SUGISAKA MASANORI

Journal of Advances in Artificial Life Robotics
Vol. 3(3); December (2022), pp. 155–162
ON LINE ISSN 2435-8061; ISSN-L 2435-8061
https://alife-robotics.org/jallr.html

Research Article

Automatic Dry Waste Classification for Recycling Purposes

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ARTICLE INFO

Article History

Received 11 November 2021
Accepted 28 March 2023

Keywords

Support vector machine
Recycling
Feature extraction
Classification

ABSTRACT

In recent decades, the rapid growth of urbanization and industrialization has resulted in a significant increase in solid waste, creating an urgent issue that demands attention. The accumulation of solid waste poses a significant challenge, as it can lead to environmental pollution. Recycling is a viable solution that offers economic and environmental benefits. To address this challenge, various intelligent waste management systems and methods are necessary. This research paper explores the use of image processing techniques to classify different types of recyclable dry waste. The study proposes an automated vision-based recognition system that includes image acquisition, feature extraction, and classification. The intelligent waste material classification system extracts 11 features from each dry waste image. The study employed four classifiers - Quadratic Support Vector Machine (Q-SVM), Cubic Support Vector Machine (C-SVM), Fine K-Nearest Neighbor (Fine KNN), and Weighted K-Nearest Neighbor (Weighted KNN) - to categorize the waste into distinct classes, such as bottle, box, crumble, flat, cup, food container, and tin. Among these, the C-SVM classifier performed impressively well, achieving an accuracy of 83.3% and 81.43% during training and testing, respectively. This classifier exhibited consistent performance and had a shorter computation time, making it a highly effective method. Although using the Speeded-Up Robust Features (SURF) method could enhance the classification process, it may lead to longer response and computation times.

1. Introduction

Solid waste comprises all non-liquid waste materials, with the exception of excreta, although diapers and young children's feces may occasionally be included. Inadequate solid waste management can have severe health consequences and create an unpleasant living environment. When waste is not disposed of properly, it can serve as breeding grounds for insects, pests, snakes, and vermin, thereby increasing the risk of disease transmission. Moreover, solid waste can contaminate water sources and the environment, making it one of the most pressing concerns of our time. Municipal solid waste affects every corner of the earth, and statistics show a sharp increase in solid waste generation since the beginning of the last decade [1]. The amount of solid waste produced is closely related to a country's GDP, as high GDP tends to produce more waste. The World Bank report estimates that about four billion tons of waste are generated globally every year, with urban areas contributing up to 70% of this waste. The report also predicts that the number of accumulated wastes will rapidly increase in underdeveloped nations over the next 25 years due to the accelerated pace of urbanization and industrialization [2].

According to the Department of Statistics Malaysia in 2012, the population growth rate has remained at 2.4% per year since 1994. The more people there are and the

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higher their consumption rates, the more waste is generated. There is a relationship between income and urbanization, where an increase in disposable income and living standards leads to higher consumption of products and services and an accompanying increase in waste production. With the increasing number of industries in urban areas, the efficient management of solid waste presents a crucial and challenging task for municipal authorities worldwide, given the substantial volume of waste produced. In developing nations, solid waste management is particularly intricate due to insufficient door-to-door collection, inefficient treatment, and inadequate disposal facilities [3]. Most of the solid waste is comprised of materials commonly found in the public domain, including paper, plastics, and glass waste.

Landfilling is the primary method of waste management, with 80% of trash in the United States being handled through this process. However, landfilling presents significant health and ecological concerns, making it an inefficient solution. The high cost of operation and environmental pollution make this method undesirable, particularly for those living in close proximity to landfill sites. Another waste management solution is the use of incinerators to reduce the volume of waste. However, this approach has negative consequences and can lead to severe health problems, including cancer because of vulnerability to hazardous materials such as polycyclic aromatic hydrocarbons (PAHs) released into the air during the process. Incinerators are also expensive to build, operate and maintain. Recycling and reusing waste are currently the most effective solution for waste disposal problems. Recent research indicates that up to 150 million tons of waste can be recycled, providing a rich source of various recyclable materials. Utilizing these materials for recycling can be beneficial in reducing adverse environmental impacts and safeguarding human health. Waste sorting practices are implemented as a starting point for solid waste management, separating waste into different categories to be recycled using various techniques. Thus, recycling is an essential tool for protecting our environment and ensuring human health [2].

Numerous studies and research papers have been published regarding waste sorting and classification using various methods. This study specifically focuses on the automated sorting of dry waste materials such as plastics, bottles, paper, and tin cans using a classification and vision system. A review of the literature was conducted to gain an understanding of the various materials that are classified, and the techniques utilized for multi-material sorting. The aim of this work is to address the need for more prominent, outstanding, and discriminative features that can improve classification accuracy.

2. Methods

2.1 Vision-based recognition system

The system for dry waste classification proposed in this study utilizing vision inspection method comprises several modules, including image acquisition, image processing, feature extraction, classification, and decision determination, as illustrated in Fig. 1.

2.2 Image Acquisition

The initial step in image processing is always image acquisition. In this waste sorting system, the inspection zone is enclosed by a box housing, as shown in Fig. 2, where the images for classification are captured. A web camera (Logitech QuickCam V-UAP41 USB) is manually used to capture RGB images of the waste samples within the inspection zone. The camera is fixed at a distance of 25 cm from the test sample and mounted on the top-middle surface of the box, which is positioned upside down. The properties such as brightness, contrast, and saturation adjustment is performed according to their individual scales. For illumination, a homogenous lighting technique is employed to capture a set of geometric properties such as the size, shape, orientation, and position of the waste samples.

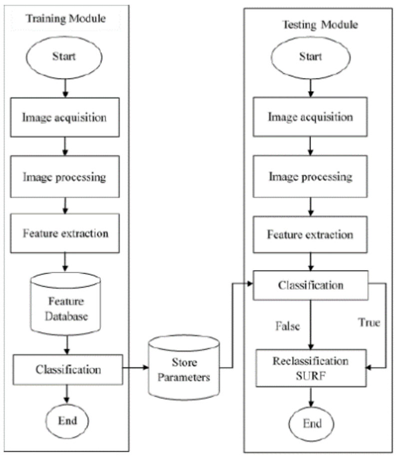


Fig. 1. Proposed conceptual framework for the training and testing stages.

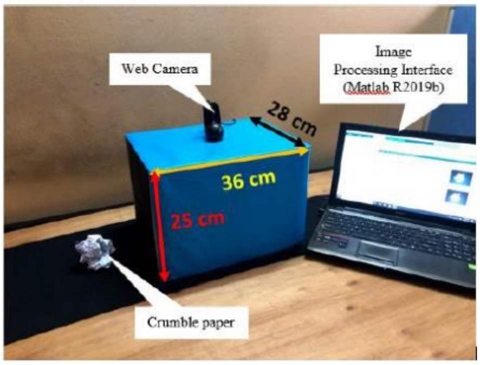


Fig. 2. A photograph of a configuration designed for a recognition system based on visual input.

The experiment involved collecting a total of 280 samples, out of which 210 were utilized for training purposes, and the remaining 70 were used for testing. The test samples were procured from a range of sources, including homes, offices, shops, and markets, and comprised of 7 distinct categories - crumble garbage, flat garbage, tin cans, bottles, food containers, cups, and boxes. Each group was comprised of 10 test samples, each varying in appearance with respect to shape, size, diameter, and orientation. Fig. 3 displays a subset of randomly selected test samples from each category. The photographs were captured at a resolution of 640×480 pixels.

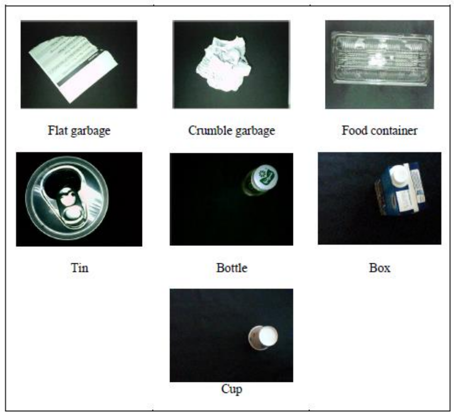


Fig.3. Test samples of dry waste image.

2.3 Pre-Processing of Image

The focus of this section is on image pre-processing techniques, specifically segmentation and thresholding, aimed at isolating the area of interest in the test sample and facilitating object detection, which is a crucial module. Various techniques have been developed for object detection, such as the boosted cascade algorithm [4], histogram of gradients [5], and shift invariant feature transform [6]. These algorithms are used to extract objects from 2D intensity images while considering the image's background. Fig. 4 demonstrates the process of segmenting the sample image. Firstly, the original RGB image, with dimensions of 640×480 pixels, is read into MATLAB R2019b and resized to 320×240 pixels by a factor of 0.5. To simplify the image and reduce its complexity from three dimensions to two, the RGB image is converted to grayscale format. Edge detection and morphological operations are employed to remove background information from the image and detect the test sample's area. The Sobel filter, with a fudge factor value of 0.9, is used as an edge detector to detect the contrast change between the object's image and background. The resulting image outline is precise, and the threshold values are determined using the Sobel operator, while edge detection is used to generate the binary mask. The outline images are dilated using linear structure elements to obtain a more precise gradient mask, and any gaps in the dilated images are filled through morphological operations. Connected objects situated on the image border are eliminated, and the segmentation process is performed to extract the crumble garbage's area. The segmentation flow process for each class sample type is depicted in Fig. 5.

Fig. 4. Process of image segmentation

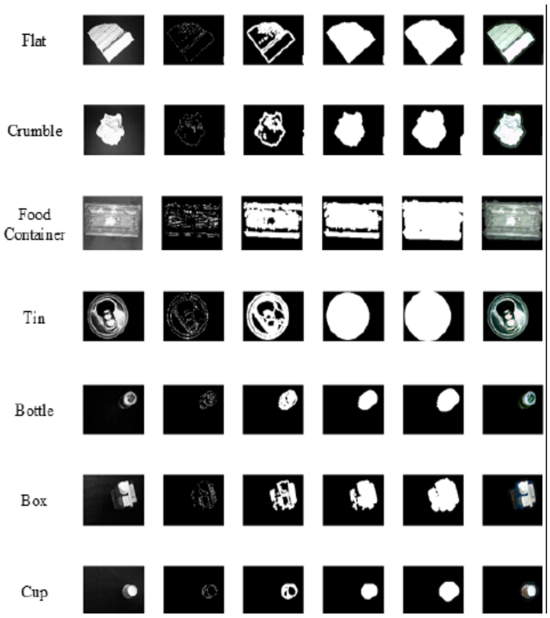
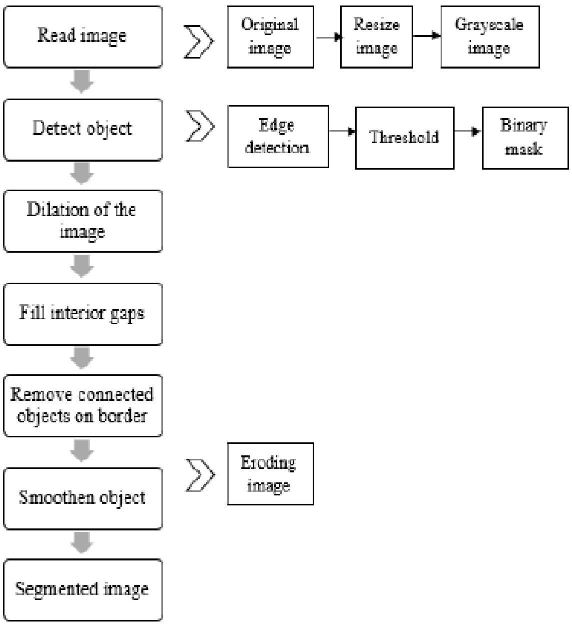


Fig. 5. The segmentation flow process for each class sample type



2.4 Feature Extraction

The classifier model utilizes features to recognize the material type and coordinates, which are obtained through image processing as demonstrated in Fig. 6. Two datasets were created for training and testing, each containing statistical and non-statistical features. The first dataset is obtained from the segmented grey image, while the second dataset is obtained from the white pixel plot of the sample. From the segmented grey image, features such as grey level co-occurrence matrix (GLCM), ratio of grey level, entropy, and standard deviation are extracted. On the other hand, the white pixel plot of each sample image has a unique shape that enables feature extraction for classification. Quantile is the statistical data used from the white pixel plot. GLCM provides a second-order statistical analysis of an image by evaluating the frequency at which pairs of pixels consisting of specific values and spatial relationships occur in an image. The probability, $p(m,n)$ is calculated using Eq. (1) [7]:

$$p(m,n) = \{C(m,n)|(d,\theta)\} \quad (1)$$

The inter-pixels displacement distance is represented by d, while orientation is denoted by θ, and $C(m,n)$ indicates the frequency of gray level occurrence in MSCN of the image.
From the GLCM matrix, four statistical textures, namely contrast, correlation, energy, and homogeneity, are extracted. The details of these textures are shown in Table 1.

Table 1: GLCM parameters [7]

Parameters	Formular	Description
Contrast	$\sum_{m,n} \lvert m-n\rvert^2 p(m,n)$	Local variations in the GLCM
Correlation	$\sum_{m,n} \frac{(m-\mu m)(n-\mu n)p(m,n)}{\sigma_m \sigma_n}$	The probability of occurrence of the specified pixel pairs
Energy	$\sum_{m,n} p(m,n)^2$	Sum of the squared components in the GLCM, and it is also referred to as uniformity or angular second moment
Homogeneity	$\sum_{m,n} \frac{p(m,n)}{1+\lvert m-n\rvert}$	How closely the distribution of elements in the gray-level co-occurrence matrix (GLCM) resembles the GLCM diagonal

Fig. 6. Overall process of Image processing used.

The brightness value of a pixel, referred to as grey level,

is a crucial factor in image processing. The maximum grey level value is determined by the bit depth of the image, such that an 8-bit image can have a maximum of 255 levels covering any value within that range. Conversely, a binary image can only assume values of either 0 or 255. Table 2 provides an overview of the grey levels. The program is designed to calculate the ratio of grey levels (H) and (L) for values within the ranges $40 < x \leq 110$ and $181 \leq x \leq 255$, respectively.

Table 2. Grey level and its respective color

Grey level	Colour
0	Black
$0 < x < 255$	Grey
255	White

Another important parameter in the field of image processing, entropy is a statistical metric used to describe the level of randomness in an input image [8]. A greater level of detail in an image is indicated by a higher entropy value. Entropy is a measure of the information contained in an image, and it represents the average uncertainty of an information source. A vector with a "low" entropy contains less information, such as [0 1 0 1 1 1 0], whereas a vector with a "high" entropy contains more information, such as [0 242 124 222 149 13]. Therefore, having a higher entropy value is crucial to obtain a more accurate segmented image after post-processing, allowing for a more precise classification based on respective groups. The algorithm for calculating entropy is presented in Eq. (2):

$$\mu_m = \sum_{m,n=0}^{i-1} p_{m,n}\left(-\ln\left(p_{m,n}\right)\right) \qquad (2)$$

Standard deviation is a commonly used statistical method that measures the level of variability or diversity in a given dataset. In image processing, it measures the degree of variation from the mean value. The overall standard deviation is frequently utilized as a more accurate gauge of the statistical distribution for each category [9] .

To calculate the maximum quantile, linear interpolation is used to determine the values between data points. The quantile function initially sorts the values in x and assigns them to the(0.5/n), …., ([n-0.5]/n) quantiles [10].

2.5 Classification of Image

2.5.1 Support Vector Machine (SVM)

MATLAB's Classifier Learner Application is used to carry out the SVM classification process in the experiment [11] The SVM category comprises six classification models, namely linear SVM, quadratic SVM, cubic SVM, fine Gaussian SVM, medium Gaussian SVM, and coarse Gaussian SVM. The experiment employs 5-fold cross-validation to evaluate the prediction accuracy of the model, which is considered the optimal number of k-fold. Increasing the number of k-fold can lead to lower accuracy, and increasing accuracy does not guarantee protection from overfitting data. The cost matrix in this experiment utilizes default settings for misclassification costs, and Table 3 presents the other parameters used in SVM.

Table 3. The parameters used to configure SVM in the classifier learner application.

Type of SVM	Parameters			
	Kernel scale	Box constraint	Multiclass method	Standardized data
Linear	Automatic	1	One-vs-One	True
Quadratic	Automatic	1	One-vs-One	True
Cubic	Automatic	1	One-vs-One	True
Fine Gaussian	0.79	1	One-vs-One	True
Medium Gaussian	3.2	1	One-vs-One	True
Coarse Gaussian	13	1	One-vs-One	True

2.5.2 K-Nearest Neighbor

The k-nearest neighbor (k-NN) algorithm functions by treating the training examples as vectors in a feature space that includes a class label for each vector. During the training phase, the algorithm stores the feature vectors and class labels of the training samples. In the classification stage, an unlabeled vector, also known as a test point or query, is classified by assigning the tag that is most prevalent among the k training datasets closest to that query point. Typically, the Euclidean distance is used as the distance metric for continuous variables, while a differentiation metric like the Hamming distance is used for discrete variables such as text classification. In gene expression microarray data, k-NN is applied using coefficients such as Pearson and Spearman as distance metrics. The accuracy of k-NN can be enhanced by using specialized algorithms to learn a distance metric, such as Large Margin Nearest Neighbor and Neighborhood Components. However, k-NN has a drawback in cases of skewed class allocation, where examples of a more common class tend to dominate the new example prediction. To overcome this issue, the distance between the test point and each of its closest neighbors is evaluated, and each of the nearest k points is multiplied by a weight proportional to the inverse of its distance to the test point by a class (or value in regression problems). Table 4 displays the parameters used for k-NN, and the cost matrix in this experiment employs default settings for misclassification costs.

Table 4 The parameters used to configure KNN in the classifier learner application.

Type of KNN	Parameters			
	Number of neighbor	Distance metric	Distance weight	Standardized data
Fine	1	Euclidean	Equal	True
Medium	10	Euclidean	Equal	True
Coarse	100	Euclidean	Equal	True
Cosine	10	Cosine	Equal	True
Cubic	10	Cubic	Equal	True
Weighted	13	Euclidean	Squared Inverse	True

3. Results and Discussions

The experiment involved using seven categories of dry waste, including bottle, box, crumble garbage, flat garbage, cup, food container, and tin cans. For each category, a set of 30 images were collected as samples. The experiment was split into two phases, namely the training phase and the testing phase. Table 5 provides a summary of the dataset containing the dry waste images used in the experiment.

Table 5: Dataset of dry waste images.

Type of dry wastes	Number of training samples	Number of testing samples
Bottle	30	10
Box	30	10
Crumble garbage	30	10
Flat garbage	30	10
Cup	30	10
Food container	30	10
Tin can	30	10
Total	**210**	**70**

Table 6 presents the training outcomes of the four classifiers used in the experiment, while Table 7 summarizes the average classification accuracy of each classifier. The main objective of training these classifiers as predictive models was to validate their performance.

Table 6. Training classification accuracy results.

Classifier	Number of training									
	1	2	3	4	5	6	7	8	9	10
Quadratic SVM	80	79	76.7	77.1	79	75.7	79	73.3	78.6	75.7
Cubic SVM	83.3	81.9	81	80	82.4	79.5	80	78.1	81	80.5
Fine KNN	81.4	83.8	82.4	81.9	84.8	80.5	83.3	81	82.4	81.9
Weighted KNN	81.4	83.8	82.4	81.9	84.8	80.5	83.3	81	82.4	81.9

Table 7. Average training accuracy.

Classifier	Average training accuracy (%)
Quadratic SVM	77.41
Cubic SVM	80.77
Fine KNN	82.34
Weighted KNN	79.62

Table 8 presents the classification accuracy of each classifier during the testing phase. It is worth mentioning that the column labeled "Models" in Table 8 denotes the most accurate classification models that were saved and applied as predictive models during the testing phase of the experiment.

Table 8. Training classification accuracy result.

Type of classifier	Models (training session)	Number of testing sample predicted correctly	Classification accuracy (%)
Quadratic SVM	1	52	74.29
Cubic SVM	1	57	81.43
Fine KNN	5	45	64.29
Weighted KNN	9	44	62.86

Table 8 indicates that during the testing phase, the highest classification accuracy was achieved by Cubic SVM with a rate of 81.43%. Although Fine KNN had the highest training accuracy of 82.34%, its performance in the testing phase was much lower.

4 Conclusion

The objective of this research was to use image processing techniques, including pre-processing methods and feature extraction, to recognize different types of dry waste for recycling purposes. The study successfully identified seven types of dry waste, including bottle, box, crumble garbage, flat garbage, tin can, food container, and cup. To differentiate these types of dry waste into their respective classes, various image pre-processing approaches such as edge detection, image dilation, image filling, and image smoothing were used. At the initial stage, the white pixel plot was used to distinguish the data and provide a clear picture of each class. Further approaches were employed to identify each type of dry waste based on sample image loads.

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