A cloud based smart recycling bin for waste classification

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***Abstract*—Due to the Earth's population rapid growth along with the modern lifestyle the urban waste constantly increases. People consume more and the products are designed to have shorter lifespans. Recycling is the only way to make a sustainable environment. The process of recycling requires the separation of waste materials, which is a time consuming procedure. However, most of the proposed research works found in literature are neither budget-friendly nor effective to be practical in real world applications. In this paper, we propose a solution: a low-cost and effective Smart Recycling Bin that utilizes the power of cloud to assist with waste classification. A centralized Information System (IS) collects measurements from smart bins that are deployed all around the city and classifies the waste of each bin using Artificial Intelligence and neural networks. Our implementation is capable of classifying different types of waste with an accuracy of 93.4% while keeping deployment cost and power consumption very low.**

***Index Terms*—cloud, smart bin, classification, computation offloading, recycle, recycling bin, IoT**

I. Introduction

Due to the Earth's population rapid growth, billions of tons of garbage are generated annually across the globe. In European countries, 6 metric tons of garbage being generated by each person per year [1]. The growth of the population, however, is not the only reason for the increased waste generated. Each person individually consumes an increased amount of products and therefore produces more waste. Disposable products have also been very popular lately due to their ease of use and low cost. The majority of these waste is dumped in landfills and water bodies. If this trend continues to grown, the Globe will soon be a giant garbage bin. This can cause a major impact on the environment. The sorting of waste should be performed at the earliest stage possible, in order to maximize the amount of recycled materials and reduce the possibility of being contaminated by other waste materials. This will help to minimize health and environmental problems, such as greenhouse gas emissions, water and air pollution. This is why recycling plays a very important role in preserving the environment. It is extremely important to preserve valuable resources, reduce non-reusable waste and minimize pollution. Reusing materials and prolonging their lifetime is the only way to make a sustainable environment [2]. This is why that over the last few years, the EU has established many laws and policies regarding recycling [3] (Fig. 1 [4]).

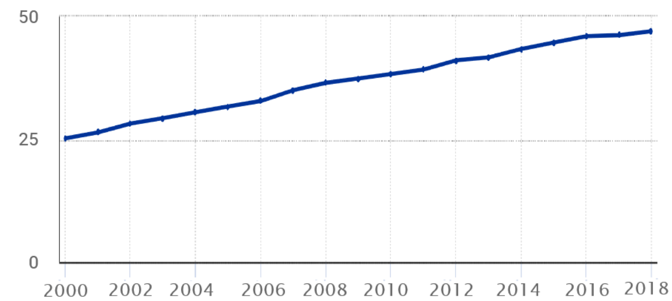

Fig. 1. Average recycling rate of municipal waste in EU of total waste generated

Because of the nature of the recycling process, the separation of the waste materials is necessary. Many organizations believe that by learning people's behavior they can improve the recycling process. Some researchers investigate pro-environmental behaviors such as Theory of Planned Behavior [5], Norm-Activation-Theory [6], and Value Belief Theory [7] to predict how people behave independently. Gathering sufficient information on recycled materials can prompt improved recycling conduct [8]. The optimal way to learn people's behavior, however, is not by questionnaires and studies but by analyzing the disposed materials in real time and predicting recycle patterns.

As the problem of recycling has worsened over the last years, it has also become a political issue. In a typical modern city, multiple waste bins are being used for waste disposal; usually glass, plastic, aluminium and paper. Because of this, citizens play a very important role as they are the ones who collect and assort waste by material. The assortment process is one of the reasons why citizens don't get involved to recycle. We are confident that we can offer a solution to this issue by designing a system to automate the waste classification process and lift some weight off of citizens. In this paper, we propose an extension of our previous research work [9]. A modern smart-bin; an IoT device that uses Computer Vision (CV), Artificial Intelligence (AI) techniques and computational offloading to the cloud to detect and assort waste that is being disposed into by material (such as paper, plastic etc) and type (such as bottles).

The structure of the paper is as follows. In Section II, the background of this paper is presented along with related work. Section III presents the proposed implementation of the hardware and software. In Section IV, the experimental results are presented. Finally, the conclusions of this paper are outlined in section IV.

II. Related Work

In their research paper, Yang *et al.* [10] presented an interesting approach. They used CV techniques for waste classification and waste processing. The core idea of their research is to capture photos of each item and categorize it in one of few categories (glass, paper, metal, plastic, cardboard, and trash). The proposed models utilized support vector images (SVM) with scale-invariant feature transform (SIFT) and a convolutional neural network (CNN). The experimental results indicate that the SVM had superior performance compared to CNN. The problem with their implementation though was that they were not capable to train the CNN because of troubles finding the optimal hyper parameters.

Zhu *et al.* [11] developed an intelligent bin prototype that sends a signal once it is full. The bin prototype is equipped with camera and ultrasonic distance sensors that capture an image every time the bin is opened. By comparing the new images with the previous captured ones, the bin determines the amount of new waste the bin has collected. Even though the core idea was great, the features of the bin were very limited as they did not perform any waste classification nor implement any modern technologies.

In order to solve the problem of waste collection and automatic waste level inside the bin, advanced computer vision and image processing techniques have been tested [12]. A method of bin level detection has been implemented using a GW filter GLCM and BGLAM as a feature extractor with artificial neural network (ANN) and K-nearest neighbor (KNN) as classifiers to provide a robust solution for solid waste automated bin level detection, collection and management [13].

The key point that differentiates our work from the aforementioned ones that we utilize computation offloading to the cloud in order to perform the waste classification process. The embedded system installed on the Smart-Bins is mainly used for capturing images and taking sensor measurements, the processing capabilities are lower than other implementations. This allows us to use an inexpensive embedded system on the smart-bins and keep the manufacturing cost as low as possible.

III. Implementation

There are two main hardware components in our Smart-Bin implementation: A Raspberry Pi Zero W and a Raspberry Pi Zero W camera module version 2.1. The Raspberry Pi Zero W board is very suitable for our prototype needs for 3 reasons: (a) it has very low cost, which is necessary for our project, (b) it is very energy efficient since it consumes less than 200mA under normal load and (c) it has a very small form factor (Dimensions: 65mm × 30mm × 5mm). It is equipped with a 1GHz single-core ARMv6 CPU (BCM2835) and has integrated WiFi (802.11n wireless LAN) and Bluetooth 4.0.

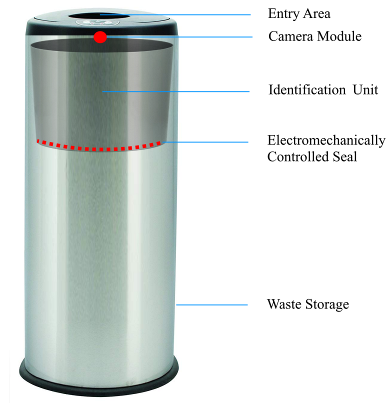

Fig. 2. The proposed Smart-Bin prototype

The computing power of the Raspberry Pi Zero W is more than enough for our project needs, since computations will only be performed on our Information System (IS) on the cloud. Compared to a typical micro controller, the processing power of the Raspberry Pi Zero W allows us to process captured pictures and measurements much faster. The other main component of our smart-bin prototype is a camera module version 2.1 which features an ultra high quality 8 megapixel Sony IMX219 image sensor (up from 5 megapixel on the version 1 camera board), and a fixed focus camera lens. The version 2.1 camera module is capable of capturing pixel static images up to 3280 x 2464 resolution and also supports video capturing in three configurations, 1080p at 30 Frames Per Second (FPS), 720p at 60 FPS and 480p at 90 FPS.

The Smart-Bin prototype can be divided in two main parts: a waste entry area on the top and an identification unit, which features an electromechanically controlled seal on the bottom. In a typical use case scenario, as items are being inserted into the bin one by one, the entry button is triggered and the camera captures a frame of the identification unit. After the aforementioned process has been completed, the Raspberry Pi Zero W transmits the captured image to the IS by using the WiFi protocol. The waste recognition process takes place after the cloud based IS has received the captured image.

A. Waste Classifier

The main software component of our proposed Smart-Bin implementation is a Convolutional Neural Network (CNN) used to perform waste classification based on captured images (every pixel of the captured image is used). The waste can be classified in one of the following classes: cardboard, glass, metal, paper, plastic, or trash. We have decided to utilize the fastai library[1], because it simplifies the training procedure. The data set spans six classes and consists of 2527 images. We divide images up into train, validation, and test image folders with a 50-25-25 split.

The CNN used is the resnet34, a residual neural network with lots of layers. The resnet34 CNN has 34 pretrained layers

[1] https://docs.fast.ai

on the ImageNet database [14]. The pretrained CNN performs better on new image classification tasks because it has already learned some visual features and can transfer that knowledge over (hence transfer learning).

As deep neural networks are capable of describing increasing complexity, in theory, their performance can be greater than shallow networks on the training data set. However, in more practical scenarios like ours, deep neural networks tend to perform worse than shallow ones. To make our neural network perform better, we decided to use a Resnet which utilizes shortcut connections; therefore sub optimal values can be adjusted (weight and bias) while the optimal ones (with zero residual) can be completely skipped. As adjustments need to be made, shortcut connections apply the identity function to pass information to subsequent layers. This shortens the neural network when possible and allows the network to have deep architectures and behave more like a shallow neural network.

We performed model training for 20 epochs with a learning rate of 5.13e-03 as the learning rate finder suggests (Fig. 3). In Fig. 4 we have an visualization of the most incorrectly classified images. Those images were excluded as they are actually degraded and the false classification is not a model issue.

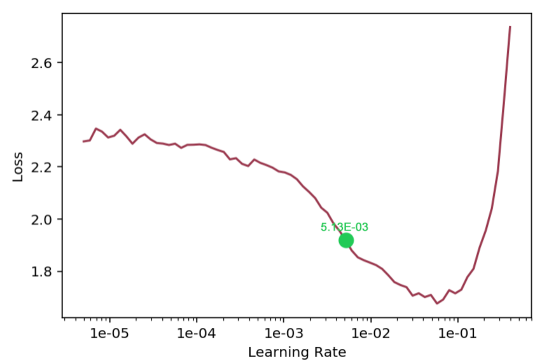

Fig. 3. The minimum numerical gradient 5.13E-03 as suggested by LR Finder

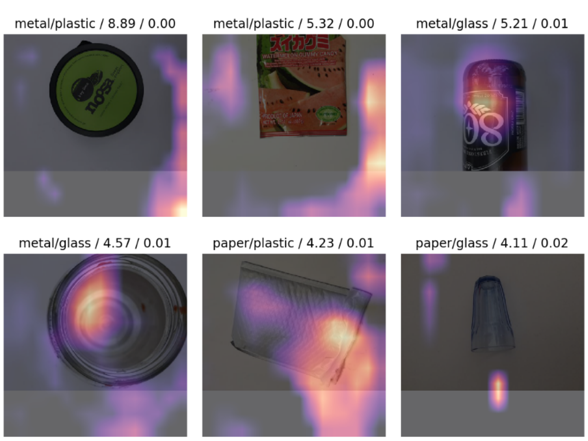

Fig. 4. The images that the recycler performed poorly were actually degraded and not a fault with the model

B. Connectivity

Another major difference from other systems is the connection between the bins and the main platform. In our work, we use WiFi. WiFi is a family of wireless networking technologies, based on the IEEE 802.11 family of standards, which are commonly used for local area networking of devices and Internet access. The actual data rates depend on the specific WiFi network, the connected users on the network and the overall server load. The most important advantage of using open WiFi networks is the quick implementation process. Since open WiFi Access Points (AP) are practically everywhere in most modern cities, using WiFi to communicate with the IS allows us to keep the implementation cost of the bins even lower and not spend time installing antennas or any other equipment in general. For our project, this is the ideal solution because we need a network with those characteristics. For example, if the distance between two bins is too long, mesh techniques cannot be used. On the other hand, GSM based solutions increase the running cost and render the project unfeasible. The captured images along with other sensor measurements (such as temperature and humidity) are stored to an external drive like an SD card and the user of the IS can set the batch transmission size from 1 to 100 and the period of time when the data will be sent. The choices vary accordingly to the number of smart bins and their use (Fig. 5).

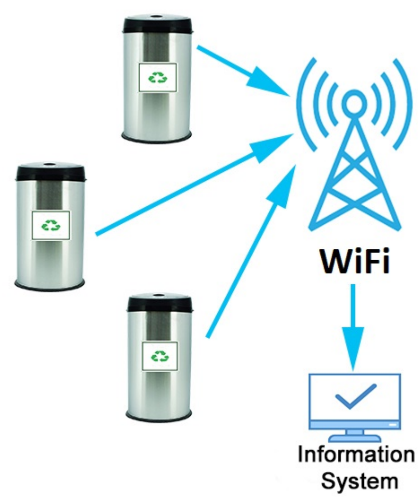

Fig. 5. Smart-bin connection with WiFi

C. Software

As already mentioned, the embedded system communicates via WiFi on specified intervals with the IS and transmits all captured images and measurements. Before the transmission process begins, all data are being compressed and encrypted. For the captured images, lossless compression formats are being used, such PNG and WebP. For encryption, smart-bins use the asymmetric encryption algorithm RSA, so that in the extreme case where a smart-bin is stolen, the thieves will not be able to decrypt the data as they will not have access to the private RSA key.

The IS is divided into two parts: the front-end and the back-end. The front-end allows registered users and administrators to access the data regarding the smart-bins. Each Smart-Bin has a unique identification number transmits encrypted measurements to the server. The back-end of our IS is based on MySQL, an open-source relational database management system and PHP, a general-purpose scripting language.

IV. Experimental Results

In order to evaluate our system, we installed several Smart-Bin devices in the city of Kozani, each within the range of an open WiFi station. We conducted multiple experiments from 16th of June to 30th of September in the city of Kozani with random sampling. Fig. 6 shows some of the locations in which we tested the Smart-Bin devices embedded systems.

The single 1GHz core equipped Raspberry Pi Zero W proved to be more than enough to capture images, take sensor measurements and compress, encrypt and transmit the data in a timely manner. The proposed CNN is capable of achieving an accuracy of 93.4% on the test data, which meets our design constraints and provides a reliable estimation as to the first step of the waste management procedure. Due to the computation offloading on the cloud, the processing time of our neural network is minimal and the battery life of the Smart-Bin is maximized. Results show that the proposed system architecture, utilizing secure computational offloading to the cloud is feasible in small and large scales.

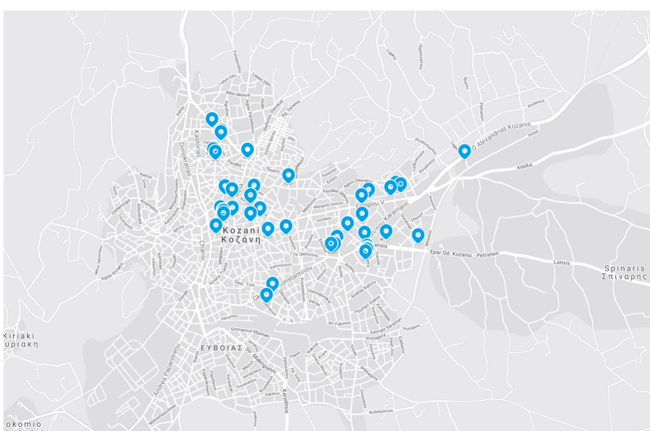

Fig. 6. Smart-Bin locations in Kozani

V. Conclusions

A secure cloud based Waste Classifier system has been successfully designated by using a camera as image capturing device integrated with modern techniques such as machine learning and neural networks. In this paper, our image processing technique has focused for object detection and feature extraction using a residual network for waste level classification. The efficiency of the proposed technique was justified by demonstrating a good number of sample images. By utilizing cloud computation offloading techniques, we used very inexpensive equipment on the Smart-Bin devices. Our approach proved to be efficient, low cost and able to meet field application requirements. Consequently, this classification system can be a promising solution for bin level detection. Also, because we utilize servers located in the cloud (a persistent cost), this project becomes more and more efficient as we increase the total number of installed smart bins. In the future, this project could be further improved by using custom designed PCB and micro controllers instead of the Raspberry Pi Zero W. In order to improve the user experience, the processing speed of the waste inside the bin could also be improved by allowing two items to be inserted at once. Finally, enhancements could also be made on the software side, by improving the execution time of the CNN.

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