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# Classification of Vegetable Types Using Singular Value Decomposition (SVD) and K-Nearest Neighbor (KNN) Algorithms

Fenny Jong[1✉], Dyah Erny Herwindiati[2]
Tarumanagara University, Jakarta, Indonesia
Email: fenny.535210001@stu.untar.ac.id[1✉]

Abstrak

Sayuran merupakan salah satu jenis tanaman yang banyak ditanam di Indonesia. Namun terkadang sayuran dapat dipersiapkan dengan kurang baik dan menimbulkan risiko bagi konsumen. Oleh karena itu, diperlukan sebuah sistem berkualitas tinggi yang dapat mengidentifikasi sayuran yang baik dan aman. Penelitian ini bertujuan untuk menciptakan sebuah sistem klasifikasi sayuran menggunakan gambar dan algoritma. Sistem ini melakukan analisis terhadap berbagai jenis gambar sayuran, termasuk informasi tentang warna dan bentuknya. Dalam proses klasifikasi menggunakan Singular Value Decomposition (SVD) dan K-Nearest Neighbor (KNN) untuk mengklasifikasikan sayuran berdasarkan fitur- fitur yang dimilikinya. Penelitian ini menggunakan kumpulan data sebanyak 121 gambar sayuran dengan resolusi 40 × 40 piksel dalam format JPG, yang terdiri dari 73 gambar latih dan 48 gambar uji. Hasil penelitian menunjukkan bahwa ini mampu mengklasifikasikan sayuran dengan tingkat akurasi yang tinggi mencapai 85,42%. Penelitian ini berpotensi memberikan kontribusi dalam meningkatkan kualitas sayuran dan memajukan pengembangan sistem otomatis di industri pertanian.

Kata Kunci: *Klasifikasi Sayur, Singular Value Decomposition (SVD), K-Nearest Neighbor (KNN), RGB, HSV.*

Abstract

Vegetables are widely grown in Indonesia, but sometimes they can be prepared poorly and pose risks to consumers. To solve this problem, we need a high-quality system that can identify good and safe vegetables. This study aims to create a vegetable classification system using pictures and computer algorithms. The system analyzes different types of vegetable images, including color and shape. It uses special techniques called Singular Value Decomposition (SVD) and K- Nearest Neighbor (KNN) to classify the vegetables based on their features. The researchers used a dataset of 121 vegetable images, which were divided into 73 training images and 48 test images. The results showed that the system was able to classify the vegetables with a high accuracy rate of 85.42%. This study has the potential to help improve the quality of vegetables and contribute to the development of automated systems in the agricultural industry.
Keyword: *Vegetable Classification, Singular Value Decomposition (SVD), K-Nearest Neighbor (KNN), RGB, HSV.*

## PENDAHULUAN

Image-processing technology and pattern recognition are widely used in daily life. One useful application of these techniques is in image classification. Image classification helps determine the category or label of an image grounded on its characteristics. Two popular methods for image classification are Singular Value Decomposition (SVD) and K-Nearest Neighbors (KNN).

Singular Value Decomposition (SVD) is a technique used to reduce the complexity of an image and to create new and more informative features. It divides the image into three parts: singular values, left singular vectors, and right singular vectors. These singular values can be used as features in the image-classification process.

K-Nearest Neighbors (KNN) is a classification algorithm that is known for its simplicity and ease of understanding. It works by finding the training data most similar to the test data and using that information for classification. The algorithm also requires parameter k, which determines the number of nearby neighbors to be considered during the classification process.

In addition, the findings of this study can be the foundation for developing more advanced applications that identify different types of vegetables. This technology can also assist in selecting and processing healthy food ingredients. For example, farmers can use software to evaluate their crop yields and ensure that the vegetables they grow are of high quality. The food industry can use this application to assess the nutritional content of vegetables and other food items, leading to the creation of healthier and more nutritious meals.

RESEARCH METHODS

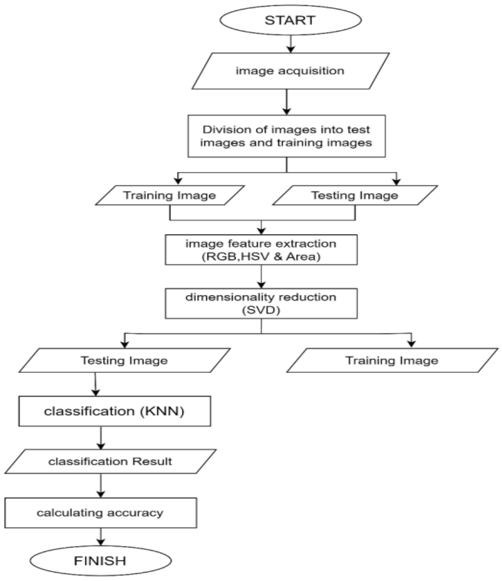



Figure 1. Flowchart

Image acquisition was the first step to be performed. Image acquisition is the process of collecting the vegetable images used in this study. Subsequently, the images were divided into training and testing images. Once the images are divided, the feature extraction process is conducted using the RGB, HSV, and area methods. Not all features obtained from the feature extraction process are optimal therefore, these features will be reduced using the Singular Value Decomposition (SVD) algorithm. After obtaining the optimal features, those from the training data were used as references for the classification process. Classification was performed using the K-Nearest Neighbors (KNN) method. Once the classification results were obtained, accuracy calculations were performed to evaluate the system performance.

Feature Extraction

An image refers to a visual depiction, resemblance or replication of an object. It can be obtained through optical means such as photography, analogically by displaying video signals on a television monitor or digitally, where it can be directly stored on a storage device. A digital image is represented by a matrix with dimensions N x M, where N represents the number of rows or height, M represents the number of columns or width, and L represents the maximum color intensity.

$$N = \text{number of rows}, 0 \leq y \leq N-1$$

$$M = \text{number of columns}, 0 \leq x \leq M-1$$

$$L = \text{maximum color intensity}, 0 \leq f(x, y) \leq L-1 \text{ (gray position)}.$$

There are several commonly used types of digital images, including:

1) Color Image (RGB): In a color image, each pixel represents a combination of the three primary colors red, green, and blue known as RGB. Each primary color is stored using 8 bits, which is equivalent to 1 byte, allowing for a range of 255 different shades. As a result, each pixel can display over 16 million color combinations by varying the intensities of the primary colors.
2) Binary Image (Monochrome): A binary image also referred to as a monochrome image, is a digital image that can only exhibit two possible colors for each pixel black and white.
3) Grayscale Image: A grayscale image is an image that possesses only one color channel, which consists of tones ranging from black to gray to white.

Digital Image Processing

The objective of Digital Image Processing is to enhance the quality of an image, making it more easily understandable by humans or computers. This technique involves transforming the image into a different form that enables efficient computation. Digital image processing serves as the initial step, known as pre-processing, in the field of computer vision. It involves information processing where the input is an image and the output is either an image or a specific portion of the image. The operations in digital image processing can be broadly classified as follows:

1) Image enhancement such as sharpening and brightness/darkness adjustment.
2) Image restoration.
3) Image compression.
4) Image segmentation.
5) Image edge detection and boundary extraction.
6) Image reconstruction [7].

Singular Value Decomposition (SVD)

Singular Value Decomposition (SVD) is a mathematical technique commonly employed in image classification and various other applications. It is particularly useful for factorizing matrices in linear algebra. The main purpose of SVD is to break down a rectangular matrix A, which has m rows and n columns (with m ≥ n), into the product of three matrices: U, Σ, and VT.

In the SVD decomposition, U is an m x n matrix that contains orthonormal eigenvectors of

AAT (left singular vectors). Σ is an n x n diagonal matrix with non-negative diagonal entries referred to as singular values. These values are the square roots of the eigenvalues of ATA. The SVD equation can be represented as follows:

$$A = USV^T$$
$$U^T U = I_{n\,x\,n}$$
$$V^T V = I_{p\,x\,p}$$

$$S = \begin{bmatrix} \sigma_1 & 0 & . & 0 & 0 \\ 0 & \sigma_2 & . & 0 & 0 \\ 0 & 0 & . & 0 & 0 \\ . & . & . & . & . \\ 0 & 0 & . & \sigma_{n-1} & 0 \\ 0 & 0 & . & 0 & \sigma_n \end{bmatrix}$$

The singular values in Σ are arranged in descending order, such that where σ1 ≥ σ2 ≥ · · · ≥ σp, where p is the minimum of m and n. In the context of image segmentation, the minimum singular value (σp) can be utilized as a distinctive feature for each image segment.

K – Nearest Neighbors (KNN)

K-Nearest Neighbor (K-NN) is a supervised learning algorithm that is commonly used for classification task. K-NN is categorized as a Case-Based Learning algorithm because it identifies similar groups of events or instances in large databases. By finding instances with similar features, K-NN can make predictions based on the known outcomes of those instances. K-NN finds applications in various domains including Data Mining, Statistical Pattern Recognition, Image Processing, and more.

The algorithm operates by calculating the distance between two points, represented as vectors, using the Euclidean method. The distance between two points Xs and Xt is determined by the formula.

$$d_{st} = \sqrt{\sum_{j=1}^{n} (X_{sj} - Y_{tj})^2}$$

One of the advantages of the K-Nearest Neighbor algorithm is its effectiveness when dealing with large training datasets. It can handle a significant amount of data without significant computational overhead. However, a drawback of K-NN is the need to determine various parameters, such as the value of K (the number of nearest neighbors to consider) and the distance metric to use. Selecting appropriate parameters can be challenging and may require experimentation and tuning to achieve optimal performance for a specific problem.

Implementation

The MATLAB R2016b software was used for the system design phase of this study. The vegetables considered in this study were broccoli, chili, potato, cabbage, Chinese cabbage, tomato, and carrots. Red, Green and Blue (RGB) images were converted into grayscale images to facilitate segmentation. The thresholding method was used for image segmentation after image feature extraction based on the average Hue Saturation Value (HSV) and object area. Finally, the images were classified using the k-nearest neighbor (KNN) algorithm.

The vegetable image dataset consists of 121 images of seven types of vegetables (73 for training and 48 for testing). Figure 3.1 shows the example training data and Figure 3.2 shows the example data used for testing. The dataset images and MATLAB code can be accessed through the following link: https://drive.google.com/drive/folders/19h_YRONfrRudPse11SdZNlmAUGx_VDyg?usp=drive_link

Fig.2. Example Image Training Data Photo

Source: Taken from the internet

Fig.3. Example Image Testing Data Photo

Source: Taken from the internet

Import Library

In this paper, several libraries are used for image processing and data analysis. Here is a brief explanation of each library used:

1) Image Processing Toolbox

   This library is very useful for image manipulation and processing. In this study, this library is used to perform various operations on images. Some important functions provided by this library include:

   a) imread: Used to read images.
   b) rgb2gray: Converts images from RGB format to grayscale.
   c) im2bw: Converts images to binary images.
   d) imcomplement: Inverts the colors of an image.
   e) imfill: Fills the holes in an image.
   f) bwareaopen: Removes small objects in a binary image.

2) Statistics and Machine Learning Toolbox

   This library is useful for statistical analysis and machine learning. In this study, this library is used for two main purposes. First, to normalize data using the zscore() function. This function is used to transform the data to have a mean of zero and a variance of one, which is useful in statistical analysis. Second, to perform dimensionality reduction using Singular Value Decomposition (SVD) with the svd function. Dimensionality reduction helps to reduce the complexity of data while retaining the most significant information.

3) Classification Learner Toolbox

   This library is used to train a classification model using the k-Nearest Neighbors (k-NN) algorithm and make predictions. In this study, this library is used to train a k-NN model using the fitcknn() function. This model can be used to predict the class of new data using the predict function. The k-NN algorithm utilizes the provided training data and selects the k nearest neighbors to predict the class of new data.

Training Process Algorithm

The algorithm for the data training process is as follows:

1) Read images from the training data (consisting of 7 cabbage images, 4 Chinese cabbage images, and 5 carrot images).
2) Perform image segmentation using the Otsu thresholding method.
3) Perform morphological operations to refine the segmentation results.

4) Extract color features based on RGB and HSV values.
5) Extract size features based on area values.
6) Convert the extracted features into Singular Value Decomposition (SVD).
7) Reduce the principal components to 2 SVD components (SVD1 and SVD2).
8) Plot the data distribution for each class.

Testing Process Algorithm

The algorithm for the data testing process is as follows:

1) Read images from the test data (consisting of 4 cabbage images, 3 Chinese cabbage, and 3 carrot images).
2) Perform image segmentation using the Otsu thresholding method.
3) Perform morphological operations to refine the segmentation results.
4) Extract color features based on RGB and HSV values.
5) Extract size features based on area values.
6) Convert the extracted features into Singular Value Decomposition (SVD).
7) Reduce the principal components to 2 SVD components (SVD1 and SVD2).
8) Perform classification based on the number of nearest neighbors.
9) Plot the data distribution for each class.

## RESULTS AND DISCUSSION

### Image Feature Extraction

Feature extraction techniques, such as RGB, HSV, and area, are used to classify vegetable types, such as cabbage, Chinese cabbage, and carrot. RGB (Red-Green-Blue) is a color model that measures the intensity of three basic color components in each pixel of an image. In this context, RGB feature extraction can be performed by obtaining the average intensity values of red, green, and blue from the vegetable image. This feature can provide information about the distinctive color combinations for each vegetable type.

Additionally, HSV (Hue-Saturation-Value) feature extraction can be used to obtain information regarding color nuances and brightness in vegetable images. The Hue component describes the type of color (such as red, green, or yellow), saturation indicates the strength or brightness of the color, and value indicates the overall brightness. HSV feature extraction can provide additional information regarding the unique color characteristics of each vegetable type.

Furthermore, area feature extraction involves measuring the area occupied by vegetables in the image. This method can yield information on the relative physical sizes of cabbage, Chinese cabbage, and carrot. Area size can be useful in distinguishing between vegetable types that have similar sizes but different characteristics.

By using feature extraction techniques, we can identify and classify vegetable types such as cabbage, Chinese cabbage, and carrot based on the RGB color combination, color nuances, brightness in HSV, and the area size extracted from the images. This approach

Training Data:

| Image | Red | Green | Blue | Hue | Saturation | Value | Area |
|---|---|---|---|---|---|---|---|
| 1 | 106.13 | 131.92 | 48.10 | 0.22 | 0.65 | 0.52 | 615 |
| 2 | 120.13 | 145.90 | 71.19 | 0.23 | 0.53 | 0.57 | 674 |
| 3 | 83.92 | 141.08 | 66.92 | 0.31 | 0.56 | 0.55 | 651 |
| 4 | 97.15 | 131.90 | 77.08 | 0.28 | 0.45 | 0.52 | 582 |
| 5 | 110.92 | 140.99 | 58.05 | 0.23 | 0.62 | 0.55 | 778 |
| 6 | 117.58 | 138.11 | 61.10 | 0.22 | 0.58 | 0.54 | 852 |
| 7 | 93.33 | 119.39 | 72.79 | 0.27 | 0.41 | 0.47 | 293 |
| 8 | 87.94 | 131.18 | 66.53 | 0.28 | 0.51 | 0.51 | 886 |
| 9 | 82.36 | 114.85 | 76.33 | 0.32 | 0.36 | 0.45 | 425 |
| 10 | 91.76 | 109.14 | 79.79 | 0.28 | 0.28 | 0.43 | 670 |
| 11 | 87.78 | 128.85 | 68.93 | 0.29 | 0.48 | 0.51 | 755 |
| 12 | 95.68 | 136.61 | 63.05 | 0.27 | 0.56 | 0.54 | 676 |
| 13 | 29.27 | 22.13 | 21.32 | 0.37 | 0.25 | 0.12 | 1600 |
| 14 | 207.11 | 74.85 | 66.69 | 0.36 | 0.70 | 0.81 | 562 |
| 15 | 202.63 | 71.68 | 66.43 | 0.34 | 0.67 | 0.80 | 327 |
| 16 | 169.64 | 85.09 | 76.32 | 0.55 | 0.59 | 0.68 | 361 |
| 17 | 195.36 | 85.98 | 75.46 | 0.21 | 0.63 | 0.77 | 471 |
| 18 | 187.64 | 48.83 | 53.59 | 0.77 | 0.76 | 0.74 | 338 |
| 19 | 184.92 | 66.39 | 70.94 | 0.71 | 0.68 | 0.73 | 212 |
| 20 | 76.65 | 53.69 | 48.22 | 0.31 | 0.30 | 0.31 | 1599 |
| 21 | 163.91 | 61.10 | 54.38 | 0.17 | 0.66 | 0.65 | 263 |
| 22 | 179.71 | 87.17 | 84.94 | 0.38 | 0.54 | 0.71 | 223 |
| 23 | 193.75 | 47.52 | 41.38 | 0.30 | 0.79 | 0.76 | 151 |
| 24 | 150.54 | 57.74 | 59.10 | 0.73 | 0.66 | 0.60 | 202 |
| 25 | 181.16 | 75.17 | 64.13 | 0.35 | 0.67 | 0.71 | 304 |
| 26 | 169.85 | 75.95 | 82.42 | 0.73 | 0.57 | 0.67 | 227 |
| 27 | 159.71 | 46.53 | 32.84 | 0.09 | 0.80 | 0.63 | 347 |
| 28 | 194.80 | 155.98 | 95.03 | 0.10 | 0.52 | 0.76 | 546 |
| 29 | 164.60 | 123.28 | 83.53 | 0.08 | 0.51 | 0.65 | 328 |
| 30 | 201.97 | 166.95 | 137.23 | 0.08 | 0.32 | 0.79 | 963 |
| 31 | 225.51 | 165.29 | 95.04 | 0.09 | 0.58 | 0.88 | 540 |
| 32 | 209.40 | 158.79 | 87.94 | 0.09 | 0.58 | 0.82 | 717 |
| 33 | 193.97 | 153.96 | 102.56 | 0.09 | 0.47 | 0.76 | 1048 |
| 34 | 209.30 | 170.65 | 87.07 | 0.11 | 0.60 | 0.82 | 489 |
| 35 | 183.35 | 145.58 | 104.95 | 0.09 | 0.44 | 0.72 | 818 |
| 36 | 209.40 | 158.79 | 87.94 | 0.09 | 0.58 | 0.82 | 717 |
| 37 | 241.14 | 209.69 | 133.95 | 0.12 | 0.44 | 0.95 | 699 |
| 38 | 196.64 | 156.72 | 78.45 | 0.11 | 0.60 | 0.77 | 531 |
| 39 | 208.57 | 161.98 | 79.58 | 0.11 | 0.64 | 0.82 | 454 |
| 40 | 162.75 | 116.39 | 73.62 | 0.09 | 0.55 | 0.64 | 712 |
| 41 | 149.63 | 113.27 | 70.61 | 0.09 | 0.54 | 0.59 | 453 |
| 42 | 214.42 | 175.38 | 101.24 | 0.11 | 0.53 | 0.84 | 912 |
| 43 | 156.16 | 125.22 | 75.19 | 0.10 | 0.55 | 0.61 | 567 |
| 44 | 81.65 | 64.88 | 34.30 | 0.32 | 0.62 | 0.33 | 1563 |
| 45 | 242.43 | 216.80 | 97.67 | 0.14 | 0.60 | 0.95 | 687 |
| 46 | 193.29 | 146.91 | 88.63 | 0.09 | 0.56 | 0.76 | 608 |
| 47 | 197.48 | 169.94 | 115.01 | 0.11 | 0.44 | 0.77 | 468 |
| 48 | 168.35 | 205.43 | 133.02 | 0.25 | 0.36 | 0.81 | 805 |
| 49 | 204.24 | 220.70 | 132.50 | 0.20 | 0.40 | 0.87 | 782 |
| 50 | 131.57 | 184.28 | 100.12 | 0.27 | 0.46 | 0.72 | 851 |
| 51 | 162.30 | 204.71 | 91.44 | 0.23 | 0.56 | 0.80 | 937 |

Testing Data:

| Image | Red | Green | Blue | Hue | Saturation | Value | Area |
|---|---|---|---|---|---|---|---|
| 1 | 106.13 | 131.92 | 48.10 | 0.22 | 0.65 | 0.52 | 615 |
| 2 | 117.58 | 138.11 | 61.10 | 0.22 | 0.58 | 0.54 | 852 |
| 3 | 87.94 | 131.18 | 66.53 | 0.28 | 0.51 | 0.51 | 886 |
| 4 | 82.36 | 114.85 | 76.33 | 0.32 | 0.36 | 0.45 | 425 |
| 5 | 91.76 | 109.14 | 79.79 | 0.28 | 0.28 | 0.43 | 670 |
| 6 | 97.15 | 131.90 | 77.08 | 0.28 | 0.45 | 0.52 | 582 |
| 7 | 58.14 | 83.60 | 49.23 | 0.30 | 0.45 | 0.33 | 394 |
| 8 | 83.92 | 141.08 | 66.92 | 0.31 | 0.56 | 0.55 | 651 |
| 9 | 179.71 | 87.17 | 84.94 | 0.38 | 0.54 | 0.71 | 223 |
| 10 | 163.91 | 61.10 | 54.38 | 0.17 | 0.66 | 0.65 | 263 |
| 11 | 193.75 | 47.52 | 41.38 | 0.30 | 0.79 | 0.76 | 151 |
| 12 | 181.16 | 75.17 | 64.13 | 0.35 | 0.67 | 0.71 | 304 |
| 13 | 169.85 | 75.95 | 82.42 | 0.73 | 0.57 | 0.67 | 227 |
| 14 | 159.71 | 46.53 | 32.84 | 0.09 | 0.80 | 0.63 | 347 |
| 15 | 207.11 | 74.85 | 66.69 | 0.36 | 0.70 | 0.81 | 562 |
| 16 | 169.64 | 85.09 | 76.32 | 0.55 | 0.59 | 0.68 | 361 |
| 17 | 195.36 | 85.98 | 75.46 | 0.21 | 0.63 | 0.77 | 471 |
| 18 | 187.64 | 48.83 | 53.59 | 0.77 | 0.76 | 0.74 | 338 |
| 19 | 194.80 | 155.98 | 95.03 | 0.10 | 0.52 | 0.76 | 546 |
| 20 | 164.60 | 123.28 | 83.53 | 0.08 | 0.51 | 0.65 | 328 |
| 21 | 201.97 | 166.95 | 137.23 | 0.08 | 0.32 | 0.79 | 963 |
| 22 | 225.51 | 165.29 | 95.04 | 0.09 | 0.58 | 0.88 | 540 |
| 23 | 208.57 | 161.98 | 79.58 | 0.11 | 0.64 | 0.82 | 454 |
| 24 | 149.63 | 113.27 | 70.61 | 0.09 | 0.54 | 0.59 | 453 |
| 25 | 214.42 | 175.38 | 101.24 | 0.11 | 0.53 | 0.84 | 912 |
| 26 | 156.16 | 125.22 | 75.19 | 0.10 | 0.55 | 0.61 | 567 |
| 27 | 81.65 | 64.88 | 34.30 | 0.32 | 0.62 | 0.33 | 1563 |
| 28 | 242.43 | 216.80 | 97.67 | 0.14 | 0.60 | 0.95 | 687 |
| 29 | 193.29 | 146.91 | 88.63 | 0.09 | 0.56 | 0.76 | 608 |
| 30 | 197.48 | 169.94 | 115.01 | 0.11 | 0.44 | 0.77 | 468 |
| 31 | 204.24 | 220.70 | 132.50 | 0.20 | 0.40 | 0.87 | 782 |
| 32 | 131.57 | 184.28 | 100.12 | 0.27 | 0.46 | 0.72 | 851 |
| 33 | 151.72 | 194.96 | 86.91 | 0.23 | 0.56 | 0.76 | 821 |
| 34 | 145.50 | 163.08 | 107.50 | 0.22 | 0.35 | 0.64 | 573 |
| 35 | 127.55 | 162.14 | 79.86 | 0.24 | 0.52 | 0.64 | 423 |
| 36 | 170.10 | 186.74 | 112.85 | 0.21 | 0.40 | 0.73 | 478 |
| 37 | 138.94 | 185.87 | 97.16 | 0.25 | 0.49 | 0.73 | 458 |
| 38 | 227.46 | 115.41 | 87.24 | 0.06 | 0.62 | 0.89 | 734 |
| 39 | 182.12 | 59.68 | 44.86 | 0.07 | 0.76 | 0.71 | 732 |
| 40 | 210.55 | 89.80 | 55.37 | 0.06 | 0.73 | 0.83 | 423 |
| 41 | 223.68 | 94.29 | 69.97 | 0.05 | 0.69 | 0.88 | 840 |
| 42 | 202.99 | 88.65 | 66.24 | 0.11 | 0.68 | 0.80 | 1133 |
| 43 | 185.17 | 77.40 | 58.03 | 0.09 | 0.69 | 0.73 | 700 |
| 44 | 225.60 | 79.75 | 60.07 | 0.04 | 0.73 | 0.89 | 720 |
| 45 | 195.22 | 66.71 | 55.50 | 0.38 | 0.74 | 0.77 | 578 |
| 46 | 222.20 | 138.92 | 74.81 | 0.08 | 0.66 | 0.87 | 283 |
| 47 | 219.69 | 149.82 | 93.46 | 0.09 | 0.57 | 0.87 | 228 |
| 48 | 153.53 | 144.39 | 70.86 | 0.18 | 0.60 | 0.69 | 259 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 52 | 134.53 | 189.94 | 83.23 | 0.25 | 0.58 | 0.74 | 975 |
| 53 | 151.72 | 194.96 | 86.91 | 0.23 | 0.56 | 0.76 | 821 |
| 54 | 145.50 | 163.08 | 107.50 | 0.22 | 0.35 | 0.64 | 573 |
| 55 | 195.66 | 207.79 | 141.83 | 0.20 | 0.33 | 0.82 | 519 |
| 56 | 145.00 | 172.38 | 84.91 | 0.22 | 0.52 | 0.68 | 537 |
| 57 | 138.94 | 185.87 | 97.16 | 0.25 | 0.49 | 0.73 | 458 |
| 58 | 174.30 | 187.40 | 115.87 | 0.20 | 0.40 | 0.74 | 922 |
| 59 | 227.46 | 115.41 | 87.24 | 0.06 | 0.62 | 0.89 | 734 |
| 60 | 195.22 | 66.71 | 55.50 | 0.38 | 0.74 | 0.77 | 578 |
| 61 | 182.12 | 59.68 | 44.86 | 0.07 | 0.76 | 0.71 | 732 |
| 62 | 210.55 | 89.80 | 55.37 | 0.06 | 0.73 | 0.83 | 423 |
| 63 | 211.82 | 82.99 | 42.22 | 0.05 | 0.80 | 0.84 | 670 |
| 64 | 223.68 | 94.29 | 69.97 | 0.05 | 0.69 | 0.88 | 840 |
| 65 | 202.99 | 88.65 | 66.24 | 0.11 | 0.68 | 0.80 | 1133 |
| 66 | 185.17 | 77.40 | 58.03 | 0.09 | 0.69 | 0.73 | 700 |
| 67 | 229.98 | 64.00 | 53.70 | 0.30 | 0.77 | 0.90 | 220 |
| 68 | 225.60 | 79.75 | 60.07 | 0.04 | 0.73 | 0.89 | 720 |
| 69 | 222.20 | 138.92 | 74.81 | 0.08 | 0.66 | 0.87 | 283 |
| 70 | 219.69 | 149.82 | 93.46 | 0.09 | 0.57 | 0.87 | 228 |
| 71 | 220.28 | 140.99 | 73.31 | 0.08 | 0.66 | 0.87 | 163 |
| 72 | 190.51 | 153.43 | 89.06 | 0.14 | 0.54 | 0.78 | 185 |
| 73 | 153.53 | 144.39 | 70.86 | 0.18 | 0.60 | 0.69 | 259 |

Image Segmentation

The computer analyzes the given vegetable images, and then separates and identifies the types of vegetables. This can be achieved using machine learning techniques that have been trained with a dataset containing images of broccoli, chili, potato, cabbage, Chinese cabbage, tomato, and carrots. The following table provides an explanation of the image segmentation for broccoli, chili, potato, cabbage, Chinese cabbage, tomato, and carrot.

Table 1. Segmentation Vegetables

| Vegetable | Description | Image Segmentation |
|---|---|---|
| Broccoli | Green vegetable with a dense, flower-like head and thick stalk. | The segmentation process identified and separated the broccoli head and stalk from the background or other vegetables in the image. |
| Chili | A spicy vegetable with a long, tapered shape is available in various colors such as green, red, or yellow. | The segmentation process for chili involves accurately delineating the chili's shape, distinguishing it from other vegetables, and potentially identifying its color for classification purposes. |
| Potato | A starchy vegetable with brown or yellowish skin and white or yellowish flesh. | The segmentation process identifies and separates the potato from the rest of the image, including differentiating the skin from the flesh if necessary. |
| Cabbage | It is a round- shaped vegetable with tightly packed leaves, available in different colors, such as | The segmentation process for cabbage involves accurately delineating its round shape and differentiating it from other vegetables or background elements in an image. |

| | | |
|---|---|---|
| | green or purple. | |
| Chinese Cabbage | A type of cabbage with wrinkled leaves and thick stems, with a more elongated shape than regular cabbage. | The segmentation process for Chinese cabbage aims to accurately identify and isolate its unique shape and distinguish it from other vegetables or background elements. |
| Tomato | Red or yellowish vegetable with smooth and shiny skin and soft flesh inside. | The segmentation process for tomatoes involves accurately delineating their round or slightly oval shape, distinguishing them from other vegetables, and identifying their color for classification purposes. |
| Carrot | Orange vegetable with a long, tapered shape, crunchy texture, and sweet taste. | The segmentation process identifies and separates the carrot from the rest of the image and captures its distinct shape and color. |

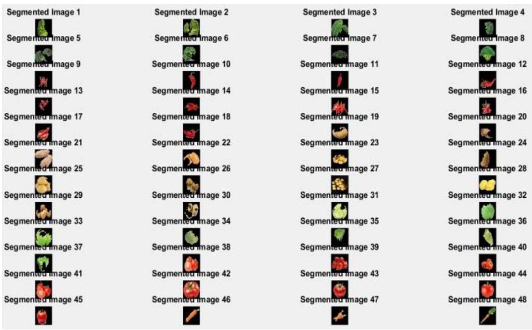



Figure 6. Vegetable Images Segmentation

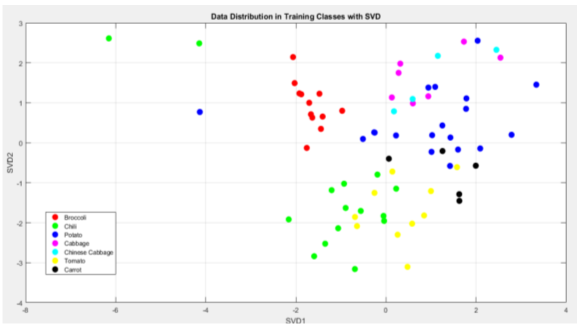
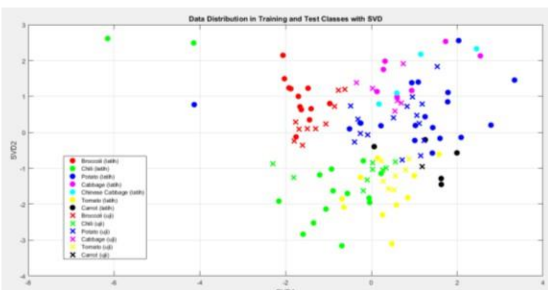



Figure 7. Distibution of Training Data

Figure 7 we can observe the distribution of data that represents the classes of

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vegetable types from the images that have been used as training objects. These serve as a comparison for the test image data to determine the vegetable type. The color red indicates the category of Broccoli, Green represents the category of Chili, Blue represents the category of Potato, Magenta represents the category of Cabbage, Cyan represents the category of Chinese Cabbage, Yellow represents the category of Tomato and Black represents the category of Carrot.

Figure 8. Distibution of Testing Data

In Figure 8 the distribution of test data is depicted, showing a comparison between the training data and the test data marked with colored crosses. The red cross represents the tested category Broccoli, Green cross represents the tested category Chili, Blue cross represents the tested category Potato, Magenta cross represents the tested category Cabbage, Cyan cross represents the tested category Chinese Cabbage, Yellow cross represents the tested category Tomato and Black cross represents the tested category Carrot.

Conducting tests on the 48 test image data using the SVD and KNN algorithm classification applications, the following table presents the classification output for the vegetable types:

Table 2. Classification Result

| No. | Testing Data | Classification Result | |
|---|---|---|---|
| 1 | Broccoli | Broccoli | True |
| 2 | Broccoli | Broccoli | True |
| 3 | Broccoli | Broccoli | True |
| 4 | Broccoli | Broccoli | True |
| 5 | Broccoli | Broccoli | True |
| 6 | Broccoli | Broccoli | True |
| 7 | Broccoli | Broccoli | True |
| 8 | Broccoli | Broccoli | True |
| 9 | Chili | Chili | True |
| 10 | Chili | Chili | True |
| 11 | Chili | Chili | True |
| 12 | Chili | Chili | True |
| 13 | Chili | Chili | True |
| 14 | Chili | Chili | True |
| 15 | Chili | Chili | True |

| | | | |
|---|---|---|---|
| 16 | Chili | Chili | True |
| 17 | Chili | Chili | True |
| 18 | Chili | Broccoli | False |
| 19 | Potato | Potato | True |
| 20 | Potato | Potato | True |
| 21 | Potato | Potato | True |
| 22 | Potato | Potato | True |
| 23 | Potato | Potato | True |
| 24 | Potato | Potato | True |
| 25 | Potato | Potato | True |
| 26 | Potato | Potato | True |
| 27 | Potato | Potato | True |
| 28 | Potato | Potato | True |
| 29 | Potato | Potato | True |
| 30 | Potato | Potato | True |
| 31 | Cabbage | Cabbage | True |
| 32 | Cabbage | Cabbage | True |
| 33 | Cabbage | Cabbage | True |
| 34 | Cabbage | Cabbage | True |
| 35 | Chinese Cabbage | Cabbage | False |
| 36 | Chinese Cabbage | Cabbage | False |
| 37 | Chinese Cabbage | Broccoli | False |
| 38 | Tomato | Tomato | True |
| 39 | Tomato | Tomato | True |
| 40 | Tomato | Tomato | True |
| 41 | Tomato | Tomato | True |
| 42 | Tomato | Tomato | True |
| 43 | Tomato | Tomato | True |
| 44 | Tomato | Tomato | True |
| 45 | Tomato | Potato | False |
| 46 | Carrot | Potato | False |

| | | | |
|---|---|---|---|
| 47 | Carrot | Potato | False |
| 48 | Carrot | Carrot | True |

The formula used to calculate the accuracy of the test results was as follows:

$$accuracy = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} X\ 100\ \%$$

The accuracy testing between the training data and test data resulted in an 85,42% accuracy, with 7 inaccurate data results from the 48 test image data. This indicates room for improvement to enhance the accuracy of the output of the system.

## CONCLUSIONS

Based on the implementation and testing of the classified vegetable types, the following conclusions can be drawn:

1) The classification process involves analyzing the original image, binary image, and grayscale image of various vegetable types. The extracted features, including RGB, HSV, and area, serve as inputs for singular Value Decomposition (SVD) and K-nearest neighbor (KNN) algorithms for classifying vegetables.
2) The singular Value Decomposition (SVD) and K- Nearest Neighbors (KNN) algorithms may perform well in classifying vegetable types with 73 training data images and 48 test data images. These images have a resolution of 40 by 40 pixels and are in JPG format.
3) The classification evaluations on the image of vegetables using K-Nearest Neighbor (KNN) with the number of neighbors at k = 7 based on extraction Singular Value Decomposition (SVD) give 85,42% accuracy.
4) This technology can also assist in selecting and processing healthy food ingredients. For example, farmers can use software to evaluate their crop yields and ensure that the vegetables they grow are of high quality. The food industry can use this application to assess the nutritional content of vegetables and other food items, leading to the creation of healthier and more nutritious meals.

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