015). However, the demand for rapid progress in genetic gain within breeding programs has led to a growing emphasis on the development and adoption of reliable, automatic, multifunctional, and high-throughput phenotyping technologies (Zhao et al., 2019). These technologies facilitate the rapid and accurate collection of vast amounts of morphological data, enabling more efficient and precise breeding strategies. Recent advancements in image analysis have revolutionized morphological characterization, offering a nondestructive and time-efficient alternative to conventional methods (Gehan et al., 2017). By automating the process, researchers can collect vast amounts of morphological data quickly and accurately, leading to more efficient breeding programs. Image-based phenotyping, in particular, has gained significant traction due to its ability to integrate computer vision, pattern recognition, and data mining approaches with advanced machine learning algorithms (Chitwood et al., 2013; Gehan et al., 2017). Several researchers have demonstrated the potential of combining these technologies to analyze plant morphology and phenotypic characteristics. For example, Du et al. (2006) utilized image processing techniques to extract morphological features and invariant moment features of various shapes of different plant leaves to classify leaf species. Lu et al. (2023) used image-based analysis integrated with machine learning to distinguish rice varieties based on panicle traits. Wang et al. (2023) developed a convolution block attention module and added to CNN framework to enhance and extract critical features of leaf images and results showed that the proposed leaf detection method outperforms state-of-the-art object detection methods. However, this study did not consider any classification approach for varietal classification of sweetpotato. This study focuses on the development of a leaf-shape-based varietal classification technique for sweetpotato using image processing techniques coupled with a K-means clustering algorithm. The study aims to improve sweet potato research and provide valuable insights into identifying and categorizing leaf variants. These findings have practical applications in agriculture, breeding programs, and crop management, supporting more efficient and informed decision-making processes.

MATERIAL and METHOD

Sample Collection

The experimental sweetpotato leaf samples were collected from UAPB Agricultural Experimental Farm in Pine Bluff, Arkansas. Two different genotypes, UAPB 18 (Variety 1) and UAPB 39 (Variety 2), were selected from thirty-eight accessions of sweetpotato leaves initially used. Each of the nineteen images was used in this study. After collecting the sweetpotato leaf samples, the leaves were cleaned to remove dirt and foreign matter from the leaf surface. This experiment was conducted at the Horticulture Laboratory at the University of Arkansas at Pine Bluff (UAPB), Arkansas, USA.

Analysis of Vitamin C, Oxalate and Chlorophyll

The accessions' Vitamin C, oxalate, and chlorophyll content were determined using the spectrophotometric method described previously (Islam et al., 2023; Alam et al., 2020; Li et al., 2017).

Extraction and Measurement of Total Anthocyanin

The leaf samples (500 mg) had 10 mL of 0.5% H2SO4 solution added and were steeped overnight at room temperature. A color value (CV) for the extract, which is an indicator of total anthocyanin, was determined using the formula: CV= 0.1 × OD 530 × 4 × 20/g DW, where OD530 is a spectrophotometric reading (530 nm), four corrects for the dilution, and 20g DW represents the dry weight of the sample (Islam et al., 2005).

Image Acquisition

Due to its availability, high performance, low price, and portability, the cellphone camera has emerged as a potential digital imaging device (Liang et al., 2005). Si et al. (2016) reported promising results in the case of potato tuber grading when they used images captured under normal room lighting conditions. Considering these recent endeavors, the images of sweet potato leaves used in this research were acquired using a 12 MP camera without flash under stationary conditions. A focal distance of about 25 cm was maintained during the image acquisition to obtain quality images. The image resolutions were 1536 x 2048 pixels each and were stored in jpeg format. Besides, an image of a measuring scale was acquired for further use as a reference for dimensional calibration. The acquired sweet potato leaf images were sampled and denoted as Variety 1 and Variety 2 for further analysis.

Image Processing

The image processing operation includes image preprocessing, color space conversion, background segmentation, and feature extraction. Since acquired images may have distortion and shadow effects (which could cause challenges with segmentation and feature extraction), image preprocessing was done to obtain a better-quality image (Li et al., 2017). The segmentation techniques for removing the background from an image include thresholding and clustering. This work used a color thresholding method to eliminate the background from each sweet potato image. The MATLAB Color Thresholder App within the MATLAB® computational environment was used for color thresholding (MathWorks, USA, version R2020b).

First, the RGB (red, green, and blue) image was converted to HSV (hue, saturation, value) color space, which defines the threshold value based on the channel histogram. Then, a masked image was created based on the chosen histogram threshold setting and applied with the *imfill* and *bwareaopen* operations to eliminate tiny (pixel <100) artifacts that may appear during the data collection (Yao et al., 2009; Islam et al., 2021). Finally, the masked output image was obtained for the segmented sweet potato leaf sample image (Figure 1). These procedures were repeated for all potato sample images. Then, the feature extraction algorithm was run to collect the minor axis, major axis, surface area, and perimeter for further classification model development.

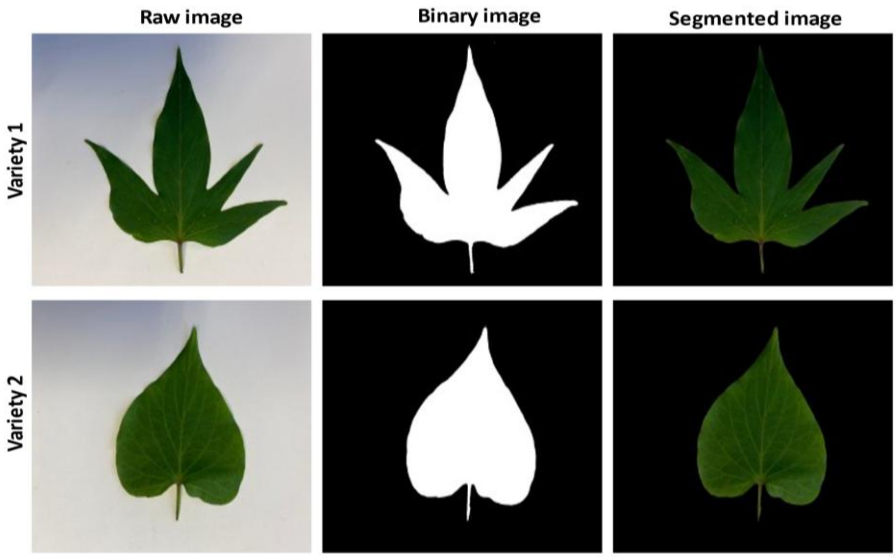

Figure 1. Example of processed sweetpotato leaf images

Each selected leaf characteristic was subjected to the following measurements explained in

Table 1. The leaf characteristics data was then exported into a Microsoft CSV file for calculating the breadth ratio and circularity factor. The breadth ratio was calculated by dividing max length by breadth, and the circularity factor was calculated using Equation 1 (Sun et al., 2017).

$$Circularity\ Factor\ (CF) = 4\pi \frac{A}{P^2} \qquad \text{(Equation 1)}$$

Where P is the perimeter of the leaf in pixels; A is the area of the leaf in pixels.

Table 1. Explanation of leaf characteristics measurement

Parameter	Description
Area*/	The total area of the leaf, measured in pixels
Perimeter	The length of the leaf's outer boundary is measured in pixels.
Circularity Factor (CF)	A dimensionless number represents the roundness of the leaf shape. CF value closer to 1 indicates more circular shapes.
Maximum Length	The longest dimension of the leaf, measured in pixels.
Breadth	The maximum width of the leaf is perpendicular to the maximum length, measured in pixels.

Statistical Analysis

Descriptive Statistics (DS) such as mean, standard deviation, minimum, and maximum values were computed for each measured leaf characteristics parameter. Using two-sample Z-tests based on the DS value, statistically significant differences between the two sweetpotato varieties were examined.

K-means Clustering

The K-means clustering algorithm is a popular method to solve clustering cases. The basic concept behind K-means clustering is to divide an input data set into a predetermined number of clusters (k) and calculate the starting centroid for each cluster (Sun et al., 2017). Here, the optimal number of clusters (k) from the sweetpotato leaf dataset was determined using the Elbow approach. The Elbow method iterates over a range of cluster numbers, computing the sum of squared distances (inertia) of samples to the nearest cluster center for each cluster number. The number of clusters is plotted against the relevant inertia values to determine the optimal cluster number (Figure 2). The value of k is chosen when the rate of decrease in inertia slows sufficiently, and the graph begins to resemble a straight line. Later, the predefined number of clusters (k = 2) generated from Elbow Analysis was utilized to perform K-means clustering with the Scikit-Learn library.

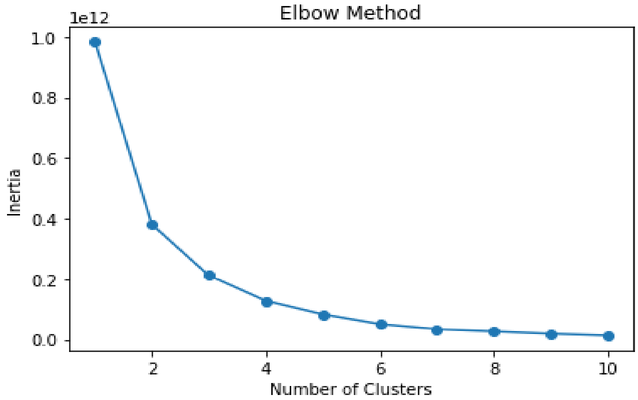

Figure 1. K-means clustering Elbow method to define the number of clusters

RESULTS and DISCUSSION

The sweetpotato has become a component of an ever-increasing range of products. Internationally, the plant has diverse uses, including ornamental, livestock feed, starch and alcohol manufacture, human consumption, biofuel, and bioplastic production. Recently, research has been conducted to determine the health-promoting functions of sweetpotato (**Table 2**). The following aspects of these functions are important when considering new uses for sweetpotato storage roots and leaves.

Table 2. Beneficial function of sweetpotatoes

Physiological Function	Related components	References
Antioxidative activity/ Radical scavenging activity (Leaves & tuber)	Polyphenol, anthocyanin	(Islam, 2006; 2008; 2014; 2016; 2019; 2024)
Antimutagenicity (Leaves & tuber)	Polyphenol, anthocyanin	(Islam, 2006; 2008; 2019; Suda et al., 1998; Peluso et al., 1995)
Anticarcinogenesis (Leaves & tuber)	Polyphenol, anthocyanin	(Islam, 2006; 2009; 2019; Islam et al., 2020; Shimozono et al., 1996)
Antihypertension (Leaves & tuber)	Polyphenolics, anthocyanin	(Suda et al., 1998; Matsui et al., 2002; 2004)
Antimicrobial activity (Leaves & tuber)	Fiber, pectin-like polysaccharide	(Yamakawa and Yoshomoto, 2002; Yoshomoto, 2001)
Antiinflammation (tuber)	Polyphenol	(Matsui et al., 2002; 2004)
Antidiabetic effect (Leaves & tuber)	Anthocyanin, polyphenol	(Toeller, 1994; Matsui et al., 2004)
Anti-HIV (Leaves & tuber)	Polyphenolics	(Mahmood et al., 1993)
Promotion of Bifidobacterium growth (Leaves & tuber)	Dietary fiber	(Yoshimoto, 2001; Yamakawa and Toshimoto, 2002)
Reduction of liver injury (tuber)	Polyphenol	(Suda et al., 1998)

Pigments and Nutritional Attributes

The chlorophyll, vitamin C, oxalate, and total anthocyanin content of sweetpotato leaves is shown in Table 3. The variation of oxalate contents among the varieties was found to be significant. The oxalate content of sweetpotato leaves was lower than that of Amaranthus (Onyango et al., 2008; Radek and Savage, 2008; Ogunlesi et al., 2010).

Table 3. Chlorophyll, Anthocyanin, Vitamin C, and Oxalate contents of the sweet potato leaves were studied.

Accessions	Chlorophyll contents (mg/100g DW*)	Total Anthocyanin (color value/g DW)	Vitamin C (nmol ascorbate /10g DW	Oxalate (nmol oxalate /10g DW)
UAPB 18	512.18** ± 2.72	22.29 ± 1.17	39.59 ± 2.11	1761 ± 12.19
UAPB 39	684.41 ± 3.91	18.62 ± 1.07	46.83 ± 3.07	2272 ± 15.32

*DW= Dry weight; **n (number of observations) = 15

Moreover, some vegetables grown in India were reported to contain high oxalate ranging from 5138 to 12576 mg/100g DWB (Radek and Savage, 2008). The ascorbate content ranges from 39.59 to 56.83 nmol/10 mg DW. A significant variation of results among varieties was observed. Our results are comparable to those of several authors who determined vitamin C in various sweetpotato leaves (Onyango et al., 2008; Away et al., 2013). Significant variations between the leaf chlorophyll and anthocyanin contents of the two accessions studied were also found. The study examined the chlorophyll, anthocyanin, vitamin C, and oxalate contents of sweetpotato leaves. By analyzing these components, researchers aimed to assess the nutritional value and potential health benefits of sweetpotato leaves. Chlorophyll content was measured to understand the plants' photosynthetic efficiency and overall health. Anthocyanin levels were assessed for their antioxidant properties, while vitamin C content was evaluated due to its essential role in human nutrition. Additionally, oxalate levels were analyzed to determine their potential impact on health, particularly calcium absorption. The findings provide valuable insights into the nutritional profile of sweetpotato leaves, highlighting their potential as a healthful addition to the diet (Onyango et al., 2008; Radek and Savage, 2008; Ogunlesi et al., 2010; Away et al., 2013).

Leaf Characteristics Analysis

A statistical analysis was conducted to evaluate the significant differences in leaf characteristics between the two sweet potato varieties, as summarized in Table 4. The results revealed that the mean leaf area for variety 1 was 534,146 square pixels, while variety 2 exhibited a significantly larger mean area of 648,741 square pixels, suggesting that variety 2 has larger leaf surfaces, potentially enhancing its photosynthetic efficiency. In contrast, the mean leaf perimeter of variety 1 was significantly higher at 6,251 pixels, compared to 4,026 pixels for variety 2, indicating a more compact leaf shape in variety 2. The compactness factor (CF), which reflects the degree of leaf compactness, was also significantly higher in variety 2, reinforcing its compact morphology. Additionally, the maximum leaf length and breadth were both larger in variety 1, with a mean length of 1,286 pixels and breadth of 1,235 pixels, compared to 1,191 pixels and 942 pixels, respectively, for variety 2. Despite its smaller dimensions, variety 2 had a higher mean leaf ratio (1.28) than variety 1 (1.06), indicating that the leaves of variety 2 are more elongated relative to their width. These findings highlight distinct morphological differences, with variety 2 producing larger, more compact, and elongated leaves, while variety 1 exhibits broader leaves with larger perimeters. Such differences may have implications for the varieties' adaptability, growth efficiency, and suitability for specific agricultural practices.

Table 4. Statistical summary of sweetpotato leaf phenotypic characteristics

Variety	Parameters	Leaf area	Perimeter	CF	Max Length	Breadth	Ratio
1	Min	396847	4892	0.110	994	872	0.730
	1Q	474116	5908	0.147	1245	1157	1.000
	Med	542463	6219	0.170	1302	1234	1.040
	Mean	**534146**	**6251**	**0.175**	**1286**	**1235**	**1.059**
	3Q	593288	6699	0.192	1350	1358	1.070
	Max	694882	8096	0.260	1486	1567	1.590
2	Min	503626	3485	0.360	884	732.0	0.800
	1Q	560862	3912	0.450	1143	926.0	1.222
	Med	662966	4006	0.500	1212	956.0	1.275
	Mean	**648741**	**4026**	**0.5039**	**1191**	**941.6**	**1.278**
	3Q	724265	4232	0.5625	1263	990.5	1.320
	Max	867348	4424	0.630	1409	1108.0	1.690

Table 5. Two-sample Z-test results

Parameter	Z-Score	P-Value	Significant (α=0.05)
Leaf area	-4.19	0.000028	Yes
Perimeter	19.28	0.000000	Yes
CF	-20.07	0.000000	Yes
Max length	4.41	0.000011	Yes

Breadth	10.28	0.000000	Yes
Ratio	-13.45	0.000000	Yes

The two sample Z-test results (Table 5) revealed significant differences between the two sweet potato varieties across all measured leaf parameters at a significance level of α=0.05. Variety 2 exhibited significantly higher mean values for Leaf Area and Compactness Factor (CF), as indicated by negative Z-statistics. In contrast, Variety 1 showed significantly higher mean values for Perimeter, Max Length, Breadth, and Ratio, with positive Z-statistics. The extremely low p-values ($p<0.0001$, $p< 0.0001$, $p<0.0001$) for all parameters confirm the robustness of these differences, suggesting that the two varieties have distinct morphological characteristics in their leaves. These findings highlight the potential variability in traits between the varieties, which could have implications for their growth, productivity, and adaptability.

K-means Clustering

The K-means clustering algorithm was applied to the dataset to explore the clustering patterns and potential groupings within the sweet potato leaf samples and evaluate the results with statistical inferences. The analysis revealed two distinct clusters corresponding to the two sweet potato varieties (varieties one and two). The results indicate that one cluster had 53% of the total samples, while another had 47%.

Table 6. Centroid position for characteristics of two different sweet potato leaf varieties

Cluster	Perimeter	Area	CF	Max Length	Breadth
0	4539	695627	0.481	1247	1018
1	5580	525895	0.243	1237	1141

Table 6 summarizes the centroid values for key morphological characteristics of two distinct clusters of sweet potato leaf varieties. Cluster 0 is characterized by a perimeter of 4539 units and a larger leaf area of 695,627 units, indicating broader leaf structures compared to Cluster 1, which has a perimeter of 5580 units and a smaller area of 525,895 units. The Compactness Factor (CF), which reflects the shape compactness, is higher in Cluster 0 (0.481), suggesting more compact leaf shapes, while Cluster 1 has a lower CF (0.243), indicating more elongated or irregular shapes. Both clusters exhibit similar maximum lengths, with Cluster 0 at 1247 units and Cluster 1 at 1237 units. However, the breadth of Cluster 0 is slightly narrower (1018 units) than that of Cluster 1 (1141 units). These morphological differences highlight the structural diversity between the two sweetpotato leaf varieties.

A scatter plot of area versus perimeter (Figure 3) was used to visualize the clusters, providing insights that the leaf area and the perimeter have contributed to the most separation of these varieties. K-means clustering analysis on sweet potato leaf samples used leaf area, perimeter, CF, max length, and breadth features. The clustering analysis resulted in two distinct clusters with well-defined centroid values. In Table 4, the centroid of cluster 0 had higher values for features like area, CF, and max length than cluster 1. This result suggests that sweet potato leaves in cluster 0 tend to have more prominent physical characteristics of sweetpotato leaves. Figure 4 shows the clear separation of two varieties of sweetpotato leaves.

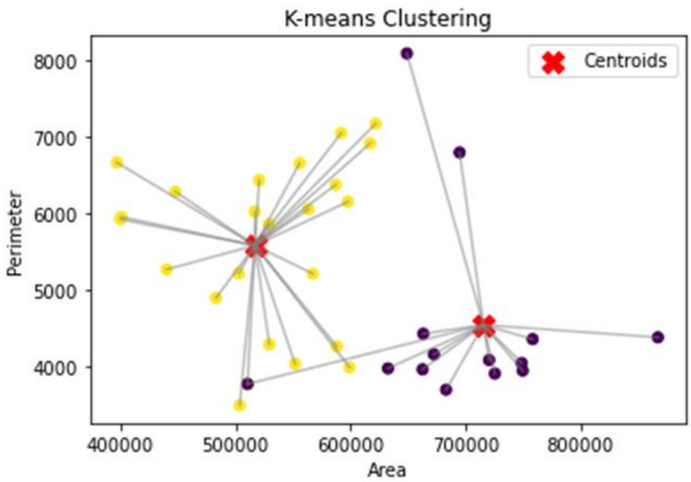

Figure 3. K-means clustering of sweet potato samples based on leaf area and perimeter
Note: The values are represented in pixels; the x mark represents the centroid of each variety.

Identification Important Features

Sweetpotato leaves exhibit distinct phenotypic characteristics that contribute to their identification and classification. The leaves are typically heart-shaped or lobed, with various variations in leaf margins, including entire, serrated, or deeply lobed edges. The leaf color varies, encompassing shades of green, and in some varieties, a purple pigmentation may be present (Away et al., 2013). The leaves are arranged alternately along the stem, and their size can vary significantly among different cultivars. Sweetpotato leaves often display prominent venation, and the leaf surface may be smooth or textured. Leaf structure plays a crucial role in photosynthesis, and the plant's adaptive characteristics are reflected in these phenotypic traits. Understanding the diverse phenotypic characteristics of sweetpotato leaves is essential for botanical classification and agricultural practices related to cultivation and breeding (Jackson et al., 2020). Image analysis of sweetpotato leaves involves various techniques to study and interpret visual data captured from the leaves. Common aspects analyzed include leaf morphology, color, texture, and signs of diseases or stress. Digital imaging tools, such as computer vision algorithms, can be applied to quantify features like leaf size, shape, and pigmentation. Chlorophyll content, an indicator of plant health, can be assessed through color analysis. Texture analysis may reveal patterns associated with specific conditions or diseases affecting the leaves. Additionally, machine learning models can be trained on image datasets to automate the identification of different leaf characteristics or potential issues (Gupta et al., 2020). Overall, image analysis in sweetpotato leaves aids researchers and farmers in understanding plant health, optimizing cultivation practices, and detecting any abnormalities for timely intervention. The relationship between image analysis and phenotypic characteristics of sweetpotato leaves is symbiotic, as image analysis is a powerful tool to quantify and interpret these observable traits. Image analysis allows for the objective and precise measurement of various phenotypic features, enhancing understanding of sweetpotato leaf morphology and health. For instance, size, shape, color, and texture—integral components of phenotypic characteristics—can be quantified using computer vision algorithms (Gupta et al., 2020; Su and Xue, 2021). Using image analysis, researchers can systematically evaluate and compare sweetpotato varieties based on their leaf attributes. This quantitative data aids in identifying patterns, assessing genetic diversity, and facilitating breeding programs to enhance desirable traits. Moreover, image analysis provides a non-invasive means of monitoring plant health, enabling the early detection of stress, diseases, or nutrient deficiencies by analyzing changes in leaf color, texture, or other visual indicators (Rosero et al., 2019; Su and Xue, 2021; Wang et al., 2023).

Image analysis of sweetpotato leaves finds diverse applications across agriculture, research, and crop management (Rosero et al., 2019; Jackson et al., 2020; Gupta et al., 2020; Su and Xue, 2021; Wang et al., 2023). Here are several critical applications: (i) Phenotypic Characterization: Image analysis enables the quantitative assessment of phenotypic characteristics such as leaf size, shape, color, and texture. This aids in cataloging and comparing different sweetpotato varieties, supporting breeding programs to develop crops with desired traits. (ii) Disease Detection and Monitoring: Early detection of diseases is crucial for crop management. Image analysis helps identify visual cues associated with diseases, such as discoloration or pattern changes in sweetpotato leaves, allowing for timely intervention and preventing the spread of infections, (iii) Nutrient Deficiency Identification: Leaf color and morphology changes can indicate nutrient deficiencies. Image analysis assists in recognizing these visual cues, helping farmers adjust fertilization practices to optimize nutrient levels for healthy sweetpotato growth. (iv) Stress Assessment: Sweetpotato plants respond to various environmental stresses. Image analysis allows for quantifying stress-related changes in leaves, such as wilting or discoloration, helping researchers and farmers assess the impact of environmental factors on plant health. (v) Yield Prediction: By analyzing leaf characteristics throughout the growing season, image analysis contributes to predicting sweetpotato yield. This information is valuable for farmers planning harvest schedules and optimizing crop production, (vi) Precision Agriculture: Image analysis supports precision agriculture practices by providing detailed spatial information about the crop. This includes leaf characteristics variations across different field areas, allowing for targeted interventions and resource optimization. (vii) Research and Development: Image analysis is fundamental in research endeavors, facilitating the study of sweetpotato genetics, physiology, and responses to various conditions. It expedites data collection and analysis, aiding scientists in making informed decisions and advancing knowledge in sweetpotato cultivation. Therefore, image analysis of sweetpotato leaves is a versatile tool with applications ranging from crop improvement to disease management, offering valuable insights for sustainable and efficient sweetpotato cultivation (Rosero et al., 2019; Jackson et al., 2020; Gupta et al., 2020; Su and Xue, 2021; Wang et al., 2023).

CONCLUSION

In conclusion, there has been an increase in the production and consumption of sweet potato and its leaves. This study demonstrates how image processing techniques and clustering algorithms can be used to analyze sweet potato leaves, providing valuable insights into the different morphological characteristics of two sweet potato varieties. These insights can help improve crops, develop disease-resistant breeding programs, and manage agricultural systems more intelligently. The research focuses on categorizing sweetpotato varieties based on their leaf characteristics, leveraging advanced image processing techniques and K-means clustering for accurate identification and classification. , This study aims to enhance the precision of varietal identification using computer vision system based on leaf features like shape, color, and texture. Results revealed that distinct morphological differences exist between two varieties, with variety 2 producing larger, more compact, and elongated leaves, while variety 1 exhibits broader leaves with larger perimeters. This approach benefits the agricultural management and breeding of sweet potatoes and promotes the inclusion of this nutritious vegetable in our diets. The findings highlight the effectiveness of combining image processing with machine learning algorithms in agricultural research and crop improvement.

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Conflict of Interest

The authors have declared that there are no competing interests.

Authors Contribution

IS:Resources, Supervision, Conceptualization, Data curation, Writing review & editing. PI of the research project. RT: Data curation, Writing review & editing. IH: Writing, review & editing. MA: Data curation, Writing review.

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