INNOVATIVE RECYCLING WITH AI

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Contents

Abstract

This project addresses the challenge of inadequate waste sorting at the source by introducing an Intelligent Recycling Bin powered by artificial intelligence (AI). With the goal of surpassing the current 67.2 accuracy in waste separation, the project utilizes a combination of two data sets, totaling 17,677 images across 18 waste categories. Various AI models, including MLP, CNN, K-NN, are employed and individually compared to achieve a minimum 70% accuracy. The data sets from Hugging Face and Kaggle provide diverse waste images for robust model training.The related works section references existing research, highlighting the project's contribution to the field. In approach section we outline machine learning methods which are forming the foundations of our project. The experimental evaluation section describes our approach to evaluate our results. By addressing the intersection of AI and waste management, this project aims to significantly enhance waste separation accuracy, contributing to environmental sustainability.

1 Introduction

In today's world, improper waste management is a significant threat to the environment. The lack of effective waste sorting at the initial stage, where different types of waste are mixed without consideration, creates numerous challenges for recycling. Despite the widespread use of recycling bins globally, there is a notable problem with accurately sorting waste. Even in countries with advanced recycling practices, like Germany, the correct waste separation rate is only 67.2% , emphasizing the need for innovative solutions.

This project tackles this issue by developing and assessing an intelligent recycling bin that utilizes artificial intelligence (AI) to precisely recognize and categorize waste. The primary objective of this project is to achieve a minimum of 70% accuracy in waste separation, exceeding the current capabilities of human efforts. Through an exploration of AI's potential in waste management, this research aims to make a substantial contribution to environmental sustainability and the conservation of resources.

2 Related Works

In the realm of waste management and artificial intelligence (AI), several studies have offered valuable insights into the challenges and opportunities inherent in this intersection.

Firstly, "Artificial intelligence applications in solid waste management: A systematic research review" by Abdallah et al. (2020) delivers a comprehensive overview of existing research, providing a roadmap for navigating this complex field [Abd+20].

Moving forward, "Recent advances in applications of artificial intelligence in solid waste management: A review" (Ihsanullah et al., 2022) delves into the latest applications of AI in solid waste management. This review not only introduces commonly used AI methods but also critically assesses their advantages and limitations, offering guidance in the selection of an appropriate model [Ihs+22].

Addressing the same issue, "Intelligent solid waste classification using deep convolutional neural networks" (Altikat et al., 2022) presents a research endeavor employing a Deep Convolutional Neural Network (DCNN) with approximately 2000 images. Their achieved 70 accuracy sets a promising precedent for our own model development [AGA22].

Lastly, "Precision measurement for industry 4.0 standards towards solid waste classification through enhanced imaging sensors and deep learning model" (Qin et al., 2021) concentrates on waste classification. Utilizing a Support Vector Machine (SVM) model, they achieved an impressive 83.46% accuracy with 2500 images, showcasing the potential of advanced imaging sensors and deep learning within our research domain [Qin+21].

Through an assimilation of insights from these studies, our thesis aims to leverage existing knowledge to make an informed choice of the most suitable AI model, contributing to the advancement of waste separation practices for a more sustainable future.

3 The Approach

3.1 Dataset and Data Collection

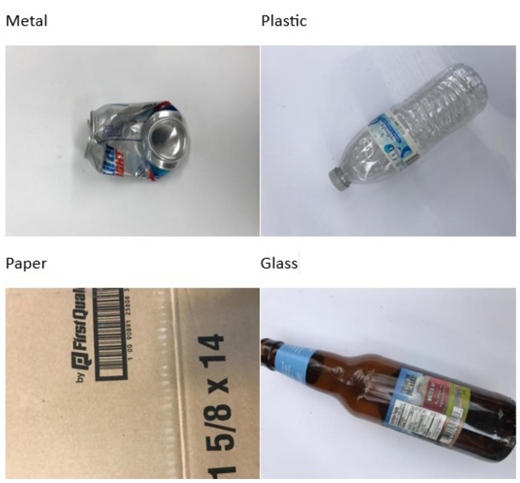

Figure 1: Example images

Public sources were searched to find data. The dataset we are using is a combination of two existing dataset. One of them is hosted at huggingface.com consisting of 2527 images of 6 categories. Other one is hosted at kaggle.com and consisting of 15150 images of 12 categories. By combining these two datasets we got 4000 images and 4 categories which are glass, metal, paper, and plastic shown in Figure 1. To avoid class imbalance, we used 1000 images for each category, you can see the distribution in Figure 2.

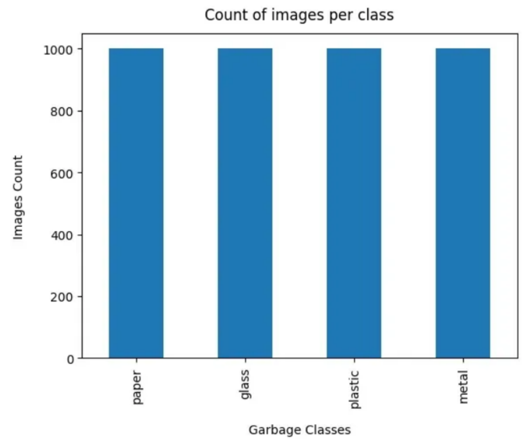

Figure 2: Class Distribution

3.2 Models and Methods

In order to achieve our goal,we decided to try more than one method to get the most optimal result. For this, each of us trained the model with a different method and achieved 3 different results. We compared the results obtained at the end of the experiment. As you can see in Figure 3 these methods are K-Nearest Neighbors, Multi-Layer Perceptron and Convolutional Neural Network.In this section we will explain these models.

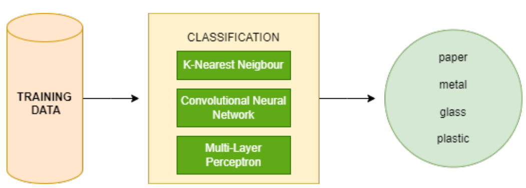

Figure 3: Model

3.2.1 K-Nearest Neighbors (KNN)

An KNN was used for the first run through for the classification of trash into recycling categories. The KNN was chosen because it is considered one of the best initial classification algorithms and is not as complicated compared to other algorithms. KNN, in its simplest sense, is based on estimating the class of the vector formed by the independent variables of the value to be predicted, based on the information in which class the nearest neighbors are concentrated. When starting the process, the most optimal k is selected. It is more logical to choose k values among odd numbers in terms of reducing the uncertain area. As you can see in the figure, we chose k = 1, which has the highest accuracy in our model.

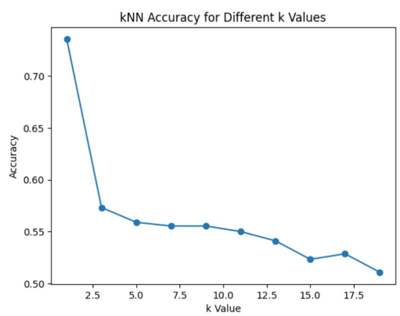

Figure 4: Choosing k value

Then we trained the model with KNN and used euclidean distance when calculating the distance. Also we tried Manhattan distance metric, however euclidean distance gave better result. Figure 5 shows how euclidean distance calculated.

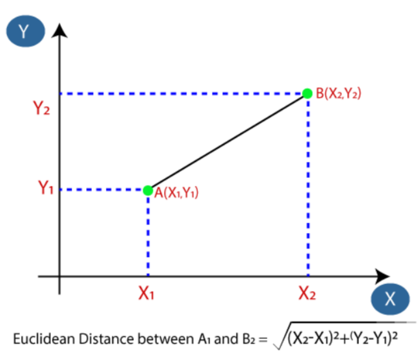

Figure 5: Euclidean distance

We made label prediction with our test data. As you known we have four labels ,including glass,paper,metal,plastic.

3.2.2 Multi-Layer Perceptron (MLP)

Think of a neural network like a simplified model of the human brain. It consists of interconnected nodes, or artificial neurons, organized in layers. An MLP consists of multiple layers of perceptrons. The layers are typically divided into an input layer, one or more hidden layers, and an output layer. As you can see in the Figure 6, information flows from the input layer to the output layer, passing through the hidden layers.

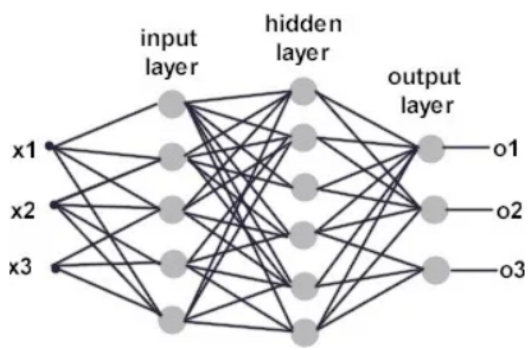

Figure 6: Hiearchy of MLP

The input layer receives the incoming data and sends it to the middle layer. Incoming information is transferred to the next layer. The number of intermediate layers varies depending on the problem, at least one, and is adjusted according to need. The output of each layer becomes the input of the next layer. Thus, the exit is reached. Each processing element, that is, a neuron, is connected to all neurons in the next layer. Additionally, the number of neurons in the layer is determined according to the problem. The output layer determines the output of the network by processing data from previous layers. The number of outputs of the system is equal to the number of elements in the output layer. We used 5 hidden layers, input and output layers in our model. In Figure 7 you can see the dimensions of the layers and the activation functions used.

Layer	Shape	Activation
Input	100x100x3	-
Hidden1	512	relu
Hidden2	256	relu
Hidden3	128	relu
Hidden4	64	relu
Hidden5	32	relu
Output	4	softmax

Figure 7: Architecture of MLP

A training set consisting of sample inputs and outputs is required for the network to learn. The learning method of the system generally consists of two stages. The first part is forward calculation. The second part is the backward calculation. In the forward calculation phase, the input given to the system passes through the intermediate layers and reaches the output. The net input is calculated by summing the inputs to each processing element. This net input is passed through the activation function to find the output of the current processing element and this output value is sent to the processing elements in the next layer. By repeating these processes, outputs are obtained from the last output layer.

The first stage of learning is completed when the output is received from the network. The second stage will be to distribute the error. If the expected output value and what we get are different, there is an error. In the backward calculation phase, the error is expected to be reduced in each iteration by distributing it to the weight values. The weight values given to the system randomly at the beginning are updated in each iteration by distributing the errors to the weights. In this way, the training of the model is completed.

3.2.3 Convolutional Neural Network (CNN)

CNN, or Convolutional Neural Network, is a specialized type of artificial neural network specifically designed for handling images and videos. It excels in computer vision tasks by recognizing patterns and creating hierarchical representations from visual data, making it well-suited for our project. We utilized TensorFlow and Keras to build our CNN models, focusing on finding the right architecture to yield good results.

After experimenting with different architectures and making adjustments, we narrowed down our options to two CNN models. Ultimately, we selected the one that delivered better results. The architecture of our chosen model is depicted in Figure 8. We used an image size of 100x100, a batch size of 48, and opted for random weight initialization, without any specific weight initialization method.

Layer	Shape	Stride	Activation
Input	100x100x3	-	-
Conv(8)	3x3	(1,1)	relu
Maxpool	2x2	(1,1)	-
Conv(16)	3x3	(1,1)	relu
Maxpool	2x2	(2,2)	-
Conv(32)	3x3	(1,1)	relu
Maxpool	2x2	(2,2)	-
Hidden	255	-	relu
Output	4	-	softmax

Figure 8: Architecture of CNN

During the model training process, we set

50 epochs, but instead of selecting the model achieved at the end of training, we adopted a strategy to save the weights each time the validation accuracy surpassed the previous best. This approach allowed us to obtain a model with optimized weights. The progression of this process is visually illustrated in Figure 9.

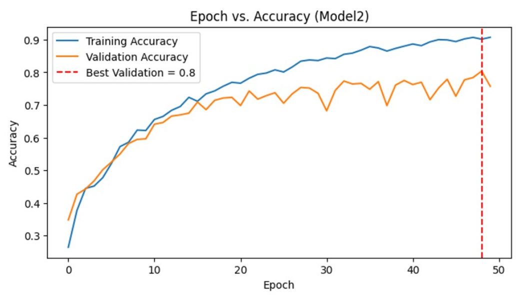

Figure 9: Training process of CNN

4 Experimental Evaluation

Our goal was to surpass the current highest recycling rate worldwide, which is 67.2%, using artificial intelligence models. Therefore, we set a target to separate items with at least 70% accuracy. For this purpose, we utilized three different models: KNN, MLP, and CNN. The reason for choosing these three models stemmed from our research on the internet and the examination of related works, revealing their excellence in image classification. We have detailed our models and metrics in the respective sections. To evaluate the results of our models, we used three different assessment scales: Accuracy, Confusion Matrix and Classification Report. When analyzing the Confusion Matrices for all models, we observed that the "Paper" class consistently had the lowest accuracy in predictions. On the other hand, the "Metal" class had the highest prediction accuracy across all models. The accuracy values for our models are as follows:

Figure 10: Comparing accuracy

All our models have surpassed the target accuracy of 70%, indicating successful achievement of our goal. The higher accuracy of the CNN model compared to the other models can be attributed to several reasons. Firstly, CNN is designed for image processing tasks, aligning with the main focus of our project. CNN tends to perform better in large and complex datasets compared to other models. Lastly, despite experimenting with different parameters for each model, we may have found more suitable parameters for CNN, contributing to its superior performance. To further enhance accuracy, we could have used a larger and more complex dataset. However, models working with images tend to operate much slower compared to other models, and as the dataset grows more intricate, the processing time of the model also increases. Additionally, exploring different optimization algorithms could have improved the training stages of our models.

	KNN		*MLP*		*CNN*	
Material	Precision	Recall	Precision	Recall	Precision	Recall
Glass	0.75	0.76	0.68	0.78	0.79	0.84
Metal	0.81	0.88	0.76	0.88	0.73	0.86
Paper	0.83	0.49	0.82	0.59	0.89	0.71
Plastic	0.62	0.86	0.65	0.67	0.75	0.76

Figure 11: Classification Reports

5 Conclusion

The classification of trash into various recycling categories is possible through machine learning and computer vision algorithms. One of the biggest pain point is the wide varieties of possible data (i.e. any object can be classified into one of the waste or recycling categories). Therefore, in order to create a more accurate system, there needs to be a large and continuously growing data source. We achieved the best result with CNN and we aim to increase this with the changes we will make in the model.Furthermore, we would like to extend this project to identify and classify multiple objects from a single image or video. This could help recycling facilities more by processing a stream of recycling rather than single objects. Another important addition could be multiple object detection and classification. This would improve large scale classification of recycling materials. Finally, we want to continue expanding our dataset by adding more photos.

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garbage-classification, title=(15150 images of 12 categories)

x, title=Waste recycling in Europe,url = `https://www.eea.europa.eu/en/analysis/indicators/waste-recycling-in-europe`