**Smart Waste Classification System: A Deep Learning-Based Approach for Sustainable Waste Management**

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**Abstract**

With the surge in global waste production, efficient and automated waste sorting mechanisms have become essential for sustainable waste management. This project presents the development of a **Smart Waste Classification System** leveraging state-of-the-art deep learning architectures for accurate and real-time waste categorization. We utilized pre-trained convolutional neural networks (CNNs) and transfer learning on publicly available datasets to classify waste into six categories. Our system achieved a validation accuracy of up to 95% with **ResNet-50**, demonstrating its potential for practical deployment in smart waste bins and recycling facilities.

**1. Introduction**

Global waste production poses severe environmental risks, and conventional waste sorting systems are insufficient due to labor-intensive processes and low accuracy. The use of **Artificial Intelligence (AI)**, particularly **deep learning** and **computer vision**, is revolutionizing waste management by automating waste classification.

Drawing inspiration from the PMC research article, which highlights the use of advanced deep learning techniques to optimize waste classification, our project seeks to bridge the gap between academic research and real-world applications.

**2. Literature Review**

The research paper by *Shantha Kumar et al. (2021)* from PMC8309851 outlines various machine learning and deep learning models applied to waste classification, emphasizing the significance of CNNs in image-based waste segregation.

Key observations from literature:

* **CNN-based architectures**, such as ResNet and Inception, have shown superior performance in image classification tasks.
* **Transfer Learning** with pre-trained models mitigates the challenges of limited labeled datasets.
* Integration with **IoT devices** and **edge computing** can further enhance the real-time capabilities of such systems.

**3. Methodology**

**3.1 System Architecture**

Our system comprises three major components:

1. **Data Acquisition & Preprocessing**
2. **Deep Learning Model Training & Evaluation**
3. **Application Deployment (Web Interface & Real-Time Detection via OpenCV)**

**3.2 Datasets**

We consolidated multiple open-source datasets from Hugging Face repositories:

* **kuchidareo/small\_trashnet** (2.5k images)
* **garythung/trashnet** (5k images)
* **edwinpalegre/trashnet\_enhanced** (19.9k images)

**3.3 Data Preprocessing**

* **Label Mapping** to interpret class indices.
* **Image Resizing** to 224x224 for CNN compatibility.
* **Normalization** of pixel values.
* **Data Augmentation** (rotation, zoom, flips) to address class imbalance.
* **Train-Validation-Test Split** ensuring balanced representation.

**Sample Images from Dataset**

**Cardboard Glass Metal**

A white tile with a circle and a cross

AI-generated content may be incorrect. A brown bottle on a white surface

AI-generated content may be incorrect. A crushed can of soda

AI-generated content may be incorrect.

**Paper Plastic Trash**

A pile of books on a table

AI-generated content may be incorrect.A plastic bottle with a blue label

AI-generated content may be incorrect. A piece of white cloth

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**Image Count per Class**

We examined the distribution of image counts per class to assess balance within the dataset.

As observed:

* Paper has the highest number of images (~600).
* Trash has the fewest images (~120), indicating a class imbalance that could affect model performance.

**Class Percentage Distribution**

To further understand the balance, we visualized the percentage of total images per class using a pie chart:

Key observations:

* Paper (23.5%) and Glass (19.8%) dominate the dataset.

A graph of different sizes of objects

AI-generated content may be incorrect.

* Trash (5.4%) is underrepresented, suggesting the need for data augmentation or sampling techniques.

A pie chart with different colored circles

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**4. Deep Learning Models**

**4.1 Custom CNN**

Developed a CNN from scratch achieving **75% validation accuracy**, providing a baseline for comparison.

A screenshot of a graph

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**4.2 Transfer Learning Models**

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| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| |  |  |  | | --- | --- | --- | | **Model** | **Validation Accuracy** | **AUC Range** | | **VGG16** | 80% | 0.94-0.97 | | **ResNet- 50** | 94-95% | 0.99-1.00 | | **MobileNetV2** | 65% | 0.70-0.80 | | **InceptionV3** | 70% | 0.80-0.88 | |  |  |
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**4.2.1 VGG 16**

* VGG16 is a deep convolutional neural network known for its uniform architecture, consisting of multiple stacked 3×3 convolutional layers followed by max pooling layers and fully connected layers
* The model benefitted from robust feature extraction through frozen convolutional layers.
* The learning curves show good convergence, minimal overfitting, and reliable generalization.

A graph of different colored lines

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**4.2.2 ResNet-50**

* Implemented transfer learning by freezing convolutional layers.
* Achieved superior performance with minimal overfitting.
* Suitable for high-accuracy applications in recycling plants.

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**4.2.3 MobileNetV2 & InceptionV3**

* MobileNetV2: Optimal for low-resource devices with trade-offs in accuracy.
* InceptionV3: Balanced computational cost with improved accuracy over MobileNetV2.

**4.3 Model Evaluation Metrics**

* **Accuracy**
* **Precision, Recall, F1-Score**
* **ROC Curve and AUC Scores** per class

A graph of a function

AI-generated content may be incorrect.**ResNet-50**: The ROC curves for ResNet-50 remain close to the top-left corner across all classes, achieving AUC scores between **0.99 to 1.00**, indicating near-perfect classifications.

**A graph of a function

AI-generated content may be incorrect.VGG16:** ROC curves for VGG16, with AUC scores between 0.94 to 0.97, showing strong but slightly inferior.

**Confusion Matrix** to analyze class-wise performance

**Transfer Learning Models**

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| |  |  |  | | --- | --- | --- | | **Model** | **Validation Accuracy** | **AUC Range** | | **VGG16** | 80% | 0.94-0.97 | | **ResNet- 50** | 94-95% | 0.99-1.00 | | **MobileNetV2** | 65% | 0.70-0.80 | | **InceptionV3** | 70% | 0.80-0.88 | |  |  |

**5. Real-Time Integration & Application Development**

**5.1 Real-Time Classification**

Integrated **OpenCV** for live video feed processing:

* Real-time waste recognition using ResNet-50.
* Frame-wise inference with bounding boxes and predicted labels.

A hand holding a white envelope

AI-generated content may be incorrect.

**5.2 Web-Based Interface**

* Developed using **Flask** for backend model serving.
* HTML/CSS for frontend with image upload and results display.
* System outputs predicted waste category with confidence percentage.

A screenshot of a screen

AI-generated content may be incorrect.

**6. Results and Discussion**

* **ResNet-50** demonstrated the highest reliability with a validation accuracy of **94-95%**.
* **AUC Scores** close to **1.00**, ensuring high precision across all waste types.
* Real-time performance validated with webcam integration, enabling potential deployment in smart bins.
* Despite class imbalance in datasets, augmentation techniques enhanced generalization.

**Result and Performance Evaluation:**

|  |  |  |
| --- | --- | --- |
| **Model Name** | **Accuracy** | **Remark** |
| Model From Scratch | 75% | Baseline model trained without transfer learning; serves as initial benchmark. |
| VGG16 | 80% | Provided a strong baseline for the image classification task. |
| ResNet50 | 93% | Outperformed all models, most effective architecture for the dataset. |
| MobileNetV2 | 65% | Lightweight model; traded off some accuracy for efficiency. |

**7. Challenges & Limitations**

* **Data Imbalance:** Addressed via augmentation but still a challenge for underrepresented classes.
* **Overfitting:** Controlled using dropout, early stopping, and pre-trained models.
* **Deployment Constraints:** Mobile and embedded deployment remains a challenge due to model size (especially ResNet-50).

**8. Conclusion**

The Smart Waste Classification System effectively showcased the power of deep learning and transfer learning in automating waste categorization across six meaningful classes: cardboard, glass, metal, paper, plastic, and trash. By leveraging pre-trained models such as ResNet-50, InceptionV3, VGG16, and MobileNetV2, the project demonstrated that even moderately sized datasets can be transformed into highly functional classifiers with minimal training overhead.

Among all models evaluated, ResNet-50 emerged as the most performant, achieving near-perfect classification accuracy and AUC scores, and was ultimately deployed as the backbone of our real-time detection system. The integration of this model with OpenCV for video streaming and frame-level prediction, combined with Flask for web interfacing, validated the feasibility of building end-to-end, user-friendly, and interactive AI applications.

This project not only confirms the technical viability of real-time waste classification using deep learning but also opens doors for scalable deployment in smart cities, recycling plants, and educational institutions. This solution contributes to the broader goal of sustainable waste management by promoting automation, reducingmanual labor, and enhancing classification accuracy in real-world conditions.

**9. Individual Contributions**

**Paras Godhani:** Developed the backend infrastructure, integrated OpenCV for real-time video capture, and supported system deployment.

**Priya Patel:** Handled data preprocessing, ensuring the dataset was clean and balanced, and developed the frontend interface for user interaction

**Sukhjit Kaur:** Focused on API development using FastAPI and carried out performance optimization to ensure the system handled real-time requests efficiently.

**Rutvi Patel:** Led the model training, performed hyperparameter tuning to optimize model accuracy, and contributed significantly to the final report documentation.

**Emmanuel Araoyinbo:** Worked on project documentation and conducted validation testing to evaluate model performance on unseen data.

**10. References**

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