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Intelligent Waste Classification System Using Deep Learning Convolutional Neural Network

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Abstract

The accumulation of solid waste in the urban area is becoming a great concern, and it would result in environmental pollution and may be hazardous to human health if it is not properly managed. It is important to have an advanced/intelligent waste management system to manage a variety of waste materials. One of the most important steps of waste management is the separation of the waste into the different components and this process is normally done manually by hand-picking. To simplify the process, we propose an intelligent waste material classification system, which is developed by using the 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 etc. The proposed system is tested on the trash image dataset which was developed by Gary Thung and Mindy Yang, and is able to achieve an accuracy of 87% on the dataset. The separation process of the waste will be faster and intelligent using the proposed waste material classification system without or reducing human involvement.

Peer-review under responsibility of the organizing committee of SMPM 2019.

Keywords: Convolutional Neural Networks, Pre-train Model, Waste Separation, Automation, Machine Learning, Support Vector Machine

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1. Introduction

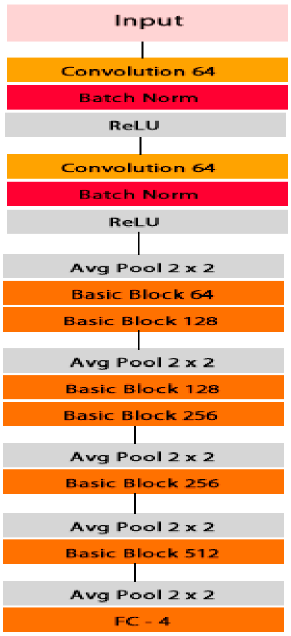
The world bank report showed that there are almost 4 billion tons of waste around the world every year and the urban alone contributes a lot to this number, the waste is predicted to increase by 70 percent in the year 2025 [1]. According to [1] in the next 25 years, the less developed countries' waste accumulation will increase drastically. With the increase in the number of industries in the urban area, the disposal of the solid waste is really becoming a big problem, and the solid waste includes paper, wood, plastic, metal, glass etc. The main method of managing the waste is landfilling, which is inefficient and expensive and polluting natural environment. For example, the landfill site can affect the health of the people who stay around the landfill site. Another common way of managing waste is burning waste and this method can cause air pollution and some hazardous materials from the waste spread into the air which can cause cancer[2]. Hence it is necessary to recycle the waste to protect the environment and human beings' health, and we need to separate the waste into the different components which can be recycled using different ways.

1.1. Motivation

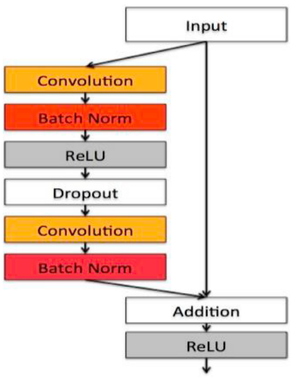
The present way of separating waste/garbage is the hand-picking method, whereby someone is employed to separate out the different objects/materials. The person, who separate waste, is prone to diseases due to the harmful substances in the garbage. With this in mind, it motivated us to develop an automated system which is able to sort the waste. and this system can take short time to sort the waste, and it will be more accurate in sorting than the manual way. With the system in place, the beneficial separated waste can still be recycled and converted to energy and fuel for the growth of the economy[3]. The system that is developed for the separation of the accumulated waste is based on the combination of Convolutional Neural Network and Support Vector Machine (SVM), the algorithms, that is, the combination of Convolutional Neural Network and Support Vector Machine deals with recognition and classification. Due to the fact that the trash image dataset is small, we used a pre-trained ResNet-50 model which is a type of Convolutional Neural Network architecture.

When the depth is increased, the recognition accuracy of the convolutional neural network can be increased[4], but due to the increase in depth, the signal that is suppose to modify the weight is reduced at the earlier layer of the CNN.

[5]. This will make learning at the earlier layers inconsequentially and this is called vanishing gradient. Adding more and more layers to the network always leads to training error. Residual Network(ResNet-50) is different from the normal convolutional Neural network[6] in that, it is able to go around this problem of vanishing gradient by designing the Convolutional neural network using modules which are called residual models, the ResNet model and the basic block is shown in Fig.1.



(a)



(b)

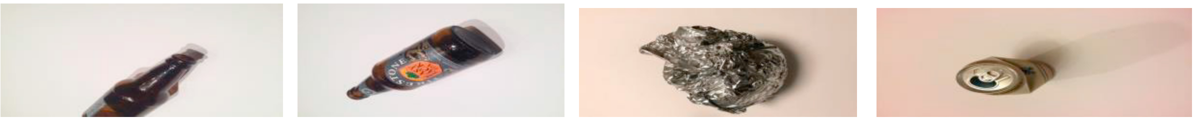
Fig. 1. (a) ResNet model for Image Classification. (b) Basic block with a dropout layer reduce overfitting(Source: Mohammad et al 2016)

1.2. Related Works

Many different algorithms have been developed for the classification of images, such has RNNs, SVMs, ANN etc, but Convolutional Neural Network which is a Machine Learning algorithm has really performed better than them all. CNNs hit the spot when the algorithm was used to win the 2012 image-Net large-scale visual recognition challenge(ILSVRC) which was proposed in [7]. Since 2012 many different CNN architectures have been developed which has solved many image classification problems [8][9][10][11]. Lulea University of technology in 1999 undertook a project, and a system was developed to recycle metal scraps using mechanical shape identifier[12]. [13] used the features from SIFT and outline shape on the Bayesian computational framework and their system was based on the Flickr material database. [14][15] in 2016 developed an Auto-Trash which was able to differentiate between compost and was recycled with Raspberry Pi, their system was developed using Google's Tensorflow. The short-come of their system was that it was only able to differentiate compost materials. A smartphone application was developed by [16] which was able to roughly identify the hip of garbage in the image. This application enables a person to give information of garbage in their area and obtained a mean accuracy of 85% using AlexNet pre-trained model.

1.3. Dataset

For this work, we are using a trash image dataset which was created by Gary Thung and Mindy Yang [17]. This is a small dataset and consist of 1989 images, which is divided into four different classes glass, paper, plastic, metal, all the pictures of the images have been resized down to 512 x 384. Few samples of the images are shown in Fig. 2



(a) Glass (b) Metal

(c) paper (d) plastic

Fig. 2 images from trash dataset (a) glass (b) metal (c) paper (d) plastic

2. Methodology

For the pre-processing stage, data augmentation method was performed on the images, because of the small size. This technique was chosen because of the different orientations of the waste materials. Some of the technique includes, random of the image, translating the image, randomly scaling the image, image shearing, randomly scaling of the image. With this technique it maximize the dataset size. The proposed method was developed based on the ResNet-50 pre-trained model, and the procedure is shown in Fig. 3.

2.1. ResNet

In CNN, several layers makes-up the network[18][19]. The layers in CNN implement some actions, which allow it to classify input images. The convolutional layer convolves the image that is inputted using a sequence of filters window sizes of 3 x3, this was used because what differentiates the objects are small and local features. The essential features are extracted from the input images. The primitive features are extracted with the help of the first few layers. Has the training goes down the layers more and more complex and detailed features are extracted, with the help of the loss function probability, that is, Softmax function [20].
Our model was developed based on the ResNet-50 pre-trained model, this model was pre-trained on ImageNet images with a size of 256 x 256 and classified into 1000 classes. As shown in Fig. 3 the ResNet-50 pre-trained model has already being trained on the inageNet dataset and a set of weights has been acquired, but we removed the top classification layer by setting the include_top = False, only the feature comes out of the network. The features are passed to the Multi-Class SVM model where the classification

takes place, based on the features extracted.

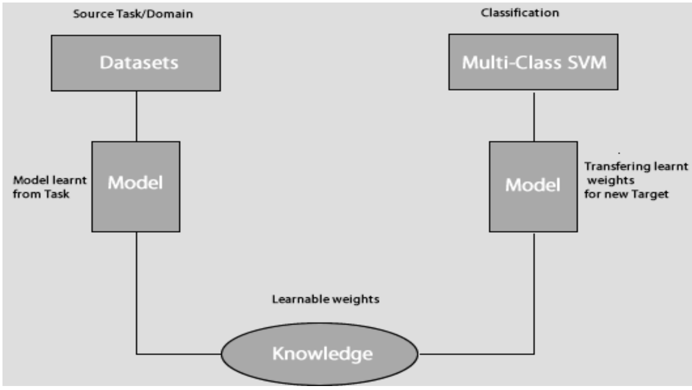


Fig.3 Flowchart of the proposed method

2.2. Support Vector Machine (SVM)

SVM can be used to solve both classification and regression problems. It is a machine learning technique and it is considered to be one of the best classification algorithms. With this algorithm, the data item is plotted as a particular point in n-dimensional space against the feature value of a specific co-ordinate. The items in SVM are classified based on the separation of hyperplane for each of the multidimensional data. It finds the hyperplane which the minimum distance is greater for the training data.

$$min_{\gamma,w,b} \quad \frac{1}{2}||w||^2$$
$$s.t \quad y^{(i)}(w^T x^{(i)} + \mathrm{b}) \geq 1, \quad i = 1 \dots \dots m \tag{1}$$

(1) shows the optimization of SVM. Here, w and b represent the parameters of the constraint function $y^{(i)}$. For the peculiar example, $x^{(i)}$ is the i^{th} example of m. the minimum geometric margin of the training examples is also represented by m.

3. Experiment and Result

The weight of the network is fixed, and the fully connected layer is removed and replaced by SVM which is trained and used for the classification. We used the following parameter for SVM optimization, the radial basis kernel was used, the SVM C- parameter was set to 1000 and the gamma was set to a value of 0.5. The pre-train ResNet-50 used was implemented on ImageNet dataset with an image size of 224 X 224. Standard colour augmentation and batch normalization were used after the convolution and before activation. The momentum and weight decay are 0.9 and 0.0001 respectively. The training was done on a core i5 Intel CPU with 12 epochs. The ResNet-50 CNN was used as the extractor for the features using Kera python with the trash dataset with 1989 images. Stochastic Gradient Descent with Momentum (SGDM) was used during the training. With the help of SGDM, the weights and biases were updated. The sample was selected at random, with a mini-batch of 12. The whole dataset was divided into two parts with a ratio of 8:2, which are used for training and testing samples, respectively. The feature extracted is then classified using Multi-Class SVM[21][22]. After the entire training, we got an accuracy rate of 87%, after the 12th epochs the accuracy was not increasing anymore. The criteria for stopping after the 12th epoch is the test loss stopped decreasing and it was on the same value. Figures 4 and 5 show the training loss vs the validation loss and training accuracy and validation accuracy respectively. For the each of the epoch of the training, the dataset is feed into the network and backpropagation is run against each sample. The losses are stored after each epoch and the mean is calculated. The loss is plotted against the epoch which gives us the training and validation loss and it is shown in Fig. 4. The average training accuracy was 94.5% when plotted against the epoch and it is shown in Fig. 5 which was almost perfect.

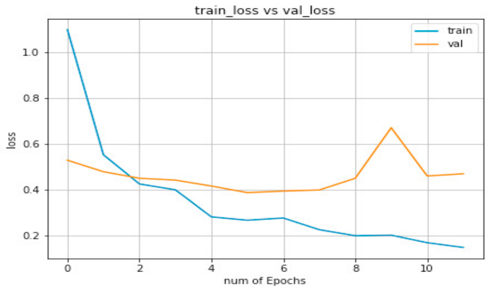


Fig. 4. Training loss and validation loss

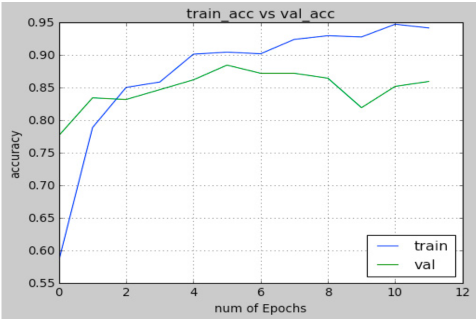


Fig. 5. Training accuracy and Validation accuracy

4. Conclusion

In conclusion, we proposed a waste classification system that is able to separate different components of waste using the Machine learning tools. This system can be used to automatically cl**assify** waste and help in reducing human intervention and preventing infection and pollution. From the result, when tested against the trash dataset, we got an accuracy of 87%. The separation process of the waste will be faster and intelligent using our system without or reducing human involvement. If more image is added to the dataset, the system accuracy can be improved In the future, we will tend to improve our system to be able to categories more waste item, by turning some of the parameters used.

Acknowledgments

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