SPubBin: Smart Public Bin Based on Deep Learning Waste Classification: An IOT system for Smart Environment in Algeria

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Over the past few years, Internet of things (IoT) has become one of the most important technologies of the 21st century. Nowadays, it is possible to connect different objects to the internet via embedded devices. By means of this technology, physical objects can share and collect data with minimal human contribution. In this inter-connected world, digital systems can record, monitor, and adjust each interaction between connected things. The IoT technologies support smart cities initiatives around the world in order to promote greener and safer urban environments, with cleaner air and water, and better public services and mobility. Smart environment is an inseparable part of smart cities. In our environment, wastes are objects that we put in the Bin. Waste management sorting and recycling are two central elements in the fight against climate change. Existing solid waste management policies and methods are being challenged by the exponential population expansion in urban areas. In fast-growing cities, where increasing garbage output exceeds the capacity of current facilities, the issue becomes even more difficult. Waste avoidance, recycling, reuse, and recovery are essential factors for reducing solid waste discharged in landfills, particularly in rapidly increasing cities where more sustainable management techniques are required. In smart home, effective household waste management is essential to building habitable cities however remains a challenge for many developing countries and cities. In this context, as any other important aspect of city management, a good waste disposal strategy plays a crucial role for making cities more glamorous. In this paper, a novel approach for waste sorting is proposed. Baptized SPubBin (Smart Public Bin), the presented solution is based on transfer learning, and uses, three CNNs models: VGG16, Dense201 and Resnet50. In order to validate the proposed approach, we have developed a tool supporting it.

Povzetek: Razvit je pametni javni smetnjak, ki zna klasificirati smeti na osnovi sistema globokega učenja.

1 Introduction

Due to the rapid increase in population density in urban areas, substructures and services have been needed to supply the requirements of the citizens. Consequently, there has been a remarkable growth of digital devices, such as sensors, smart phones and smart appliances. Since its arrival, the internet has experienced great development in all areas; and has become almost a primary source of information. The Internet of Things (IOT) relates to installing sensors (RFID, IR, GPS, laser scanners, . . . etc.) for everything, and connecting them to the Internet through specific protocols for exchanging information and communications. Many researchers are working on projects to improve people's daily lives, and make life and smart cities, with connected objects and infrastructure. This has become easier with the appearance of the IoT, the most important technology of the 21st century [19].

Usually, the main form of online communication is human-human. Nowadays, forms of communication are expanded to human-thing, and it brought a new era of computing and connectivity everywhere and changed people's lives [1].

Smart City is one of the major applications of the Internet of Things (IoT). A smart city can be created by integrating two advantages: being equipped and interconnected into its advanced stage of IoT development [2]. New IoT's applications enable Smart City initiatives around the world, provide the ability to monitor, manage and control devices remotely. Key features of the smart city include a high degree of IT integration and a comprehensive application of information resources. In order to deal with several issues related to smart applications, Algeria has installed a national strategy for research and innovation on artificial intelligence (AI) 2020-2030. Presented on Monday, 18 January 2021 17:36 at the Ministry of Higher Education and Research scientific, this strategy aims, over the next few years, to improve performance in a number of so-called priority segments, such as higher education, health, environment, transport, energy and technologies. It will also allow the rapid execution of development programs and projects, the emergence of an innovative working climate, support for initiatives and increased productivity.

The said strategy aims to build a solid base in terms of research, to apply the latest techniques of artificial intelligence in various fields and to better exploit available human and material resources. SPubBin (Smart Public Bin) project [37, 38] is part of this global strategy of innovation and digitization of various sectors, in particular the environment sector, decided by the higher authorities of the country and adopted by the ministry of higher education and research scientific. In our traditional environments, wastes are objects that we put in the Bin, like, for example, bottles, cans, plastic bags, papers, and vegetable peelings. Sometimes we find plastic bags or other waste in water. It makes the water dirty and then we cannot drink it anymore. To overcome this problem, it would be very useful to make these environments smarts. Smart environments are considered important parts of smart cities. One of the problems that should be solved to protect these environments is the sorting of waste. a)

At home, we have several Bins (generally each one with a distinguished color), which must be sorted in order to permit reusing some wastes. Although waste management and recycling are two central elements in the fight against climate change, having multiple bins and good waste management can sometimes be complicated by lack of time, money or knowledge. Therefore, to protect our environment, fight pollution and economize time, money or knowledge, it seems mandatory to think about Smart bins, which allow the sorting and recycling of wastes.

In the literature, several researches [24, 26, 27, 29, 34, 35, and 36] have been carried out as part of the development of smart bins. Despite these approaches have achieved good results in the context of wastes sorting, but, firstly the high prices make the purchase operation very difficult here in Algeria. So we will see how our SPubBin can add a value in this domain compared to other ones, and, help to reduce import costs.

In the second, all Smart Public Bin have some development in the last years, but it still need to more search and update, price side, design type of waste taken into consideration, sorting, connectivity, recycling and we hope that our work can add value in this domain in Algeria. In order to contribute in the strategy adopted by our Country, we have launched a project called SPubBin [37, 38]. This later is made concrete by following a novel approach for waste sorting based on transfer learning, and uses, three CNNs models: VGG16, Dense201 and Resnet50. The main objectives of the proposed approach are essentially: (1) Develop an intelligent public bin based on waste sorting. (2) Intelligent waste management using IOT techniques. (3) Intelligent waste classification using (AI) techniques (Deep learning). (4) Reduce import costs (5) Eliminate unpleasant odors, insects and pathogenic germs at the level of the trash. (6) Save effort and time by sorting at bin level and transferring waste directly to recycling. For validation reasons, we have developed a visual tool supporting the proposed approach. This tool is a SmartPublic Bin (SPubBin) which composed of 2 parts:

Smart classification Part: (Deep learning waste part): the main objective of this part is the sorting of waste into 6 classes, using deep learning and transfer learning techniques. For this, we propose an algorithm able to sorting (classification) different types of waste (Paper, Glass, Metal, Plastic, Cardboard and Trash) with a high accuracy; the proposed system is trained with the dataset Trash-net [3]. To do this, we have used the transfer learning technique based on CNN model; (VGG16, Dense201, and Resnet50) and different tools for implementation. We present the description of our algorithm from loading the dataset to used functions then how did we divided the "Trash-net dataset" before training our models until we get the results of the accuracy, loss and the confusion matrix then we will see if we could achieve our aim which getting a +95% accuracy in waste sorting or not, with 100 epochs

Waste collection part: after sorting, wastes are collected into 6 Smart Trash Can (STC), which composed 2 parts (logical and physical).

a. Logical part: A Mobile application to manage and monitor a Smart Trash Can remotely in real time, the concerned persons will be notified about the Smart Trash Can status to achieve the removal of trash in a proper way.

b. Physical part: realization of a Smart Trash Can using different devices, protocols and sensors: the ultrasonic sensors is used to open and close the lid of the can whenever the persons are nearby the Smart Trash Can and measure the trash level and send notifications to the mobile application users that it's full and ready to be emptied, the temperature and humidity sensors to measure the humidity in the Smart Trash Can. They take the resulting data from the external environment; the Smart Trash Can values are stored in a database and monitored by a mobile application.

The rest of this paper is organized as follows: In Section 2, we give some definitions. Section3 presents the related work. In Section 4, we present our SPubBin (Smart Public Bin). The famous Smart Trash Cans in the market are presented in section 5. Finally, we draw some conclusions and give some future work directions.

2 Definitions

In this section, we will present definitions for all notions related to the solution we propose; IOT, Smart environment, deep learning and Transfer learning.

Internet of Things (IOT): The IoT is a digital revolution that has never stopped developing; it affects nearly every aspect of life, including economics, politics, and social issues, and it is also a prerequisite for developing an intelligent system and creating a so-called intelligent city. According to [32], the core of the smart city implementation is the Internet of Things (IoT). Smart cities must have three major characteristics: intelligence, connectivity, and devices, all of which the Internet of

Things can deliver. It may be argued that the Internet of Things (IoT) [40] allows for the implementation of smart cities. The Internet of Things enables the communication of a wide range of systems and applications, by the use of a wide range of sensors, including RFID, IR, and GPS, connect buildings, infrastructure, transportation, networks, and utilities via ICT to perform various activities such as information sharing.

Smart environment: A smart environment is an interconnected tiny world in which sensor enabled connected objects cooperate to make resident's lives more comfortable. The word smart means the capacity to obtain and use information on one's own, and the term environment relates to one's surroundings. As a result, a smart environment is one that is capable of acquiring knowledge and applying it to adapt to the requirements of its residents in order to improve their experience of that environment. Smart environment is a field of smart cities, which is the response to the increasing pressure from globalization as defined by Coe et al. [36].

Deep Learning: Deep learning is part of a broader family of machine learning methods based on artificial neural networks with representation learning. Learning can be supervised, semi-supervised or unsupervised. Deep learning architectures such as deep neural networks (DNN), recurrent neural networks (RNN) and convolutional neural networks (CNN) have been applied to fields including computer vision, machine vision, speech recognition [4]. Convolutional Neural Network (CNN) (figure 1) is a type of artificial neural network. It is a multilayer neural network that was biologically inspired by the animal visual cortex [5]. The architecture is particularly useful in image-processing applications as well as recommendation systems. In particular, it is widely used in the field of image analysis. CNN has the advantage of using kernel filters and implements pooling. There are a several types of CNN, we count the most used: Dense201, VGG16 and ResNet.

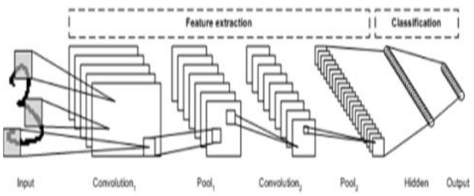


Figure 1: CNN layer sample [5]

VGG-16. is a convolutional neural network model (figure 2) proposed by K. Simonyan and A. Zisserman from the University of Oxford in [33]. The model achieves 92.7% top-5 test accuracy in ImageNet, which is a dataset of over 14 million images belonging to 1000 classes. It was one of the famous models submitted to ILSVRC-2014. It makes the improvement over AlexNet by replacing large kernel-sized. VGG16 was trained for weeks and was using NVIDIA Titan Black GPU's.

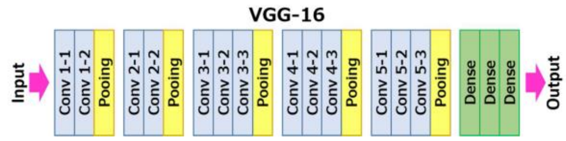


Figure 2: VGG16 layers [33]

ResNet. A residual neural network (ResNet) (figure 3) is an artificial neural network (ANN) of a kind that builds on constructs known from pyramidal cells in the cerebral cortex released in December 2015. Typical ResNet models are implemented with double - or triple layer skips that contain non-linearities (ReLU) and batch normalization [6]. ResNet has a simple idea: feed the output of two successive convolutional layers and also bypass the input to the next layers

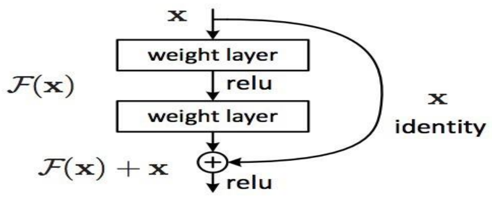


Figure 3: ResNet architecture [6]

DenseNet. DenseNet (see figure4) is a network design in which each layer is feed-forwardly linked to every other layer (within each dense block). The feature maps of all previous layers are considered as distinct inputs for each layer, while its own feature maps are passed on as inputs to all following levels. This connection pattern achieves cutting-edge accuracy on CIFAR10/100 (with or without data augmentation) and SVHN. DenseNet achieves equal accuracy as ResNet on the large scale ILSVRC 2012 (ImageNet) dataset while utilizing less than half the number of parameters and nearly half the number of FLOPs. [35]

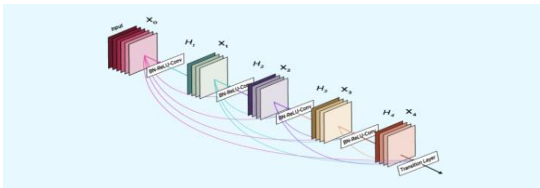


Figure 4: A dense block with 5 layers and growth rate 4 [35]

Transfer learning is a deep learning method that allows reuse of broad models that have already been trained (for example, to recognize images) in order to speed up the creation of a model that matches your company's specific demands. When it comes to developing an artificial intelligence model, transfer learning eliminates the need to start from zero. The developer identifies an existing model that performs functions similar to the ones he wishes to see achieved by the model he seeks to build. According to [34], to increase learning in the target task, we use knowledge from source models. A part from allowing you to reuse previously created models, transfer learning can help you learn the target job in the following ways: (1) Better initial model, (2) Higher learning rate, (3) Higher accuracy after training and (4) Faster training.

3 Related works: AI-based approaches for smart waste classification

Waste has become a big problem all over the world due to uncontrolled disposal of household waste from citizen's homes and industries without an effective waste management program that can lead to health risks and a negative impact on the environment for this and every time scientists try to do their best to obtain the best solution for waste sorting. Some approaches depended on machine learning (ML); others relied on deep learning (DL) [8]. In the literature, several approaches have been proposed based Machine Learning (ML), we cite among others: The aim of this study [9], is to automate waste sorting by using machine learning techniques to identify the form of waste based solely on photographs. Deep learning with convolution neural networks (CNN: AlexNet) and support vector machines (SVM) are used as learning algorithms. Using only a 256 x 256 colored .png images of the waste, each algorithm generates a different classification that divides waste into three key categories: plastic, paper, and metal. On the test set, AlexNet was able to achieve a classification accuracy of 83 percent, but SVM out performed it with a score of 94.8 percent. In [10], present an efficient framework for the above purpose that separates waste into cardboard, glass, metal, waste, paper, and plastic using supervised machine learning algorithms. Initially, data is gathered and then augmented. The algorithm converts the image sets in various directories to gray scale before converting it to a 2D matrix. Following that, the images are transformed and placed in a 1D array, which is then used for labeling during testing. The edges in the images are determined by sampling the input images and then convolving them using CNN. The testing process was completed with an efficiency of 80%. Mindy Yang and Gary Thung [3] proposed an approach, which the aim is to take a picture of a single waste of recycling or waste and divide it into six categories: glass, paper, metal, plastic, cardboard, and trash. They have created a dataset of approximately 400-500 hand-collected images for each class. They make this dataset available to the general public. Support vector machines (SVM) with scale-invariant feature transform (SIFT) features, as well as a convolutional neural network, were used (CNN). Their tests revealed that the SVM outperformed the CNN; however, the CNN was not fully trained due to difficulties in finding optimal hyper-parameters. Their classification issue involves receiving photographs of a single item and classifying it into a recycled material category in order to imitate a stream of materials at a recycling plant or a customer taking a picture of a material to identify it. Images with a single object on a clean white background are fed into their pipeline as data. Using a 70/30 training/testing data split, it achieved a test accuracy of 63 percent. The training error rate was 30%. In [11], proposed 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 acts as the extractor, and the Support Vector Machine (SVM), which is used to classify the waste into different groups/types such as glass, metal, paper, and plastic. The proposed framework is evaluated on the waste image dataset created by Gary Thung and Mindy Yang, and it achieves an accuracy of 87% on the dataset.

For the approaches based Deep learning, CenkBircanoglu and Al. [12] worked on well-known deep convolutional neural network architectures in order to have the most effective solution. Inception- Resnet, Inception-v4 outperformed all others with 90 percent test precision for training without any pre-trained weights. DenseNet121 provided the best result with 95 percent test accuracy for transfer learning and finetuning of weight parameters using ImageNet. However, one drawback of these networks is that their prediction time is slightly longer. They changed the link patterns of the skip connections within dense blocks to improve the model's prediction efficiency. Jobin Joseph and Al In [13] given the large population in India, the mentioned scientists proposed a system based on deep learning to be able to sort waste to keep pace with the evolution of the population. The proposed concept focuses on identifying and classifying waste that is on the verge of being dumped in a waste bin. Unsegregated waste is typically discarded in a landfill and allowed to decompose, which can take hundreds of years in the case of non-biodegradable waste, and combining hazardous and unsafe wastes can destroy land and water supplies. This project proposes an idea in which a computer can recognize waste without the need for human involvement based on a collection of datasets, regardless of its shape or scale, and classify it. Their proposed framework is self-learning and can therefore continuously upgrade itself in the event of new materials. The proposed system's benefits include easy decomposition, fewer health risks, and a quicker method that needs only a small initial investment and is fully automated. Accuracy=83%. Bernardo S.Costa, and Al. [14] proposed a computer vision approach to sorting trash into recycling groups may be a time-saving waste management solution. The aim of this project is to sort waste images into four categories: glass, paper, metal, and plastic. For each class, they use a waste image database with about 400 images. Pre-trained VGG-16 (VGG16), AlexNet, Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Random Forest were the models used in the experiments (RF). Experiments revealed that their models had a 93 percent accuracy rate they suggest an automated framework that aims to correctly separate waste into recycling categories using a deep learning approach and conventional techniques. Glass, metal, paper, and plastic were all considered as trash categories. The results show that VGG-16 methods are an effective approach for this issue, with the best scenario achieving 93 percent accuracy. As we see above, a number of classifiers were trained and tested based on ML and DL techniques, using the Trashnet dataset and other datasets; in table1 below, we find a comparative study, with ours models and those related work, this comparison is based on some criteria's: categories of waste, used dataset, used model, model characteristics and test accuracy.

Table 1.1: Comparison between our models and models cited in the related work

Criteria / **Approaches**		**Categories of waste**	**Used dataset**	**Used Model**	**model characteristics**		**Test Accuracy**
					Number of filters	**Form of Max pooling**	
Mahine Learning classifier .	[9]	Plastic, paper, and metal	FlickrMaterial Database (Trashnet)	SVM	96	3*3	**94.8%**
				AlexNet			**83%**
	[10]	Cardboard, glass, metal, waste, paper, and plastic	Trashnet	InceptionResNet V2	4	3*3	**80%**
	[3]	Glass, paper, metal, plastic, cardboard, trash.	Trash net	SVM	11	5*5	**63%**
	[11]	glass, paper, metal, plastic, cardboard, and trash	Trashnet	SVM	50	3*3	**87 %**
Deep learning	[12]	All types	ImageNet	DenseNet121/ RecycleNet	121	5*5	**95%**
	[13]	a waste image database with about 400 images	Mnist (Trashnet)	CNN	4	3*3	**83%**
	[14]	glass, paper, metal, and plastic	Trashnet	VGG-16	16	3*3	**93%**
Deep learning (transfert learning)	Resnet50						**94.16%**
	VGG16						**95.28%**
	DenseNet201						**95.59%**

Discussion: According to table 1.1, approaches that use machine learning models have realized scores that vary between [63% [3], 94.8 [9]] on the Trashnet dataset using the SVM model. The models based on deep learning (DL) achieve a score that varies between 83% [13] on the Mnist Trashnet dataset using a CNN models,

The model in [12] achieves a score of 95% for all types of waste using transfer learning DenseNet121 on ImageNet. Our models based on transfer learning have achieved a score that varies between [94.16% with Resnet50, 95.28% with Vgg16 and 95.59% with DenseNet201) using Trashnet. Table 1.2 presents a summary table that includes results of overviewed research in the SOTA (State-Of-The-Art).

According to Table1.1 and Table 1.2, we can conclude that the models based on Machine Learning techniques have the lowest score compared to others based on DL. While the approaches that use the DL with the transfer learning have the highest score (95%). Therefore, we have opted for this technique for our work, and the Model based on DenseNet201 using Trashnet, has the highest score for all existing Models (classifiers) (95.59%).

Table1.2 Summary table of the related works

SOTA approaches	***Used Dataset***	***Used Model***	***Results (score): Accuracy***
[9]	*FlickrMaterial*	*SVM*	*94.80%*
		AlexNet	*83%*

[10]		*Trashnet*	*InceptionResNetV2*	*80%*
[3]		*Trashnet*	*SVM*	*63%*
[11]		*Trashnet*	*SVM*	*87%*
[12]		*ImageNet*	*DenseNet121/RecycleNet*	*95%*
[13]		*Mnist*	*CNN*	*83%*
[14]		*Trashnet*	*VGG-16*	*93%*
Our Models	M1	*Trashnet*	*Resnet50*	*94.16%*
	M2	*Trashnet*	*VGG16*	*95.28%*
	M3	*Trashnet*	*DenseNet201*	*95.59%*

4 SPubBin: Smart Public Bin based on Deep learning waste classification

In this section, we will present our solution based on IOT and AI techniques. The aim of our contribution is a Smart Public Bin based on deep learning waste classification (SPubBin). It is composed of 2 parts: Smart classification part and Waste collet part (See figure 5).

The process starts when the user put the waste on a dynamic counter. The camera is attached to the microcontroller linked to the Raspberry Pi board of the proposed SPubBin and it is responsible for capturing images of the Waste. Primarily, the system (SPubBin) will be initialized and prepared for image acquisition. The camera captures an image and sends it to the microcontroller.

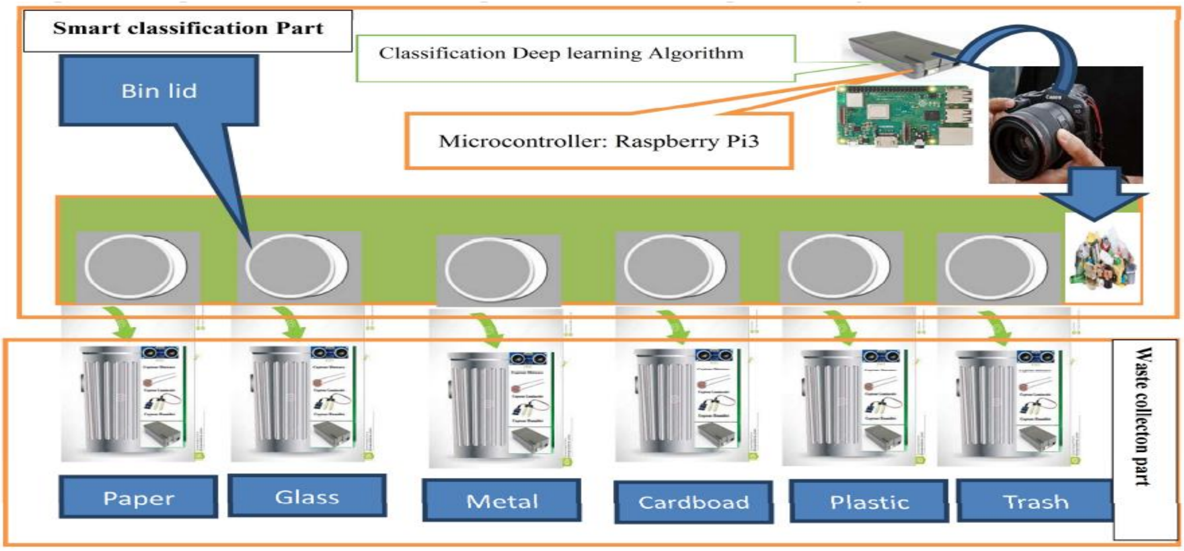


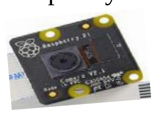
Figure 5: General architecture of SPUBBIN

After receiving the image, the microcontroller sends the image to an already installed CNN algorithm (our algorithm of classification based on DenseNet201), and the algorithm makes a response about this picture.

The microcontroller uses the response of the CNN algorithm to order the appropriate Smart Trash Can (STC) servo motor to put the waste in the respective smart trash can. When this latter becomes full or humid it sends notifications to the authority to empty it. Therefore, this waste will be taken directly for recycling. In the following, we will detail, these parts.

4.1. Smart classification waste part

The main objective of this part is the sorting of waste, using a Deep learning-based classification algorithm and specific electronic components, as follow:

***A Raspberry Pi V3 board*:**	***A camera* : Raspberry Pi NoIr camera V2- Case**
Aims to manage the sorting module, on which the camera is connected and also the classification algorithm is installed 	Is intended to capture the waste and sends the image to the Raspberry Pi V3 

In the following, we will present the used Dataset [3] and the main steps of the proposed deep learning classification algorithm (see figure 7), and we will present all details of our algorithm, from loading dataset and train it with 3 CNN Models: VGG16, Dense201 and Resnet50 (in order to choose the best model, to be installed into Raspberry Pi V3), until the classification of the highest possible number of wastes, which is our objective.

4.1.1 Trashnet dataset

For this work, we are using a Trashnet dataset which was created by Gary Thung and Mindy Yang [3]. Considered as the most used dataset for the classification of Waste (Table 2), the Trashnet dataset consists of 2527 images, which is divided into six different classes (figure 6): 501 images for the type glass, 594 images for the type paper, 403 images for the type cardboard, 482 images for the type plastic, 410 images for the type metal and 137 for the type trash. The pictures were obtained by positioning the object on a white poster board and using natural and/or artificial light. The images were scaled to 512 x 384 pixels on Apple iPhone 7 Plus, Apple iPhone 5S, and Apple iPhone SE smartphones. The original dataset was 3.5GB in size, while the shrunk version is 41.2 MB.

Figure 6: Samples of the images

In order to choose a dataset, we have performed a comparison of the most used datasets for the classification technique (see table 2).

According to Table 2, we can conclude that Trashnet is the appropriate dataset for the classification. In another hand, all datasets for classification represent the waste in outdoor and background environment, but in our studies we are interested in the indoor waste environment.

Table2. Most used Waste datasets [7]

Dataset	**Classes**	**images**	**instances**	**Type annota-tion**	**Environn-ement**
Open litter	>100	>100k	>100k	Multi labels	outdoor
Trash-Net	6	2527	2527	labels	indoor
Waste pictures	34	23633	23633	labels	outdoor
Places	205	2.5M	2.5M	labels	background

4.1.2. Algorithm steps

The proposed algorithm is based on transfer learning using the "Trashnet" dataset and three CNNs (VGG16, ResNet50 and Dense201) for selecting the model with the high accuracy, to be installed into Raspberry Pi V3. The model based on Dense201 gave us high accuracy 95.59% for 100 epochs. For the implementation of our classification algorithm, we have used the following libraries: Python, Google Colaboratory, Fastai, Sklearn library, Pandas package, Numpy package. The characteristic of the used PC is: “Dell Inspiron 15-3521”, Intel (R) Core (TM) i5-3337U CPU 1.80 GHZ/ RAM 4.0.

Firstly, we have load the dataset: The result is a folder on Drive named: “dataset”, containing 6 sub /folders with 2527 images, such us: [‘glass’, ‘paper’, ’metal’, ’plastic’, ’cardboard’, ’trash’]. For the Dataset pre-processing: All images have been resized down to (128,128). In order to augment the performances of the used dataset, we have applied an augmentation operation.

After, to get a high accuracy for test, we choose to divide our dataset on 3 folders namely: train 50%, validation 25%, and test 25%. We train our Dataset on: the train images and validation images, and we use the test images for testing our models. In this step, we use some helper functions. The result is a dataset splitted into 3 folders (train, valid, test), and each folder is splitted into 6 sub / folders: 'glass', 'paper', 'metal', 'plastic', 'cardboard', 'trash'. Afterwards, as quoted above, for the train of our model we use the “Trashnet dataset”, and we execute the following 3 CNN Models: VGG16, ResNet50, Dense201 and we import: error rate and accuracy.

After, defining the model training we can start the execution for 100 epochs and batch size =16, for the 3 used Models. Finally, after completing the training process of our models on the dataset divided on 3 folders (train, valid and test), we can obtain Accuracy and error-rate graphs for each models.

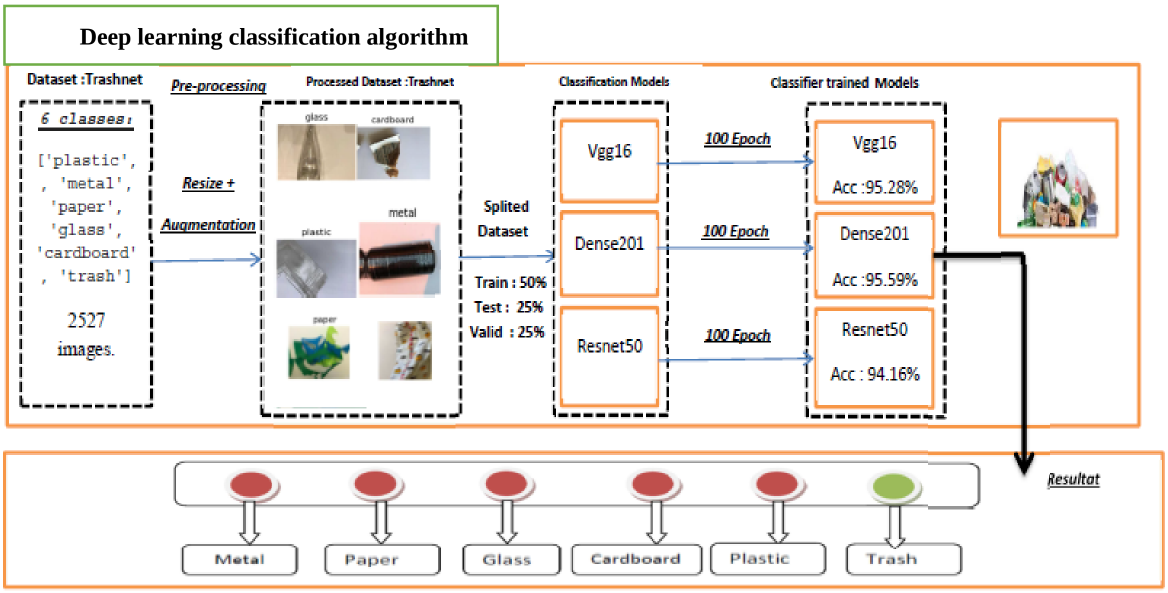


Figure 7: Process of the waste classification

4.1.3. Discussion of the results and algorithm performance

Our classification results are presented in table 3 for each used model. For this we present the Accuracy and error-rate graphs, a confusion matrix where each color signifies a different class ('glass', 'paper', 'metal', 'plastic', 'cardboard', 'trash'), Losses Graphs (train, validation) and the model score (Accuracy).

According to table 3, the algorithm with Vgg16 model has given accuracy of 95.28 %, loss=0.5 and error_rate = 0.05. The Resnet50 model attains an accuracy of 94.16%, loss=0.5 and error_rate =0.05 , while the Densenet201 model has given the high score with an accuracy of 95.59%, loss of de 0.5 and error_rate less of 0.05. See table 4.1 for a summary of the models.

Table 4.1: summary of our models results

Models	Epochs	Accuracy	Loss	Arror _rate
Vgg16	100	95.28%	0.47	0.05
ResNet50	100	94.16%	0.45	0.05
DenseNet201	100	95.59%	0.41	0.05

The score of DenseNet201 Model is the high score of all the existing models for the waste domain classification. So, it is the selected model we installed on a Raspberry Pi 3.

Discussion of our accuracy with the approaches of SOTA.

The majority of waste classification approaches used Machine Learning techniques, which are poor to extract the characteristics of images, and as shown in the scores obtained, they vary between [83%, 94.8%].

Approaches based on Deep learning models and CNN in particular have achieved a higher recognition and classification score than the others, varying between [93%; 95%]. Our models based on transfer learning have achieved a score that varies between [94.16% with Resnet50, 95.28% with Vgg16 and 95.59% with DenseNet201) using Trashnet.

Models based on Machine Learning techniques have the lowest score compared to others based on DL. And the approaches that use the DL with the transfer learning have the highest score (95%).

For that, we have opted, in our work, for this technique for the advantages it procures, we have proposed 3 models (VGG16, ResNet50 and DenseNet201), the Model based on DenseNet201 using Trashnet, has the highest score=95.59%); than all existing Models (classifiers) in the SOTA See table 4.2 below).

Table 4.2: summary of our models results and SOTA approaches accuracy

SOTA approaches		*Accuracy*
[9]		83%
[10]		80%
[3]		63%
[11]		87%
[12]		95%
[13]		83%
[14]		93%
Our Models	**VGG16**	***95.28%***
	ResNet 50	***94.16%***
	DenseNet201	***95.59%***

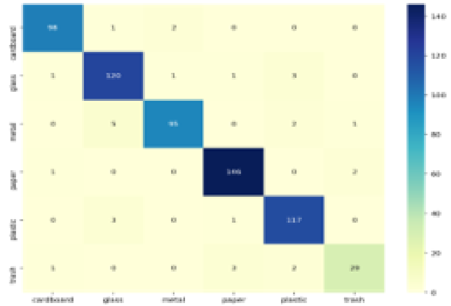
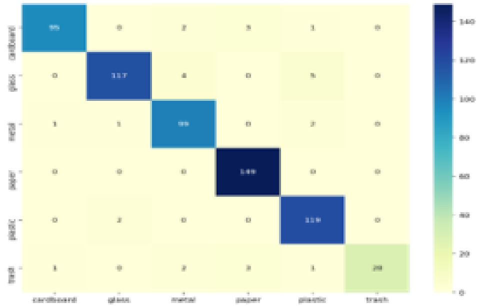
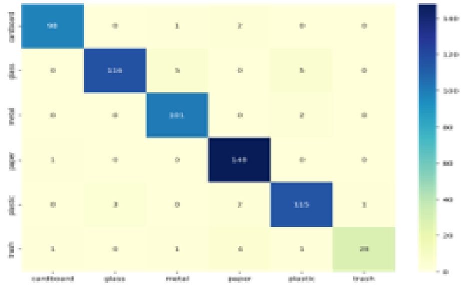
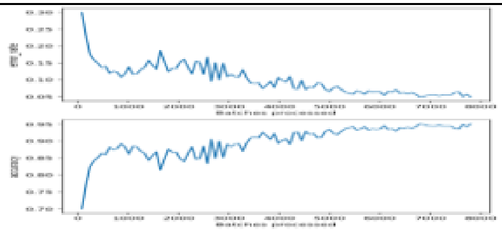
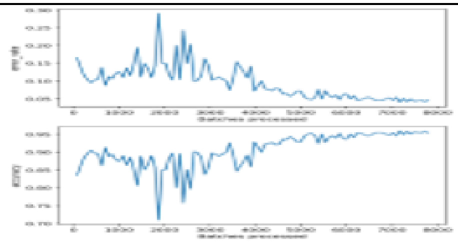
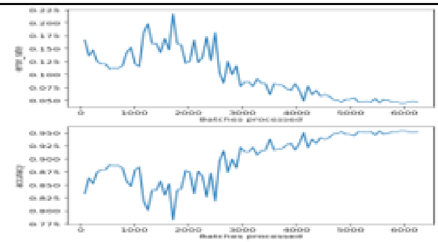
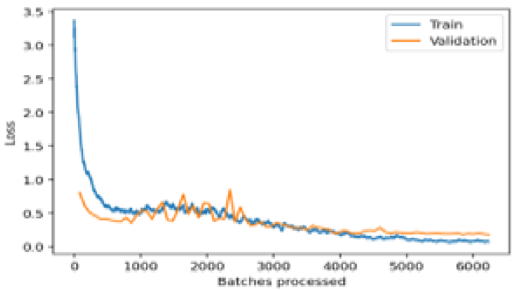
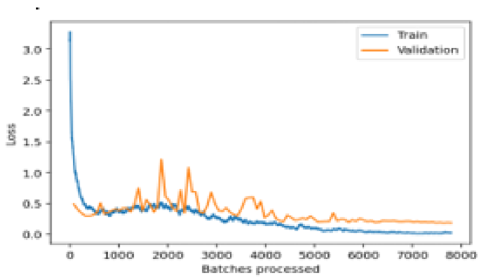
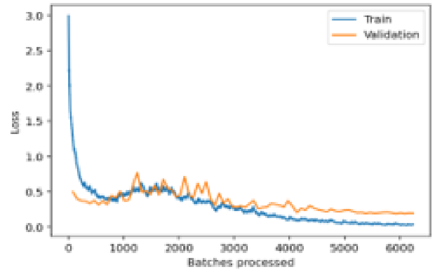
Models / Criteria of performance	VGG16	Densenet201	Resnet50
accuracy	95.28%, with 100 epochs	95.59%;with 100 epochs	94.16%; With 100 epochs
confusion matrix			
Accuracy and error-rate graphs			
Losses Graphs (train, validation)			

Table 3: Results and Performance of 3 models

4.2. Waste collection part

According to our solution, after the classification step, the waste is collected in the appropriate bin. This waste collection process is carried out at this part. This part is composed of six (6) Smart Trash can(STC) (see figure 8) for allowing the smart collect of 6 types of wastes:(paper, glass, Metal, Cardboard, Plastic and Trash).We realized this trash can and also a mobile application that manages its functions. In the following we will present in detail the realization steps of STC and the mobile application.

Figure 8: Smart Trash Can (STC)

4.2.1. Logical Part: Mobile Application

This part consists in the Mobile Application (MA) that manages and monitors the Smart Trash Can remotely in real time. The concerned persons will be notified about the Smart Trash Can status to achieve the removal of trash in a proper way. As any other software, we start the development of the MA by providing graphical specification and design, which allow to reduce the complexity of the implementation of the Smart Trash Can, and organize the realization of the project by defining the modules and the achievement stages. Developers have to transform fuzzy ideas into a precise specification of needs, and requirements expressed by a community of users. Thus they define a relationship between a system and its environment. In this section, we will present a detail description of Smart Trash Can functioning with its functional and no-functional requirements, then we use case diagram (figure 9) to represent the user's interactions with the Smart Trash Can, and then sequence diagram (figure 10) to describe those interactions in chronological order. We will present the software architecture, and we will identify the class diagram (figure 11) in order to implement the mobile application.

Functional requirements: represents the related requirements the functioning of the system to be developed. The system must be able to establish the following functionalities: (1) Ensure the authentication of the different users of the mobile application. (2)Acquire the information from the used sensors (humidity sensor, ultrasonic sensors) and the Raspberry Pi V3 board. (3)Allow the consultation of data. (4)Account management for Smart Trash Can users. (5) Local storage of data. (6) Analysis of the collected data and visualization of the statistics about this data.

No-functional requirements: the considered requirements are: (1) Data security, (2) Ergonomics of graphic interfaces, (3) speed of processing and (4) performance

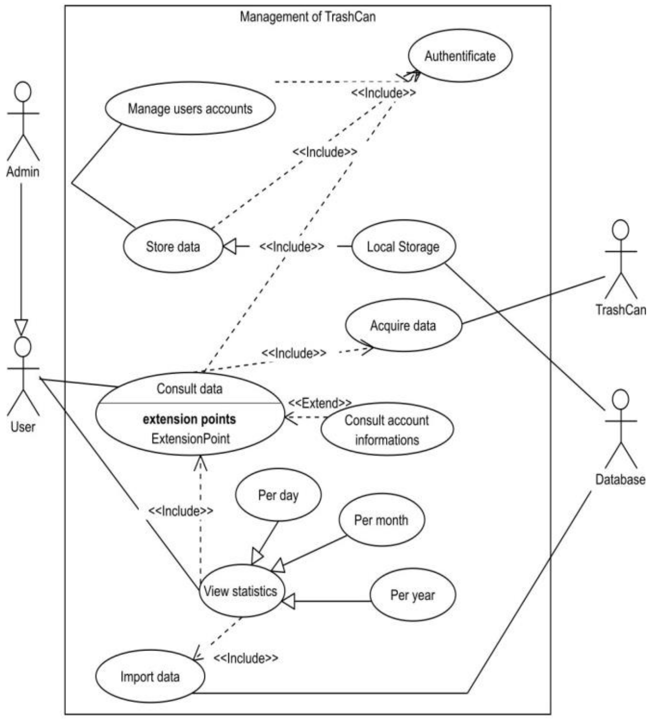


Figure 9: Use case diagram of the Smart Trash Can

In order to realize all the use cases, we have established a sequence diagram for each one. We present, in what follows, the sequence diagram corresponding to the use case "acquire data" (figure 10).

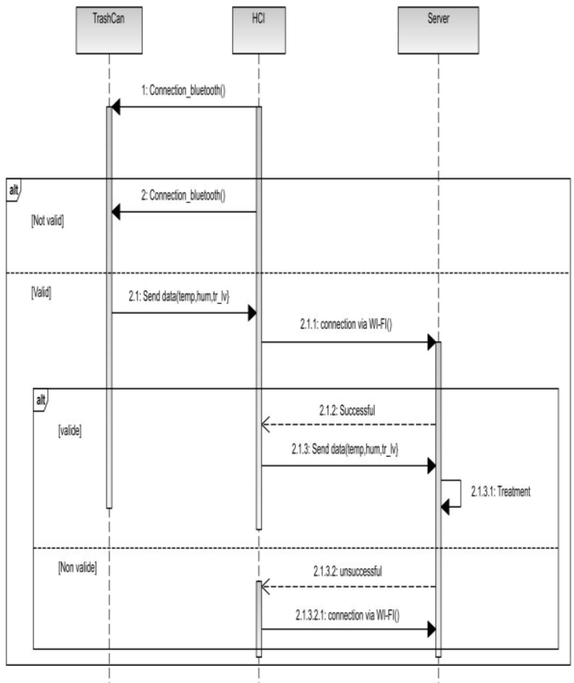


Figure 10: The sequence diagram for the use case "Acquire data"

Figure 11 illustrates the class diagram we propose for describing the static part of the Smart Trash Can we realized.

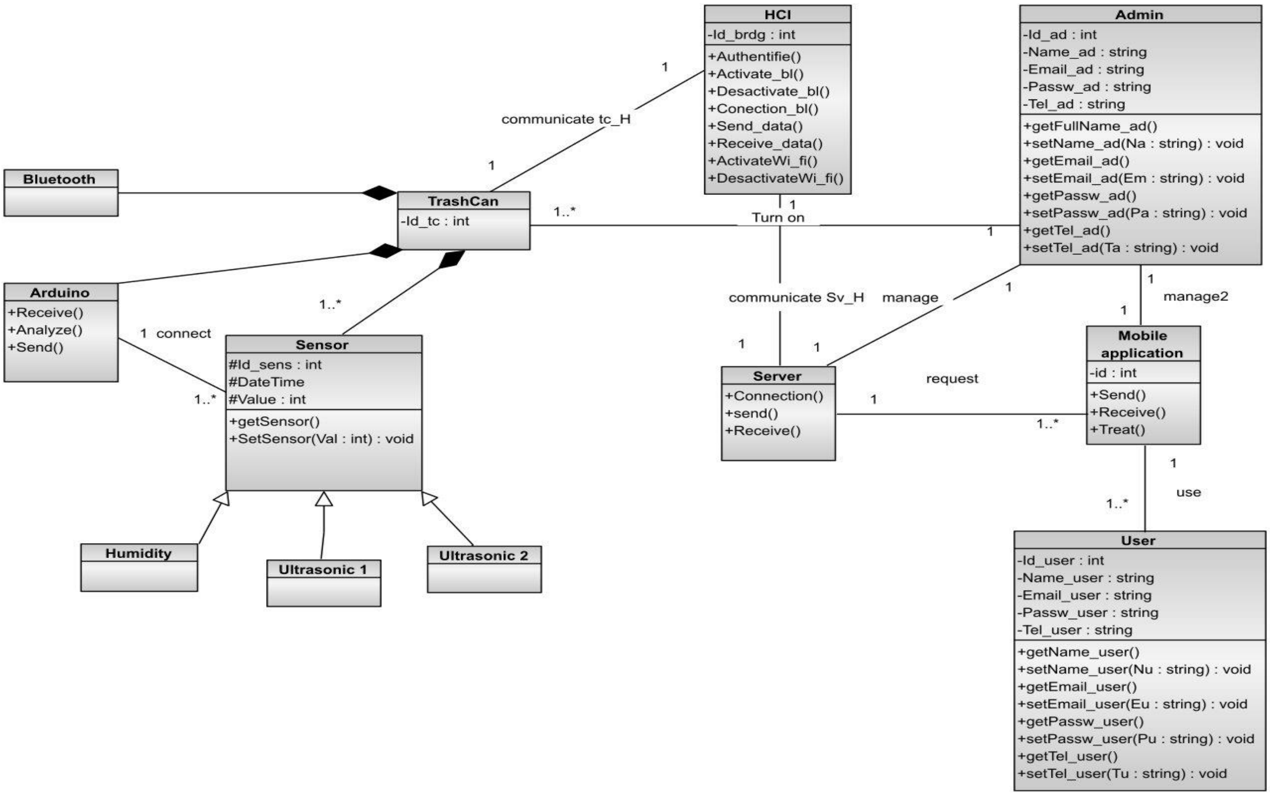


Figure11. Class diagram of the Smart Trash Can

Software architecture. It is dedicated for structuring the Smart Trash Can from its functional specifications; it consists of dividing the Smart Trash Can into logical communicating layers, in order to reason about its functioning. It includes: perception layer, Communication layer, and Application layer.

- *Perception layer*: it consists of all the hardware components used in the Smart Trash Can.
- *Communication layer*: present all the protocols that we used to ensure the communication between the application layer and the physical layer. (1) HTTP: ensure the communication between the server and the mobile application. (2) HCI: The HCI is a standardized Bluetooth interface for sending commands, receiving events, and for sending and receiving data, it is used to ensure the communication between the Smart Trash Can and the server (figure 12). (3)Wi-Fi: a set of wireless communication protocols, connecting different devices by radio waves (the server, the smart phone).
- *Application layer:* describes all the realized requirements by the Smart Trash Can: (1) Acquirement of data: with the different sensors.
- (2) Storage of data: in the database. (3) Presentation of data: review the data on the mobile application.

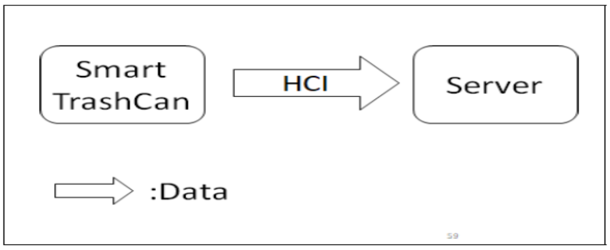
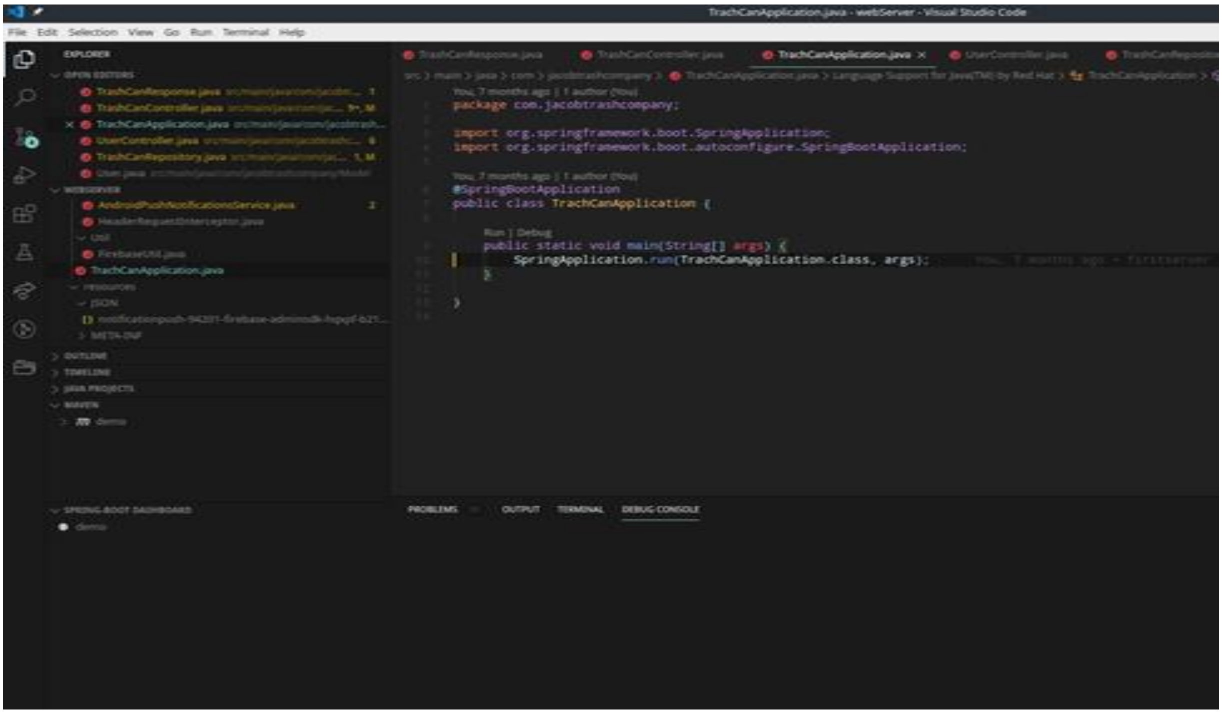


Figure 12: Communication between the STC and the Server

During the development of Mobile Application (MA) we have used a set of languages and tools, which are: (1) Java: For programming the mobile application and the server, (2) C++: for programming the Smart Trash Can hardware, (3) Android studio: For the development of the mobile application, (4) VS Code: For the development of the server, (5) Arduino Software(IDE): For programming the Smart Trash Can hardware.(6) MySQL: For the data storage. (7) Spring Boot: To develop the REST API that obtains data and generates operations on those data in JSON format.

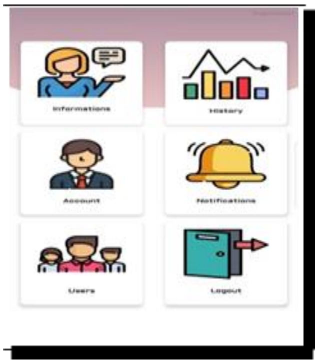
Mobile Application Interfaces: We use the Android Studio platform to implement the mobile application. This application can manage by two accounts (administrator account and user account), the administrator account has other features than the other account. Next, we find some interfaces of the MA.

Server side application



Arduino code for the connected object (STC)

Mobile Application Interfaces: We use the Android Studio platform to implement the mobile application. This application can manage by two accounts (administrator account and user account), the administrator account has other features than the other account. Next, we find some interfaces of the MA.

Home page (the admin)	**History**	**Notification**
		
In this page, the admin will be able to access to different features of the application: 1.check the current state of the Smart TrashCan.2. Consult the history.3.Consult his account.4.consult the notifications.5.Manage the users' accounts. 6.Logout the application	In this page, the admin/the user will be able to see the statistics of the Smart Trash Can**.**	In this page, the admin/the user will be able to check the Smart Trash Can in the last 5 times and he can know if the Smart Trash Can should be emptied or no. if the distance is less than 8, or the humidity is more than 40, or if the temperature is more then 27; then the number will be with the red color to warn the user that there is a change and the Smart Trash Can should be emptied.

4.2.2. Physical part

This part is the real realization of the Smart Trash Can: The choice of development tools has a huge impact on the programming time, as well as the flexibility of the product to be produced. This phase consists of transforming the conceptual model previously established into software and hardware components forming our Smart Trash Can. In this section, we present and describe the hardware (See figure13), we describe the physical realization of our Smart Trash Can, we explain the connection of each hardware component with the Arduino board.

In fact, The Smart Trash Can receives and takes as data the events that happen outside, from the different sensors, transmits them to the server via HCI protocol, which in turn transmits it to the database in order to store it and to review them by the mobile application when needed.

To realize our STC we have used the following devises

1. *The Arduino UNO:* to develop and control the Smart Trash Can [15].
2. *Sensors*: we have 3 sensors :

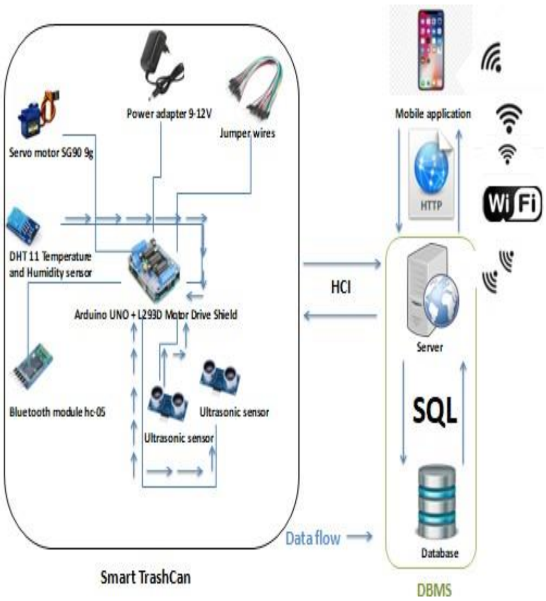


Figure 13: Hardware architecture

a. *The DHT-11 Temperature and Humidity sensor:* to measure the humidity in the Smart Trash Can [17].

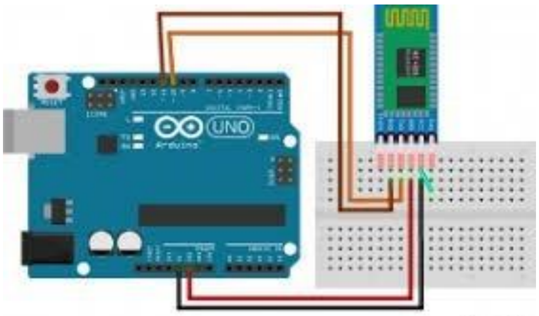
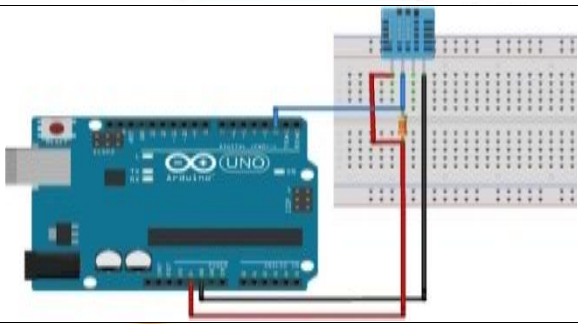
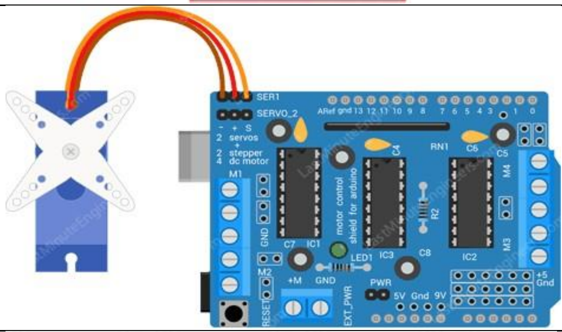
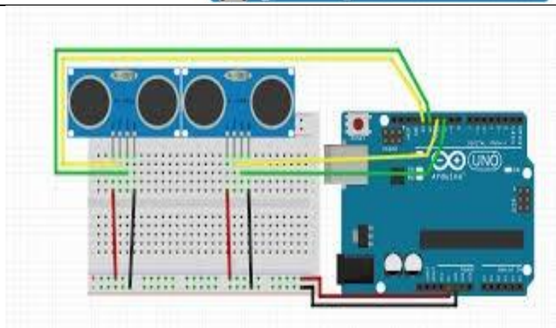
b. The HC-SR04 Ultra sonic sensor: In our Smart Trash Can, we used two ultra- sonic sensors [18]: First sensor to measure the trash level in the

Smart Trash Can. Second sensor to open and close the Smart Trash Can automatically.

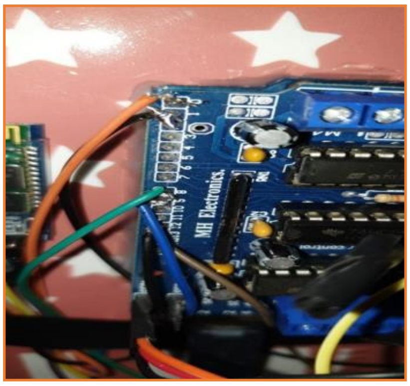
3. *The HC-05 bluetooth module* :to send the measured data by The Smart Trash Can to the server via HCI[16]
4- *<u>The Micro Servo SG909g</u>*:to control the opening and the closing of the Smart Trash Can [39].
5- <u>The AC adapter</u>: to power the Smart Trash Can [21].
6- *<u>The L293D motor drive shield</u>*: to drive the servomotor [20].
7- *<u>Jumper wires</u>* to interconnect the components.

In the following, we describe step by step the physical realization of the Smart Trash Can. Firstly; we explain the connection of all hardware to the Arduino. Secondly, we explain the installation of each hardware on the Can.

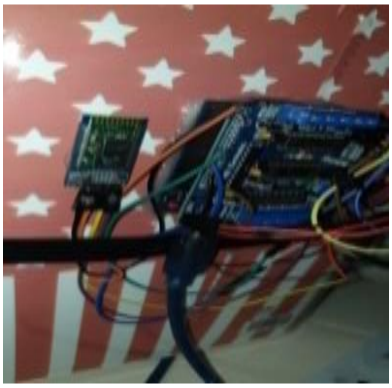
Connection of the used hardware to the Arduino*:* In the next table, we find the connection of all hardware to the Arduino

N°	Steps	Figures
1	Connection of the HC-05 bluetooth module	
2	Connection of the DHT-11 Temperature and Humidity sensor	
4	Connection of the Servo Motor MG g with L293D motor drive shield and the Arduino	
5	Connection of the ultrasonic sensors	

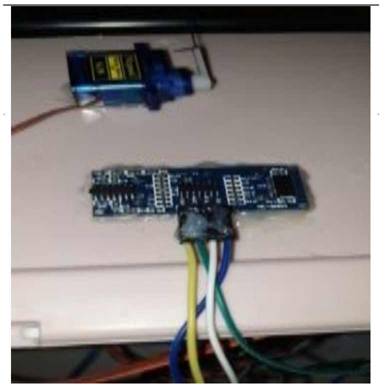
Connection of the hardware at the Smart Trash Can: In this section, we present the connection of the Smart Trash Can hardware.



Connection of Arduino UNO and the L293D motor drive shield

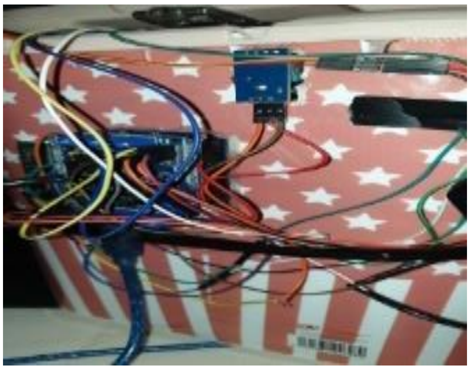


Connection of the HC-05 Bluetooth module with The Arduino UNO at the Smart Trash can, using the jumper wires



The connection of the Servomotor SG909g with the Arduino UNO at the Smart Trash Can using a jumper wires

Connection of the Ultra sonic sensors



Connection of DHT-11 temperature and humidity sensor

The different states of the Smart TrashCan: The figures14, 15 represents the different states of the Smart TrashCan, which can be open or close according to the received events from the external world

Figure 14: The Smart Trash Can is closed

Figure 15: The Smart Trash Can is open

S. Bourougaa-Tria et al.
56 Informatica **46** (2022) 41–66

5 Famous Smart Trash Cans in the market

In this section, we present some Smart Trash Cans, we will describe for each one the design and the features, the way of working, advantages and disadvantages and we will compare between them in order to identify the relationship between the works and the topic (Table 5,6,7,8).

Table 5: Famous Smart Trash Cans in the market (1)

Name	Image	Design and Features	Working	Advantages	Disadvantages
iTouchless Squeeze TrashCo m- pactor		According to [22]: • Combine hand motion technology with a manual compacting tool to get the best results • Absorbs garbage smells using carbon odor filter technology • For battery-free operation, an optional AC adapter is provided.	• To compact the garbage, the user removes the compacting tool, • locks it in place, and presses it down.	According to [22]: • Put money in garbage bags to keep it safe, • The Smart Trash Can may be opened manually or with a hand motion, • Removes smells from the air, Large storage capacity, Don't forget to bring the AC adaptor, • Trash compression.	• The compaction tool's design. • Extremely hefty. • Expensive.
Simple human		According to [23] • The voice and motion sensor is touch-free. • A motor that works in such a way that the lid shutting is significantly quieter. • A stronger and more durable liner pocket than comparable garbage bags. • A liner rim, which is quite useful when changing garbage bags since it keeps the bag in place and hidden.	• User say "open can" and throw away the trash. • Or he just stands above the Smart Trash Can. It opens, and it wait the user until he finish throwing trash to close.	• People can throw trash away "open can". • The Smart Trash Can will wait people until he finish throwing the trash. • Quiet while closing the lid. • Easy to clean.	• Too expensive. • User can’t disable the motion sensor.

Informatica **46** (2022) 41–66 **57**
SPubBin: Smart Public Bin Based on Deep Learning Waste…

Table 6: Famous Smart Trash Cans in the market (2)

Name	Image	Design and Features	Working	Advantages	Disadvantages
iTouchless 16gallon Dual-CompartentRecycle Bin		According to[24]: • Buckets are easily cleaned • since the inside buckets are removable. • Manual open/close function; two compartments, each with a capacity of 30 liters • optional AC adapter	All the user has to do is put their hand near the lid and it will open During use, the lid remains open. After 3 seconds of usage, the lid shuts..	• Sensors were turned on and off on their own. • Safe to use in any setting. • Handles and four caster wheels for easy mobility. • AC Adapter is included. • Stainless steel that resists fingerprints	• Too expensive
Townew T1		According to [25]: • Automatic open lid, Self-changing and replacing trash bags technology., Infrared sensor to detect the motion of the hand., refill rings contains 25 trash bags, • A button which is for 2 uses:Enable the open lid mode. Seals the bag and open the lid so user can remove the trashbag. • In the back, there are the power port and the On/Off button.	With Townew T1, the user may utilize a hand swipe gesture to open the lid of the Smart Trash Can automatically. After filling the waste basket, the user presses the device's front button for three seconds. To take out the garbage, the trash bag will automatically rise to the top and be sealed. The garbage bag will be immediately replaced with a new one.	• Automatic open lid. • Detects movement from the distance of 35 cm. • Prevents the spread of trash smell. • Its white color made it suitable for any decor. • Automatic sealing, changing and replacing bag. • Trash bags are recyclable and durable.	• The size isn't so practical. • It needs special bags. • Lifes panis not long. • Shipping time: 10H. • its low battery alarm is annoying.
R3D3		According to [26]: • A connected garbage can that identifies, sorts, and compacts plastic cans, cups, and bottles automatically. • Coffee cups, bottles, and cans are all sorted, compressed, and kept in their own containers.	This item functions similarly to a real-life sorting robot. It can automatically detect, sort, and compress beverage packaging. It's designed for businesses and, more broadly, public areas where a lot of beverages are consumed.	• Recognizes sorts and compacts plastic cans, cups and bottles. • Facilitates collection and especially sorting. • A simplified and efficient way to approach waste management in companies.	• The design of the compactor tool. • Very heavy. • **Too expensive: exceeds 4000 euros, equivalent to 700,000 Algerian dinars.** • For companies.

S. Bourougaa-Tria et al.
58 Informatica 46 (2022) 41–66

Table 7: Famous Smart Trash Cans in the market (3)

Name	Image	Design and Features	Working	Advantages	Disadvantages
Eugène		According to [27]: • Is a connected trash can, from the start-up Uzer • Indicates to consumers where to throw their waste, • Equipped with a barcode scanner.	The clever multi-distributor trash can also retrieve your shopping list via an app, and it comes with a scanner that can detect thrown items based on their bar codes and notify the user whether or not they need to be sorted.	• A stylish object, which makes you want to use, • Saves you time and money, • Scans packaging before discarding it to see sorting instructions, • Contains two (02) bins, each bin (25) liter. • An application allows you to retrieve the list of resources	• The design of the compactor tool. • Small. • **Tooexpensive:300 euros, équivalent de 50.000 dinars algériens** • **For** kitchen
Insignia innovation		According to [28]: • Is a sorting and compacting bin, intelligent and connected and powered by solar energy (better solar autonomy) • A more urban, more modern design. • The alert system is equipped with a self-driving system machine diagnostics. • A LED screen allowing information to be disseminated or as a communication medium.	This device has a capacity of 140 liters and compacts seven times more waste than a regular trash can. The compactor, which is software-enabled, can communicate with garbage collection providers and send out a signal when it is full.	• intelligent and connected • powered by solar energy (better solar autonomy), • A LED screen.	• The design of the compactor tool. • Very heavy. • **Too expensive: 5000 euros, équivalent de 900.000 dinars algériens** • For companies
Lemon tri		According to [31]: this bin contains several models, and new technology that create an innovative waste collection service, as it facilitates the (selective) recycling of plastic bottles, cans and cups (recognize the packaging).	Another description of this device is that it comes in an Ultra variant with a touch screen and can process up to 40 packs per minute.	The trash can (Lemon sorting) is a machine that prevents sorting errors on the part of individuals, improving waste collection, in addition it accepts all types of waste.	Very expensive

Informatica **46** (2022) 41–66 **59**
SPubBin: Smart Public Bin Based on Deep Learning Waste…

Table 8: Famous Smart Trash Cans in the market (4)

<table>
<tr><th>Name</th><th>Image</th><th>Design and Features</th><th>Working</th><th>Advantages</th><th>Disadvantages</th></tr>
<tr><td>Klarstein Trash Gordon</td><td></td><td>According to [29]:
• Is a sorting trash can,
• And also swallows all waste and separates them from each other in its two interior spaces.
• This greatly facilitates the sorting of recyclable materials from household waste.</td><td>This bin contains two sorting bins due to its high interior volume. They are constructed of durable plastic and can be removed independently, each having a capacity of 15 liters (30 liters for both), and pushing the pedal opens and closes the lids .</td><td>• Easy to clean
• selective sorting,
• voluminous,
• practical,
• quality,
• elegant sorting of waste (Food).</td><td>Expensive exceeds 139 Euros, equivalent to 20,000 Algerian dinars</td></tr>
<tr><td>Majestic cuisine</td><td></td><td>According to [30]:
• Is a smart connected bin
• Works with an infra-red system,
• Which is one of the best bins in the Kitchen with a large capacity of 68 liters, in addition to the type that accepts all types of waste) .</td><td>The big capacity trash collector, high-end materials, and the automated quiet lid shutting (convenient and hygienic) when you pass your hand or an object 15 cm away.</td><td>• Connected
• An infra-red system
• Accepts all types of waste.</td><td>• Cheap: exceeds 52 Euros equivalent to 8,000 Algerian dinars
• does not sort</td></tr>
<tr><td>AINIYF</td><td></td><td>According to [30]:

is a simple trash can, the ideal waste solution for the workplace, , and accepts all types of waste, and with a capacity of 100 liters,</td><td>lightweight, portable and easy to clean, anti-fouling, pedal type trash</td><td>accepts all types of waste capacity of 100 liters,</td><td>• Cheap: exceeds 149 Euros equivalent to 25,000 Algerian dinars
• does not sort and recycle waste,
• and not connected</td></tr>
</table>

S. Bourougaa-Tria et al.

In Tables 5,6,7,8, we have presented some famous smart trashcan in the market; we have described for each approach the design and the features, the way of working, advantages and disadvantages.

In the next section, in table 9, we will compare between the famous Smart Trash Cans in the market cited in the table 1 using the following criteria we suggest: **Length(cm), Width (cm), Height (cm), Capacity(L), Color, Weight(Kg), Price ($), Company, Trash type, Connectivity, Sorting, Notifications, Recycling and Compacting.**

Table 9: Comparative table

Smart TrashCans - **Critarias**												
Name	iTouchl-ess Squeez	Simple-human	iTouch-less	Tomn-new T1	R3D3	Eugéne	Insignia innovation	Klarstein Trash Gordon	Majestic cuisine	AINI YF	Lemon tri	STC
Length(cm)	64.52	63	58.42	40								**Prototype**
Width (cm)	35.82	46.99	35.56	31								**Prototype**
Height (cm)	32.01	33.03	55.88	24								**Prototype**
Capacity()	49 L	49.21 L	60 L	15.5 L	100 bottles, 300 cans, 400 cups	50 L	**140 L**	30L	68L	100L		
Color	Stainless steel	Black stainless steel	Stainless steel	White	White and orange	White	Black	Black	white	Green	White	
Weight(Kg)	5.96	6.02	8.61	3.5								
Price()	**149.95$**	**210.00$**	**99.32$**	**119.95$**	**4000Eur**	**300 Eur**	**5000EUR**	**1139.99Eur**	**52.99 Eur**	**149.0Eu**	//	//
Company	iTouch-less	Simplehuman	iTouch-less	XIAOMI	Ile-de-France	UZER	Paul Miniconi	**K**larstein	KITCHEN MOVE	**AINIYF**	Lemon tri	//
Trash type	All	All	All	All	Plastic :Cans, cups, bottles	Kitchenwaste	ALL	Food	All	**ALL**	plastic bottles, cans and cups	**all**
Connectivity	Yes	Yes	Yes	Yes	yes	Yes	Yes	non	Yes	**No**	No	**yes**

60 Informatica 46 (2022) 41–66

Sorting	No	No	Yes	No	yes	Yes	Yes	Selective	No	**No**	Selective	**No**
Notifications	No	No	No	No				No	Non	No	No	**Yes(in real time)**
Recycling	No	No	No	No	Yes	Yes	Yes	No	No	No	Yes	**No**

Informatica **46** (2022) 41–66 **61**
SPubBin: Smart Public Bin Based on Deep Learning Waste…

Discussion

After this comparison, we find that all bins share common disadvantages, such us:

1. They are too expensive in the case where the State buys these products, cost of importation in particular in the case of after-sales services, and maintenance is the responsibility of the manufacturer, which increases the cost.
2. The sorting: none of the bins do smart sorting except: R3D3 ensures selective sorting for a single type of waste: plastic; Eugene: do a smart sorting for kitchen waste, Insignia innovation all trash of companies, Klarstein Trash Gordon do an intelligent sorting of food wastes.
3. None of the bins transform waste for recycling because they don't sort intelligently the wastes.
4. Most bins sort plastic or food waste
5. None of the bins use deep learning techniques for the smart sorting of wastes.
6. The purchase price and the high import price
7. Most existing smart trash cans are domestic intended for household waste management.

In summary, all smart trashcan in the market, despite the advantages they present, the bins which ensures the sorting of waste do not use deep learning techniques and do not take all types of waste into consideration. Furthermore, the high prices make the purchase operation very difficult here in Algeria. To overcome these difficulties, our SPubBin brings added value to this domain compared to other ones, and, helps to reduce import costs.

6 Synthesis

In this section, we will summarize SOTA (State-Of-The-Art) Lacks and our contribution.

SOTA Lacks: In addition of the points cited in the discussion above:

1. The majority of waste classification approaches use Trashnet [3] dataset. The only dataset intended for the classification of waste (see table 2).
2. The majority of waste classification approaches used Machine Learning techniques, which are not satisfactory to extract the characteristics of images, and as shown in the scores obtained, they vary between [83%, 94.8%].

Contribution of our work: We can explain the add values of our work in the following points:

1. For the classification of waste, we used a smart technique based on deep learning and transfer learning models.
2. Our models achieved the highest scores compared to SOTA approaches: [ResNet50= 94.16%; Vgg16= 95.28%, DenseNet=95.59%]
3. DenseNet201 model has achieved the highest score compared to all the scores of the approaches cited in the SOTA (See table1), using TraschNet[3] with 100 epochs and batchsize=16 which is 95.59%.
4. We used transfer learning, which is highly recommended, because it eliminates the need to start from zero. The developer identifies an existing model that performs functions similar to the ones he wishes to see achieved by the model he seeks tobuild, transfer learning can help you learn the target job in the following ways: (1) Better initial model, (2) Higher learning rate, (3) Higher accuracy after training and (4) Faster training. [34].
5. For the Dataset pre-processing, the following operations have been carried out:
   - All images have been resized down to (128,128).
   - In order to augment the performances of the used dataset, we have applied an augmentation operation.
   - To get a high accuracy for test, we choose to divide our dataset on 3 folders namely: train 50%, validation 25%, and test 25%.

In another hand, our work allows:

1. The development of an intelligent public bin based on waste sorting.
2. Intelligent waste management using IOT techniques: The STC (see section 4.2)
3. Intelligent waste classification using (AI) techniques (Deep learning): the 3 proposed Models based en transfer learning techniques (see Table3)
4. Reduce import costs by the use of Smart Public Bin made in Algeria. [37, 38]
5. Eliminate unpleasant odors, insects and pathogenic germs at the level of the trash. Our SPubBin uses a set of sensors witch accomplish these functions (see section 4.2.2).
6. Save effort and time by sorting at bin level and transferring waste directly to recycling: the main object of SPubBin is the classification of 6 types of wastes using Deep learning techniques, (see Figure5)
7. Realization of a Smart Public Bin which is the first in Algeria for its specificities.

For that, we used:

1 AI techniques for image classification (an algorithm based DenseNet201 Model installed on the Raspberry Pi3)

2 Advanced tools such as: Raspberry Pi3 and A camera: Raspberry Pi NoIr camera V2- Case camera with different sensors for the realization of the first prototype (STC see section 4.2).

7 Conclusion and Perspectives

Cities are growing in population and size and so is doing the waste generated by citizens. The daily collection of this waste generates traffic problem in crowded cities due to the slowness of the garbage collection process. Smart spaces should be completely frictionless for the average person. This involves the inclusion of electronic devices into the environment, and it is vital in this regard to discuss suitable materials and how they react.

Collecting, sorting and recycling of the different types of waste are a serious problems in Algeria. Waste management costs the state a lot of burdens in terms of efforts and the high budget directed to this field. Despite all the efforts made in this field, waste management remains a major problem for the state. The used techniques for ensures the management of waste are very traditional. The use and the installation of the novel techniques based on TIC technology: AI, IOT and DL are very expensive in terms of: prices, charges of importation and maintenance cost. It is time to install Algerian solutions for waste management. In this paper, we have presented a novel approach, which based on IOT and AI (deep learning and transfer learning) for the smart waste sorting.

We have proposed a novel approach for waste sorting Baptized SPubBin (Smart Public Bin). The presented solution is based on transfer learning, and uses, three CNNs models: VGG16, Dense201 and Resnet50. Compared to the approaches quoted above, the proposed approach allows essentially:

1. The sorting of different types of waste (‘glass’, ‘paper’, ’metal’, ’plastic’, ’cardboard’, ’trash’) using deep learning classification techniques, based on transfer learning.
2. The Intelligent waste management: sorting, collecting, and recycling waste using IOT techniques (smart sensors, smart camera, Raspberry Pi and Mobile Application).
3. Reduce import costs
4. Eliminate unpleasant odors, insects and pathogenic germs at the level of the trash.
5. Saves effort and time by sorting at bin level and transferring waste directly to recycling.

For validation reasons, we have developed a visual tool supporting the proposed approach. This tool is a Smart Public Bin (SPubBin) witch composed of 2 parts:

1. **Smart classification waste Part (Deep learning classification waste part):** the main objective of this part is the sorting of waste into 6 classes, using deep learning and transfer learning techniques
2. **Waste collection part:** wastes are classified into 6 Smart Trash Can (STC), witch composed 2 parts (logical and physical): **a**.Logical part: A Mobile application to manage and monitor a Smart Trash Can remotely in real time. **b.** Physical part: realization of a Smart Trash Can using different devices, protocols and sensors.

As future directions to this work, we plan to:

1. Complete the realization of different parts of SPubBin.
2. The use of solar energy to power our SPubBin.
3. Add other features for STC, such as: lid blocking in case of full bin.
4. Add a waste segmentation algorithm from images based on deep learning techniques: Mask Rcnn, Unet and YOLO.
5. Using others datasets for wastes classification.

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References

[1] Lu Tan, Neng Wang in 2010 3rd International Conference on Advanced Computer Theory and Engineering (ICACTE), Vol. 5, 2010, pp. V5-376-V5–380. https://doi.org/10.1109/icacte.2010.5579543

[2] T.-h. Kim, C. Ramos, S. Mohammed, Smart city and IoT, 2017. https://doi.org/10.1016/j.future.2017.03.034

[3] Mindy yang and Gary thung.”Classification of trash for recyclability status”. 2016. 4 Corpus ID: 27517432

[4] Coe A, Paquet G and Roy J. E-governance and smart communities: a social learning challenge. Soc Sci Comput Rev 2001; 19(1): 80–93. https://doi.org/10.1177/089443930101900107

[5] Palmisano SJ. A smarter planet: the next leadership agenda. IBM 2008; 6: 1–8. https://www.ibm.com/ibm/cioleadershipexchange/us/en/pdfs/SJP_Smarter_Planet.pdf

[6] Cook DJ and Youngblood M. Smart homes. In: Bainbridge WS (ed.) Berkshire encyclopedia of human computer interaction. Great Barrington, MA: Berkshire Publishing Group, 2004, pp.623–626. https://doi.org/10.1108/09504120610685373

[7] Sylwia Majchrowska a, Agnieszka Mikołajczyk , Maria Ferlin , Zuzanna Klawikowska Marta Planty kow , Arkadiusz Kwasigroch , Karol Majek ,2022 . Deep learning-based waste detection in natural and urban environments. journal https://doi.org/10.1016/j.wasman.2021.12.001

[8] Islam et al. 2012. Overview for solid waste bin monitoring and collection system. In Innovation Management and Technology Research (ICIMTR), 2012 International Conference on, pages 258–262. IEEE . https://doi.org/10.1109/icimtr.2012.6236399

[9] george e. sakr and al .comparing deep learning and support vector machines for autonomous waste sorting. 2016 . DOI: 10.1109/IMCET.2016.7777453

[10] Sindhura jendran and al.” waste segregation using artificial intelligence” 12 december 2019 international journal of scientific & technology research volume 8, issue 12, december 2019 issn 2277-8616.

[11] Olugboja Adedeji, Zenghui Wang intelligent waste classification system using deep learning. Procedia Manufacturing Volume 35, 2019, Pages 607-612. https://doi.org/10.1016/j.promfg.2019.05.086

[12] Cenk bircanoglu and al. “recyclenet: intelligent waste sorting using deep neural networks”. july 2018. DOI:10.1109/INISTA.2018.8466276

[13] Available online at http://www.warse.org/ijns/static/pdf/file/ijns10832019.pdf. April - May 2019

[14] bernardo s. costa and al. “artificial intelligence in automated sorting in trash recycling”. october 2018. DOI:10.5753/eniac.2018.4416

[15] store.arduino.cc, ARDUINO UNO REV3, https://store.arduino.cc/arduinouno-rev3.

[16] Hc-05 bluetooth module de transmission Sans Filsérie Bluetooth microcontrôleur hc-05, https://french.alibaba.com/product-detail/ hc-05-bluetooth-module-wireless-transmission-serial-bluetooth-microcontrollerhc- 05-60589966968.html. https://french.alibaba.com/, https://doi.org/10.1088/1757-899x/490/7/072007

[17] kuongshun.en.made-in-china.com, Dht11 Temperature and Humidity Sensor Module with LED, https://kuongshun.en.made-in-china.com/product/dCUxoQnMhXWp/ China-Dht11-Temperature-and-Humidity-Sensor-Module-with-LED.html.

[18] D. Jost, What is an Ultrasonic Sensor?, Oct 7,2019, https://www.fierceelectronics. com/sensors/what-ultrasonic-sensor.

[19] S.Bourougaa-Tria, H.Seridi-Bouchelaghem, F.Mokhati. “An Ontology-Based Context Model to manage Users Preferences and Conflicts”. Informatica (Slovinia): An International Journal of Computing and Informatics, ISSN: 0350-5596. Vol 40 N°1 (2016), pp 71-94

[20] sainsmart.com, L293D Motor Drive Shield For Arduino, https://www.sainsmart. com/products/l293d-motor-drive-shield-for-arduino

[21] tradewheel.com, Switching dc wall adaptor 5V 9V 12V 19V 24V power 1A 2A 3A 0.65A ac adapter, https://www.tradewheel.com/p/switching-dc-wall-adaptor- 5v-9v-12628/.

[22] amazone.com, iTouchless Squeeze Trash Compactor Garbage Can with Sensor Lid, Battery Free Operation to Compact Waste from 13 to 20 gallon Capacity, Stainless Steel, Includes AC Adapter, https://www.amazon.com/iTouchless-Compactor- Operation- Capacity-Stainless/dp/B079NPRQVS/ref=as_li_ss_tl?ie= UTF8&linkCode = sl1 & tag = fee0f9 - 20 &linkId = 26b95b335126249227712b520a22598e & language=en_US#HLCXComparisonWidget_feature_div.

[23] amazone.com, simple human, Black Stainless Steel 58 Liter / 15.3 Gallon Rectangular Voice and Motion Sensor Automatic Kitchen Trash Can, https://www.amazon. com/simplehuman-Stainless-Touch-Free-RectangularActivated/dp/B07T2G5Q6B/ref=as_li_ss_tl?ie=UTF8&linkCode=sl1&tag=fee0f920 &linkId=ff41f91cadb87f9ddafca32360 language=en_US&th=1#HLCXComparisonWidget_feature_div.

[24] brookstone.com, iTouchless 16 Gallon Dual-Compartment Stainless Steel Kitchen Recycle Bin/Trash Can, https://www.brookstone.com/16-gallon-dual-compartmentstainless- steel-kitchen-recycle-bin-trash-can.

[25] amazone.com, TOWNEW Self-Sealing and Self-Changing 4 Gallon Trash Can | Automatic Open Lid and Motion Sense Activated Garbage Bin | Smart Home Electric Trash Cans - White x1 Refill Ring Included (Up to 25 Bags), hhhh, https://www. Amazon.com/TOWNEW- Self-Sealing- Self- Changing- Automatic-Activated/dp/ B07TXKHB95.

[26] http:// www.green-creative.com/r3d3 + https://www.amazon.fr > (29/06/2020).

[27] https://eugene.fr / https://www.amazon.fr > (29/06/2020)

[28] https://www.insignia-innovation.com / https://www.amazon.fr > (29/06/2020).

[29] https://www.klarstein.fr / https://www.amazon.fr > (29/06/2020).

[30] https://www.amazon.fr >(29/06/2020).

[31] https://www.lemontri.fr >(29/06/2020).

[32] S. P. Mohanty, U. Choppali, E. Kougianos, IEEE Consumer Electronics Magazine 2016, 5, 60–70 https://doi.org/10.1109/MCE.2016.2556879

[33] Karen Simonyan_ & Andrew Zisserman. Very Deep Convolutional Networks for Large-Scale Image Recognition “. Published as a conference paper at ICLR 2015. https://doi.org/10.48550/arXiv.1409.1556

[34] https://research.aimultiple.com/transfer-learning/

[35] https://github.com/liuzhuang13/DenseNet

[36] Ejaz Ahmed, Student Member, IEEE, IbrarYaqoob, Student Member, IEEE, Abdullah Gani, Senior Member, IEEE, Muhammad Imran, Member, IEEE, and Mohsen Guizani, Fellow. “Internet of Things based Smart Environments: State-of-the-art, Taxonomy, and Open Research Challenges”. https://doi.org/10.1109/mwc.2016.7721736

[37] https://www.facebook.com/Startup.Incubator.Tebessa/videos/420456692998800/

[38] https://univ-constantine3.dz/%D8%A7%D9%84%D9%85%D8%A4%D8%AA%D9%85%D8%B1-%D8%A7%D9%84%D8%AC%D9%87%D9%88%D9%8A-%D8%A8%D8%A7%D9%84%D8%B4%D8%B1%D9%82-%D8%A7%D9%84%D8%AC%D8%B2%D8%A7%D8%A6%D8%B1%D9%8A-%D9%84%D9%84%D8%B4%D8%B1%D9%83/

[39] cdn.instructables.com, SG90 9g, http: / / cdn. instructables .com / ORIG / FA2 / O1SS/J7ARLNBW/FA2O1SSJ7ARLNBW.pdf.

[40] Tanweer Alam. IBchain: Internet of Things and Blockchain Integration Approach for Secure Communication in Smart Cities. Informatica (45). 2021. https://doi.org/10.31449/inf.v45i3.3573