Waste Classification

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Abstract

In this project, we used a Kaggle dataset called "Garbage Classification V2" [4]. The dataset is then preprocessed and divided into test and train sets.
The approaches used are two: the Machine Learning approach, which employs traditional classifiers such as Support Vector Machines (SVM), K-Nearest Neighbors (K-NN), Decision Trees, and XGBoost. The second phase leverages Deep Learning techniques, specifically convolutional neural networks (CNNs) such as ResNet and EfficientNet.
The last part is dedicated to the comparison of the results coming from the two approaches.

Introduction

Effective waste management is crucial to address environmental challenges and support sustainable development. Automated classification of waste using image recognition can significantly enhance the efficiency of recycling processes and reduce human intervention. This study aims to contribute to these efforts by exploring multiple approaches to waste classification.
Recent advancements in AI technologies, such as Convolutional Neural Networks, have demonstrated exceptional precision in identifying and classifying waste materials. We aim to apply artificial intelligence models to this issue and analyze the results.

Related Work

Our work is inspired by prior studies on waste classification using machine learning and deep learning techniques. Kunwar (2024) demonstrated the effectiveness of transfer learning models like MobileNet, ResNet50, and EfficientNetV2, achieving up to 96.41% accuracy, while also analyzing computational carbon emissions [1].

Other studies, such as Lilhore et al., combined CNN and LSTM models to achieve high accuracy, highlighting the versatility of transfer learning, while Mehedi et al. showed the importance of model selection by comparing architectures like VGG16 and MobileNetV2 [2].

Building on these approaches, our project evaluates both traditional classifiers, such as SVM and KNN, and CNN models to provide a comprehensive comparison of their performance in waste classification.

Dataset Structure

The images are 19.762 and distributed across the classes as follows:

Class	**Number of Images**
Metal	1020
Glass	3061
Organic	997
Paper	1680
Batteries	944
Trash	947
Cardboard	1825
Shoes	1977
Clothes	5327
Plastic	1984

Table 1: Dataset structure.

Preprocessing

Initially, we performed data augmentation to ensure that all classes contained 1500 images. We performed this step to prevent class imbalance issues during training.
After the data augmentation process, the dataset was divided into two main subsets:

- **Training Set:** Consisting of 80% of the total images. For the deep learning the training set is further divided into 85% training set and 15% validation set.
- **Test Set:** The remaining 20% of the images

We utilized the same datasets for training and testing in the Machine Learning and Deep Learning approaches, ensuring that both techniques analyzed the same images. This allowed us to perform a much more accurate and meaningful comparison of the results.

1. **Image Resizing**
   All images were resized to a uniform size of 224x224 pixels, ensuring consistency in input dimensions for model training.

2. **Normalization**
   Pixel values were normalized to the range [0, 1] and standardized using predefined mean and standard deviation values for the RGB channels.

3. **Gaussian Filter**
   Applied to reduce noise and improve image quality.

4. **Autoencoders(only for Machine Learning models)**
   Used for feature extraction and dimensionality reduction.

5. **Color Histograms(only for Machine Learning models)**
   Computed to capture the distribution of colors within the images, which served as the feature vectors for the machine learning models.

Machine Learning Models Evaluation

We tested multiple models to efficiently classify waste, employing different preprocessing techniques to achieve better results. The performance of each model was evaluated using metrics such as accuracy, precision, recall, and F1-score. Below, we present the results achieved with the models implemented in our analysis.

Model	Accuracy Train	Accuracy Test	Precision Train	Precision Test	F1-score Train	F1-score Test
XGBoost (using color histograms)	0.88	0.56	0.89	0.53	0.88	0.56
K-NN (using color histograms)	1.00	0.47	1.00	0.48	1.00	0.40
Decision Tree (using color histograms)	0.60	0.38	0.63	0.34	0.57	0.33
SVM(using Autoencoders)	0.60	0.51	0.61	0.49	0.55	0.44

Table 2: Performance Comparison of Machine Learning Models

As we can see the metrics of the machine learning models are not very satisfying. They showed clear signs of overfitting; as evident from the table above, due to high training accuracy but low test accuracy.

Deep Learning Approach

For the deep learning approach, we tried three convolutional neural networks: ResNet50, DenseNet121, and EfficientNet-B0. EfficientNet-B0 consistently outperformed the other models, achieving the highest accuracy across the test dataset. We can see the performance of the models in the following table.

Mode	Test Accuracy
ResNet50	87.09%
DenseNet121	91.83%
EfficentNet-B0	94.41%

Table 3: Test accuracy evaluation

Deep Learning Model Evaluation

To evaluate the model, we can see the confusion matrix that shows how the predictions of the model have been different for each class. The classes in which the model misclassifies most are battery and plastic, in fact, we can see that in some cases plastic is classified as glass and battery as metal.

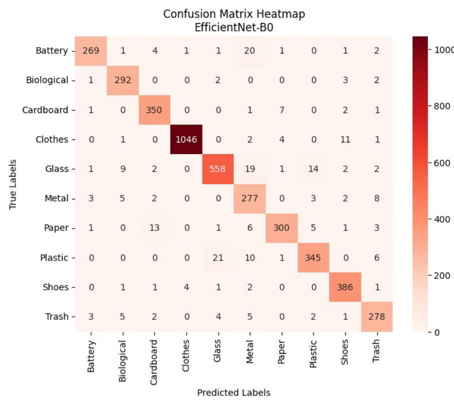

Figure 1: Confusion Matrix for EfficientNet-B0.

To evaluate the misclassified images we decided to show some examples of images that were wrongly predicted. As we can see the images reported below show objects whose class is not easily discernible without context even by the human eye.

Figure 2: Examples of misclassified images.

Conclusions

The results show that we can achieve better outcomes using the Deep Learning approach compared to traditional machine learning models.
In particular, convolutional neural networks such as EfficientNet-B0 consistently outperformed other models, demonstrating higher evaluation metrics.
In this study, we chose to test both deep learning and traditional machine learning models to obtain broader and more diverse results. By doing so, we aimed to understand how each approach performed under the same conditions and identify which model was better suited for the waste classification. This evaluation allowed us to compare the strengths and weaknesses of each method, offering valuable insights into their suitability for different scenarios.

Roles

- Data Preparation: Everybody
- Machine Learning approcach: Gabriele Cabibbo, Luca De Ruggiero, Elena Di Grigoli
- Deep Learning approach: Emanuele Gallo, Emilio Leone

References

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2. Lilhore, U.K.; Simaiya, S.; Dalal, S.; Damaševicius, R. (2023). A Smart Waste Classification Model Using Hybrid CNN-LSTM. *Multimedia Tools and Applications*, 83, 29505–29529. Available at: `https://doi.org/10.1007/s11042-023-16677-z`.

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4. Kaggle. Garbage Classification V2 Dataset. Available at: `https://www.kaggle.com/datasets/sumn2u/garbage-classification-v2`.

Github Repository

`https://github.com/elenadigrigoli/FDS-project`