



An Assessment of Machine Learning Integrated Autonomous Waste Detection and Sorting of Municipal Solid Waste

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ABSTRACT

Municipal solid waste deposition in metropolitan areas has become a major concern that, if not addressed, can lead to environmental degradation and possibly endanger human health. It is important to adopt a smart waste management system in place to cope with a range of waste materials. This research aims to develop a smart modelling method that could accurately predict and forecast the production of municipal solid waste. An integrated convolution neural network and air-jet system-based framework developed for pre-processing and data integration were developed. The results showed that machine learning algorithms could be used to detect different types of waste with high accuracy. The best performers were obtained from neural network models, which captured 72% of the information variation. The method proposed in this study demonstrates the feasibility of developing tools to assist urban waste through the supply, pre-processing, integration, and modelling of data accessible to the public from a variety of sources.

INTRODUCTION

The World Bank study found that nearly 4 billion tonnes of solid waste are generated in the world every year, and only cities are the biggest contributors to this number, with waste expected to rise by 70 % by 2025 (Gupta et al. 1998). Researchers estimate that the accumulation of waste from the least developed countries will rise significantly over the next 25 years (Sharholi et al. 2008). With the growing number of businesses in the urban areas, solid waste disposal is becoming a big concern for the municipality. The principal method of waste disposal is landfill, which is inefficient and costly, and which pollutes the natural environment. For example, the landfill may cause health problems to the people living near the landfill site. Another traditional means of handling waste is burning waste, which contributes substantially to air pollution. Moreover, some compounds are combined to blend the air and cause cancer. Hence waste must be recycled to improve the air quality and protect the health of humans, and waste needs to be separated into various categories which can be recycled in different ways. This work addresses the present details on waste disposal selections at Dehra Dun Uttarakhand, and also the possible indirect and direct effect of waste control tasks on individual wellness, even though principal concentration is primarily on MSW. In India, the primary concern with garbage management is the filling of lands and

properties, with draining of wastes also being considered in some cases. The fact that there is evidence of negative health consequences to those living near landfill sites is one of the most significant effects of this entire review of the research. There are strong indications that germs originating in sewer treatment plants are more likely to cause gastrointestinal problems. For decades, the majority of waste produced on the earth has been steadily increasing, particularly in rich nations. Though information on waste sources can be dismal and unreliable, current estimates suggest that more than two billion tonnes of municipal solid waste (MSW) is generated globally each year. The amount of MSW produced in the OECD countries in 2006 was more than 620 million tonnes, or 580 pounds per person (Gupta et al. 2006). Huge quantities of wastes are generated in more complex nations like India, from industries and households, even though generation per capita is far less than $0.5 \text{ kg.day.capita}^{-1}$ in India, and remains comparatively small when compared to waste generation in OECD countries. (up to $2.1 \text{ kg.day.capita}^{-1}$ in the USA) (Rathi 2006). However, this overlooks the fact that cities generate a significant portion of MSW. The forecasts for China's municipal garbage generation were based on three distinct waste development scenarios (i.e., waste generation increasing slowly from $0.9 \text{ kg.day.capita}^{-1}$ to $1.2 \text{ kg.day.capita}^{-1}$ to $1.5 \text{ kg.day.capita}^{-1}$) (Kumar et al. 2017). Even if waste generation is very low, the total amount of MSW

generated in 2030 would be double that of the United States. Despite the fact that China's GDP growth rate is no longer double-digit, the international financial crisis is unlikely to have an impact on the countries' estimated waste generation. A number of high-profile and widely condemned pollution incidents involving improper waste management have caused people to be concerned about lack of controls, weak policies, environmental harm, and overall health impact. As a result of this positive effect, several federal governments have been forced to start a new regulatory strategy to manage hazardous, dangerous, and unsustainable waste management strategies. In Western nations, landfilling is still the most important disposal system. In 2000, in western Europe, around 18 percent of MSW was incinerated and 25% was recycled, while incineration and recycling accounted for around 6% and 9% in eastern and central Europe, respectively (Talyani et al. 2008). Hence, waste recycling in Western Europe is increasing (Talyan et al. 2008). As regulations are highly

effective and also landfilling is often an expensive choice, alternative ways are considered. The quantity of waste landfilled in the United Kingdom and Italy, for example, has decreased substantially.

In 1995, Italy and the United Kingdom both landfilled 93 % and 83% of MSW, respectively, but by 2005, the figures had dropped to 58 percent for Italy and 42 percent for the United Kingdom. The disposal of sewage sludge affects the environment as the sludge may contain harmful components such as pathogenic organisms, organic compounds, heavy metals, and excess phosphorus and nitrogen. Water that is discharged from factories, for example, can pollute rivers and lakes with substances like chemicals, waste, and dyes. This water pollution can kill wildlife and harm the overall ecosystem, and the effects of polluted water have left several plants and animal species endangered.

Table 1: State-wise waste generation in India.

State	Total waste generation TDP	Percentage of waste processing	Estimated per capita waste
Andaman & Nicobar	70	30%	0.45
Andhra Pradesh	5,980	8%	0.33
Arunachal Pradesh	110	15%	0.30
Assam	650	0%	0.13
Bihar	3,703	0%	0.28
Chandigarh	340	100%	0.30
Chhattisgarh	1,896	0%	0.27
Dadra & Nagar Haveli	35	0%	0.12
Daman & Diu	85	0%	0.25
Delhi	8,390	52%	0.46
Goa	183	25%	0.18
Gujarat	9,227	28%	0.31
Haryana	3,490	25%	0.33
Himachal Pradesh	300	20%	0.41
Jammu & Kashmir	1,792	2%	0.46
Jharkhand	3,750	0%	0.42
Karnataka	8,784	34%	0.33
Kerala	1,576	50%	0.07
Madhya Pradesh	5,079	12%	0.23
Maharashtra	26,820	10%	0.48
Manipur	176	50%	0.18
Meghalaya	268	58%	0.40
Mizoram	253	4%	0.40
Nagaland	270	0%	0.37
Odisha	2,460	2%	0.32
Puducherry	495	20%	0.52
Punjab	3,900	10%	0.34
Rajasthan	5,037	15%	0.26
Sikkim	49	0%	0.20
Tamil Nadu	14,532	15%	0.38
Telangana	5,520	18%	0.39
Tripura	407	0%	0.32
Uttar Pradesh	19,180	7%	0.39
Uttarakhand	1,013	0.5%	0.29
West Bengal	8,674	0%	0.27

Table 1 shows the statewide distribution of the waste generation in India. In India, around 8.8 million tonnes of sewer waste are implemented or removed each year, with approximately 60% of it being suitable for agricultural use (Patil & Shekdar 2001). Sewage sludge has potential fertilizer properties and can be used to enrich agricultural soils due to its high nitrogen, phosphorus, and organic matter content. Dried sludge is often used as manure. Sludge is nothing but accumulated solid content from the wastewater. It is often used as manure because those are biodegradable materials that are made mostly of food and human waste which acts as good manure for the plants. Therefore, sludge is often used as manures.

The types of waste control systems used in each country are usually based on financial considerations, but they also include different factors based on the type of waste to be disposed of. For example, if coal burning has been used to heat buildings and homes, large amounts of coal ash may be disposed of alongside additional municipal waste. Because coal ash contains high levels of metals and other toxins, ash when combined with urban waste in landfills may be difficult to eliminate. In addition, coal ash tends to make incineration more expensive. Thus it is very harmful to coal ash to be released into the environment. Spills of coal ash can pollute waterways, groundwater, drinking water, and the air. The number and types of categories into which wastes are divided usually depends on the collection system used and the final destination of the wastes. Waste separation at the source enables the removal of substances that are hazardous (inflammable, poisonous), that can which can be recycled, or composted. Effective segregation of wastes means that less waste goes to landfills which makes it cheaper and better for people and the environment. ... Segregated waste is also often cheaper to dispose of because it does not require as much manual or mechanical sorting as mixed waste. Hence, for the effective disposal and treatment methods of waste, knowing the composition of wastes is important.

PLASTIC WASTE SEPARATION METHODS

Direct Methods

The hydro-cyclone separates materials of various densities using centrifugal power. This method is often used to separate materials, such as acrylonitrile butadiene styrene, polyethylene high impact polystyrene, and polyvinyl chloride (Kannangara et al. 2018). Different types of variables affect the buoyancy of a particular material, such as thickness, shape, and separation level from other materials, and are used to separate other parts from MSW. In the process called jiggling, a water stream is pulsed, or moved by pistons upward and downward, through the material bed. Under the influence

of this oscillating motion, the bed is separated into layers of different densities, the heaviest concentrate forming the lowest layer and the lightest product the highest. Important to this process is a thorough classification of the feed since particles less than one millimeter in size cannot be separated by jiggling (Kontokosta et al. 2018). The waste is decomposed into small fragments and mixed with water. Air is dispersed into the mixture of water and waste mesh under high tension. The dispersed air is then moved into the lightness field under pneumatic tension. This permits the water-waste mixture's foam to expand outwards. The hydrophobicity of the attached plastic fragments binds them together.

Indirect Sorting

X-ray transmission (XRT) is a fast circuit arranging method that requires just a few milliseconds to capture X-ray images. A high-intensity beam of radiation is used by the imaging module. Once the material is assimilated, part of this beam is transferred to the identifier under the test material. To extract details about the atomic density of the material, the radiation detected by the indicator is dissected. Two types of X-ray sorting systems exist: Double x-ray energy (DE-XRT) and X-ray fluorescence (XRF) (Guo et al. 2020). The experience of XRF can be used to retrieve plastic waste fragments. Unfortunately, this process is only for recovering PVC from different types of plastic. The XRF approach is focused on the acceptance of individual molecules from an external laser source, which allows the release of X-ray photons (Abbasi & Hanandeh 2016). The emitted photons form a mark for atomic weight, which helps determine the type of material. The spectral signature of plastic is a superposition of the spectral signatures of parts that can be classified using ML. Another approach for sorting waste is Energy Dispersive X-ray fluorescence, which uses markers applied to the polymer structure to sort plastic particles. These marks are framed by a number of materials dispersed within the material, maximizing the polypropylene arrangement's selectivity (Adedeji & Wang 2019). The X-ray is focused on a small area of material and guided to the detector. The signal is then transferred from the identifier to the handling unit. The radiation source is monitored by this unit, whose spectral signature is dissected and used to distinguish materials with unique marker concentrations. Detecting dim polymers and grim waste with XRF is a non-destructive process.

Optical Based Sorting

For the most part, techniques use real characteristics while ignoring visual properties such as colour, patterns, surface, and scale while organizing waste. Optical sorting (sometimes called digital sorting) is the automated process of sorting solid products using cameras and/or lasers. Organizing methods

that rely on highlights such as form and concealment. This approach incorporates a 3D shading camera and a laser beam on the transportation axis. This method is known as triangulation checking because it creates triangles on the camera image of the fundamental laser beam. For the plastic segmentation, the technique achieves an accuracy of 99 percent. Ghostly imaging is a strategy based on phantom reflectance estimations and image handling procedures. There are a few unusual imaging techniques that use NIR (near-infrared), VIS (visual image spectroscopy), and HSI (hyperspectral imaging) (Srinilta & Kanharattanachai 2019). A hyperspectral sensor generates images on an infinite range of small spectral types, and the following framework investigates spectroscopic data (Gyawali et al. 2004). The transport system transfers tiny volumes of waste under the phantom camera, securing photos. The knowledge is pre-prepared and reduced in the accompanying point. An exceptional equation is then used to play out the material grouping. A swarm of packed air spouts is placed at the end of the transport line, and depending on the classifier's selection, one of the spouts is set off by loss-specific canisters (Ding et al. 2018). Waste control can also be achieved by the use of computerized logic. The recycling in the work is carefully designed by a major improvement in the neural network algorithm for the grouping of unique types of recyclable articles. In a layered organization, this new model has reduced the number of boundaries from 121 to about 3 million (Dixit & Vaze 2013). In previous studies, they proposed the concept of programmed recycling of plastic and metal waste in conjunction with another method

for monetary motivation of end-user works. The utilization of AI to characterize waste turned into the principal help for specialists. The prospects got by neural organizations in the field of picture arrangement and acknowledgment show that it is possible to assemble viable frameworks additionally in the field of waste determination, however, the intricacy of the entire framework should be rearranged.

WASTE SORTING METHODOLOGY

Plastic wastes can be segregated into different types once it has been separated from MSW using a computerized image processing method. The device we utilize has an RGB sophisticated camera and a computer with programming for the classification of heavy waste. Airflow, on the other hand, is used to transfer waste to a specified container, with the assumption that the waste can be sent separately through the conveyor belt. In the neural network image pre-processing, the object used in this framework uses image processing methods. To identify objects, deep learning methods are used.

The local arrangement of pixels is crucial for perceiving the shape of an object. CNN usually contains a convolving layer, a grouping layer, and a fully connected layer. The convolutional layer and grouping layer are stacked one on top of the other (Thanawala et al. 2020, Ma et al. 2020). Fig. 2 presents the CCN methodology used in MSW sorting.

Due to the small size of images, an approach for data enhancement was used for the pre-processing of images. This approach was chosen because of the different orientations of

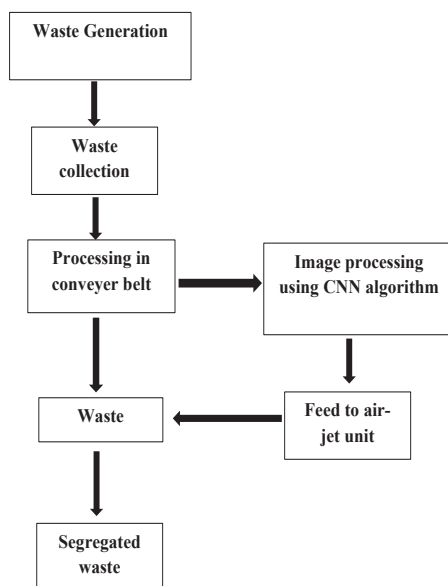


Fig. 1: Block diagram of the proposed technique for waste sorting.

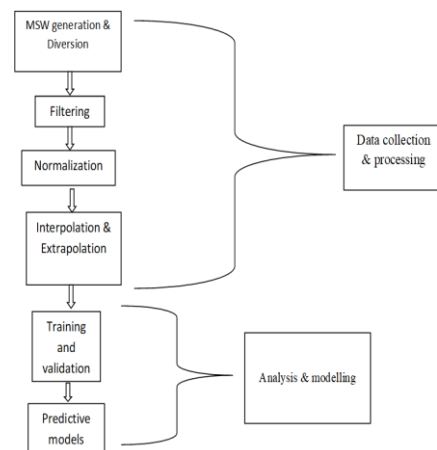


Fig. 2: The CNN methodology used in MSW sorting (Ma et al. 2020).

waste matters. Some of the approaches include a random selection from the image, translation of the image, random scaling of the image, and image sharing. This approach makes the dataset as large as possible. The described approach was updated based on the preformed model ResNet-50, and it is depicted in Fig. 1. Certain steps are involved with CNN layers, allowing it to classify the input images. The conversion layer convolves the input image using a set of 3x3 filter window sizes, which was chosen to differentiate artifacts in small and local features (Ikhlal 2018). The basic features and primitive characteristics are extracted from the input images and first layers respectively. Moreover, the complex layers and detailed features are extracted from the probability of loss function (Softmax function). The proposed model was built on the pre-formed ResNet-50 model, which was trained on ImageNet images with a resolution of 256x256 and classified into 1000 categories. As shown in Fig. 2, a preformed ResNet-50 model has been formed on the image data set, and a weight set has been acquired, but we removed the top classification layer by setting the include_top = False, only the feature is extracted from the network (Chu et al. 2018). The extracted features are fed to the multi-class SVM model, which performs classification based on the extracted features.

SVM can be utilized to resolve classification and regression problems. It is a machine learning technique and is considered one of the best classification algorithms. With this algorithm, the data article is plotted as a specific point in the n-dimensional space versus the characteristic standards of a particular coordinate. The objects in SVM can be classified depending on the hyperplane separation for each multidimensional data. We find the hyperplane where the minimum distance is greater for training data (Talyan et al. 2008).

$$\min_{\gamma, w, b} 1/2 \|w\|^2$$

$$\text{s.t } y^i(w^T x^{(i)} + b) \geq 1, i=1 \dots m \quad \dots(1)$$

Equation (1) shows the optimization of SVM. Here, w and b represent the parameters of the constraint function y^i . For example, $x^{(i)}$ is the i^{th} example of m . The nominal geometric margin of the training samples is also represented by m (Ibrahim et al. 2019). Following the identification of waste, the system's air jets start and separate the various types of waste using air blow. As a result, the entire system may be used to detect, identify, and segregate various types of wastes, and channel them into their respective slots.

RESULTS AND DISCUSSION

The research phase consists of few steps where the first

step is to identify the waste after collecting it. As the identification phase started a lot of complex algorithms come into operation. First, the image of the waste is captured, after that, the image is passed through algorithms to extract the information such as color gradient, edge detection output, RGB output, and OpenCV histogram. All the necessary outputs for this project are given below. As waste passes through the conveyor belt, the feed from the waste detecting unit is provided to the air-jet system, which can determine which type of waste is entering the system and how much air thrust is required to channelize the specific waste to its designated slot.

The CNN algorithm, which was used to detect and identify different types of wastes, was successful in identifying the different types of wastes, as shown in Fig. 3. The waste images are captured for edge detection in the detection process, which is a sophisticated method. The Canny edge filter or canny algorithm is used in the edge detection process. A wide range of information may be extracted from image data using edge detection, making it easier for the system to grasp what kind of material it is recognizing.

The Canny algorithm uses a Gaussian filter to smooth the image and to remove noises. It helps the viewers to understand the intensity gradient of the image. The gradient algorithm step identifies the edge intensity and direction by measuring the image using the edge detection operator. Edges correspond to a change of pixels' intensity. To identify this, a better procedure is to utilize filters that focus on the change in intensity for both the directions such as horizontal (x) and vertical (y). When the image is smoothed, the derivatives I_x and I_y w.r.t. x and y are calculated. It can be implemented by convolving I with Sobel kernels K_x and K_y , respectively:

$$K_x = \begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix} \quad \dots (2)$$

$$K_y = \begin{pmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & 1 \end{pmatrix} \quad \dots (3)$$

Then the magnitude G and the slope θ of the gradient are calculated as follows.

$$|G| = \sqrt{(I_x^2 + I_y^2)} \quad \dots (4)$$

$$\theta(x,y) = \arctan(I_y/I_x) \quad \dots(5)$$

Overall, the canny algorithm helps to lower the error rate in the field of edge detection of image data. The edge detection of various types of waste is shown below where the canny algorithm successfully works. Fig. 4 shows the detected edge of the cardboard, glass, metal, paper, and plastic wastes.

The convolution neural network (CNN) has been applied to the sample data of the waste of different types to train the data set and provide a convenient conclusion for the system to recognize the type of waste that has been collected, the convolution neural network (CNN). CNNs are employed in image processing because of their high accuracy for classification and recognition since they create a hierarchical model of networks through which image data is processed

and exact outputs are produced. With an open CV histogram and RGB analysis, the processed output of municipal solid wastes such as cardboard, glass, metal, paper, and plastic are shown in Fig. 5

It should be understood from these outputs that it is possible to classify and identify different types of municipal solid wastes by using the CNN algorithm using this waste detection system. In an image processing context, the his-

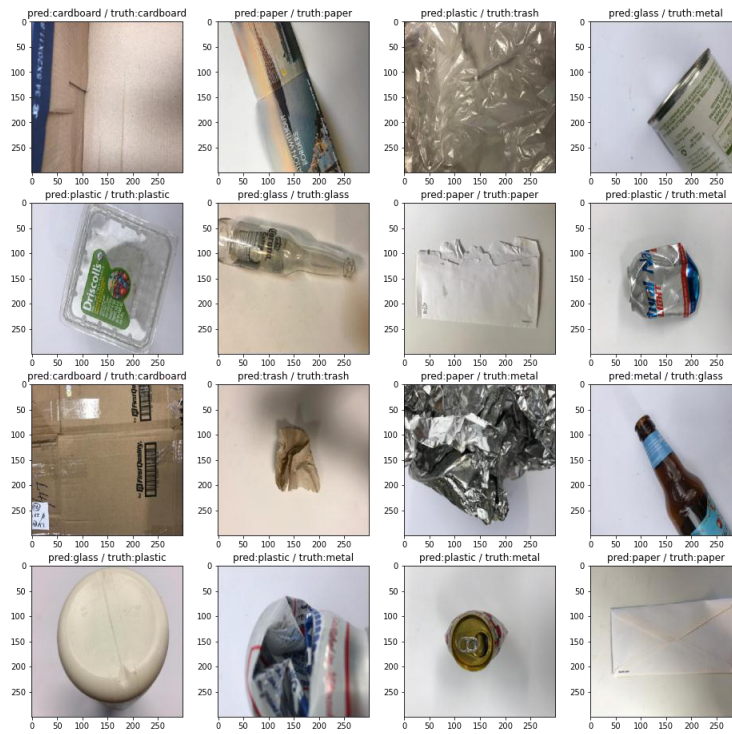


Fig. 3: Sample waste data successfully detected by CNN algorithm.

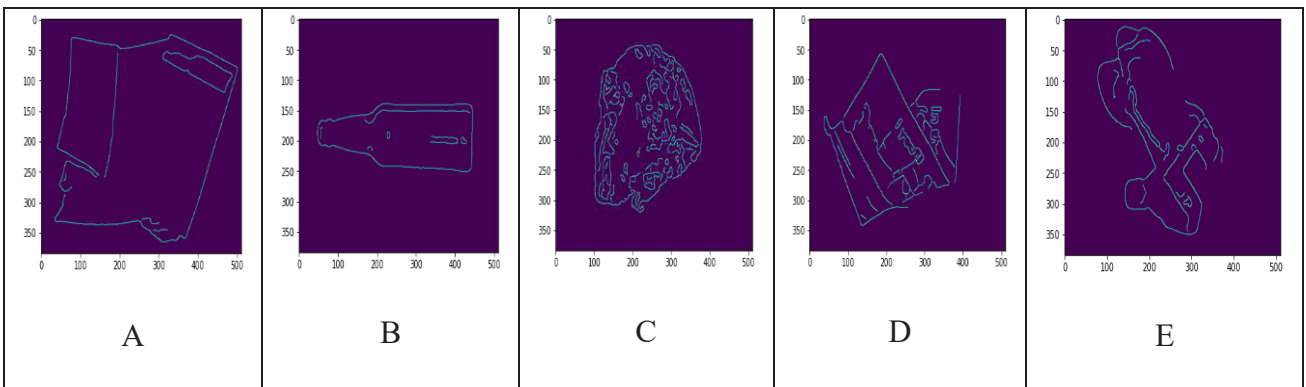
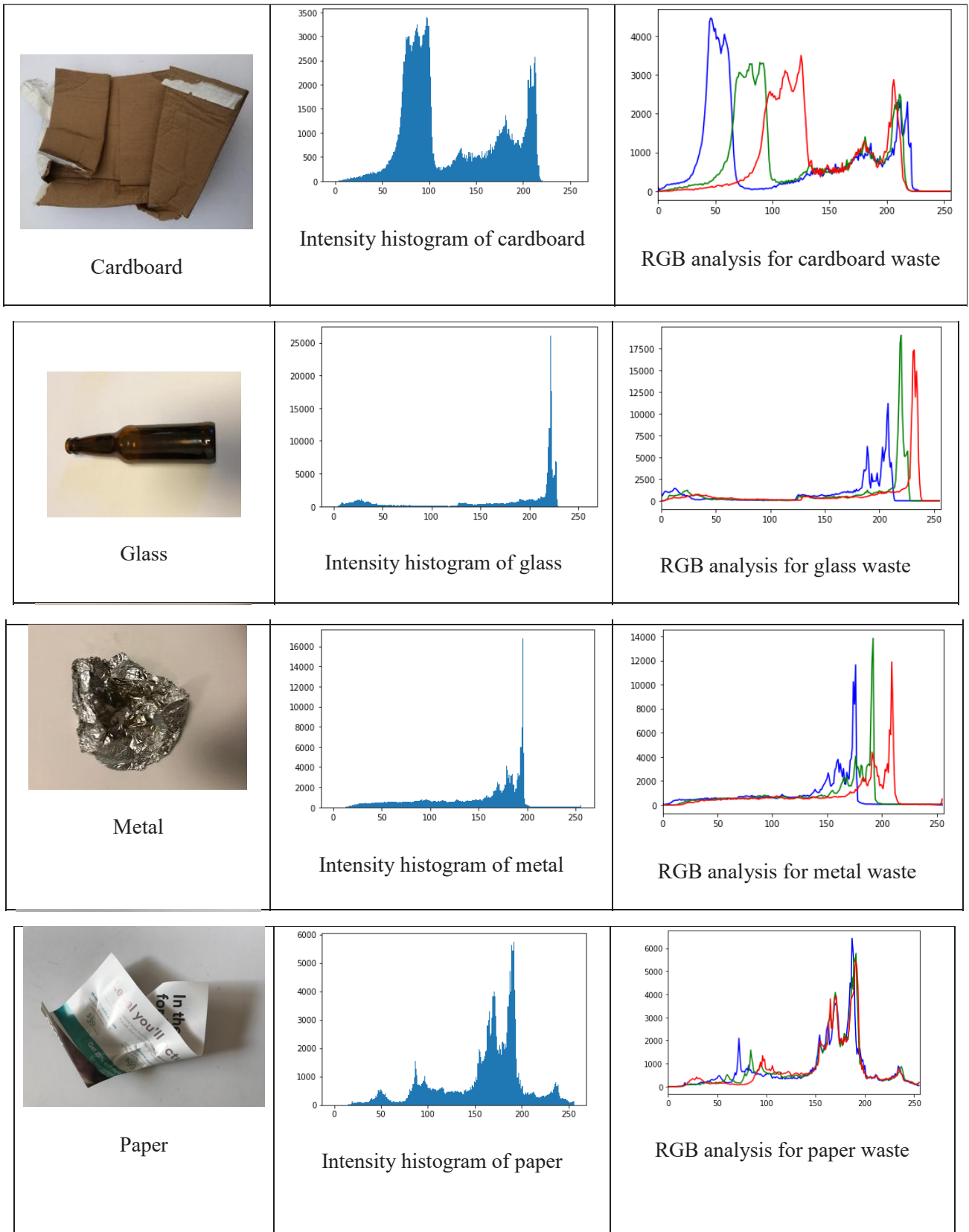


Fig. 4: Edge detection of (A) Cardboard, (B) Glass, (C) Metal, (D) Paper and (E) Plastic.



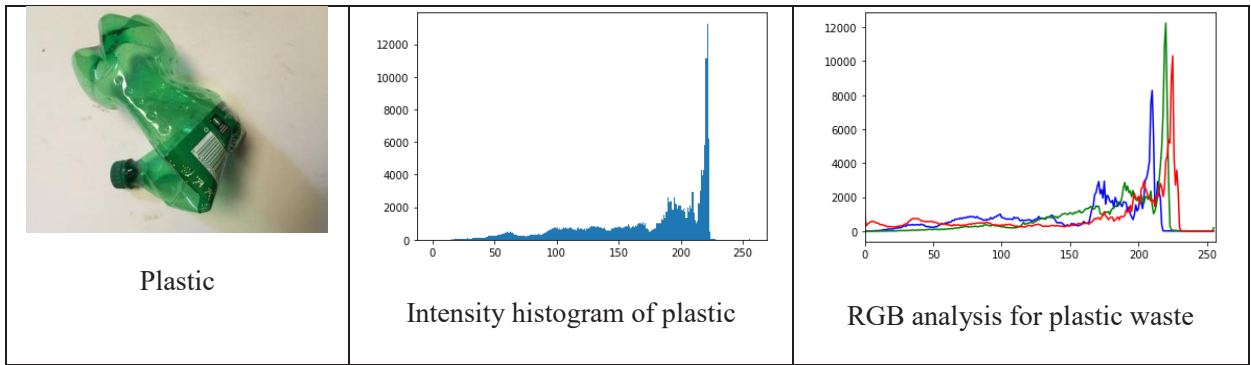
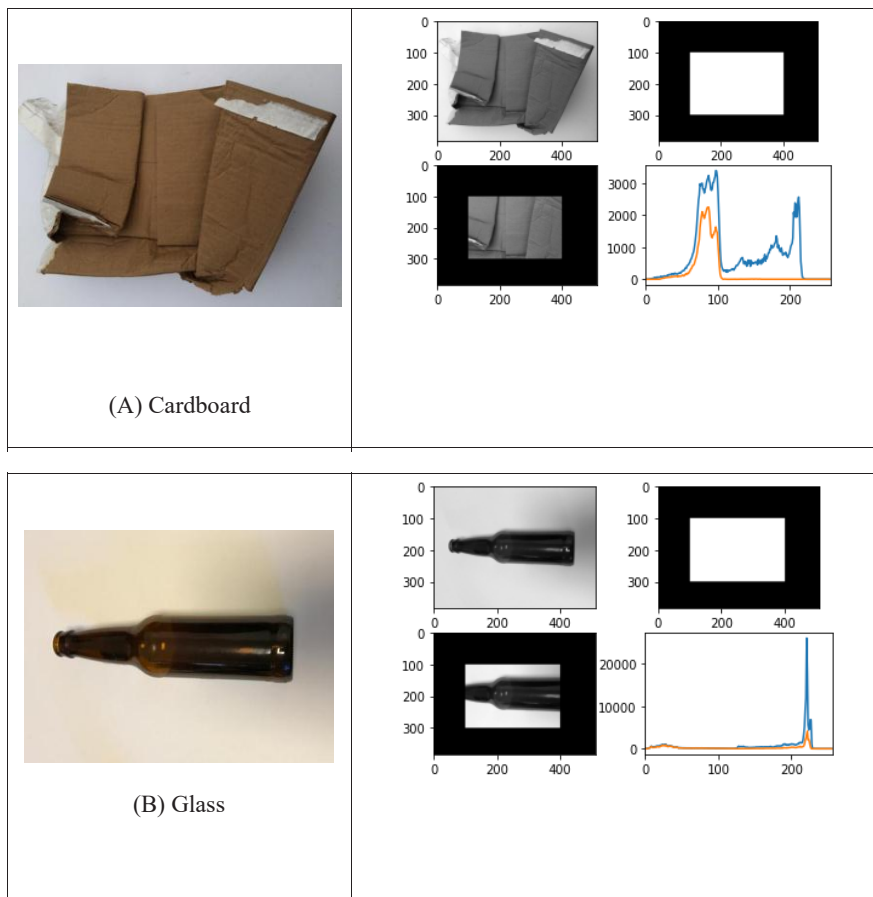


Fig. 5: List of different types of waste elements that have been analyzed for this paper with open CV histogram and RGB analysis.

ogram of an image normally refers to a histogram of the pixel intensity values. This histogram is a graph showing the number of pixels in an image at each different intensity value found in that image. The intensity histogram is a graphical representation of any object that allows us to understand how many different color values appear in an image or, in other words, it helps to know the intensity distribution of an image.

These histograms (Fig. 6) provide masked data of various kinds of wastes, which helps us and the proposed system to understand and identify the type of wastes and separating the wastes in a particular manner. Fig. 7 shows the detection accuracy plot of the applied technique.

This study has proved to be an effective solution for the detection and segregation of different types of wastes.



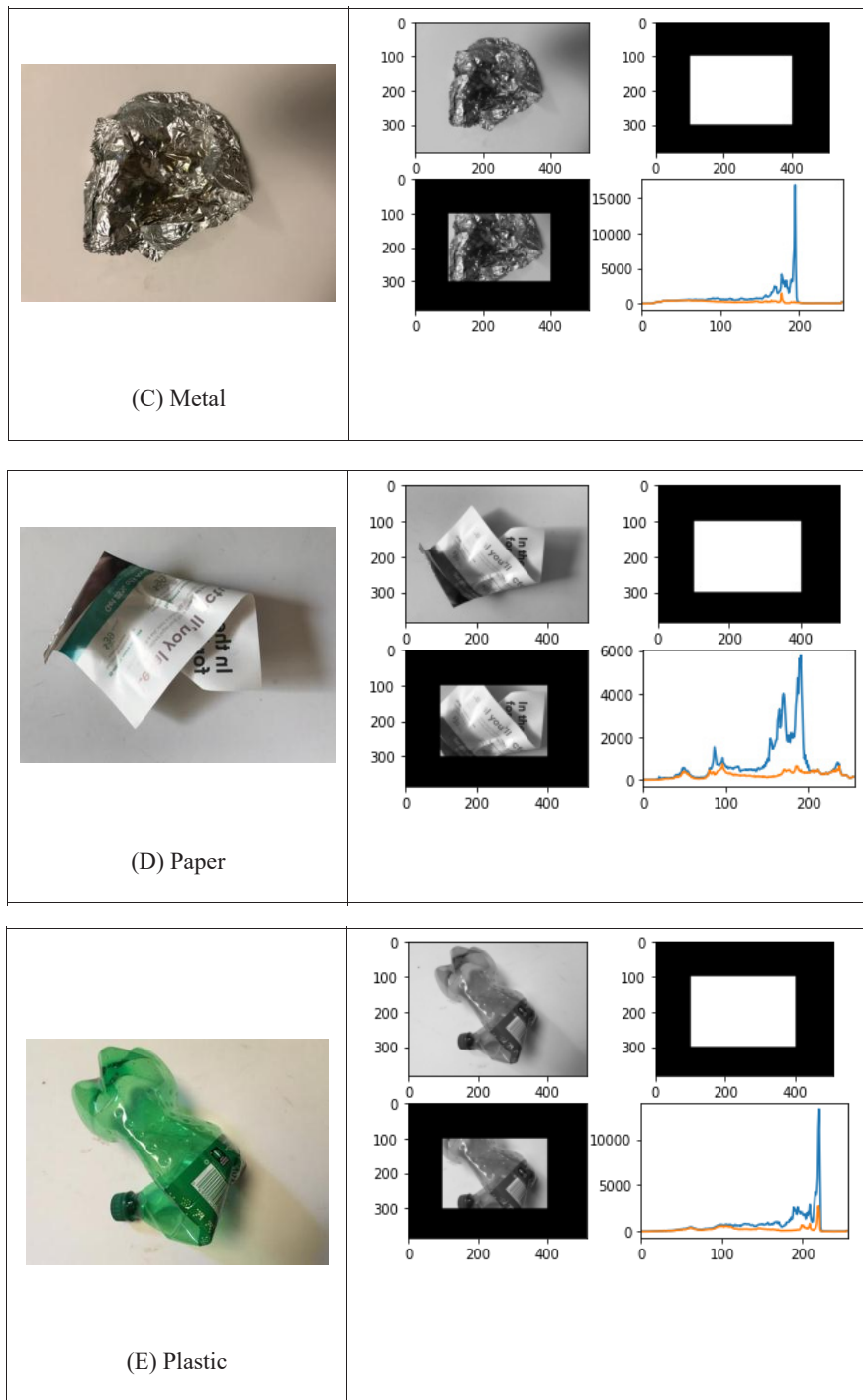


Fig. 6: Histogram with mask and without mask of different types of wastes (A) cardboard (B) glass (C) metal (D) paper (E) plastic.

Municipalities facing big challenges with solid waste management will quickly fix their issues by implementing this type of system where they only need to gather the waste from workers, while the majority of the waste segregating jobs would be handled automatically by this system. It will

allow municipalities to maintain clean and healthy cities.

CONCLUSIONS

In this study, we developed MSW generation and manage-

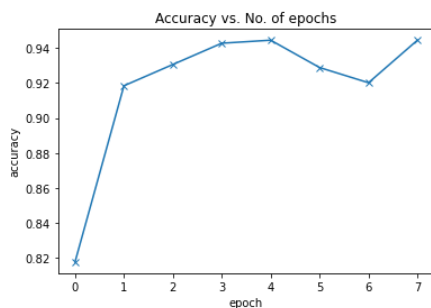


Fig. 7: Detection accuracy plot of the applied technique.

ment models to solve waste-related problems for Dehradun. The developed model is capable of detecting the MSW and can sort it by its form. CNN and decision tree AI algorithms were used to build the models. The neural network approach was based on unparalleled models than the choice tree approach. It rendered MSW detection models with a test data accuracy rate of 72%. Results demonstrate that given sufficient financial logical factors, AI techniques can deliver high precision for waste detection applications. The existing model for the identification of waste can be extended across India in light of the fact that the financial limits of the information can be defined using assessment information that is available to all regions in India.

The ability to predict waste generation allows municipalities to plan and maximize their waste management operations. The current research model could be used to identify waste automatically, reducing human work, and preventing diseases and pollution. With an accuracy of 87 percent, our model was validated against the waste data set. As a result, it delivers a more efficient and effective waste segregation approach that may be used with or without manual effort. If images are added to the informational index, the accuracy of the framework can be considerably improved. In general, we will improve our framework to include an option to classify and detect more waste items, by transforming a portion of the edges/boundaries used. Our future work will be focused to train the model using large sample data so that it can identify different types of waste materials with high precision.

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