Efficient and Smart Waste Categorization System using Deep Learning

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Abstract

The demand and importance of recycling are inevitable, considering either economic reasons or environmental reasons. This paper explains a smart waste categorization for a waste management system to efficiently segregate waste. This involves the deep learning model VGG16 which creates a waste management system that is capable to segregate the municipal waste into organic and inorganic waste and detecting the waste products that can be recycled. Doing these manually requires a lot of human power and managing the waste can be hazardous and can cause harm to both the health of the person collaborating with it and the environment. Using smart object identification software in waste sorting is a more strategic approach than traditional recycling methods because it identifies more objects in a shorter amount of time. The traditional approach relies on human goodwill and labour, both of which are vulnerable to failure in waste separation for recycling. As a result of this analysis, these can be avoided and advanced, as well as a fully automated waste management system constructed.

Keywords:

Convolutional Neural Networks, Pre-train Model, Waste Separation, Automation, Support Vector Machine.

1. Introduction

As the amount of solid trash in the metropolitan area grows, so does the risk of environmental degradation and human health if effective management isn't taken. To deal with a wide range of waste, an advanced/intelligent waste management system is required. In waste management, one of the most critical phases is the physical sorting of the garbage into its many components, and this is often done by hand-picking. Using a 50-layer residual net pre-train (ResNet-50) Convolutional Neural Network model, which is a machine learning tool and serves as the extractor, and Support Vector Machine (SVM), which is used to classify the waste into different groups/types such as glass, metal, paper, and plastic, we propose an intelligent waste material classification system that is developed using the SVM. The garbage picture dataset generated by Gary Thung and Mindy Yang is used to test the suggested system, and the proposed system can obtain an accuracy of 87 percent. Without or with less human intervention, the suggested trash categorization system can speed up and intelligently separate the garbage.

Due to increased population growth, the major challenge that Human Beings face as a group is waste segregation and management. As per World Bank data, four billion metric tons of waste are generated each year, with nine metric tons produced every day. This necessarily requires a large call for new landfills, faster waste treatment for segregation, and the elimination of human error throughout segregation and transportation. Waste management has become a major concern, and the waste management system we use today is critical and must be efficient. Waste can be recycled if it is collected and managed properly. Mismanagement of waste can result in a variety of contaminants that are toxic in nature and harm the people who live nearby. The three R's, Reduce, Recycle, and Reuse, are essential in today's world. Because the importance of recycling is well understood whether for environmental or economic factors, avoiding it is impractical, and thus the industry challenges its effectiveness. South Korea ranks first among the best-rated nations for waste management, according to the Global Waste Index 2022. South Korea generates 400 kg of waste per inhabitant and recycles approximately 243 kg per inhabitant, ranking the country first among all nations. Sixty-eight percent of waste generated is recycled. This is

Manuscript received June 5, 2022
Manuscript revised June 20, 2022
https://doi.org/10.22937/IJCSNS.2022.22.6.60

one of the best examples of how recycling is one of the best and most efficient waste management methods.

We frequently forget to thoroughly separate our household waste, but technically speaking, the companies responsible for this part should always spend a lot of money on labor. Manual labor and traditional industrial sorting practices are incapable of meeting the international community's objectives. Using smart object identification software in waste sorting is a more strategic approach than traditional recycling methods because it identifies more objects in a shorter period. The traditional approach is based on human goodwill and labour, although both are vulnerable to waste segregation failure for recycling.
Resolutions aided by vision - based can automate a portion of waste management tasks. As a result, by utilizing a CNN algorithm, this project contributes to waste organization.

2. Literature Survey

The authors constructed an image analysis and a config neural network for garbage categorization systems in a study conducted (Bobulski and Kubanek, 2019). (CNN). During their investigation, they focused solely on finding polyethylene. The authors also performed various studies on high-density terephthalate, polyethylene, polyethylene, and polystyrene.

In a study (Sreelakshmis et al.,2020), the authors used Cabinet (Capsule-Net) to manage hard surplus and were able to distinguish between plastics and non-plastic waste. The writers worked with two public data sets, and 95.3 percent and 96.7 percent of them were correct. The entire extension has been designed and tested on numerous different plans.

In 1985, Rumelhart, Hinton, and Williams proposed the neural network P. Its calculation is based on the error back-propagation algorithm technique of feed-forward artificial neural learning and training. This method of calculation is commonly employed in image classification to address the challenge of training and modifying the connection weight of neurons in the hidden layer of a multilayer network. Compared to the traditional BP neural network algorithm, our method is superior. According to simulation data, the new method is 30% quicker than the previous algorithm. And it is far faster and more precise than the proposed method.
Research on the algorithm of urban rubbish categorization and recycling using deep learning technology was authored by the author (Baiqiang Gan and Chi Zhang). They employed the Alex net model for their classification. The experimental results reveal that the method presented in this paper has a significant impact on the categorization and recognition of rubbish images in complex scenarios, indicating that it is applicable.

The author of the study, titled A Study of Garbage Classification Using Convolutional Neural Networks, is (Shanshan Meng and Wei-Ta Chu). Among the models studied were support vector machines (SVM) with HOG features and a simple convolutional neural network (CNN). The paper Automation of Waste Sorting with Deep Learning uses a hierarchical deep learning system for waste identification and tracking in food trays. In the proposed two-step method, the benefits of contemporary object detectors are maintained. The Adaptive and Interactive Modelling System (AIMS) is a system that employs an induction process to characterize sensor data and generates a concise description of object features that explains material separation methods.

A team designed AutoTrash at the TechCrunch Disrupt Hackathon, which automatically identified trash and could sort rubbish using compost and recycling functions. For classification, they used a revolving top and a Raspberry Pi camera in their system. For trash categorization, the team used Google's Tensorflow AI engine and created their layer on top of it.

Oluwasanya Awe offered a project for region proposals and object categorization, in which they used a faster Region-based Convolutional Neural Networks (Faster R-CNN) technology to achieve a map with a 68.3 percent accuracy. The trash was divided into three categories: landfill, recycling, and paper.

2.1 Need for the proposed system

A general waste management system requires a lot of time and human power. The human power which is involved in the process of managing the waste tends to get affected by or requires a large amount of workload. to overcome these and to make the management of waste precise and not time-consuming there is a need for a smart waste management system. in this system, the waste is segregated into various categories which are furthermore into the recycling process. It specifically concentrates on the recyclable waste and tries to sort it out in an easy process.

Waste that is managed properly can reduce lots of damage that is caused by it. This project is used to identify and classify the waste from the dump and proceed with the inputs for further categorization and sorting it out for recycling. The input is fed through an application and processed to the system and the categorization is done. The categorization process begins with the capture of a waste image or video, which is then loaded into the model's application and classified as recyclable or biodegradable waste.

In this system design, as a primary step of collecting biodegradable and non-biodegradable datasets are collected in Kaggle. There will be separate datasets for every type of product. Plant products were classified as biodegradable and medical wastes, metals, glasses, and electronic wastes were classified as non-biodegradable but they will be further classified into recyclable and non-recyclable in further process. Then data-preprocessing is completed with the clinical dataset to remove the unwanted classification images in the dataset. After this process, a Neural Network model is used by VGG-16 in Tensorflow. It is the open-source machine learning model to develop and research for image processing and deep learning applications.

3. Implementation of Proposed System

In this system design, as a primary step of collecting biodegradable and non-biodegradable datasets are collected in Kaggle. There will be separate datasets for every type of product. Plant products were classified as biodegradable and medical wastes, metals, glasses, and electronic wastes were classified as non-biodegradable but they will be further classified into recyclable and non-recyclable in further process. Then data-preprocessing is completed with the clinical dataset to remove the unwanted classification images in the dataset. After this process, a Neural Network model is used by VGG-16 in Tensorflow. It is the open-source machine learning model to develop and research for image processing and deep learning applications. Our model is trained to predict the sort of waste from the dataset. The following illustrates the entire design of the system.

In their publication "Very Deep Convolutional Networks for Large-Scale Image Recognition," K. Simonyan and A. Zisserman from the University of Oxford proposed VGG16, a simple and commonly used Convolutional Neural Network (CNN) model.

We are utilising a garbage picture collection generated by Gary Thung and Mindy Yang for this project. Glass, paper, plastic, and metal are all included in this little dataset, which has been downsized to 512 × 384 for each of the photographs in the collection.

Because of the short file size, photos were used in the pre-processing step for data augmentation. Distinct material orientations led to this method's selection. Random image translation, random image scaling, random image shearing, and random picture scaling are a few of the techniques used. This method allows for the largest possible dataset to be created. The ResNet-50 pre-trained model was used to build the suggested technique, and the steps are outlined in Figure 1.

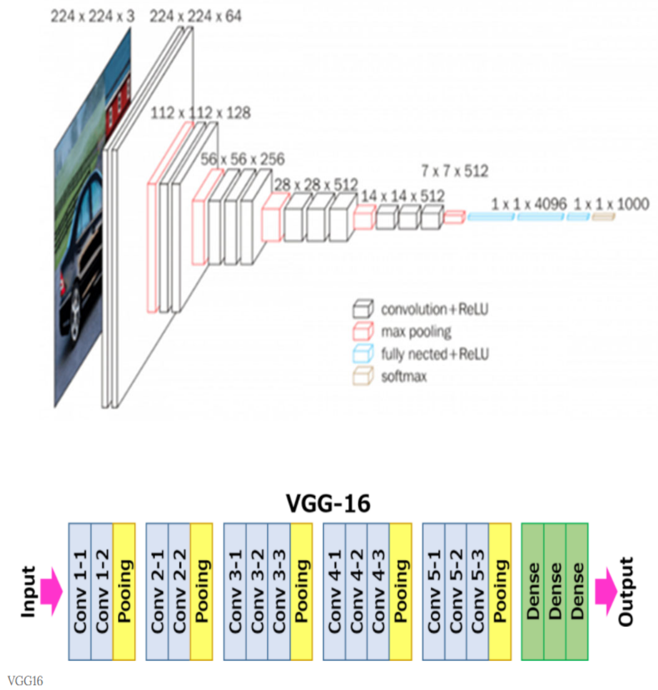

Fig.1 : Architecture of VGG-16

In ImageNet, which comprises a dataset of over 14 million images belonging to thousand classes, it obtains 92.7 percent test accuracy. Because of its simplicity, it is widely used in deep learning picture classification. It is one of the best models for image processing based on vision architectures. This VGG-16 consists of many hyper-parameters in which they used convolution layers of 3x3 filters with stride 1 and used a 2x2 filter for padding and max-pooling throughout the system. Then, in the end, they used 3 fully connected layers fully of dense layers and added SoftMax for output.

3.1 System Design

To figure out what kind of plastic the garbage is composed of, a system using a microprocessor devoted to image processing can be utilised. Using an RGB camera and a microprocessor with computer vision software, we present a method for identifying plastic rubbish. Programs in the shape of nozzles are used to direct trash to the proper container. For picture preparation, the system's software makes use of image processing algorithms. Classifiers based on convolutionary artificial neural networks and deep learning are an essential part of the system. It will be a Raspberry Pi type microcomputer that detects the object, and the user must manually deposit the trash in a specified container in the home version of the device This version is also suitable for use in the workplace.

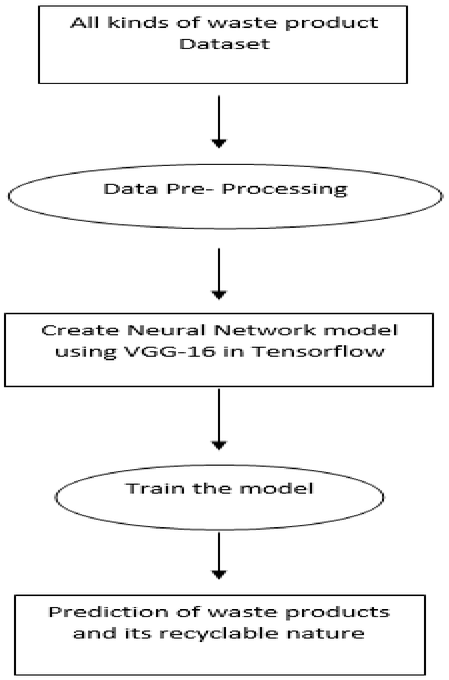

Fig 2. System Design

The figure 2 shows a sample of the training process generated by the VGG-16 model. Accuracy is recorded in each of the training sets to do the prediction in a better manner.

A 224-by-224 RGB image appears to be the optimal method for the cov1 layer. The image has to pass through a series of convolutional layers, with an incredibly small receptive field size of 33. In addition, one arrangement includes eleven convolution filters, which can be viewed as a linear combination of the input channels. The convolution stride is set to one pixel, and the spatial padding of Conv. layer input is set to one pixel so that the pixel size is maintained after convolution, i.e., the padding for 33 Conv. layers is one pixel. Spatial pooling is given by five max-pooling layers that adhere to a variation of the Conv. Max-pooling is performed over a 22-pixel window with a stride of 2.

The datasets utilized in this investigation were collected using a single bag under strictly controlled conditions. Given that this is a proof-of-concept utilizing a reduced methodology, it is uncertain how well these models will perform with data from the actual gathering procedure. The fact that numerous bags are emptied simultaneously is a potential issue with the collecting vehicle since it may raise the categorization difficulties. If this proves to be an issue, viable solutions include installing a funnel-like device on the collection truck that compels the bags to fall through one at a time, or just training the model with numerous bags at once. In either scenario, we advocate collecting training data from a genuine collection truck, which will have more background noise that is harder to account for with a bespoke setup. Detecting the presence of glass and metal in each individual bag is not critical, as only the locations of the garbage cans are known and not those of the individual bags. For each garbage can emptied by the collection vehicle, if glass or metal is identified in at least one of the bags, it is a helpful piece of information for identifying the general region where erroneous sorting happens over time.

While this strategy has been created primarily for use in collection trucks, its implementation would be simple and successful in other contexts as well. This strategy can, for instance, assist the sorting facility in segregating bags depending on their contents, however information about the source of improper sorting behavior will be lost during this stage. In addition, several condominium complexes have common garbage disposal units, which are frequently buried below, and the chute is an ideal area for sensor installation. These systems frequently employ RFID, allowing a connection to be made between the customer and their sorting behavior. Three Fully Connected layers are adhered to a few convolutional layers: the first two have 4096 channels apiece, while the third conducts 1000-way waste categorization and so has 1000 channels. The soft-max layer is the final layer. The configuration of the fully interconnected layers is identical across the board. All concealed layers feature rectification nonlinearity.

4. Evaluation of the Results

Three distinct CNN models were evaluated, each with a different number of layers and model parameters. As a starting point, the first model (M-1) was a basic model with five convolutional layers, one fully connected layer, and kernels (3 x 3). Two additional convolutional and fully connected layers, as well as declining kernel sizes, were used to evaluate the depth of CNN models in model 2 (M-2). Using a rectangle kernel in the first layer (4 8) to see whether gaining more information in the time domain while being concentrated along the frequency band may enhance classification accuracy, Model 3 (M-3) fell somewhere in the middle of M-1 and M-2 in terms of layer count. In the ablation investigation, M-1 was the test subject. For M-1, we experimented with various convolutional layer counts and discovered that five layers was the sweet spot for this dataset. Because of its capacity to assess each item individually regardless of the sample's mix of materials, the multi-labeling labelling system was adopted....

We utilized conventional measures for evaluating ML-models, such as accuracy, precision, and recall, to analyses and discuss the classification performance. ROC curves were also provided, which provides a straightforward depiction of the classification thresholds and their influence on the true positive and false positive rates. In order to measure model bias and variance, learning curves for each dataset show how the amount of training samples affects performance. The accuracy is calculated for modeling techniques. The following output is obtained from the VGG-16 model that shows the comparison of validation accuracy and accuracy from Figure 3. And also shows the comparison of validation loss and loss in Figure 3. The highest accuracy is obtained from this model in predicting the waste classification using this respective model.

4.1 Training Accuracy and Loss

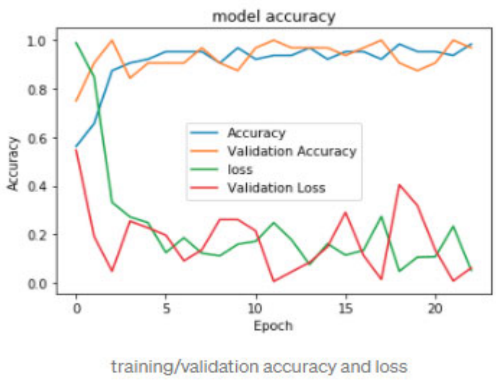

Fig 3 : Training accuracy and Loss

Figure 4 illustrates studies of training accuracy and loss based on different approaches. As can be noted, the VGG-16 model is well-converged in terms of training accuracy and training loss. VGG-16 begins training with a high level of precision and a low loss rate. Precision and loss are depicted on the same graph for the VGG-16 model, which exhibited comparable precision and training accuracy, as well as loss and validation loss.

4.2 Training Accuracy

We evaluate the precision of the suggested system's execution by testing its precision. This factor is greater due to its dataset and model. The accuracy is increasing from poor to high because the training of the model in VGG requires time. This factor decreases in comparison to the conventional trash categorization approach. The graph is depicted in Fig. 4. Consequently, the suggested system with the VGG-16 model outperforms the present classification system usually.

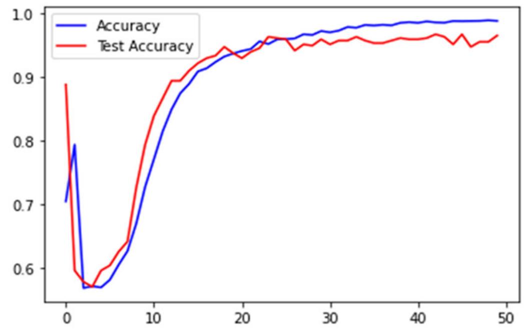

Fig 4: Accuracy of the system

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4.3. Training Loss

Fig 5 shows the rate of loss is comparable to the rate of test loss. The results indicate that our suggested system's classification loss is extremely low due to its high level of accuracy. Traditional garbage categorization systems utilize various models and often contain outdated information that cannot successfully identify new things. And may enhance the level of loss.

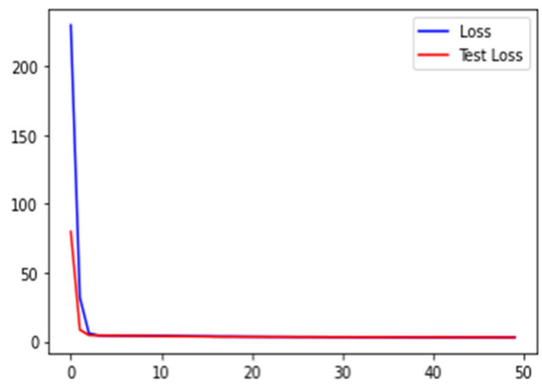

Fig 5: Loss of the system

4.4 Advantage of the proposed system

- A new approach for determining the presence of metal and glass in waste bags.
- To locate appropriate sensors, an ablation investigation was carried out.
- A convolutional neural network was fed information from sound and metal detection.
- Accuracy of CNN models ranged from 98 percent to 100 percent.
- Detection of the quality of consumer trash sorting during garbage collection is supported.

5. Conclusion

In order to deal with the problems that the current system of classifying solid waste has. This paper's results were solved with a high degree of precision using the VGG-16 model. By combining specialized features with CNNs, it increases the dataset's precision significantly. When it comes to categorizing waste, our methodology is far more effective than the previous method at sorting organics and inorganics into recyclables and non-recyclables. Adding more diversity to the dataset is one of our long-term goals, and we hope to do so in the future when testing different CNN designs. Robotic arms can be used to autonomously separate video rubbish, which is forecasted using an application model. Due to the greater variety of waste types in real life, the model still needs more data sources to improve accuracy.

Targets have been set to improve home waste recycling within the next several years as the world's environmental concerns grow. Sustainable waste management begins with consumer sorting, which has been widely implemented. Our goal is to help waste management systems better understand consumer waste generation and behavior by allowing trash bags to be classified during the normal collection procedure. As a demonstration of concept, this device can identify the presence of glass and metal in trash bags with excellent accuracy. Our solution, which relies on RFID technology to gather municipal waste, can assist identify problem areas of erroneous sorting without making significant alterations to the current system.

Using sound recording and a beat-frequency oscillation metal detector, we developed an effective categorization method. A CNN model that has been taught to look for glass and metal in trash bags can do so with an accuracy of 98%. Considering the study's experimental design and the high accuracy levels reached with a minimal amount of data, the method's potential for use in real-world circumstances looks intriguing. Using more realistic garbage bag datasets to train CNN algorithms is recommended for future research. It's time to try out the results of sound recorders and metal detectors in a more realistic environment. The study of customer behavior will benefit from long-term monitoring of garbage sorting quality. Waste management systems can benefit from fact-based decision making by employing our technique to improve the convenience of consumers by optimizing the locations of collection points.

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