Recyclable Waste Classification Using Computer Vision And Deep Learning

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***Abstract*—Recycling solid waste is an important step to reduce harmful impact such as sanitary and health problems resulting from the over use of landfills. Yet, recycling requires the sorting of solid waste, which is complex and expensive. In an attempt to ease this process, our work proposes a Deep Learning approach using computer vision to automatically identify the type of waste and classify it into five main categories: plastic, metal, paper, cardboard and glass. Our conceptual system consists of an automated recycling bin which automatically opens the lid corresponding to the type of waste identified. This work focuses mainly on the Machine Learning algorithms which can be trained for efficient identification. Pre-existing images have been used to train a minimum of 12 variants of the Convolutional Neural Network (CNN) algorithm over three classifiers: Support Vector Machine (SVM), Sigmoid and SoftMax. Our results show that VGG19 with SoftMax classifier has an accuracy of around 88%.**

Keywords—Waste Classification, Recycling, Deep Convolutional Neural Network, Classifiers, Machine Learning, Computer Vision

I. INTRODUCTION

Solid waste management is a growing global phenomenon which affects every single human being. Inappropriate management of solid waste leads to water contamination, disease transmission in human and animals and increase flooding due to the blocking of drains. These adverse effects have a direct consequence on economic growth and weighs heavier for developing countries. The World Bank estimates that 2 billion tonnes of solid waste have been generated worldwide in 2016, averaging to around 0.74 Kilograms of waste per person [1]. According to the same report, it is expected that waste generation will increase by 50% in 2030 and 70% in 2050 if no proper actions are taken.

The most popular waste disposal method worldwide is through landfills [1]. This method has a very high damaging impact on the environment, with the release of toxins, leachate and greenhouse gas. Recovery through recycling and composting can considerably reduce the impact of landfills. Recycling inherently consists of a complex and expensive process to sort out various waste materials into different categories such as: metal, glass, plastic and paper. Some of the existing solutions can be classified into mechanical sorting, manual sorting, automated identification with tags and computer vision systems.

Manual sorting, mainly implemented in developing countries proves to be more efficient than mechanical sorting [15]. Nevertheless, hand picking involves the manipulation of hazardous materials and can have various adverse health problems. The application of tags, such as barcodes and Radio Frequency Identifiers (RFID) have been used and proposed by various studies for efficient sorting of waste materials [2, 16, 17,18, 19]. Yet, embedded tags also have a negative impact on the environment [20]. The use of computer vision to classify a particular waste product involves the use of sensors and/or cameras, connected to a system to perform identification and an actuator to perform the sorting. We proposed a low cost and energy efficient recycling system based on bar codes in [2]. This work focuses on enhancing our solution to provide an automated recycling bin system which can automatically identify the type of waste being thrown and open the corresponding lid. The main research question focuses on whether Machine Learning (ML) algorithms can effectively identify solid waste materials and classify them into paper, metal, glass, plastic, food waste and cardboard.

II. LITERATURE REVIEW

Yang et al. [3] used the TrashNet dataset [11] to compare two Machine Learning techniques, Support Vector Machine (SVM) and Convolutional Neural Network (CNN) also known as AlexNet) for the classification of waste into five main classes (glass, paper, metal, plastic, cardboard). The results demonstrate that the SVM was more efficient with an accuracy of around 63% while the CNN achieved only 22% accuracy. An attempt to classify multiple objects in a single input has been mentioned as future works.

Adedeji et al. [4] proposed a combination of CNN (ResNet50) with SVM to classify 4 classes of waste (glass, paper, plastic, metal) and reached an accuracy of around 87% with data augmentation optimization. The main limitation of this work was the small dataset size containing a small number of trash images. It was concluded that their approach is faster than manual sorting.

A few attempts have been noted using computer vision for automation of recycling bins. Desai et al. [5] proposed a CNN to classify 2 classes of waste (degradable or non-degradable) to reduce human intervention replacing the current waste sorting method with a robotic arm based on Raspberry Pi opening the bin. Aral et al. proposed to compare different CNN that are Xception, MobileNet, DenseNet, InceptionResNetV2 using the Trashnet Dataset [11]. They reached 95% accuracy with DenseNet121 followed by 95% with DenseNet169 and 94% with InceptionResNetV2 with data augmentation optimization. They increased the size of the dataset using various techniques, which improved their results. Ziouzios et al. [7] proposed a low-cost smart bin system using CNN

(ResNet34) to classify 6 classes of waste(cardboard, glass, metal, paper, plastic, trash) on TrashNet dataset [11]. They reached a 92% accuracy and used Raspberry Pi to open the bin where images are sent using LoRaWan connectivity.

Özkaya et al. [8] ccompared the different CNN (AlexNet, InceptionV3, ResNet, VGG-16, SquezeeNet) with SoftMax and SVM as classifiers to classify 6 classes (glass, paper, cardboard, plastic, metal, trash) on the TrashNet dataset. SVM was more efficient with an accuracy of 97.86% for InceptionV3 + SVM followed by VGG-16 + SVM with 97.46% and AlexNet + SVM with 97.23%.

Bircanoglu et al. [9] compared their own CNN called RecycleNet to others (ResNet, MobileNet, InceptionResNet, DenseNet, Xception) using different optimizers like Adam, Adadelta and Stochastic Gradient Descent (SGD). DenseNet121 with Adam and SGD tops with 95% accuracy while theirs obtained 81% using data augmentation techniques.

Bernado et al. [10] compared different model that are CNN (VGG16, AlexNet), SVM, K-Nearest Neighbour (KNN) and, Random Forest (RF) to classify 4 classes (glass, metal, paper, plastic) on the TrashNet dataset [11]. VGG16 obtained better result with 93% accuracy and they tend to apply data augmentation and fine-tuned the models in future.

III. METHODOLOGY

A. Proposed System

The main focus of this research work is on the machine learning algorithm, we used an empirical approach to study various machine learning algorithms classify solid waste, mainly recyclables. Figure 1 shows a simplified approach of the system which uses a camera to capture the image of the object (waste/trash). This image is fed into a trained machine learning algorithm which performs the identification and a classifier further determines the class and opens the corresponding lid of the bin.

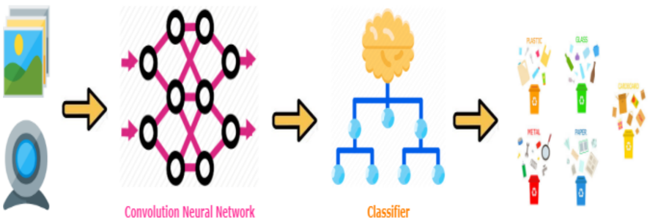

Fig. 1. System architecture diagram

Based on Transfer Learning techniques, it is being proposed that a total of 18 different versions of the CNN are considered, as listed in Table 1, with 3 main classifiers, namely SVM, Sigmoid and SoftMax. We identified TrashNet as the dataset to be used for the experiments due to its availability, number of classes and wide range of images. The approach, as depicted in Figure 2, consists of training each CNN algorithm with each classifier and comparing the results using the following parameters: training and testing accuracy, loss and training time.

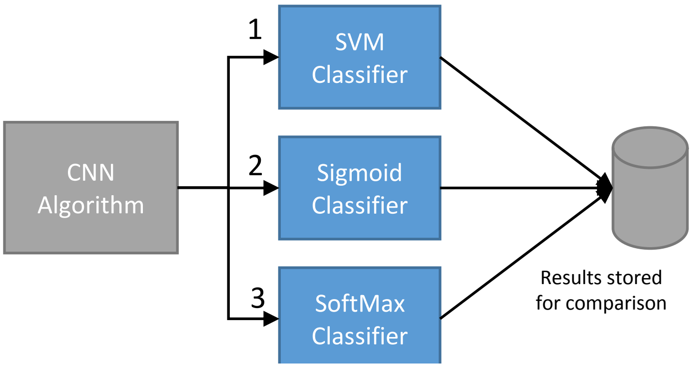

Fig 2. Methodology

B. Dataset

Due to high availability and being open-sourced, TrashNet dataset was chosen for this project [11, 12]. The original dataset is around 3.5GB in size, containing 2527 images divided into 6 classes that contains 594 paper, 501 glass, 482 plastic, 410 metal, 403 cardboard and 137 trash. A sample is shown in Figure 3. Each image is preset with a white background, which has not been removed due to computation complexity. In an attempt to improve the training response time, we have chosen to programmatically resize each image to 512 x 384 pixels, reducing the size of the dataset to around 42MB. The dataset was further randomly divided into 70% for training and 30% for testing.

TABLE I: CNN Algorithms

	CNN VERSIONS
1	InceptionResNetV2
2	InceptionV3
3	Xception
4	VGG16
5	VGG19
6	ResNet50V2
7	ResNet101V2
8	ResNet152V2
9	MobileNet
10	DenseNet201
11	NASNetLarge
12	NASNetMobile

C. Data Augmentation & Optimization

Data augmentation is a technique used to increase the size of data set during the training phase. Deep learning models often require a large training set to come up with a reliable model for predictions. It an attempt to create a more robust model for generalization, the existing images in the dataset have been augmented by position and color. Position Augmentation includes: Scaling. Cropping, Flipping, Padding, Rotation, Translation and Affine Transformation.

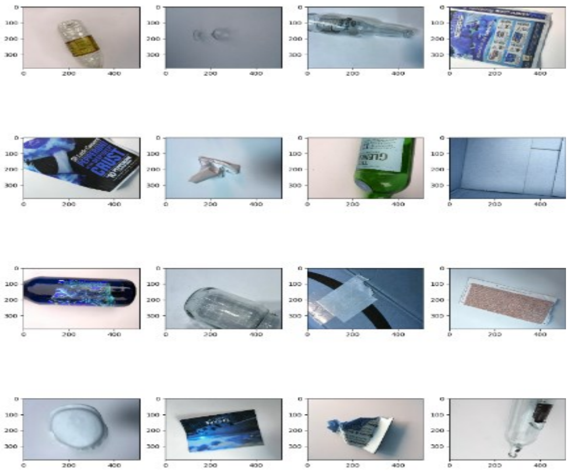

Fig. 3. Sample images from dataset

Color Augmentation includes: Brightness, Contrast, Contrast and Hue. The images were also resized based on the CNN images input guide available on [13] using OpenCV library.

The Adam optimizer (Adaptive Moment Estimation) has been used across all the experiments. As mentioned by Bircanoglu et al. in [9], Adam optimizer is more efficient than Adadelta in the context of trash classification when using the proposed TrashNet dataset. Also, Adam is computationally efficient and has a small memory footprint.

D. Experimental Setup

All the experiments for this study were carried on a laptop with configuration described in Table 2. The main software used are Anaconda [20] and CUDA [21] using Keras library [22] with TensorFlow [23] and OpenCV [13].

TABLE II: Hardware Configurations

CPU	Processor Intel(R) Core (TM) i7-9750H CPU @ 2.60GHz, 6 Cores, 12 Logical Processors
GPU	NVIDIA GeForce GTX 1660 Ti
RAM	16.0 GB
HARD DISK	256GB NVMe KINGSTON SSD

IV. RESULTS

The first set of experiment consists of using SVM, Sigmoid and SoftMax classifier on 256+50 epochs and Adam set of 0.001 on all the 12 different models, and the results are depicted in Table 3.

Using SoftMax classifier, most of the models reached above 96% of training accuracy except for VGG19 which tops at 93%. For the test accuracy, VGG19 reached around 84% followed VGG16 and ResNet101V2 of 83% and 80% respectively. The others have more than 60% of test accuracy.

TABLE III: Results for CNN Models

MODEL	**SVM (50 epoch)**		**Sigmoid (50 epoch)**		**SoftMax (50 epoch)**	
	Accuracy in %					
	Train	**Test**	Train	**Test**	Train	**Test**
Inception-ResNetV2	90.94	**65.42**	95.74	**72.62**	96.7	**65.89**
InceptionV3	91.98	**68.94**	94.37	**72.62**	97.10	**66.51**
Xception	95.70	**74.81**	97.62	**69.72**	98.44	**78.52**
VGG16	90.42	**86.13**	96.42	**84.37**	96.47	**82.71**
VGG19	98.17	**14.30**	94.78	**83.39**	93.43	**83.90**
ResNet50V2	97.52	**72.36**	99.31	**72.77**	99.11	**61.23**
ResNet101V2	97.52	**79.19**	99.11	**83.8**	99.18	**80.49**
ResNet152V2	98.04	**71.72**	99.01	**75.36**	99.28	**67.24**
MobileNet	96.80	**76.20**	99.11	**68.27**	98.81	**70.65**
DenseNet201	97.43	**66.81**	98.75	**61.23**	98.97	**62.78**
NASNetLarge	96.77	**74.39**	98.78	**77.64**	98.86	**76.35**
NASNetMobile	93.14	**72.47**	97.0	**73.91**	97.83	**73.34**

To better compare and interpret the results, a second experiment was conducted, whereby all non-performing models were eliminated. The approach consisted of 256 + 50 epochs and Adam set to value 0.001, with SoftMax, SVM and Sigmoid classifiers. Following this experiment, the five most performing models have been identified, namely: VGG16 with SVM, VGG19 with SVM, VGG16 with Sigmoid, VGG16 with SoftMax and VGG19 with SoftMax. These five models where further trained on 256 + 100 epochs and the results are depicted in Table 4.

TABLE IV: Five Best Performing Models

Model & Classifier	**Train Accuracy %**	**Train Loss**	**Test Accuracy %**	**Test Loss**	**Training Time (hours)**
VGG16 + SVM	98.5	0.0221	**87.3**	0.7522	2.13
VGG19 + SVM	97.4	0.0385	**87.3**	0.7649	2.00
VGG16 + Sigmoid	98.1	0.0496	**87.6**	0.7649	2.00
VGG16 + SoftMax	98.2	0.0491	**87.7**	0.6042	2.18
VGG19 + SoftMax	96.6	0.0979	**87.9**	1.075	2.25

The first two models from Table 4 reached a test accuracy of around 87%, while the remaining models reached around 88%. VGG19+SoftMax proved to be the most accurate as it can be depicted in Figure 4. This is mainly due the deep 19 layered approach of VGG19.

Compared to the traditional CNN or VGG16, the depth of layers makes a major difference, with a minor increase in training time.

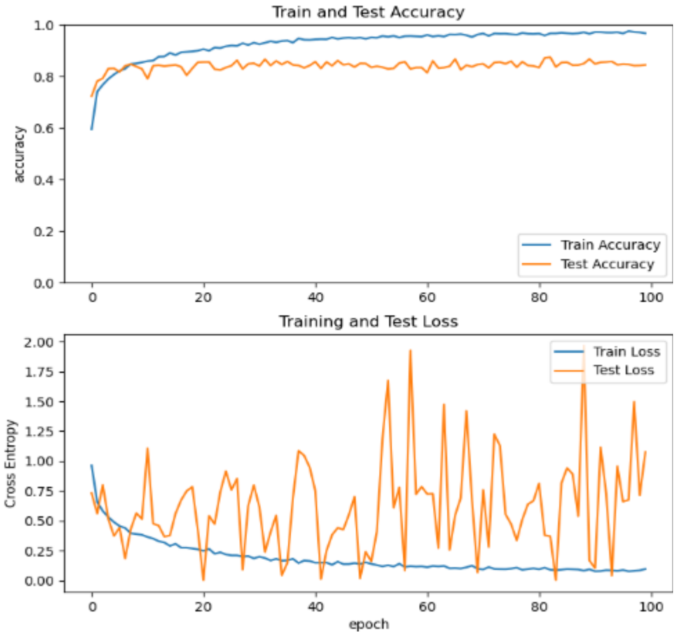

Fig. 4. Selected model VGG19 + SoftMax Train vs Test Accuracy and Train vs Test Loss.

In an attempt to benchmark and further analyze our results, a comparative analysis is presented in Table 5 below. Results from our experiments have been compared with results mentioned in the literature review.

TABLE V. COMPARISON OF THE PROPOSED MODEL

Ref	No. of Classes	Model Used	Fine - Tuning	Data Augmentation	Accuracy (%)
[3]	5	SVM	No	No	63.0
[4]	4	ResNet50 + SVM	No	No	87.0
[6]	6	DenseNet121	Yes	No	95.0
		DenseNet169	Yes	No	95.0
		InceptionResNetV2	Yes	No	94.0
[7]	6	ResNet34	Yes	No	92.1
[8]	6	Inception ResNetV2	Yes	Yes	87.0
		DenseNet121	No	No	85.0
		RecycleNet	Yes	Yes	81.0
[10]	4	VGG16	No	No	93.0
Proposed Model	5	VGG19 + SoftMax	No	Yes	87.9

Our proposed model is more accurate than the SVM of [3], ResNet50+SVM of [4] and the DenseNet212 and RecycleNet of [9]. Still, it has maximum of 7% less accuracy than the results of [6] and [10]. Further analysis reveals that data augmentation of the original TrashNet dataset is a major factor contributing to the lower accuracy level of the proposed approach. The results presented by O. Umut and L. Seyfi. [8] also demonstrates that some models may yield lower accuracy after the application of fine-tuning and data augmentation. Yet, data augmentation greatly contributes to the reduction of overfitting risks [26 ,27, 28]. It is also expected that the collection of images for an operational smart bin system keeps on increasing, as such, our approach already caters for a reasonable offline training time with the large dataset resulting from the data augmentation process. Still, we have considered the basic standard algorithms, without any fine-tuning. Manual parameter configuration or use of Nature Inspired Algorithms in the likes of the BAT [24] or ANT Colony [25] can be considered to better fine-tune the model and improve the test accuracy.

V. CONCLUSION

In an attempt to find the best possible Machine Learning algorithm for the detection of recyclable trash, we compared 12 versions of CNN over 3 different classifiers. We designed and run all the experiments and our results demonstrate that the VGG19 with SoftMax classifier achieved an accuracy of around 88%. It successfully classifies waste into 5 different classes (glass, paper, plastic, metal, cardboard). Although 6 classes of waste were desirable, as per the main research question. Only five were achieved, leaving out the food waste. This is mainly due to the limitation with the dataset. In specific cases, the results achieved demonstrate some degree of improvement compared to other approaches. Nevertheless, fine tuning and optimization are required before implementing the solution in an automated recycling bin system.

VI. LIMITATIONS AND FUTURE WORKS

The future work focuses on two main aspects: 1) data and model optimization and 2) recognition of trash from images containing multiple objects/classes. For the first task, the data set used have images on a white background which is taken into consideration during the training by all the models. Therefore, when images with other color/type of background is used, the accuracy is not as expected. From Figure 5 below, we can note that the model failed for the last image, predicting it as paper instead of plastic.

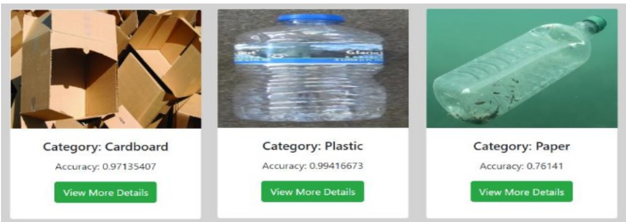

Fig. 5 Images tested on VGG19 with SoftMax model.

The next step consists of improving the results of the current experiments for the top five models by implementing various ML optimization techniques. Eventually, once the accuracy of the algorithm improves, real time detection via webcam or smartphone camera using segmentation algorithms with an IoT device like Raspberry Pi to automatically open a bin lid can be implemented in the prototype.

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