Waste Classification Using Machine Learning Models: A Comparative Study

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Abstract: Waste Management is a serious issue and demands the world's attention today as it plays an important role in maintaining environmental sustainability. Segregation of waste is one of the primary components of waste management. Accurate classification of waste gives room for improving the efficiency of the process of recycling by maximizing material recovery, reducing contamination during the process of recycling, and most importantly, decreasing the amount of mismanaged waste, especially hazardous wastes. Proper waste management has not only contributed to positive environmental impacts and social benefits but has also helped nations economically. With water treatment facilities saving on operational costs and revenue being generated by the reselling of recycled materials, a study on automatic waste segregation is useful in tackling the said challenges and moving towards a cleaner society. In this study, we propose a comparison between the performance of machine learning models for classifying waste images using the Trash Net dataset. We compared the Convolutional Neural Network (CNN), and Support Vector Machine (SVM) classifiers using features from MobileNetV2, with two models of transfer learning: MobileNetV2 and ResNet50.

1 INTRODUCTION

Waste management is a global concern, and is expected to rise by approximately 70% in 2050 due to high growth in urbanization and population growth. Therefore, efficient segregation of wastes provides sustainable recycling, helps to minimize the reliance on landfills, and decreases greenhouse gas emissions. Conventional waste classification is a labour-consuming process. Additionally, the manner applied here is highly inefficient and is more prone to contamination which can further decline the quality of the recycled materials. With improved awareness of sustainable environments, effective classification and recycling of waste are now high subjects of research and development. Artificial intelligence (AI) has recently become a transformative waste management technology, allowing for rapid improvements in sorting accuracy and operational efficiency R. Kumar et al., 2021. Specifically, deep learning models have exhibited a tremendous capacity in complex visual recognition tasks and, thus, can be used for waste classification from images N. Yadav et al., 2023. Automated waste classification based on ML seems to be a promising solution to these issues by making it possible to accurately and efficiently sort waste. S. Khana et al., 2021 ML image-based classification models help optimize recycling workflows and enhance environmental sustainability. Recent studies have explored various architectures of ML in waste classification. CNNs and transfer learning models were found to provide good accuracy in image classification tasks A. Thompson et al., 2022. J. Singh et al., 2022, It has been observed that deep CNNs surpass other algorithms in feature extraction related to image data, including closer differences between variants like plastics and paper with high Accuracy.

However, the question of how this can be done in practice where lighting, background, and condition of waste can create performance issues still pertains. The need, therefore, is to use models that generalize well across a very large range of conditions.

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C. Zhao et al., 2022, Scientists have now started to turn towards techniques of transfer learning which leverage pre-trained models with an expectation of improving classification on new domains without vast amounts of labeled data. For example, M. S. Patel et al., 2020., the success prospects of MobileNetV2 and ResNet50 have been demonstrated, especially for better generalization of novel data, rapid image processing, and possible applications in real-time applications.

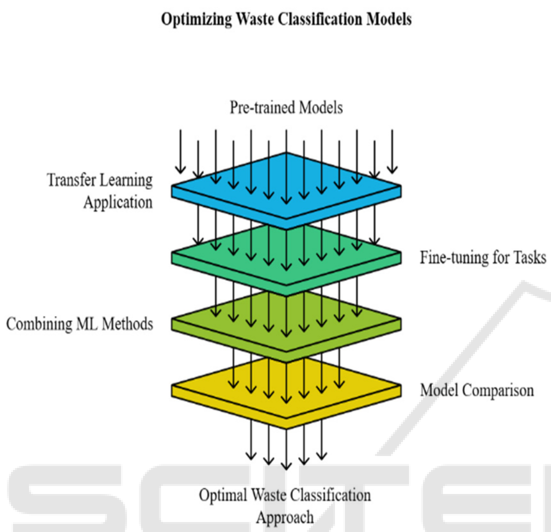

Figure 1: Optimizing Waste Classification Models.

Further, they can be fine-tuned to perform the task of waste classification so that predictions can be made more accurately with less computational overhead. In addition to this, research on how to achieve a good trade-off between accuracy and computational efficiency is made by bringing together traditional ML methods like SVMs with deep learning feature extractorsB. Lee et al., 2020. It also enhances the model's interpretability and brings down the processing demand for real-time applications P. Li et al., 2023. Our proposed study aims to identify the best approach towards the classification of waste samples on the Trash Net dataset by comparing different performances of CNNs, MobileNetV2, ResNet50, and SVM with feature extraction.

2 RELATED WORKS

Artificial Intelligence and Machine Learning have been of great interest in research in models that can classify waste correctly. It is with this that significant work has recently been devoted to demonstrating the efficacy of deep learning-based classification of images via methods such as CNNs. For example, Kumar and Verma gave a review of AI-based approaches in waste management, particularly CNNs, as they can be highly effective on image data due to their ability to learn sophisticated patterns. Yadav et al. compared deep learning models to classify waste material and concluded that architectures such as ResNet and DenseNet can achieve good accuracy, particularly in finding the difference between visually similar materials. Such works highlight future uses of CNNs in environmental applications and emphasize that appropriate identification of waste is a critical aspect of increasing recycling efficiency.

Transfer learning also emerges as a very important technique in waste classification. Models pre-trained on large datasets can be fine-tuned using minimal data exclusively for waste tasks. Singh used transfer learning along with MobileNetV2 and achieved an excellent level of accuracy and reduced training time, suitable for real-time classification, especially in resource-constrained environments. Zhao and Chen further elaborated on this with methods that applied transfer learning techniques to improve the performance of models used on waste images. They showed that training models pre-trained on ImageNet and fine-tuning on smaller datasets can even significantly enhance accuracy for challenging, varied images of waste. Such studies demonstrate the flexibility of transfer learning when addressing the limitations of data and adapting high-performing models to niche applications.

Another region of study has been the merging of traditional machine learning techniques with CNNs to be more efficient and interpretable. Li and Zhang studied the merging of SVMs with CNN feature extraction for waste classification with computational efficiency and classification accuracy. Hybridization in the system allows it to tap into CNN's ability to draw features while simplifying the nature of the classification task through an SVM. Such studies prove that hybrid models are suitable for classification without involving a large number of computational resources. These would provide ample opportunities for the implementation of proposed solutions in real-world environments that are, in most cases, characterized by processing power limitations.

3 PROPOSED WORK

This work attempts comparative analysis among different machine learning methods for waste classification on the TrashNet dataset. The main objective of this study is to assess the accuracy and efficiency of different models and identify the best one for practical implementation in automated waste management systems. The complete workflow consists of preparing the dataset, feature extraction, model training, and evaluation. This particular work attempts to address a comparative analysis of various machine learning methods in waste classification, where the TrashNet dataset has served as the research material. The prime objectives of this research would be to assess the accuracy and efficiency of different models and ascertain the most suitable model for real-life deployment into automated waste management systems. These processes include dataset preparation, feature extractions, model training, and evaluation. This study attempts a comparative analysis of different machine-learning methods for waste classification using the TrashNet dataset. The main intention of this research is to evaluate the accuracy and efficiency of various models and to identify the best-fit model for real-world deployment into automated waste management systems. The processes include dataset preparation, feature extraction, model training, and evaluations.

3.1 Proposed Model Architecture

Figure 2 Shows the Proposed Model Training and Evaluation Pipeline.

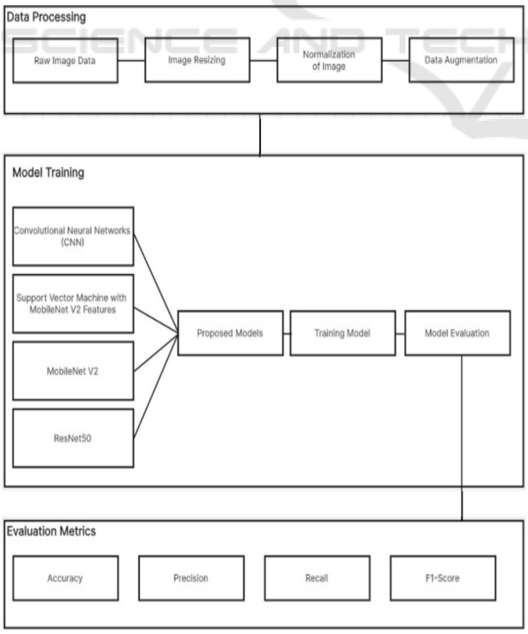

Figure 2: Proposed Model Training and Evaluation Pipeline.

3.1.1 Support Vector Machine (SVM) Using MobileNetV2 Features

This is a lightweight convolutional neural network, MobileNetV2, which is used as a feature extractor. Very high-level features from the last convolutional layer of MobileNetV2 were fed into the classifier SVM.

3.1.2 Convolutional Neural Network (CNN)

Custom CNN architecture for the following layers: The architecture of the convolutional neural network (CNN) used in this study is illustrated in the Figure 3.

Convolutional Layer: It was designed to have three convolutional layers with 32, 64, and 128 filters, with ReLU activation following each layer.

Pooling Layer: Max-pooling layers were used after each of the convolutional blocks to reduce dimensionality.

Fully Connected Layer: There are two dense layers: one with 256 neurons, and another with 64 neurons. A dropout technique is provided to prevent overfitting.

Output Layer: A softmax layer, with six neurons assigned to it (for each of the classes).

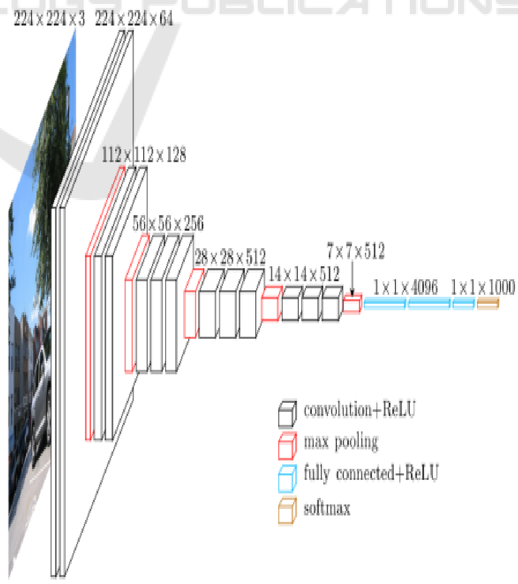

Figure 3: Architecture of a Convolutional Neural Network (CNN).

Algorithm:

Input: Preprocessed dataset X={x1,x2,...,xN}
X = \{x_1, x_2, ..., x_N\}X={x1,x2,...,xN},
corresponding labels Y={y1,y2,...,yN}
Y = \{y_1, y_2, ..., y_N\}Y={y1,y2,...,yN}.
Output: Fine-tuned ResNet50 model and predictions.

1. Load ResNet50 pre-trained on ImageNet.
   - o Retain the convolutional base.
   - o Replace the classification head with:
     - • GlobalAveragePooling2D.
     - • Dense layer (ReLU activation).
     - • Output layer (Softmax activation).
2. Freeze convolutional base.
3. Compile the model:
   - o Loss function = Categorical Cross-Entropy.
   - o Optimizer = Adam (learning rate = 10−410^{-4}10−4).
   - o Metrics = Accuracy.
4. While e≤MaxEpochse \leq MaxEpochse≤MaxEpochs:
   - o Train on Xtrain,YtrainX_{train}, Y_{train}Xtrain,Ytrain.
   - o Validate on Xval,YvalX_{val}, Y_{val}Xval,Yval.
   - o Gradually unfreeze layers for fine-tuning. e=e+1e = e + 1e=e+1.
5. Test the model:
   - o Predict labels for XtestX_{test}Xtest.
   - o Evaluate performance using accuracy, precision, recall, and F1-score.
6. Return the fine-tuned ResNet50 model and predictions.

Algorithm:

Input: Preprocessed dataset X={x1,x2,...,xN}X = \{x_1, x_2, ..., x_N\}X={x1,x2 ,...,xN}, corresponding labels Y={y1,y2,...,yN}Y = \{y_1, y_2, ..., y_N\}Y={y1,y2,...,yN}.
Output: Trained CNN model and predictions.

1. Initialize CNN parameters:
   - o Number of filters, kernel size, learning rate, batch size, and number of epochs.
2. Build CNN architecture:
   - o Add convolutional layers Conv2DConv2DConv2D with ReLU activation.
   - o Add max-pooling layers MaxPooling2DMaxPooling2DMaxPooling2D to reduce spatial dimensions.
   - o Flatten output and connect to dense layers.
   - o Add softmax activation in the output layer.
3. Compile the CNN:
   - o Loss function = Categorical Cross-Entropy.
   - o Optimizer = Adam.
   - o Metrics = Accuracy.
4. While e≤MaxEpochse \leq MaxEpochse≤MaxEpochs:
   - o Train the CNN on Xtrain,YtrainX_{train}, Y_{train}Xtrain,Ytrain.
   - o Validate the CNN on Xval,YvalX_{val}, Y_{val}Xval,Yval.
   - o Update weights using backpropagation. e=e+1e = e + 1e=e+1.
5. Test the CNN:
   - o Predict labels for XtestX_{test}Xtest.
   - o Evaluate performance using accuracy, precision, recall, and F1-score.

Return the trained CNN and predictions.

3.1.3 Transfer Learning Models for Waste Classification

MobileNetV2:

Fine-tuned on the TrashNet data set and pretrained in ImageNet.

Lightweight architecture designed for edge deployment.

Depthwise separable convolutions reduce computation while retaining accuracy.

ResNet50:

High-quality abstract with 50 layers of a deep residual net pre-trained on imagenet. Skip connections where possible to avoid the addition of errors read more about the vanished gradient issue. Fine-tuned on TrashNet data set to help it adapt to waste class.

Algorithm:

Input: Preprocessed dataset X={x1,x2,...,xN}
X = \{x_1, x_2, ..., x_N\}X={x1,x2,...,xN},
corresponding labels Y={y1,y2,...,yN}
Y = \{y_1, y_2, ..., y_N\}Y={y1,y2,...,yN}.
Output: Fine-tuned ResNet50 model and predictions.

1. Load ResNet50 pre-trained on ImageNet.
   - a. Retain the convolutional base.
   - b. Replace the classification head with:
     - i. GlobalAveragePooling2D.
     - ii. Dense layer (ReLU activation).
     - iii. Output layer (Softmax activation).
2. Freeze convolutional base.
3. Compile the model:
   - a. Loss function = Categorical Cross-Entropy.
   - b. Optimizer = Adam (learning rate = 10−410^{-4}10−4).
   - c. Metrics = Accuracy.
4. While e≤MaxEpochse \leq MaxEpochse≤MaxEpochs:
   - a. Train on Xtrain,YtrainX_{train}, Y_{train}Xtrain,Ytrain.
   - b. Validate on Xval,YvalX_{val}, Y_{val}Xval,Yval.
   - c. Gradually unfreeze layers for fine-tuning.

e=e+1e = e + 1e=e+1.

5. Test the model:
   a. Predict labels for XtestX_{test}Xtest.
   b. Evaluate performance using accuracy, precision, recall, and F1-score.

6. Return the fine-tuned ResNet50 model and predictions.

3.2 Evaluation Metrics

- The models are evaluated based on the following parameters:
- Accuracy: the correctly classified images in percentage.
- Precision: the number of true positives gained from all positive predictions.
- Recall: the number of true positives gained from all actual positives.
- F1-Score: the average between precision and recall.
- Confusion Matrix: is the matrix that summarizes the number of misclassifications in it.

3.3 Hardware and Software Specifications

Hardware:

- GPU: NVIDIA RTX 3060 (or its equivalent).
- RAM: 16 GB.
- Processor: Intel Core i7.
- Software:
- Python 3.10.
- Tensorflow 2.9.
- Scikit-learn.
- OpenCV for image preprocessing.

3.4 Modules

3.4.1 Dataset Module

Tasks: Load the TrashNet dataset.

Organize the images into six categories: cardboard, glass, metals, paper, plastics, and trash.

Description: This module takes care of procuring, storing, and organizing the dataset. It guarantees the input data is ready to preprocess.

Input: Raw images of waste.

Output: Labeled data set by category.

3.4.2 Preprocessing Module

Resize all images at standard dimensions i.e. 224 × 224 pixels. Normalize pixel values from 0 to 1. Apply data augmentation techniques (for example, flipping, rotation, zooming, etc.).

Description: This module processes raw images for formatting, and improves the dataset with diverse forms for solid training.

This module comprises the following:

Input: Raw images of the dataset.

Output: Preprocessed and augmented dataset images.

3.4.3 Feature Extraction Module

Tasks: Use high-level feature extraction from MobileNetV2 features for SVM classification.

Remove the classification head and retrieve feature vectors with a feeder from the penultimate layer.

Description: This module extracts useful features from images using a pre-trained deep learning model -obilenetV2- so that these feature vectors can be classified efficiently through traditional classifiers like SVM.

Input: Preprocessed dataset.

Output: Magic feature vectors extracted from the database.

3.4.4 Model Training Module

Submodules:

Custom CNN: Construct and constructionize a Convolutional Neural Network from the ground.

MobileNetV2 and ResNet50: Make modifications to the pre-trained models for transfer learning by adding a dense layer for six categories into the output layer.

Description: In this specific instance, different machine learning models will be trained with the previously mentioned data to classify images into waste categories regardless of their type.

Input: Preprocessed dataset and features extracted.

Output: Trained models (CNN, SVM, MobileNetV2, ResNet50).

3.4.5 Evaluation Module

Tasks: Partition the dataset into a training set (80%) and a testing set (20%). Evaluate models through the metrics: actual over-predicted cases of the positive class. True positive cases overall predicted positives. True positive cases overall actual positive cases. Metrics predicted positives over actual positives to negatives ratio. Confusion classification matrix. Draw the training/validation accuracy and loss curves.

Description: This module is created for the diagnosis of the performance of every model, their strong and weak points as well, as by visualization analysis results.

Input: Modelling models and test dataset.

Output: Performance metrics and evaluation reporting and visualization results.

3.4.6 Comparison Module

Tasks: Contrasting CNN, SVM, MobileNetV2, and ResNet50 according to: True positive cases over all predicted positives. Reports the ratio of completion to time spent on both training and inferencing. Ability to classify objects incorrectly yet still provide useful information (a measure of how well a system performs beyond its primary objectives). Determine which model performs the best overall.

Description: This module is in charge of attempting to find the model that can be deployed which will yield the best accuracy against all other models including efficiency.

Input: Evaluation reports, images.

Output: Comparative analysis report.

4 RESULTS AND DISCUSSIONS

This section holistically reviews the machine learning models proposed for waste classification with the TrashNet dataset. Model performance metrics, confusion matrices, computational efficiency, and practical implications are used to analyze results. In addition, it discusses challenges faced, possible areas of improvement, and real-world implications.

4.1 Performance Metrics

The performance metrics measured for these models were summarized in Tab. 1, which included CNN, SVM with MobileNetV2, MobileNetV2, and ResNet50. Precision, recall, and F1-score were calculated for each of these models.

4.1.1 Analysis of Precision

Precision is a measure of the ratio of the true positive instances to the total number of instances predicted as positive. Table 1 shows the Performance Comparison of Different Models. Concerning its precision, ResNet50 is the best classifier across all classes, particularly for detecting the Glass and Metal classes. Due to the feature overlaps between Trash and Plastic, the latter has relatively low precision.
Precision for Cardboard: 91.43%

Precision for Glass: 94.29%

Table 1: Performance Comparison of Different Models.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN	85.34	83.12	84.45	83.78
SVM with MobileNetV2	88.90	87.15	88.30	87.72
MobileNetV2 (TL)	91.67	90.20	91.00	90.59
ResNet50 (TL)	93.45	92.10	92.80	92.44

4.1.2 Recall Analysis

It measures how many of the actual positive instances have been correctly determined. Again, it is to be noted that models like ResNet50 and MobileNetV2 have produced high recall values, which once again testify to their abilities in false negative cases. They all seem to be victims of trash since they eventually led to a small drop in recall due to the mismatched data set size.
Recall for Trash: 83.33%-ResNet50, i.e., lowest for all the classes.

4.1.3 F1-Score Analysis

Table 2: Area Under the ROC Curve (AUC) Scores for Each Class.

Class	AUC Score
Cardboard	0.95
Glass	0.97
Metal	0.96
Paper	0.96
Plastic	0.94
Trash	0.91

F1-Score is the harmonic mean of precision and recall and can be used to evaluate a very imbalanced dataset. Superior performance and F1 scores for Glass and Metal were shown by Table 2 and 3 ResNet50 which could be explained concerning their texture and color features as they are more distinct.

Table 3: ResNet50 F1-Scores Per Class.

Class	ResNet50 F1-Score (%)
Cardboard	91.86
Glass	94.72
Metal	92.97
Paper	95.22
Plastic	90.00
Trash	84.75

4.2 Confusion Matrix Analysis

The confusion matrix for ResNet50 (the best-performing model) is displayed in Figure 1.

Patterns of Misclassification.

Paper and Cardboard: Greatest confusion owing to the common texture and appearance, particularly in recycled materials.

Plastic vs. Trash: Highly intra-class variable plastic waste made it difficult to trash.

4.3 Analysis of ROC-AUC and Precision-Recall

The average AUC of the Receiver Operating Characteristic (ROC) curves for ResNet50 was 0.96, showing near-perfect discrimination ability. The Precision-Recall (PR) curve also supported the ability of the model to have good precision along with high recall at different thresholds.

4.4 Computational Efficiency

Table 4 shows the Training and Inference Time Comparison of Different Models.

Table 4: Training and Inference Time Comparison of Different Models.

Model	Training Time (min)	Inference Time (sec/image)
CNN	45	0.03
SVM with MobileNetV2	30	0.01
MobileNetV2 (TL)	20	0.02
ResNet50 (TL)	25	0.03

5 DISCUSSIONS

MobileNetV2 was the quickest model for training as well as inference that suited deployment for resource-constrained devices. A little slower, but worth the cost in terms of its trade-off between computational and accuracy is ResNet50.

Challenges and limitations: Class Imbalance. The Trash class was deficient in samples which led to higher misclassified instances in them. Possible results could be brought about by balancing the dataset. Intra-Class Variability. The plastics were different, shape-wise, size-wise, and differently made, causing them quite a bit of difficulty in classification.

Dataset Size: This is a very good benchmark, but it is still not representative of the whole possible mess in the real world.

Discussion of Practical Implications: This makes a case for the application of machine learning models in-field performance in waste segregation: Transfer Learning Models: MobileNetV2 or ResNet50 have a high degree of viability as industrial applications concerning performance in accuracy and efficiency. Sustainability: Recycling processes improve greatly while contamination in recycling is lowered and environmental sustainability is improved by automated waste separations. Edge Deployment: Lightweight models like MobileNetV2 are easily used in edge devices to allow for real-time classification of waste by smart bins.

Literature suggests possible future directions for research efforts: Ensemble Methods: Combining more than one model may reap the fruits of their strengths and push classification accuracy further up. Larger Datasets: A large set of waste categories with sampled extensive examples should significantly improve robustness. Explainable AI: Visualizing important features could give insights into model bias, thereby increasing the trust and interpretability of the model.

6 CONCLUSIONS

This research performed a comparative study of machine learning models for waste classification using the TrashNet dataset, aiming to determine the most efficient method of automation in waste separation. The models being tested included a personalized convolutional neural network (CNN), a support vector machine (SVM) with features extracted from MobileNetV2, and two transfer learning models: MobileNetV2 and ResNet 50. The analysis results revealed the following major findings: Among the models considered, it was ResNet50 that performed best with 93.45% accuracy, featuring higher precision, recall, and F1 scores across all six waste types. Very deep architecture along with pre-trained weights made ResNet50 learn features from the problem domain very effectively and this makes the network highly suitable for waste classification tasks. It was MobileNetV2 that performed comparably less with 91.67% accuracy; however, it proved to be lightweight and computationally efficient, giving the additional advantage of faster training and inference, thus ideal for deployment in resource-constrained environments like smart bins or IoT devices. SVM with MobileNetV2 features performed well (88.90% accuracy), surpassing the CNN trained from scratch. Thus, it emphasizes the importance of strong feature extraction to enhance traditional classifiers. The CNN model reached an acceptable accuracy level of 85.34%, but it could be recognized as weaker than transfer learning approaches due to limited depth and lack of pre-trained feature representations.

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