Waste Classification and Segregation: Machine Learning and IOT Approach

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Abstract - **In this paper, we have proposed a fully automated waste management system to implement waste segregation. The method adopted is computer vision and deep learning paired with an internet of thing (IOT) system that is capable of segregating municipal waste into Organic and Recyclable waste. Eliminating manual segregation in the process of waste management significantly reduces the risk to the health of municipal workers by preventing the contraction as well as the spread of transmissible diseases. Automation will also increase the speed while significantly reducing the cost of the waste segregation process. This study was conducted in order to ideate and bring to life innovative and sustainable ideas for effective waste management systems with little to no human intervention.**

Keywords- Convolutional Neural Network, Internet of Thing, Machine Learning, Segregation, Classification.

I. INTRODUCTION

The biggest problem faced by Human Beings as a society is the segregation and management of waste due exponential population growth. According to World Bank reports, 4 billion tonnes of waste is produced annually and 9000 tonnes each day. This calls for a huge demand for new landfills, faster processing of waste for segregation and also the need to eliminate human error during segregation and transportation. Hence, our project automates the process by using a deep learning algorithm known as Convolutional Neural Networks and image classification along with IOT.

Solid Waste Management (SWM) is the process that involves the process of collecting Municipal Solid Waste (MSW) and treating it in an appropriate manner before disposing Municipal Solid Waste. However, it is also one of the largest problems faced by Human Beings as a society. The major factor affecting waste management is the exponentially growing population along with poor infrastructure and lack of financial planning and management.

Poor and inefficient waste management systems are usually observed in cities with high population density in underdeveloped or developing countries. According to World Bank reports, 4 billion tonnes of waste is produced per year and 9000 tonnes each day collectively around the world. A large portion of the generated waste consists of organic waste which can be decomposed, roughly about 50%. 30% of it is recyclable and 20% is non-recyclable and is disposed of in landfills.

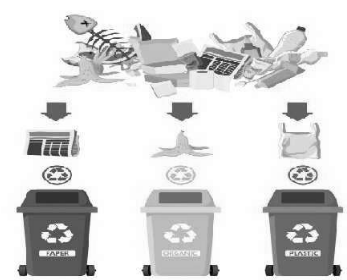

Figure 1: organic and recycle waste bins

An ideal waste management cycle is segregation followed by recycling or dumping as shown in fig.1. Manual segregation is the most common and cheapest method employed for the segregation task. The segregated waste is then transported to landfills or recycling facilities where it is discarded. This process is time-consuming and in many cases, highly inefficient as it is difficult to process large quantities of Municipal waste. There is a huge demand for fast and efficient processing of waste, especially during segregation.

Computer vision and Deep learning paired with appropriate hardware devices gives rise to intelligent systems with the capability to mimic human behavior, these systems are quickly replacing manual laborers in repetitive tasks that require some level of decision making. These systems could soon automate tasks to speeds multiple times greater than that of human beings while also eliminating human error.

This paper proposes one such waste management system to tackle the global waste management problem.

II. RELATED WORK

As we know garbage has created problems to the environment and cause health hazards we need to reduce the negative impacts of this towards the environment [1-2]. For many years' people have worked at reducing the impact of waste Technology like RFID radio frequency identification devices have been used for minimizing the waste by classification [4-5]. In [6-7], used methods to segregate like landfill waste recycling waste and organic waste use CNN to classify the waste into the different categories our model works in the similar fashion and we have used layers of CNN to classify the waste and have used (IOT) internet of things to segregate it properly. Since 2015 a number of different CNN structures have flourished which have enabled easy and efficient ways of classification problems. Characteristics from SIFT and shape on the Bayesian computational network framework and their system was based on the database. Zaman [8] developed an Auto Trash which enabled differentiation between compost and was recycled with help of pi camera and with Raspberry-Pi, their system was developed using Google Tensor flow and high level APIs from google. Using these multiple instructions was handled for segregation. The short-come of their system was that it was only able to differentiate compost materials. Authors, P. da Costa, Santos, A.C. Duarte, and T. Rocha-Santos [3], have stated and produced the ill effects of plastic to the environment, and humans in the year 2016. Y. Xu, J. Li and Q. Tan, A. L. Peters, and C. Yang [9] Gave a technique of recycling waste solar panels, which was a review on waste management for recyclable waste in 2018. The latest trends for classification is done by use on CNN, and NEURAL NETWORKS. Many latest classifications are done using machine learning algorithms.

The traditional form of waste segregation is done by manual sorting. And by surveying we found that there are major 2 categories of waste generated which we are dealing with. They are Organic and Recyclable waste. So using machine learning we have built a model to safely classify and segregate the 2 categories of waste into the respective bins by using convolution neural networks (CNN). So based on shape, size, colour and training from data set we have built strong classifier and then a segregation device using (IOT), where we are using Arduino Atmega- 328P which gives instruction to a servo arm this servo arm segregates the waste into respective bin. There are layers of convolution neural networks (CNN) used for classification of waste. In present times methods using the images for classification have become very popular. The machine learning approach makes the use of a data-set which is easily available to everyone.

We have used the data-set from KAGGLE, such as image net. Which in turn leads to making of a convolution neural network. This allows the model to get more accurate and work without any errors in classification. So once the type of waste is identified, depending on the test image we have the hardware part for segregation using IOT. We have Arduino which gets instructions on it, and segregates into the bin which is done by servo arm.

III. WASTE CLASSIFIER AND SORTER

In the city environment and at household level there are bins placed. But these bins have all mixed garbage which is not segregated properly and this mix creates hazards to the environment and disease to humans. In this paper we propose our neural networks where we use layers to classify the waste into respective bins. The servo-arm carrying the waste moves in the respective Bin carrying the garbage.

The classification is done first by capturing the waste image, the image captured is fed into the memory of the computer main location used by the model and then classified as a recyclable or organic waste. Model gets instruction from the classifier. As the type of waste is known, the Arduino is able to control the arm direction by using ICL293-D driver. In this whole process there is no human interference which is the best thing in today's generation automation techniques.

Model Pipelining

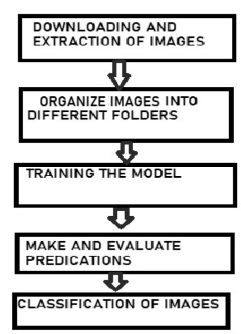

Figure 2: Model pipe lining

Step-1: Downloading and extraction of images we use a data set from Kaggle which is loaded into the machine or our device.
Step-2: We then extract the image which has 20,000 images in the data set.

Step-3: Next we organized the image into different folders. There are mainly two types of subfolders, where we have organic and recyclable waste folders.

Step-4: Training the model is the third step where we use data in the form of input images from a data set which acts as an image classifier to make and evaluate the predictions competition which is to classify the waste as organic or recycled.

Step-5: The classification of the image which is captured from the web camera and giving a result of the prediction.

Importing Libraries

```
from keras.models import Sequential
from keras.layers import Conv2D
from keras.layers import MaxPooling2D
from keras.layers import Flatten
from keras.layers import Dense
from keras.preprocessing.image import ImageDataGenerator
from keras.preprocessing import image
from PIL import Image
import numpy as np
```

Figure 3: importing all the basic libraries

We Import all the basic libraries and layers required from KERAS. It is an open source library which provides a Python interface for the artificial neural network models. It is developed for fast implementation and experimentation. It supports multiple back-end neural network computations. We use KERAS 2.3 for efficient numerical computations. Keras conv2d- it creates a neural network kernel which includes layer Input and helps to produce a tensor of output. Then comes the MAXPOOLING2D- this operation calculates the maximum or largest value in each patch available for each feature map POOLSIZE=(2,2) is selected.

Then we have the FLATTENING LAYER: This operation reshapes the tensor we have the ship exact to the number of computation and components in the tensor.

DENSE: The Dense class implements the task output equals to activation.in kernel which activates components wise function is passed as an argument this is a regularly deep connected neural network layer used for this model.

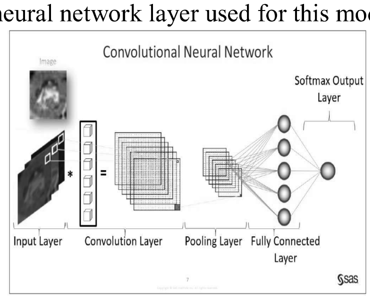

Figure 4: Convolutional Neural Network.

Convolution Neural Network or Covenants, are the neural networks that share their specifications, used to analyze visual imagery. It works exactly like the human brain. The model is able to classify by looking at features. The CNN in our model is used to apply and visualize data images; based on shared weights. There are 4 layers in CNN used in our model.

Convolutional Layer

```
#Initialising the CNN
classifier = Sequential()

# Step 1 - Convolution
classifier.add(Conv2D(32, (3, 3), input_shape = (64, 64, 3),
         activation = 'relu'))
```

Figure 5: Convolution layer

It is called a feature interaction layer as features of the image are extracted in this layer. The mathematical functions of convolution tasks are operated between the input image and filtered image size. (H x H) The outcome is termed as a feature which enables the information about the image, as the edges and corners. We used Conv 2D in this layer, the function takes argument first, then a 32-numbered filter set, and in the second argument the shape of every filter is going to be 3x3 (HxH). The third one is each and every type of image (RGB)of every image, that is, the CNN is taking 64x64 resolution and when RGB is “3”. The fourth argument is the actuation of the function ‘Relu’ which is for rectifier function purposes.

Pooling Layer

```
# Step 2 - Pooling
classifier.add(MaxPooling2D(pool_size = (2, 2)))
```

Figure 6: pooling layer

The next layer used in CNN is the pooling layer. This is used to minimize the spatial length and size of representation and minimize the overall number of parameters, memory computation. We start by consolving classifier objects and add the pooling layer. We have taken a 2x2 matrix to have less pixel loss and get an accurate region where functions can be spotted.

Fully Connected Layer

```
# Step 3 - Flattening
classifier.add(Flatten())

# Step 4 - Full connection
classifier.add(Dense(units = 128, activation = 'relu'))
classifier.add(Dense(units = 1, activation = 'sigmoid'))
```

Figure 7: fully connected layer

In this dense function is used to add a whole connected layer number of nodes in a hidden layer, which is taken as 128 and output nodes so that number of nodes are chosen experimentally the activation function is assigned as a rectifier and at last We combine all layers which makes a fully connected layer.

- *Data-Enrichment:* We have taken pictures in low light and inverted images so that were classified can have minimum errors exposure to light and dim light images. Different positions are taken where we have total of 20,000 images in data set which consists of 502 Organics and 1502 recycle images 64x64 pixels image is considered when it is fed into the classifier for our classifier we use image data generator available at keras which gives number of transformations many new images which include operation of zooming flipping of image inverting and vertical and horizontal manner.

Figure 8: Dataset for organic waste

IV. EXPERIMENTAL SETUP

A. Dataset

The model is evaluated on a subset of a larger dataset. It consists of 22564 images in all belonging to two classes namely, 'Organic' and 'Recyclable' with 2513 images each. The pictures include objects shot in different camera angles and various lighting conditions. The images are resized to 64 by 64 pixels before being trained on the model. The original data-set is roughly 2.44 gigabytes in size and is split into a test and training set for each class. Classifier performance: The model is trained for 15 epochs with a training step size of 706 and validation step size of 2000. The performance metrics are as shown below of the accuracy of the model at the end of 15 epochs is 0.9504 and loss is 0.4508.

Figure 9: waste images dataset

B. The Classifier Performance

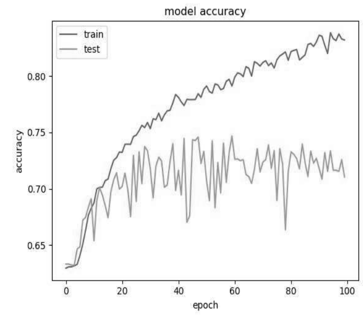

Figure10: accuracy v/s epoch

As we know the epoch is used in our model and it shows The number of passes in the training dataset. We consider steps per epoch as 706 and epochs as 4. The number of validation steps taken are 2000. We are able to get accuracy of 0.8041 and loss of 0.4362 in the first pass. Similarly, in the second pass we get accuracy of 0.83411 and loss of 0.37. In the third pass we get accuracy of 0.85411 and at 4^{th} pass our accuracy almost touches to 90% accuracy.

```
classifier.fit_generator(training_set,
            steps_per_epoch = 706,
            epochs = 4,
            validation_data = test_set,
            validation_steps = 2000)
```

Figure 11: classifier function

This shows that if we take more epoch levels our model may even increase efficiency up to above 95% easily. But we are able to achieve almost 90% accuracy at just epoch=4 in 2 minutes.

Model	Accuracy	Precision
ResNet-101	0.873	0.873
ResNet-50	0.907	0.907
ResNet-34	0.918	0.918
Alex-Net	0.913	0.913

Figure12: Comparison with other CNN models

```
Epoch 1/4
706/706 [==============================] -
1WARNING:tensorflow:Your input ran out of dat
your dataset or generator can generate at leas
n this case, 2000 batches). You may need to use
ur dataset.
706/706 [==============================] -
acy: 0.8041 - val_loss: 0.3122 - val_accuracy: 0.8
Epoch 2/4
706/706 [==============================] -
y: 0.8397
Epoch 3/4
706/706 [==============================] -
y: 0.8532
Epoch 4/4
706/706 [==============================] -
y: 0.8655
```

Figure 13: epoch levels

V. THE HARDWARE SEGREGATOR

The Hardware part of the system consists of an Arduino controller and a camera module. The Arduino controller drives the Servo arm with respect to the output obtained. Organic waste is classified as 1 and Recyclable waste is classified as 0. The servo arm clockwise if the result is 1 anticlockwise if the result is 0. An ICL293D servo motor driver is used for the controlled rotation of the servo arm. The process followed by the setup is as follows:

Step 1: Waste is placed in the range of observation of the camera module.

Step 2: The Image captured is transmitted to the Deep learning model and re-sized to a 64 by 64 pixel image. ***Step 3:*** The classification is performed by the model using multiple layers of Convolutional.Neural Networks.

Step 4: The result is transferred to the Arduino controller which moves the servo arm in the appropriate direction based on the prediction.

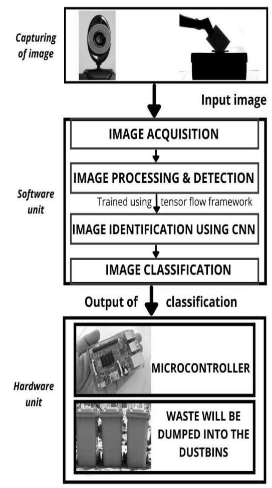

Figure 14: Proposed System complete model setup.

We use Arduino which drives the Servo Motor in particular direction and hence the web camera module takes an image and classifies them as organic or recycled. Based on the prediction of the machine. The instruction is '1' for Organic when the server or moves towards the right direction '0' is a direction for am moving in the right direction each bin is connected with LED and when the waste enters the LED glows and finally the arm returns to its initial state until no garbage is detected.

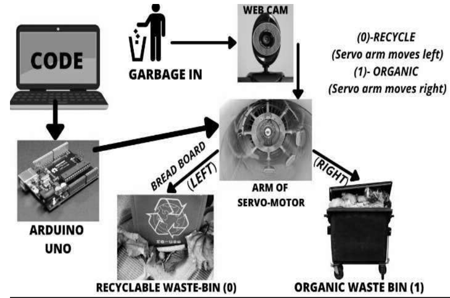

Figure 15: Proposed System hardware model.

The segregation is done by SERVO ARM which is controlled by using an IC-l293d driver. We use ARDUINO which feeds one instruction at a time and IC-L293D is responsible for movement of motor in particular direction. And hence the Servo arm is able to segregate the waste in the proper bin assigned. There are 2 digital pins in Arduino to control the direction of the motor. The ENA pin of PWM PIN-2. 600 Milliampere at voltage of 4.5 V and we use Atmega 328-P micro-controller for this purpose.

VI. Conclusion And Future Scope

In this paper, we have compared our proposed four layer CNN method performance with Alex-net and Res-net model which include ResNet34, Resnet50 and ResNet101 to evaluate the impact of the model size has on the efficiency and accuracy metrics. We found that as number of epoch level increased, the accuracy of CNN classifier increased. We started from epoch=1, to epoch =4. We were able to obtain accuracy from 80 percent to 90 percent with the available Data set from kaggle which was used. This proves that the model performance enhanced at good rate. Further increasing the epoch number, we could obtain more than 90 percent accuracy, which shows the good performance of our proposed CNN classifier containing four layers. As a result, we see that CNN is a strong network using in image classification techniques.

As we know, waste segregation is the biggest problem in today's world. We generate huge amounts of waste everyday which has great impacts on the environment, and humanity. So we have designed a model using the latest trending technology. Our model has provided a good insight of future scope of using CNN and classification of waste materials. High accuracy of nearly 90% is achievable here, as the epoch number increases the efficiency also increases. In future at industrial level or even at society level by using high level GPU. Large sorting techniques can be used by no human interference at all for future work. We can focus on more classes of waste and a user database which can be used to store the data. This work can heal all environmental issues. This can help our mother earth Heal easily and we can eliminate many diseases in society. This process of using the latest technology can lead towards a much cleaner environment.

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