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Waste management system - A wastage classifier using DeepLearning with IoT

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Abstract—**Waste management is essential for protecting the environment, especially in the current scenario with increasing issues such as pollution, population and land management. Thus managing this waste is a huge task that requires a plethora of new techniques and innovation. Classification of waste into degradable and non-degradable elements is a crucial step to be followed by everyone. However, one of the biggest problems faced by waste management authorities is classification. The conventional method of placing separate bins for degradable and non-degradable are not fool-proof. Segregation leads to identifying useful degradable waste, which, when appropriately processed, can be used as manure or organic fertilisers, which have been proven to have a positive effect on the growth of crops. This is also environmentally and economically friendly as the waste is used appropriately instead of disposed of. Some of these are Reduced landfill impact and Improved air and water quality. Hence a smart system needs to identify whether or not the waste is biodegradable and then allow only that waste to be thrown into the bin.**

Keywords-component; *Waste Management system; classifier; Deep learning; biodegradable waste.*

I. Introduction

Convolutional and Artificial Neural Networks have evolved since their inception and have come a long way, playing an important role in our everyday lives. Deep Learning techniques are essential in today's world, allowing us to innovate and create smart devices capable of replacing manual labour with higher precision and accuracy. These techniques pave the way for a completely automated world in the future.

Internet of Things devices are ultimately the future of hardware devices; these Artificial Intelligence technologies are embedded in IoT devices, thus making "smart" devices. Hence, integrating IoT with Deep Learning techniques will allow us to create devices that can be used in real-world applications. Furthermore, IoT devices allow us to control all equipment using mobile devices, thus making it easier to control [1, 2].

This paper is about using Deep Learning techniques embedded in an IoT device. In addition, a Convolution Neural Networks technique is embedded in a Raspberry Pi device. The end product of this proposed work is a module that can effectively identify and classify degradable and non-degradable wastes. This is achieved by integrating IoT and Deep Learning techniques [3-5].

The DL technique employed here is Image Processing, where the model can identify the product/item using a camera module, convert this image into its input format, and then classify it as programmed by the user. In this case, the algorithm decides whether the item in the image is biodegradable. The IoT aspect of the project includes a Raspberry Pi model and a camera fitted to it. This camera is used to take images of the waste product that is presented to it. This image will be fed to the deep learning decision-making algorithm, which will conclude whether or not the waste product is biodegradable. Internet of Things describes devices with sensors, processing ability and software which are usually small, portable and can easily be integrated with multiple devices and software[6-9]

CNN can be utilised to distinguish digestible and indigestible waste. Furthermore, this model can be integrated with IoT to create a real-time waste monitoring system, thus creating a smart dustbin that uses Bluetooth and microcontrollers.

II. Proposed Methodology

The first part of the proposed work is to create a DL model (Fig 1). First, the Deep learning algorithm is used to develop a model that can identify and classify images of waste products. Then the model is trained with the help of a dataset that contains 22,500 images of various waste products. Finally, two deep learning models were chosen to classify the waste images, train the two models separately and pick the one with better classification results. The two models were a basic Convolution Neural Network (CNN) and a transfer learning model.

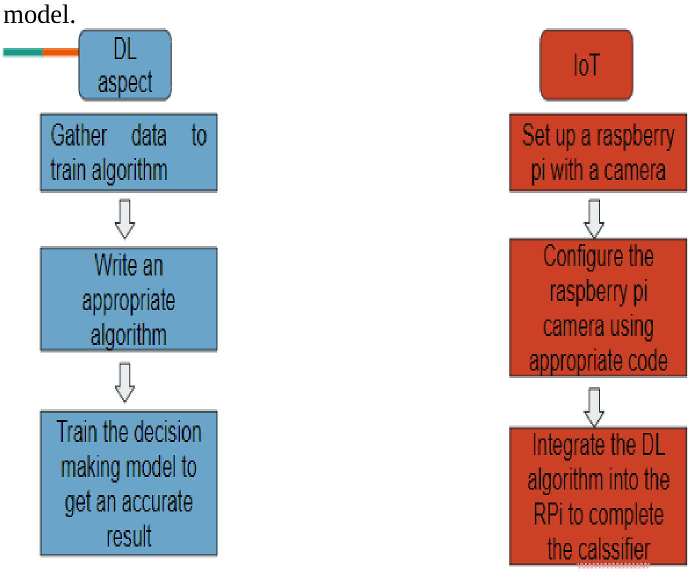

Figure 1. Bloc diagram of the proposed Waste Classifier

TABLE:1 COMPARISON OF VARIOUS LAYERS IN CNN

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 150, 150, 3)]	0
conv2d (Conv2D)	(None, 148, 148, 16)	448
max_pooling2d (MaxPooling2D)	(None, 74, 74, 16)	0
conv2d_1 (Conv2D)	(None, 72, 72, 32)	4640
max_pooling2d_1 (MaxPooling2	(None, 36, 36, 32)	0
conv2d_2 (Conv2D)	(None, 34, 34, 64)	18496
max_pooling2d_2 (MaxPooling2	(None, 17, 17, 64)	0
flatten (Flatten)	(None, 18496)	0
dense (Dense)	(None, 512)	9470464
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 1)	513

Total params: 9,494,561
Trainable params: 9,494,561
Non-trainable params: 0

The field of deep learning owes a lot to the human nervous system. Therefore, the whole deep learning paradigm has been inspired by the amazing and complex nature of the human nervous system.

Hence the name Artificial Neural Network. The idea behind ANN is that it mimics the nervous system to solve a general problem. That problem can range from predicting the weather, classifying images and even catching criminals. Convolutional Neural Network is an Artificial Neural Network designed to classify images and analyse visual imagery. A CNNbreaksdowntheimage to individual pixels and process them. Every deep learning modelhasan‘Architecture’.InaCNN architecture, there are usually four layers: the convolutional layer, pooling layer, correction layer and fully connected layer.

The convolutional layer is key in CNN architecture and is almost always the first layer in the model. The convolutional layer extracts features from the input image, which can be low and high. There can be more than one Convolutional layer. The first layer would identify the low-level features such as colour, gradient, edges and soon, and the successive layers in the convolutional layer will capture the high-level features resulting in a complete understanding of the image visually. The consequence of Convolutional operation on an image is a feature map. A feature map captures the result of applying filters to input images, basically just the output of a convolutional layer. Making use of a previously trained model on a new problem is called Transfer Learning. In classical problems like image classification and natural language processing, the computing power required is vast and is not easily available. Hence transfer learning enables us to use predefined models as a starting point in our model and build upon it. Using the transfer learning model as our base, we can tune it to suit our needs.

III. RESULTS AND DISCUSSION

An image data generator is a tool which allows us to reshapeandrotateimagesrandomlythrough0 to 360 degrees. It also allows the use of multi-processing to speed up the training process. It allows us to train smaller chunks of images rather than the whole data set at once. Suppose the dataset is large and can’t fit into memory in one go. This is the only possible solution most times. The most important useful feature of data generators is the availability of data augmentation.

The CNN model has three blocks. The first block has a 2D Convolutional Layer that extracts 16 filters, followed by a max-pooling layer having a 2×2 window. The second block has a 2D Convolutional Layer that extracts 32 filters followed by a max-pooling layer having a 2×2window. And the third block has a Convolutional Layer having 64 filters followed by a 2×2 max-pooling layer. In the Fully Connected Layer, the Sigmoid Activation function is used. The sigmoid function is the squashing function, as the output will always be between 0 and 1, no matter how large the input is. The sigmoid function is used to learn the non-linearity in the dataset.

The loss metric used is the Binary Cross-Entropy Loss function. The binary cross-entropy is a loss function used in binary classification tasks. These tasks have only two classes or two target classes, and the model predicts which class the input belongs to. The accuracy after training is 91.14% (Table 1).

TABLE 2: REPORT ON CLASSIFIER

Classification report :

	precision	recall	f1-score	support
1	0.91	0.92	0.91	1112
0	0.92	0.91	0.91	1112
accuracy			0.91	2224
macro avg	0.91	0.91	0.91	2224
weighted avg	0.91	0.91	0.91	2224

As the CNN model built from scratch performed slightly better than the Transfer Learning model, we will be using the CNN as the primary model. One obvious way to check the model's accuracy is to deploy it against the test set. The model classified 2027 images out of 2224 correctly, misclassifying only 197 (Table 2)

IV. CONCLUSION AND FUTURE SCOPE

An automated wastage classifier is an essential tool that paves a pathway for a completely automated network of tools. The deep learning aspect allows automation, which can be further enhanced into wider aspects. IoT allows us to implement this algorithm at any place at any time. Another alternative for RaspberryPi is the usage of an ESP32device which is cheaper and even more compact when compared to the Raspberry Pi. The ESP32 can be directly connected to a central computer device placed through Wi-Fi, and the data is transferred from the ESP32 to the computer. Thus for an industrial scale, this waste classifier can be extremely reliable as a step towards creating a flawless dustbin which can help with wastage management.

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