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A SURVEY ON SOLID WASTE SORTING AND CLASSIFICATION TECHNIQUES

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Abstract*-Around the world millions of tons of garbage are generated daily. In many countries such amounts of garbage generation pose great threat to environmental health and increase the risk of contaminating the living condition for humans and animals. Presently nations around the world conduct research and explore the possibility of management of garbage collected. Management of waste is a complex work which requires more number of human resources and the cost of managing few tons of garbage become high due to lack of right technology to support. Sorting and processing of waste is complex due to the diversity of materials dumped is large and require many specialized techniques. This paper surveys on waste classification methods and techniques using image processing.

Keywords: image processing, waste classification, data mining, image classification, waste recycling, machine learning

I. INTRODUCTION

The global environment is polluted and affected by large amount of garbage accumulated. The garbage wastes are thrown away in lands and water bodies which contaminates the environment and ground water. Approximately in India, 63 tonnes of municipal waste is generated annually and expected to affect the environment in a large scale if not managed properly. Waste management is a process of identifying, treating and disposal of waste. Technology growth and advancement gives immense opportunity to convert waste into wealth. Waste management targets for managing waste through reuse, recycle, and reduction of waste. The difficulty in solid waste management continues to grow with increasing population and more number of lands are urbanized.

The process of solid waste management starts with sorting of wastes into degradable and non degradable. This sorting of waste require large number of human labors to manually segregate into plastic, glass, paper, food etc. When plastics are separated and the plastics can be recycled to save energy, cost and environment. The cost of waste management is high and requires capital to automate the process where human labors could be reduced. However there are more opportunities to improve waste recycling through creating regulations, allocating funds, improving awareness on waste segregation, improving recycling technology, and reducing the cost of management of waste collection and processing.

Presently the waste sorting is carried out using machines still require high precision is discriminating objects into appropriate categories. The waste objects are fed in a conveyor where the objects are separated manually and by tools. The cost of separating manually becomes high and time consuming with humans and the performance of separating tools depends on the precision of classifying the objects automatically. The classification of each object is presently aided through computer vision and machine learning technology. Data mining is a process of extracting useful information and patterns hidden inside large volume of data. Machine learning is a division of data mining through which algorithms gain the ability to improve their performance through self-learning. Data mining and machine learning algorithms are used in variety of data formats which includes numerical data, signals, multimedia formats, spatial data, sensor data etc.

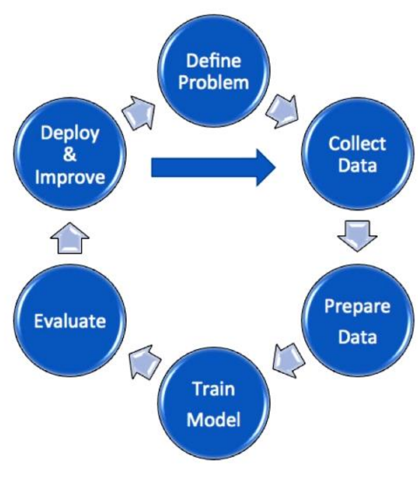

Fig 1 Machine Learning Process

Machine learning algorithms and computer vision technology together forms the image processing unit where digital images are acquired, processed and analyzed. The machine learning algorithms are broadly classified based on the learning type. The type of learning includes supervised, unsupervised, reinforced learning and associations. Supervised learning models include classification while unsupervised models include clustering or grouping. Digital images can be processed through both supervised and unsupervised learning models.

This paper is organized into three sections, section I gives an introduction about waste management and Machine learning, section II presents the literature survey on various image processing techniques used for waste management, image classification, object identification and section III concludes the survey paper.

II LITERATURE SURVEY

(Wang et al., 2019) classified plastic bottles based on their position into adjacent, overlap and disjoint using distant measurement and threshold segmentation. The work also extends to classify plastic bottle colors using ReliefF algorithm for selection of color features and the extracted color features are classified using SVM. The classification accuracy achieved 94% and promised more opportunity to separate bottles based on color aspects.

(Srinilta et al., 2019) studied different CNN models on waste classification. The solid waste dataset uses four categories of waste namely general waste, compostable waste, recyclable waste and hazardous waste. The experiments were conducted on four different CNN architectures such as VGG-16, ResNet-50, MobileNet V2 and Dense-Net-121. ResNet-50 achieved a highest accuracy of 98%. The study concluded that CNN models are effective in waste classification.

(Zhang et al., 2019) proposed a novel method for segmenting solid wastes that are connected using adaptive spatial projection. The objects are segmented using building object surface plane. The object surface angles are adjusted using descent method. The proposed work is compared with local convexity and constrained planar cuts-object partitioning methods. The results shows that the proposed work achieve better results with 92% of accuracy where LCCP achieved 87% and CPC achieved 89%.

(Sreelakshmi et al., 2019) proposed a new CNN for classifying plastics and non-plastics solid waste. Using sigmoid activation function, a capsule net network is constructed with 32 capsules and a convolution network is used to compare the performance of the proposed network using two different dataset. The experiment results shows that capsule-net show higher accuracy on two datasets with 96% and 95% while CNN show 95% and 93%. The proposed model show better detection rate between non-plastic waste and plastic waste.

(Rabano et al., 2019) developed an android based mobile application for waste classification. The model is constructed using MobileNet transfer learning and the model is trained on 2537 trash images categorized into glass, picture, cardboard, plastic and metal and other trash. The model achieved an accuracy of 87% while classifying trash images.

(Adedeji & Wang, 2019) proposed a waste classification system using ResNet-50. Res-Net50 is convolution network that can extract features from the images. The image dataset contains glass, metal, paper and plastic. The CNN was able to classify the images with an accuracy of 87% and the study concludes that CNN based networks are suitable for waste classification.

(Valente et al., 2019) proposed a computer vision based method for detecting different bins. The waste containers are detected using a CNN (Yolo) using random images and green, yellow, blue colors. The detection of containers is aided through features extracted from the containers images and CNN network produce a 90% of accuracy in detecting the containers effectively.

(Bandal et al., 2019) proposed a framework to predict the quality of banana fruit. The framework utilizes a hybrid method of sensor and image characteristics. The sensor data is used to extract the features based on gases present in the fruit. Using image characteristics 36 features are extracted and four features of gases are finally selected for classification. Using unsupervised clustering technique the features are classified into three labeled classes. The classification framework achieved 95% accuracy.

(Liu et al., 2018) proposed a intelligent waste sorting method using a two step process. In the first step images are acquired using raspberry module and in the second step the features are extracted using an improved version of scale variant feature transform method. The captured feature BOWs are stored into the database and using k means clustering the similarity of the vector features in the training sample. The data set comprises of image categories such as batteries, bottles, jars, paper balls, paper boxes. The features are classified using SVM classifier and the algorithm achieves an accuracy of 83%.

(Aral et al., 2018) demonstrated a comparative study on different deep learning models to classify trash waste using Trashnet dataset. The dataset contains images of paper, glass, trash, metal and plastic. Xception, MobileNet, DenseNet121 performances are compared using testing accuracies of the models. To improve the performance accuracy Adam and Adadelta optimizers are used to fine tune the accuracy. The fine tune accuracy rate shows that DenseNet121 show 95% accuracy and Mobilenet show 84% accuracy while classifying waste.

(Xu et al., 2018) proposed a new method to identify three fruit fly species using image processing. The images are pre processed for image registration using Hough transform and the image is segmented at color space YCbCr. The classification of firefly is achieved through NNBP and the model achieved 100 Accuracy.

(Ramalingam et al., 2018) developed an automated cleaning robot for clearing dust in the floor. The features are extracted using MObileNetV2 CNN and SVM is used for dust classification. The CNN is trained to distinguish between solid and liquid spills, depth and length is measured using bounding box. The network achieved 95% accuracy in detecting solid and liquid dust.

(Gundupalli et al., 2017) demonstrated that classification of dry recyclables such as PVC, Wood, SS, HDPE, LDPE, Al, Cr, Fe, Paper using thermal images. The sorting of solid wastes and the products are classified through feature selection by Out's threshold method. The extracted features include mean, standard deviation and intensities which are later classified for each object using nearest neighbor classifier. The classifier achieved an accuracy of 96% and includes multiple objects in the thermal image.

(Tehrani, 2017) developed a real time sorting of plastics. The study sorted hyper spectral images of PS, PC, PP, ABS and HIPS plastic data using PCA and ANN classifier. The ANN model achieved 99% accuracy with 5 input neurons, 4 hidden neurons and 3 three output neurons.

(Milinda et al., 2017) proposed a novel method for detecting mud and dirt cleaning. The proposed method involves a image capturing module and detection model. In the detection model, the image is first converted into bit planes and the edges are identified using canny function and residual split is used to distinguish mud and dirt. The classifier achieved 70% accuracy for mud and dust detection.

(Zeng et al., 2017) proposed a new object detection method using bacterial foraging algorithm. The algorithm is modified to set up dynamic step up and replaced by dynamic probability. Using the improved version of the algorithm, the features are detected. The dataset contains images three categories namely pedestrian, cars and pets. The proposed method outperforms other methods with high accuracy rate of detection of objects.

(Hannan et al., 2016) proposed content based image retrieval systems to detect solid waste bins. The work concentrated on matching the query image with the image in the database. The proposed method uses Gabor filter, GLCM and GLAM feature extraction methods. The performance of the method is evaluated through MLP and KNN classifiers. KNN show better performance than MLP with 97% of accuracy.

(Srigul et al., 2016) investigated the classification of plastic pet bottles using RGB color histogram and multiple correlations. The image intensities from Histogram are used to construct the correlations. The classification of non-pet bottles and pet-bottles achieved 93% of accuracy favoring classification of plastic models for sorting of solid waste and plastic recycling.

(Sakr et al., 2016) compared SVM and CNN techniques in waste classification. The dataset consist of images in three categories plastic, metal and paper. The automated sorting of waste is implemented using raspberry pi 3. The classification performance of SVM is higher than CNN with 94% accuracy which is higher than CNN with 83%. The adaption of SVM model to different waste was higher than CNN, where the CNN need to trained each time, a new waste is introduced.

(Mittal et al., 2016) developed a mobile application to detect rough regions in garbage. Using a CNN Garbnet is trained on the images to detect garbage present in the image. The network is tuned to fully connected network instead of sliding widow as sliding window have already recorded that it can cause spare process due to overlapping of input-output regions. The features in the images are processed with Gabor and PCA. The model significantly achieves 87% of accuracy.

(Gottschling et al., 2016) proposed a frame work for classification of papers based on the compositions of the paper. Based on weight, shape, color, texture 26 features are extracted and classified on different machine learning algorithms such as KNN, QDA, DT, NN and SVM. The dataset taken for the study has 11 classes of paper. The classification accuracy improves to about 80% from 50% when features are selected for classification.

(Islam et al., 2014) developed a new approach for detecting bins and estimating the solid waste. DWT is used to segment bin area and Gabor wavelet is used for feature extraction. The extracted features are trained in MLP classifier to solid waste at each bin level. The model achieved an accuracy of 98% in detecting the solid waste inside the bins and suggested that the proposed model is suitable for estimation of bin level waste.

(Arebey et al., 2012) investigated the performance of KNN and MLP network using GLCM features on solid waste classification at container level. The ten features extracted from GLCM, show less than 90% accuracy on MLP classifier and KNN shows accuracy about 90%. When 10 features are reduced to 3 features, MLP does not improve in its performance which means feature selection does not affect the MLP accuracy.

Table 1 Performance of various machine learning techniques on waste classification

References	Method	Accuracy (%)
(Wang et al., 2019)	ReliefF +SVM	94%
(Srinilta et al., 2019)	ResNet-50	98%
(Zhang et al., 2019)	object surface plane + descent method	92%
(Sreelakshmi et al., 2019)	capsule-net	96%
(Rabano et al., 2019)	MobileNet transfer learning	87%
(Adedeji & Wang, 2019)	CNN	87%
(Valente et al., 2019)	CNN (Yolo) using random images and green, yellow, blue colors.	90%
(Bandal et al., 2019)	clustering	95%
(Liu et al., 2018)	BOWs+ k means clustering+SVM	83%
(Aral et al., 2018)	DenseNet121	95%
(Xu et al., 2018)	Hough transform + NNBP	100%
(Ramalingam et al., 2018)	MObileNetV2 CNN + SVM	95%
(Gundupalli et al., 2017)	Out's threshold +KNN	96%
(Tehrani, 2017)	ANN	99%
(Milinda et al., 2017)	Canny function + residual split	70%
(Zeng et al., 2017)	mBacterial foraging algorithm	-
(Hannan et al., 2016)	GLMC+Gabor+GLAM+KNN	97%
(Srigul et al., 2016)	RGB color histogram + multiple correlations	93%

(Sakr et al., 2016)	SVM	94%
(Mittal et al., 2016)	PCA+CNN Garbnet	87%
(Gottschling et al., 2016)	KNN, QDA, DT, NN and SVM	50% to 80%
(Islam et al., 2014)	DWT +Gabor+MLP	98%
(Arebey et al., 2012)	GLCM+KNN	90%

III. CONCLUSION

From the literature discussed in this survey it is evident that solid waste management has attracted many researchers. For solid waste sorting problems many machine learning algorithms are designed to use in real time applications which promise better performance. Also the extraction of features plays an important role in machine learning algorithm performances. Moreover neural networks, convoluted neural networks, deep learning methods are efficient in producing accurate sorting and classification of waste materials with accuracy above 90%. Thus machine learning techniques are more suitable for solving problems related to waste segregation in real time, which when incorporated with AI would bring more benefits and capabilities to manage solid waste.

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