AI-Powered Waste Segregation using Computer Vision & Machine Learning

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***Abstract*—Waste management has become a challenge that is increasingly taking a global dimension, and for that reason, there is a need for precise and efficient waste classification for enhanced recycling methods. The current project describes a waste classification system using artificial intelligence, which involves the use of machine learning and computer vision to classify various forms of waste based on image inputs. The proposed system makes use of transfer learning for the determination of worthwhile visual attributes for enhanced classification. The system has been trained using image sets to ensure that it performs accurately when it comes to image classification. Moreover, a web platform has been developed for the demonstration of the effectiveness of the automated waste classification system using image inputs to classify waste.**

***Index Terms*—Artificial Intelligence, Machine Learning, Waste Classification, Real-Time Segregation**

I. Introduction

Effective waste management has become a pressing global challenge due to rapid urbanization and population growth. Improper waste segregation contributes to environmental degradation, inefficient recycling, and public health hazards [1]. Traditional manual sorting methods are labor-intensive and unsafe, highlighting the need for intelligent and automated solutions. Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have opened new possibilities for smart waste management systems [2], [3].

Deep learning models, particularly convolutional neural networks (CNNs), have shown great potential in identifying and classifying waste categories such as plastic, glass, paper, cardboard, biodegradable and metal through image-based learning [4]. Integration of AI-driven models with edge computing and web-based systems can further enhance real-time performance and usability [5], [6].

This project focuses on developing an AI-powered waste classification system that can automatically detect and categorize waste using image-based datasets. Initially, a synthetic dataset is utilized for model training and evaluation, with future efforts directed toward real-world image data.The system aims to support sustainability goals by improving waste segregation accuracy and efficiency.

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II. Literature Review

Effective waste management has become a global concern due to increasing urbanization and environmental degradation. Numerous researchers have explored the use of artificial intelligence (AI) and computer vision for waste classification and segregation. Traditional approaches often relied on manual sorting, which is inefficient and hazardous. Recent advancements in deep learning and machine learning (ML) have enabled automatic waste recognition, improving accuracy and scalability. Sharma et al. [7] developed a CNN-based waste classifier using the TrashNet dataset, demonstrating that deep learning models outperform handcrafted feature-based methods. Similarly, Kumar et al. [1] proposed an IoT-integrated smart bin that uses ML for real-time waste type identification, showing the potential of AI in automated waste collection systems.

Further developments include the use of transfer learning and fine-tuning of pre-trained architectures like ResNet, MobileNet, and EfficientNet to enhance classification accuracy even with limited datasets [8], [9]. Vision Transformers (ViT) have also been explored for waste detection, achieving robust results under complex lighting and background conditions [10]. Several studies combined computer vision with sensor-based data fusion, such as moisture and weight sensors, to improve classification reliability [11]. Others emphasized edge deployment using Raspberry Pi and Jetson Nano for real-time performance in low-resource environments [12], [13]. These approaches highlight the importance of lightweight, efficient models for on-site waste sorting.

In addition, research has also shifted towards few-shot and meta-learning approaches, allowing AI systems to identify new waste categories with minimal training samples [14]. This aligns with real-world scenarios where new materials appear frequently. Comparative studies between CNNs, SVMs, and hybrid deep learning frameworks show that CNN-based architectures consistently outperform classical ML algorithms in both accuracy and generalization [15], [16]. Some works focused on improving dataset diversity through augmentation and synthetic generation techniques to handle data imbalance and domain shift [17], [18]. Moreover, the integration of web interfaces and mobile applications has made AI-driven waste segregation more accessible and scalable for smart city infrastructures [19], [20].

Overall, the reviewed literature indicates that while significant progress has been made in automated waste segregation using AI and ML, challenges remain regarding dataset generalization, handling unseen waste types, and optimizing models for edge devices. This project aims to address these challenges by developing a robust, real-time waste classification system combining computer vision and ML, with future integration of few-shot learning and multi-modal data fusion.

III. Research Gap

Despite the fact that many investigations have been conducted on the task of classification of wastes utilizing the concepts of machine learning and computer vision, most of the investigations have been conducted on simulated data or in such a setting where the result is not applicable in real-life variations of wastes. Additionally, the fact that most of the investigations highlighted above have not been focused on real-time classification and implementation for the ability of the system to adapt within the new wastes is an aspect where the gap is massive in relation to the development of an AI-based wastes segregation system that is efficient in adapting within various types of inputs.

IV. Methodology

The process involved in developing the AI-Powered Waste Segregation System methodology involves various stages ranging from data acquisition to the development of system.

Figure 1 explains the procedure involved in developing the entire system.

A. Dataset Structure and Class Distribution

The data consists of three sets, namely, the training data, validation data, and test data, used in supervised image classification. Each data set has the same six classes of waste, namely biodegradable, paper, plastic, cardboard, glass, and metal, with the images of each class in separate directories.

This organized framework facilitates data loading and label assignment in an efficient manner. The presence of varying orientations of objects and background qualities in the dataset also helps in learning and comparison of models with regard to all possible waste classes.

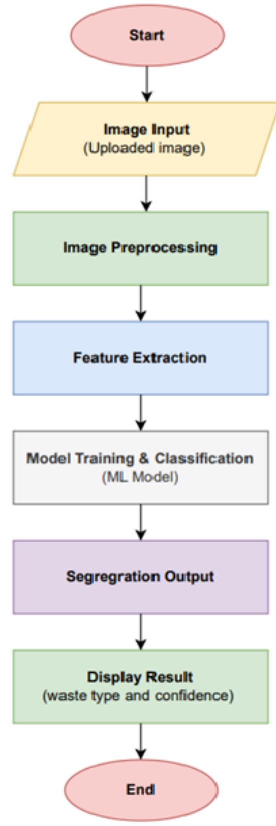

Fig. 1. Workflow of the Proposed AI-Powered Waste Classification System

B. Data Preprocessing

To maintain consistency among models, all input photos are scaled to a fixed resolution. To increase training stability and convergence, pixel values are normalised. To facilitate efficient learning and objective assessment, the dataset is created using distinct training, validation, & testing subsets.

C. Feature Extraction for Traditional Machine Learning Models

A convolutional neural network that has been pretrained is used to extract deep features for conventional machine learning models. The resultant feature maps are streamlined into predetermined-length feature vectors once the last classification layers are eliminated. Models like K-Nearest Neighbours, Random Forest, and Logistic Regression employ these representations as input.

D. Model Architectures

The suggested system assesses several learning strategies, such as deep learning models based on transfer learning, convolutional neural networks generated from scratch, and conventional machine learning models. While pretrained models like MobileNetV2, NASNetMobile, and EfficientNetB0 are implemented to take advantage of learnt visual characteristics for better classification performance, baseline CNN architectures are created with increasing depth and regularisation.

V. Feature Extraction for Traditional Machine Learning Models

A. CNN-Based Feature Extraction

A pretrained convolutional neural network is used for deep feature extraction, which makes it possible for conventional machine learning models to interpret picture input. The network is only utilised as a single feature extractor to extract high-level visual clues from input photos after its classification layers are eliminated.

B. Feature Vector Representation

Concise representations of the input images are created by flattening the retrieved feature maps into fixed-length numerical vectors. In comparison with raw image-based learning, these feature vectors enable effective training and lower computational cost when used as input for conventional machine learning classifiers.

VI. Machine Learning Models

A. Logistic Regression

Logistic Regression is the baseline classifier, which is impressed with the deep vectors that have been extracted. Though a linear classifier, it actually performed quite well due to the robust and high-level features that were extracted by the CNN-based process, due to which it was quite capable of identifying various classes of waste.

B. Random Forest

The performance of ensemble-based learning is evaluated using Random Forest operating on the extracted feature vectors. This model combines the outputs from multiple decision trees to increase robustness and reduce overfitting, but the dimensionality of the feature space limits its performance.

C. K-Nearest Neighbors

K-Nearest Neighbours uses feature-space similarity to classify data. Despite being straightforward and not parametric, its performance relies on calculating distance in high-dimensional vectors of features, which leads to a moderate level of classification accuracy.

VII. Deep Learning Models

A. Basic CNN

To assess complete image categorisation performance, a simple convolutional neural network is used as a basic deep learning model. Convolutional & pooling layers are followed by completely linked layers in the architecture, which offers a straightforward but efficient learning framework.

B. Deeper CNN

A deeper model of CNN is created by adding more convolutional layers in order to enhance feature representation. The goal of this model is to identify more intricate spatial patterns in garbage photos; however, more depth also raises the computing cost and may lead to overfitting.

C. CNN with Dropout

The CNN architecture uses dropout regularisation, which randomly deactivates neurones during training, to reduce overfitting. By avoiding undue reliance on certain feature activations, this method enhances model generalisation.

VIII. Transfer Learning Models

A. MobileNetV2

For feature extraction & classification, MobileNetV2 is used as a lightweight pretrained model. To minimise processing while maintaining a high representational capacity, the network makes use of depthwise separable convolutions. Among all the models tested, fine-tuning on the garbage dataset results in the best classification accuracy.

B. NASNetMobile

Neural architecture investigation led to the discovery of NASNetMobile, an architecture that is utilised for transfer learning to extract complicated information from garbage photos. Its greater architectural complexity causes it to train more slowly than MobileNetV2, even though it achieves competitive performance.

C. EfficientNetB0

As a small transfer learning model, EfficientNetB0 is evaluated. The model performs poorly on this dataset despite its potential efficiency, most likely as a result of insufficient fine-tuning and susceptibility to low-resolution input.

IX. Training Strategy and Hyperparameter Tuning

A. Training Configuration

The provided training set is used to train each model, and performance is tracked through validation. The Adam optimiser is used with categorical cross-entropy loss for CNNs and transfer learning models. To enhance convergence, input photos are normalised and downsized to 128 times 128 pixels. Model complexity and computing limitations are taken into consideration when selecting batch sizes and epoch counts.

X. Performance Evaluation Metrics

A. Accuracy

Accuracy quantifies the ratio of images correctly classified to the total number of images in the test set. It is the measure used for general model performance.

B. Precision, Recall, and F1-Score

Precision, recall, and F1-score are computed to evaluate the correctness of the model for identifying each category of waste correctly. Weighted averaging is used due to any class imbalance that may exist.

C. Z-Score

The statistical performance of the model compared to random guessing is evaluated through computation of a Z-score. In a multi-class problem with N classes, the random baseline is $1/N$.

D. Confusion Matrix and Heatmap

The confusion matrix summarizes the model results of classification for all classes. Heatmaps are generated from the confusion matrix to visually illustrate misclassifications and class wise performance.

XI. Experimental Results

A. Results of Traditional Machine Learning Models

Table I summarises the performance of conventional machine learning models employing CNN-extracted feature vectors. With an accuracy of 83.97%, Logistic Regression outperformed K-Nearest Neighbours 70.99% and Random Forest 60.66%.

B. Results of CNN-Based Models

CNN models that are trained from scratch perform mediocrely. The accuracy of the basic CNN was 51.40%, that of the deeper CNN was 60.58%, and that of the CNN with Dropout was 59.09%. These findings show that CNNs performed worse on extracted features than classical ML, most likely as a function of small datasets and model capacity.

C. Results of Transfer Learning Models

CNNs built from scratch were greatly surpassed by transfer learning models. The maximum accuracy was 87.4% for MobileNetV2, 73.80% for NASNetMobile, and 2.98% for EfficientNetB0. The outcomes demonstrate the sensitivity of some architectures to input resolution & tuning as well as the efficacy of lightweight pretrained networks.

TABLE I
Accuracy of Different Models

Model	Accuracy (%)
Logistic Regression	83.97
Random Forest	60.66
K-Nearest Neighbors	70.99
Basic CNN	51.40
Deeper CNN	60.58
CNN with Dropout	59.09
MobileNetV2	87.40
NASNetMobile	73.80
EfficientNetB0	2.98

XII. Comparative Analysis and Discussion

A. Model Performance Comparison

The experimental findings show that both CNNs trained from scratch & conventional machine learning models are outperformed by transfer learning models, especially MobileNetV2. Because CNN-extracted features are of high quality, Logistic Regression also performs competitively. The difficulty of learning intricate patterns with a small sample size is shown by the poorer accuracy of CNN models trained from scratch. The poor performance of EfficientNetB0 suggests that it requires little fine-tuning and is sensitive to low-resolution inputs.

B. Analysis of Performance Variations

Variations in performance can be explained by a number of factors. Pretrained weights help transfer learning models by facilitating efficient feature representation. Conventional machine learning algorithms are good at extracting information, but they are unable to capture intricate spatial relationships. Underfitting results from CNNs trained from scratch being constrained by dataset size & depth. The performance of transfer learning is further enhanced by hyperparameter adjustment, highlighting the significance of deep network setups.

XIII. System Implementation

A. Model Serialization Using Pickle (.pkl)

Python's `pickle` package is used to serialise the top performing models, such as MobileNetV2 and Logistic Regression. This enables quick loading without the need for retraining by storing the learnt model's architecture and parameters for later usage.

B. Image Upload-Based Waste Classification System

Users can upload any garbage image for classification thanks to a lightweight system created in Visual Studio Code. The projected waste category is returned once the submitted image has been preprocessed and run through the serialised model. This illustrates how the suggested method for immediate garbage sorting is practically applicable.

XIV. Limitations

The suggested technique has many drawbacks while using transfer learning models to achieve high accuracy. Due to the modest size of the dataset, generalisation to previously encountered garbage photos may be limited. Some classes, like glass and metal, have superficial similarities that may lead to incorrect classifications. Furthermore, the system's performance may differ on low-spec devices, and developing deep learning models necessitates significant processing resources.

XV. Conclusion & Future Work

An AI-powered waste classification system utilising transfer learning models, CNNs learnt from scratch, and conventional machine learning is presented in this paper. According to experimental data, CNNs and conventional machine learning classifiers are outperformed by transfer learning models, especially MobileNetV2, which reach the highest accuracy. Serialised models are used to further implement the system for useful image upload-based classification. These findings demonstrate how well pretrained deep learning architectures can facilitate precise and effective waste segregation.

Expanding the dataset to include more waste categories and a wider range of environmental variables could be one way to increase generalisation in the future. With little data, few shot learning methods can be investigated for the classification of novel waste categories. Integration with camera based systems and deployment on edge devices can improve the usefulness of smart waste management solutions.

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