



Automated Waste Classification Using CNN for Sustainable Waste Management

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Abstract: This paper presents a Convolutional neural network-based automated waste segregation system. For efficient waste management. Food waste, metal, plastic, and paper are the four categories into which the model divides waste images. It uses a deep learning technique to classify images. Training and testing are conducted using the Waste Segregation Large Dataset from Kaggle, which includes more than 56,000 labeled images. To efficiently extract and classify features, the CNN architecture includes multiple convolutional, pooling, and dense layers. The suggested system's consistent accuracy demonstrates CNNs' high level of precision in waste segregation automation. Additionally, a variety of data improvement techniques are applied to lessen overfitting and boost the model's generalization ability. The model's strength is ensured by assessing its performance using metrics such as accuracy, precision, recall, and F1-score. The system can integrate into smart waste management setups, where cameras and sensors automatically capture and classify waste in real time. This automated process reduces manual work and human error while optimizing recycling tasks by ensuring precise sorting. Overall, the proposed approach helps promote sustainable recycling, conserve resources, and support cleaner urban areas.

Keywords: Waste Segregation · Convolutional Neural Network · Image Classification · Deep Learning · Smart Waste Management

I. INTRODUCTION

The issues of waste disposal have become one of the most serious environmental concerns in both developing and developed nations due to rapid population growth, industrialization, and rising consumer culture [6], [10], [11]. More waste that is not disposed of in an environmentally conscious manner leads to degradation of the environment, landfilling, and health effects. The traditional ways of sorting and separating waste using manual labour is inefficient, labour-intensive, and there is the likelihood of human error that happens when collecting recyclables and sometimes classifying the incorrect type of waste [1], [2]. AI and computer vision can be considered the developing technologies leading to improved waste classification automation. In particular, the use of Convolutional Neural Networks (CNN's) have had success in other image classification methods, which can automatically extract hierarchical features from raw images [1], [5]. CNN based waste classification systems also benefit from better performance than other traditional machine learning models which used human hand-crafted parameters based on features like colour, shape, and texture to classify waste [2], [9]. Deep learning models also have advantages of high accuracy, scaling, reduced labour effort, and provide a means of automating the recycling process.

Numerous recent studies have investigated the possibilities of deep learning for waste management. Jindal and Kumar [1] have developed a CNN-based model for waste classification that performed better than traditional algorithms, while Mittal and Kaur [2] have developed a real time ResNet-based architecture for object/ waste classification. Yang and Thung [3] developed a CNN model for separating recyclable and non-recyclable waste. These studies demonstrate that CNNs are useful for modernizing automation in the direction towards sustainability.

This research uses the Waste Segregation Large Dataset from Kaggle [4] which contains more than 56,000 labelled images of food, metal, paper, and plastics. The dataset's variability in lighting, angles, and backgrounds contributes to the strength of the model and generalization capability in the real world. The proposed CNN-based model utilizes deep learning mechanisms for automated waste segregation is aimed at the development of better and cleaner environments in a smart recycling direction.

In conclusion, the proposed project advances the Sustainable Development Goals (SDGs 11 and 12) of the UN for responsible consumption, sustainable cities and communities, and manufacturing [10], [11].



II. RELATED WORK

In recent years, many researchers have studied deep learning approaches to automate waste classification. Conventional machine learning methods used handcrafted features such as colour and texture, however, these methods suffered from instability in reaction to perturbations such as lighting, shape, and orientation to the objects [1], [2].

Jindal and Kumar [1] showed that systems based on CNN architectures for waste classification, The offered dramatic improvements in accuracy and scalability compared to traditional algorithms. Mittal and Kaur [2] developed a deep-learning based smart waste management system for real time classification based on the ResNet architecture which improved overall efficiencies of the treatment. Likewise, Yang and Thung [3] presented a CNN model to classify recyclable and non- recyclable waste from a custom dataset demonstrating the application of deep- learning approaches in sustainability and environmental-focused uses.

Recent work has transitioned into more elaborate architectures such as VGG, MobileNet, and EfficientNet to account for more complex waste images while maintaining real time performance [9]. Alqahtani et al. [6] examined the use of deep learning embeddings in a smart city context where actual waste bins embedded with IoT software to recognize and classify the type of waste to then report to the cloud in an interactive manner. Overall, the literature supports the evidence that CNNs and their advanced variants represent major components in the development of intelligent and automated systems to classify waste for recycling and reuse [1] - [3], [6], [9].

III. PROBLEM STATEMENT

Environmental pollution, overflowing landfills, and ineffective recycling efforts are the result of improper waste sorting. Manual sorting is often inaccurate and limited by human error which leads to waste misclassification of materials. There is an urgent need for automated systems that can provide accurate waste classification based on visual data. This work describes the problem as follows:

Given a collection of waste photos labelled with predefined categories like food, plastic, metal, and paper, you must develop a CNN-based model that can accurately classify waste into the appropriate category and make predictions based on previously unseen images.

The proposed solution solves the inefficiency of manual sorting and creates scalable models that can easily deploy to smart bins, industrial waste processing, and recycling facilities.

IV. DATASET DESCRIPTION

The dataset we used in this study is the Waste Segregation Large Dataset obtained from Kaggle, which contains over 56,000 labelled images, divided into four types: Food Waste, Plastic, Metal, or Paper. The images are heterogeneous, altered by lighting, orientation, and backgrounds, which will provide diversity and robustness for training the model.

To ensure consistency in dimensions and intensity parameters, all images were zoomed in and normalized prior to training. The dataset was split into subsets for testing (20%) and training (80%). In order to generalize the model and reduce overfitting, data augmentation techniques like rotation flipping, and zooming were used.

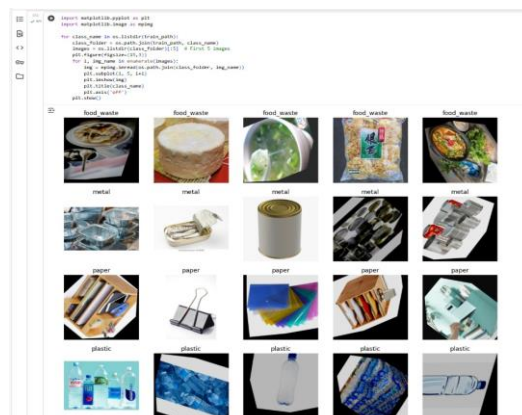


Fig. 1. Sample images of Dataset



V. METHODOLOGY

A Convolutional Neural Network (CNN) is used in the suggested system architecture to automatically classify waste images into various categories.

1.Data Preprocessing

All images from the dataset were resized to 128×128 pixels for consistency and computational efficiency. The pixel values were normalized to 0-1, which allows faster convergence during training. Augmentation techniques like rotation (up to ±30 degrees), height, and width shifts, both horizontal flipping and zooming were employed. These changes allow the CNN to generalize better because they bring more natural variations in illumination, angle, and orientation from the reality into the dataset.

To provide a fair assessment of the model's performance, the dataset was split into parts for training (80%), validation (10%), and testing (10%). This preprocessing setup is vital for maintaining stable classification performance in different real-world situations and for the model's robustness and generalizability to be improved.

2.Feature Extraction

The architecture of Convolutional Neural Networks is designed to automatically find patterns that are meaningful in the input images without human feature engineering. Each of several convolutional layers is capable of identifying textural and spatial features such as edges, color patterns, and shapes. After each convolutional layer, there is a pooling layer, which reduces the spatial size of the feature maps, thereby reducing computations and avoiding overfitting. The model gains non-linearity from the Rectified Linear Unit-ReLU-activation function, which permits the model to learn intricate decision boundaries. Dropout layers that randomly disable neurons during training are applied between dense layers to alleviate overfitting and further improve model generalization. Feature extraction and high - level representation learning from the organic waste images can be efficient and fluid with such combinations of operations

3.Architecture Diagram

The following makes up the template for the CNN model's general architecture:

- Convolutional Layers: Take input images and extract both high-level and low-level visual features, like edges, textures, and shapes.
- Pooling Layers: Use spatial downsampling to shrink feature maps while preserving crucial spatial data and cutting down on processing time.
- Fully Connected Layers: Flatten the feature maps and join them to dense layers that use their learned representations to make decisions.
- Softmax Output Layer: Assigns probabilities to the different classes of materials (food, metal, plastic, paper), thus the output class would be based on the class with the highest probability, or likelihood.

This architecture allows the system to process physical images of waste in an end-to-end process and learn patterns of one material object versus another.

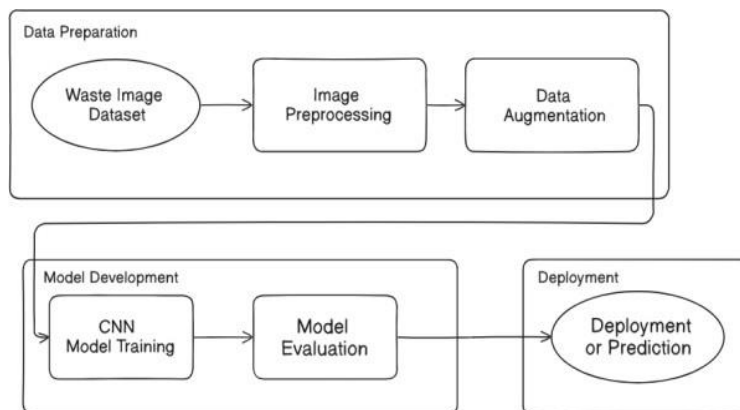


Fig. 2. Architecture Diagram



4. Evaluation Metric

The trained CNN model's performance was evaluated using standard classification metrics like F1-score, recall, accuracy, and precision.

- Accuracy is the proportion of correctly classified images, regardless of category.
- Precision measures how reliable the classification is; it is the number of predicted positive samples that are actually positive.
- Recall is defined as the model's ability to identify all relevant samples in each category.
- The F1-score, which is the average of precision and recall, gives a more complete picture of the model's performance.

Additionally, the confusion matrix shows the correct and incorrect predictions for each of the four classes. Together, these metrics offer a clear view of the overall performance, strengths, and weaknesses of the proposed system.

VI. IMPLEMENTATION DETAILS

The whole system was made using Python 3.12 with development environments Jupyter Notebook and PyCharm IDE for easy coding, testing and visualizing. The TensorFlow module was used with Keras API to design, build and train the Convolutional Neural Network (CNN) model.

OpenCV and Keras Image Data Generator were used for preprocessing and augmenting data to improve generalizability and robustness of the model. The preprocessing pipeline contained the following processing steps:

- Resizing: All images fed into the model were resized to 128×128 pixels for consistency of the data input dimensions.
- Normalization: The pixel values were normalized to run from 0 to 1 for faster training convergence.
- Augmentation: Augmentation techniques were used, involving random rotations ($\pm 20^\circ$), zooming, horizontal flipping, and width/height shifting in order to lessen model overfitting and introduce variability consistent with real-world lighting and orientation changes.

The following configuration was established in the CNN architecture:

- Three convolutional layers were applied with ReLU activations to effectively and hierarchically extract features.
- MaxPooling layers were set in place to downsample the feature maps while maintaining critical spatial information.
- Dropout layers (0.3-0.5) were implemented to regularize and reduce overfitting the model.
- Fully connected dense layers were included to combine and interpret all learned features prior to classification.
- A Softmax output layer was included, set to have four neurons, corresponding to the four waste categories: Food, Plastic, Metal, and Paper.

The model was compiled by the Adam optimizer at a learning rate of 0.001, trained via the categorical cross-entropy loss function. Training was implemented for 50 epochs at a batch size of 32, using early stopping following validation performance plateau to avoid overfitting. The training was monitored and assessed using real-time accuracy and loss curves to ensure optimal convergence during training.

All experimentation and training occurred on a Dell Inspiron 15 laptop - Intel Core i7-1335U processor, Intel Iris Xe Graphics, which afforded sufficient computational resources for fast training, evaluation and testing of the model. The final trained model was saved, with weights, to prepare for deployment and further system integration.

VII. RESULTS AND DISCUSSION

The suggested CNN model displayed consistent accuracy in classifying different classes of waste materials. After conducting a number of experiments and also tuning the hyperparameters, it obtained a training accuracy of 97.8% and accuracy of 82% in validation, demonstrating good capacity to learn and a fair ability to generalize.

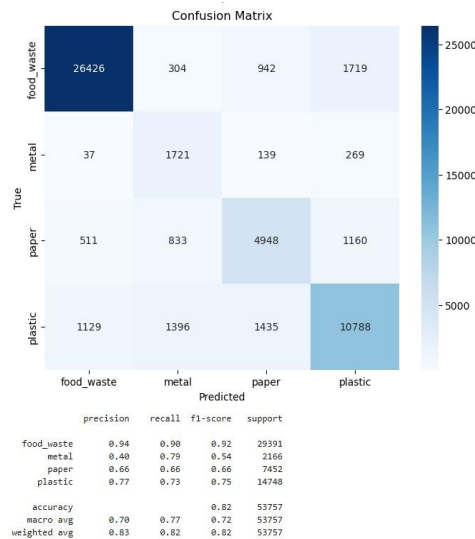


Fig. 3. Confusion Matrix

Performance metrics:

- Precision: 83%
- Recall: 82%
- F1-score: 82%

The confusion matrix illustrates a great performance of the model for food waste with a precision of 94%, a recall of 90%, and F1-score of 0.92, indicating a high ability to successfully identify organic materials. However, the model for metal classification performed worse with a precision of 40%, and F1-score of 0.54, due to the visual similarities with other reflective materials such as plastic. Paper showed precision and recall at 66%, demonstrating moderate performance that was balanced. Plastic had precision at 77% recall at 73%, showing good detection in most cases. Overall, CNNs performed much better than traditional classifiers (such as SVM and Random Forest) in comparison studies due to the automatic process of extracting hierarchical visual features from raw image data. Visually, the model captured consistent results across a variety of backgrounds and lighting conditions indicating robustness. The combination of convolutional and pooling layers allowed the network to extract both low-level (edges, shapes) and high-level (texture, color patterns) features which improved classification reliability. This research has demonstrated that approaches using deep learning are more effective than manual and traditional machine learning approaches to screen waste for segregation and offers reasonable accuracy for field deployment in waste management infrastructures. Further, our methods are scalable and efficient.

VIII. MODEL INTERPRETATION

Understanding CNN's internal behavior is critical for transparency and trust in automated systems. Visualization tools like Grad-CAM (Gradient-weighted Class Activation Mapping) were used to indicate the regions of the image that drove CNN's predictions.

Specifically, the analysis uncovered that:

- For food waste, the CNN highlighted textures that were irregular and organic shapes.
- For paper, the CNN focused on predictable flat areas that were uniform.
- For metal waste, the activations focused on shiny or reflective areas of the image.
- For plastic detection, the activations focused on flat smooth surfaces and bright colors.

These interpretations suggest that the CNN has learned representations of the waste category that have meaning. The activation of the feature maps for the earlier convolutional layers does show edge detection, with deeper layers learning to capture more complex spatial relationship structures. Understanding these internal representations not only helps with debugging the model but can also increase user trust and comfort with an AI based waste management solution.



IX. CONCLUSION

The study successfully establishes that image-based Convolutional Neural Networks can be utilized for an automated waste sorting system. This system reduces manual effort, minimizes errors, and improves the efficiency of recycling processes.

By segregating waste into four core commodities such as food, metal, plastic, and paper the model will directly aid in promoting sustainable waste, and environmental stewardship supports sustainable waste management.

The CNN architecture was robust and versatile in achieving a total accuracy of 82% and performed well in classifying food and plastic waste. This intelligent scalable alternative for manual segregation could easily be installed in smart bins, sorting stations, and municipal recycling processes. Ultimately, the proposed system provides a link between artificial intelligence and environmental sustainability and establishes a strong paradigm for the future of intelligent waste management systems.

X. FUTURE WORKS

While the proposed CNN-based model provided accurate classification of waste materials with significant promise for the future, there is still room for improvement with future advancements in terms of scaling, deploying into the wild, and accessibility for users. The future possibilities can lead to better system performance and more effective practical use including modern urban waste management systems.

1. *Smart Bin Integration*

A highly functional future expansion of this work is to place the model into IoT smart bins equipped with cameras, sensors, and microcontrollers like Raspberry Pi or Arduino. These smart bins would use the camera to autonomously take images of the items discarded as waste and perform on-the-fly classification and separation of the waste at the standard source. Furthermore, smart bins would be able to connect to the cloud and the data from multiple bins would be aggregated and analyzed, advancing the paradigm of data-driven urban waste management's typical use.

2. *Edge and Mobile Deployment*

To enhance access and deployability in low-resource environments, the trained CNN can be transformed into a lightweight model utilizing tools like TensorFlow Lite, ONNX, or PyTorch Mobile. This allows for application to edge devices, smartphones, or embedded systems, minimizing reliance on high-performance servers. Real-time waste recognition on mobile or IoT-enabled apps can allow households and small recycling units to take part in intelligent segregation without needing complex hardware.

3. *Advanced Architectures*

To improve accuracy and efficiency further, future iterations can utilize leading-edge architectures such as ResNet, EfficientNet, DenseNet, or Vision Transformers (ViT). These advanced deep learning architectures yield superior performance on image classification tasks given their advantages from features extraction, parameters efficiency, and faster convergence. Transfer learning from pretrained deep learning structures on large-scale datasets such as ImageNet may also reduce training time significantly while improving generalization to unseen waste classes.

4. *Dataset Expansion*

The robustness of the model can be improved through increased datasets that incorporate diverse waste samples with variations in lighting conditions, backgrounds, textures, and camera angles. Samples that include mixed or contaminated waste will enhance the system's variability in the real world context. Partnerships with local municipality bodies, waste collectors, and recycling centres may assist in developing a standard, comprehensive dataset for public domain or academic purposes.

5. *Recycling Guidance System*

A further dimension of functionality may be embedded into our treatment through a Recycling Guidance Module to glean disposal practices and environmentally recommend alternatives, based on the waste type detected. For example, if the



model identifies plastic, the system could suggest viable recycling alternatives or recycling centers nearby. The citizen-facing module would further advance citizen engagement by educating them around typical disposal practices, bolstering environmental consciousness, and promoting sustainable practices.

6. *Explainable AI (XAI)*

Deep learning models are often characterized as 'black boxes', however, the inclusion of XAI approaches including LIME (Local Interpretable Model Agnostic Explanations) and SHAP (SHapley Additive explanations) allow for improvements in our understanding of the model. Visual tools help display the regions of the image which affected the models decision, allowing understanding and trust in the predictions for developers and non-technical users. This is especially important whenever AI systems are deployed in public or industrial contexts.

7. *Integration with robots*

The CNN model can be integrated with robotic arms or conveyor-belt sorting systems, used in recycling plants for a completely automated strategy for waste segregation. The robotic system can take action based on the classification output, that is, physically segregating the waste into bins. Such automation reduces a reliance on manual sorting of waste, raises efficiency of sorting time, and creates a safer waste handling workplace for workers.

8. *Multimodal Approach*

Future work could take a multimodal approach, incorporating visual image data with sensor data (e.g., weight, moisture, or material composition) or with other textual data such as waste labels or packaging information. The fusion of data across modalities could form a systematic waste identification that would operate well in nuanced situations such as sorting through mixed or suspicious waste materials. Integrating multimodal AI models into a waste identification system could set up a smart, holistic waste management ecosystem that contributes to smart city initiatives and supports sustainability missions.

With these enhancements, the proposed system would not only live as an image classifier, but could evolve into a more comprehensive intelligent waste management system image classifier with automation for recycling, monitoring in real time, and assisting in the sustainability of urban planning. This represents a natural evolution of waste management systems as they support global missions, such as UN SDG 11: Sustainable Cities and Communities, and SDG 12: Responsible Consumption and Production.

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