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Automatic waste detection by deep learning and disposal system design

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As Dubai aims to become a greener city by the year 2021, efforts are currently being made by the government to devise a more efficient and innovative approach to tackling solid-waste-management issues in the city. With a much higher rate of recycling of trash, there arises a need to find a better approach to classifying this trash with increased efficiency. Machine learning techniques can be employed to classify trash into different recycling categories so that it is easier to recycle waste. In this paper, an automatic waste-classification system is proposed using a deep learning algorithm to classify waste as metal, paper, plastic and non-recyclable waste. The classification was performed through this computer vision approach by using the AlexNet convolutional neural network architecture in real time so that the waste can be dropped into the appropriate chambers as soon as it is thrown into dustbins. The data set used to train the system consisted of images collected from the Internet, as well as hand-collected images. The model used was tested for classification of different types of trash and was found to show a high accuracy, as discussed in the result section.

Introduction

Nature has blessed human beings by giving them to inhabit Earth. Human beings enjoy its natural resources to a great extent, gradually leading to environmental deterioration. Conservation has become a necessity to protect Earth and its natural resources from being exploited, in order for it to have good health. People are assets of society. A healthy society can create lots of advancements, which leads to a well-industrialised country, where economic growth is experienced, and finally a developed nation. A proper and efficient way of disposing waste materials is needed to have a hygienic society.

The world's level of waste and the poor management of this waste are posing a threat to the future; 2·12 billion t of waste are dumped every year. Wastes that reach dumpsites include organic, hazardous and non-biodegradable wastes such as plastic and polythene bags. Organic wastes give off large amounts of methane (CH_4) and carbon dioxide (CO_2), which leads to global warming (Yang and Thung, 2016). Hazardous wastes can also seep into groundwater tables, affecting plants and the ecosystem and triggering acid rain. Burning waste to get rid of it harms human beings, as this can cause bronchitis, lung inflammation and several other respiratory diseases. This problem will proliferate in the coming years if there is no solution for it (Awale *et al*., 2014; Donovan, 2016; Faccio *et al*., 2011). The UAE generates 26 Mt of waste according to a 2015 report. Most of the trash ends up in municipal dumpsites or landfills. Currently, a small amount of waste is burnt. The rate of recycling of waste has been rising rapidly. Recycling techniques have become inevitable. The best solutions are 'RRR' – reduce, reuse and recycle. The significance of this study is to reuse the waste materials and to show the effect of these waste materials on human health. Reduction of waste materials should be practiced. Waste materials dumped on landfills are dangerous, because these contaminate underground water, leading to dangerous diseases. The vital part of waste 'reduction' is conservation, in which natural resources are used wisely, to avoid waste. Reusing is passing waste materials to others who could use them. Reusing protects people from hazardous waste, generates economic savings and safeguards wild habitats, fuel, forests and underground water. By reusing waste products, the demand for natural resources can be controlled, the cost of incineration is reduced, energy can be restored and job opportunities can be created, leading to an the creation of an economically healthy society. Recycling should be done at the workplace and at home if people are to achieve the goal of reducing the amount of waste that goes into landfills. It is essential that waste be separated into plastics, metals, glass, bio-waste and so on. Dubai Municipality estimates that Dubai City recycles about 25% of its waste, and it aims to increase this percentage to 75% by the year 2021. This shows a need to find a better approach to sorting waste for more natural recycling.

Objective

Segregated materials can be recycled for reuse. Purchase materials made from recycled way to reuse. Recycled timber can be used for functions such as making furniture. Plastic wraps can be replaced by containers or paper bags. To make recycling easy, separation of waste materials, such as glass, electronics and plastics, is needed while these are disposed of, which reduces the amount of garbage in the household; produces a hygienic landfill, with agricultural waste as manure for fertile land; and is an effective way to reduce greenhouse gas emissions. There are potential risks to the environment and health from solid waste. Direct exposure of solid waste leads to diseases through chemical reactions and poisoning of atmosphere.

Currently, manual segregation in recycling plants is done, which does not have the required efficiency level for a better recycling rate, as the process is prolonged. It can also cause health hazards (Faccio *et al*., 2011; Krizhevsky *et al*., 2012). Employees at waste disposal sites can acquire air- and water-borne diseases. Waste is segregated at the collecting source itself to avoid these problems. The quality level of a waste item is known at the deposit point itself. This process leads to obtaining high-quality recycled materials when segregation is done at the beginning stage. Deep learning can make an automatic waste-classification system (He *et al*., 2015; Mittal *et al*., 2016; Pushpa *et al*., 2015) and use this technology in dustbins, which can be kept in homes or public places, such as parks, malls and beaches. Segregation is done with more speed, energy consumption is reduced, the amount of money spent on human resources is reduced and waste is sorted with less effort.

Deep learning algorithms

Deep learning is a machine learning process instructing computers to do what comes to human beings usually: learning by pattern (Krizhevsky *et al*., 2012; Liu *et al*., 2010). Deep learning is the main innovation behind automatic cars, which enables identification of stop signs or distinction between a pedestrian and a pole. It is the primary technology for controlling sound in gadgets such as mobiles, television, tablets and speakers. It is attracting much attention in recent times because of its higher level of accuracy.

A computer model learns to classify different pictures, texts and sounds in deep learning. Deep learning techniques can achieve high accuracy, surpassing human-being-level performance sometimes. Models are trained to utilise an enormous data set and neural network architectures containing multiple layers for classification.

Feature extraction has been one of the most significant challenges of traditional machine learning (Krizhevsky *et al*., 2012; Liu *et al*., 2010; Schmidhuber, 2015; Turaga *et al*., 2010). The programmer is required to tell the computer accurately what features to look for to make a decision. It is a massive burden for a programmer because, if the programmer is not insightful enough, the algorithm might be ineffective. Recognising an object or handwriting becomes a complex problem and would be a massive challenge while using traditional machine learning. In such cases, deep learning is very effective. Deep learning is a potent tool when it comes to feature extraction, as it can learn to focus on the required features by itself.

Deep learning uses a model of computing inspired by the structure of the human brain. Most deep learning techniques use neural network architectures. For this reason, the model becomes a deep neural network. The most commonly used neural networks used for deep learning are recurrent neural networks and convolutional neural networks (CNNs). Deep learning techniques are dominated mainly by CNNs because of their level of accuracy in image classifying.

In CNNs, the input features are taken groupwise like a filter. This causes the network to recall the picture in parts and perform activities effortlessly and effectively. The image is converted from hue–saturation–intensity (HSI) or red–green–blue (RGB) scale to greyscale. After conversion, the difference in pixel values helps detect edges, and the pictures can then be classified into separate classes.

AlexNet is a CNN architecture that outperformed all prior competitors in the year 2012 in the ImageNet Large Scale Visual Recognition Challenge. It has eight layers, with many filters per layer and with stacked convolutional layers. The model is trained in the AlexNet architecture, which is explained in detail in the section headed ‘Modelling’.

Materials and method

In the proposed waste-segregation method, a process sequence with the following steps is carried out, as shown in Figure 1.

(*a*) The waste is collected in the processing chamber of the dustbin.

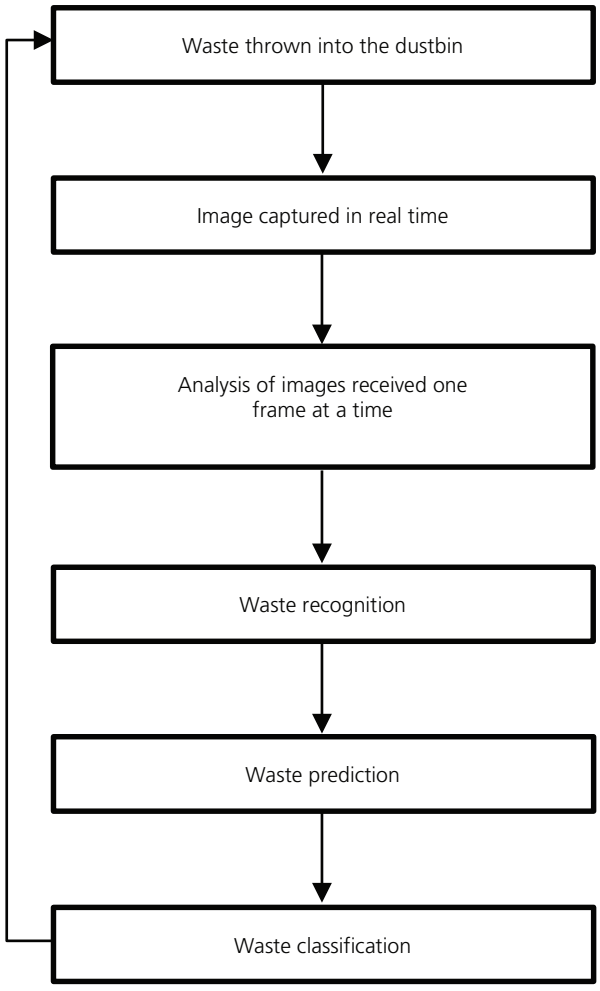

Figure 1. Steps in the proposed waste-segregation system

(*b*) A real-time image of the waste is captured, and each frame is sent to the computer system.
(*c*) Then, the image is analysed using the AlexNet architecture with the data set containing trash images.
(*d*) A prediction of the class of the waste is made with different probabilities.
(*e*) The class detected with the highest probability is chosen as the output.
(*f*) The result of the operation leads to identification of waste.

Data set collection

Since there is only one publicly available data set specifically for waste sorting – TrashNet by Mindy Yang and Gary Thung – more images were collected from Google Images and added to the data set. TrashNet consists of images of recycled objects. The proposed method classifies the data set into four different classes. The hand-collected images consisting of trash items such as plastic, metal, paper and non-recyclable waste, as shown in Figures 2–5, were also collected and added to the data set. The pictures were taken against a white background and under different lighting conditions.

Modelling

The AlexNet model used for CNN software modelling was created through Caffe and OpenCV. The details of Caffe and OpenCV are given as follows.

Caffe

The Caffe framework is used to construct CNNs. Caffe is an outstanding deep learning system for vision acknowledgement. Its speed makes it ideal for research purposes and business arrangements. It runs on various operating systems, including Ubuntu, Windows and macOS. It supports C++, Python and Matlab programming interfaces. It can process more than 60 million images per day for various tasks, such as detection and recognition, when used with the Compute Unified Device Architecture (CUDA) and a graphics-processing unit (GPU).

Figure 2. Plastic waste

Figure 3. Metal waste

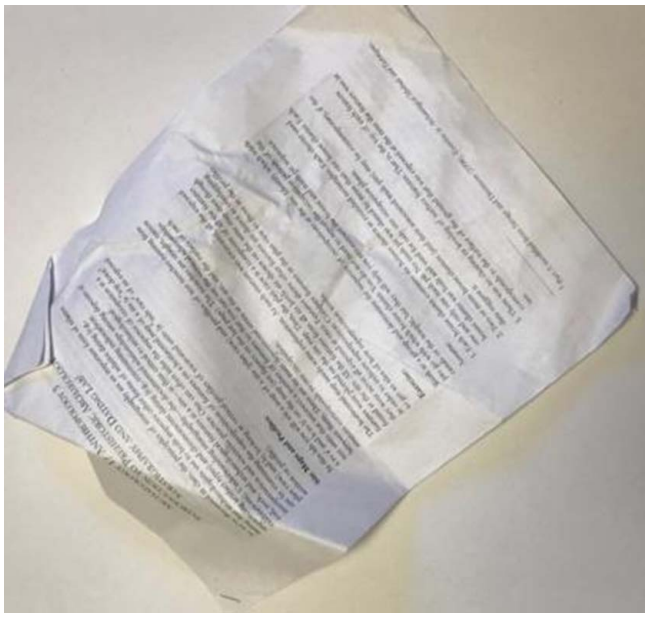

Figure 4. Paper waste

Figure 5. Non-recyclable waste

In this method, the Caffe model was trained by using Nvidia's Deep Learning GPU Training System (Digits) visual interface. It can be utilised to train quickly a highly accurate deep neural network for image-classifying, image-segmenting and object-detecting tasks. It makes more natural common deep learning steps, such as managing data, designing and training neural networks on multi-GPU frameworks, observing performance in real time with advanced visualisations and selecting the best-performing model from the outcomes browser for deployment. It is completely interactive so that data scientists can focus on outlining and preparing systems as opposed to programming and troubleshooting.

The pretrained AlexNet model is used, as shown in Figure 6. It consists of nine layers

- layer 0: input image of size 224 × 224 × 3
- layer 1: convolution with 96 filters of size 11 × 11, stride 4
- layer 2: max-pooling followed by convolution with 256 filters of size 5 × 5
- layer 3: max-pooling followed by convolution with filters of size 3 × 3
- layer 4: max-pooling followed by convolution with filters of size 3 × 3
- layer 5: max-pooling followed by convolution with filters of size 3 × 3
- layer 6: fully connected 2048 neurons
- layer 7: fully connected 2048 neurons
- layer 8: fully connected with four neurons.

A GeForce GTX 670 GPU was used for training. This training resulted in four classes of waste.

OpenCV

OpenCV is a library of coding functions for real-time computer vision. It was developed initially by Intel and later supported by Willow Garage and then Itseez. This open-source software is free to use. It was built to provide a common infrastructure for computer vision applications and to accelerate the use of machine perception in the commercial products.

The library has about 2500 optimised functions. These functions perform tasks such as identifying faces, recognising objects, recognising human activities in video recordings, joining images together to obtain a high-resolution image of an entire scene, finding identical images from a database, removing red eyes from

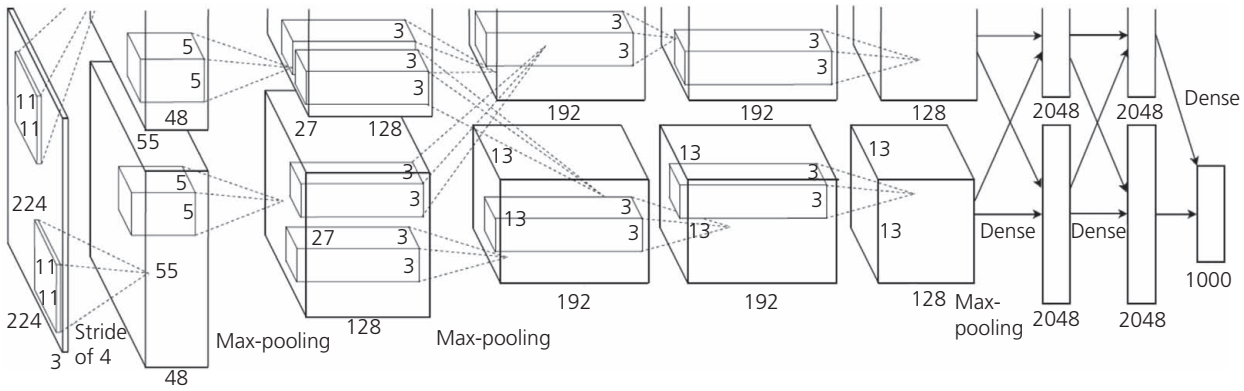

Figure 6. AlexNet architecture (Krizhevsky *et al.*, 2012)

images taken with a flash and identifying sceneries and building up markers to overlay these with augmented reality. OpenCV is broadly used by organisations, research groups and government bodies.

Like Caffe, OpenCV has C++, Python and Matlab programming interfaces along with Java and runs on various operating systems – Linux, macOS, Windows and Android. It also supports a CUDA-based GPU interface.

Training of data sets

After data set collection, the second step towards making a model is training. Data set collection is the most critical step for having the right amount of data to provide a good model with reasonable accuracy.

First, a layer of features is trained that receives a large number of input from the pixels of images. The edge-detection algorithm detects the edges present in the image. The rest of the parts of the image are identified from various other image-processing algorithms such as feature extraction. Finally, the object in the image is identified. The model is trained on the Digits Web app using a GeForce GTX 670 GPU. The user can focus more on designing the model than on programming and coding.

The number of epochs was set to 100 initially. An epoch is a single training cycle of all batches in both forward and backward propagation. The higher the number of epochs, the higher is the accuracy of the network. When a network is built, it tries to predict the output as close as possible to the actual value. The accuracy of the network is measured using the cost/loss function, as shown in Figure 7. The learning rate is defined as the amount of minimisation in the cost function in each iteration, as shown in

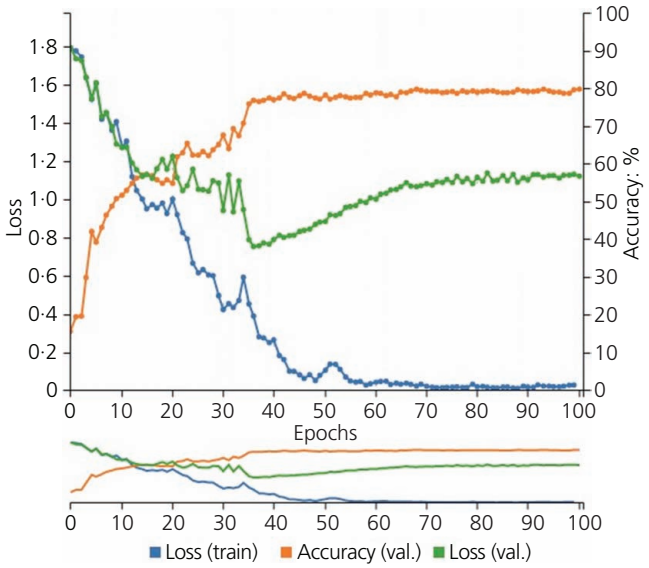

Figure 7. Loss and accuracy plotted against epochs

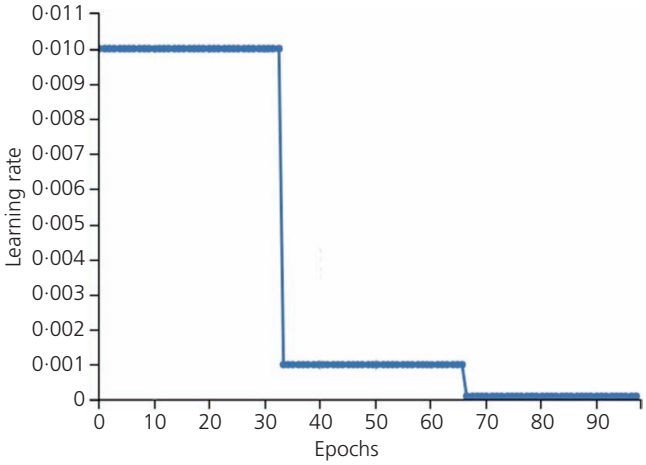

Figure 8. Learning rate plotted against epochs

Figure 8. In simple terms, the rate at which the cost function descends towards the minima is the learning rate. The learning rate is very carefully chosen since it should neither be substantial that the optimal solution is missed and nor should it be very low that it takes forever for the network to converge. The default learning rate is set to 0·01.

Results and discussions

The model was first tested and then downloaded from the Web app so that real-time image classification is possible using this model. A Python code was written to make the model run on a webcam using OpenCV, and the name of the object detected was displayed. The accuracy was high when the model was tested with the trained data set. It was not as high when tested with new data, particularly when run in real time. Figure 7 shows the

Figure 9. Plastic

Figure 10. Metal

Figure 11. Plastic

accuracy to be almost 80% in real time. The ambiance played a major role when classifying images in real time. For testing the proposed model, different types of trash were placed in the processing chamber and were identified and the type of the trash was displayed, as shown in Figures 9–12.

Conclusion

This paper proposes a complete process for classifying trash using the AlexNet deep learning method. The results show high accuracy even under real-time operation with restricted ambiance. Accurate waste classification indirectly leads to saving Earth from

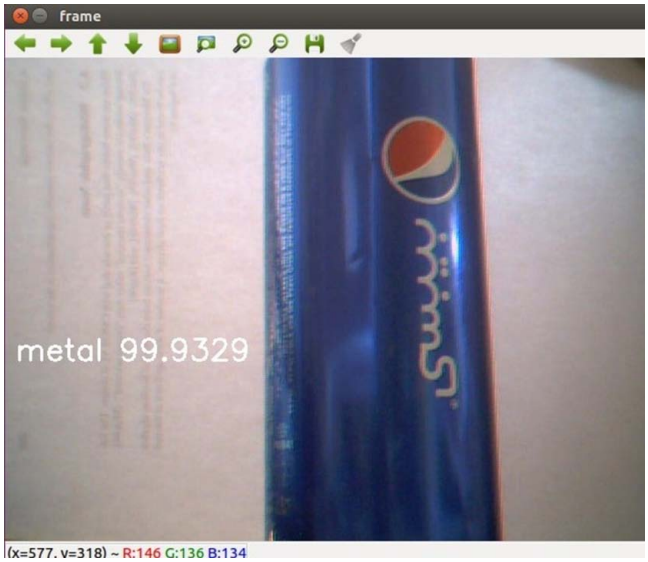

Figure 12. Metal

pollution and global warming. Segregation at the source has many benefits – saving energy, time and money. It avoids segregation of waste at landfill areas and dumpsites, which means no manual labour. There are many advantages of segregating at the source, ranging from a cleaner Earth and fewer funds used to decreased health hazards and risks caused to human beings and animals.

The global price of waste management is exponentially increasing, mostly affecting urban communities and towns in low-pay nations. Due to this reason, many countries have started to emphasise better waste-management policies. They are resorting to recycling to conserve resources, save energy, protect the environment and reduce the area used by landfills. This project is a precious asset to the society. Conservation seeks the proper use of natural resources, while preservation seeks protection of nature from being exploited. It is the duty of every citizen to hand over environmentally friendly atmosphere to the upcoming generation and educate to follow it.

REFERENCES

Awale AD, Margaje AA and Jagdale AB (2014) Automated waste segregator. *Journal of Information, Knowledge and Research in Electronics and Communication Engineering* **4(2)**: 1392–1395, https://doi.org/10.22214/ijraset.2018.5428.

Donovan J (2016) *Auto-Trash Sorts Garbage Automatically at the TechCrunch Disrupt Hackathon*. TechCrunch, San Francisco, CA, USA. See https://techcrunch.com/2016/09/13/auto-trash-sorts-garbage-automatically-at-the-techcrunch-disrupt-hackathon (accessed 31/10/2019).

Faccio M, Persona A and Zanin G (2011) Waste collection multi-objective model with real-time traceability data. *Waste Management* **31(12)**: 2391–2405, http://doi.org/10.1016/j.wasman.2011.07.005.

He K, Zhang X, Ren S and Sun J (2015) Delving deep into rectifiers: surpassing human-level performance on ImageNet classification. *Proceedings of the 2015 IEEE International Conference on Computer Vision (ICCV), Santiago, Chile*, pp. 1026–1034. See https://www.computer.org/csdl/proceedings-article/iccv/2015/8391b026/12OmNx2zjxR.

Krizhevsky A, Sutskever I and Hinton GE (2012) ImageNet classification with deep convolutional neural networks. In *Advances in Neural Information Processing Systems 25* (Pereira F, Burges CJC, Bottou L and Weinberger KQ (eds)). Curran Associates, Inc., Red Hook, NY, USA, pp. 1097–1105.

Liu C, Sharan L, Adelson EH and Rosenholtz R (2010) Exploring features in a Bayesian framework for material recognition. *Proceedings of the 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR), San Francisco, CA, USA*, pp. 239–246.

Mittal G, Yagnik KB, Garg M and Krishnan NC (2016) SpotGarbage: smartphone app to detect garbage using deep learning. *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '16), Heidelberg, Germany*, pp. 940–945.

Pushpa MK, Gupta A, Shaikh SM, Jha S and Suchitra V (2015) Microcontroller based automatic waste segregator. *IJIREEICE* **3(5)**: 104–108, https://doi.org/10.17148/IJIREEICE.2015.3528.

Schmidhuber J (2015) Deep learning in neural networks: an overview. *Neural Networks* **61**: 85–117, https://doi.org/10.1016/j.neunet.2014.09.003.

Turaga SC, Murray JF, Jain V *et al.* (2010) Convolutional networks can learn to generate affinity graphs for image segmentation. *Neural Computation* **22(2)**: 511–538, https://doi.org/10.1162/neco.2009.10-08-881.

Yang M and Thung G (2016) Classification of Trash for Recyclability Status. Stanford University, Stanford, CA, USA. See http://cs229.stanford.edu/proj2016/poster/ThungYang-ClassificationOfTrashForRecyclabilityStatus-poster.pdf (accessed 31/10/2019).