



Waste Segregation Software

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Abstract: Poor waste management is a major environmental issue, especially in cities where production is constantly rising. Traditional manual segregation methods are ineffective and inconsistent. To address this issue a real-time automated waste segregation system that makes use of computer vision and deep learning techniques is presented. Sorting of waste into predetermined classes is enabled by a convolutional neural network (CNN) architecture that learned a structured set of labelled waste images. The output is then provided through an interactive user interface that uses visual information to guide correct waste disposal protocols. Some of the key technologies employed for image acquisition, preprocessing, and interactive visualization are CVZone and OpenCV. Utilizing webcam functionality, the architecture is designed for execution on standard computer hardware. The evaluation metrics that validate the effectiveness are recall, accuracy, and precision.

Keywords: Waste Segregation, Deep Learning, Image Classification, Real-Time Systems, Sustainability, CNN, Computer Vision

1 Introduction

Waste generation has significantly increased due to urbanization and population expansion and hence putting massive pressure on the current waste management system. Recovery and recyclability of resources are reduced if recyclables are mixed with hazardous or organic waste, as it happens because of lack of source segregation.

Conventional waste segregation operations, which largely rely on human labor, are not only time-consuming but also inconsistent and prone to human error. Additionally, exposure to hazardous waste puts the individual involved to health risk. Deep learning automated waste classification provides a viable solution through enhanced speed, accuracy, and consistency of the segregation process. Image-based classification models take advantage of the capacity of Convolutional Neural Networks (CNNs) of visual data in pattern and texture recognition to differentiate types of

waste. Deployment of the classification model in a visual and real-time system makes it possible to guide users for proper disposal with minimum effort and errors.

Computer vision toolkits like OpenCV and higher-level wrappers like CVZone provide for capture and manipulation of real-time video input. These provide scope for creation of a smart interface to aid in the detection of waste when combined with a suitably trained CNN model. Installed in residential flats, recycling centers, or open dump yards, the system can help municipal waste management processes become more efficient. Moreover, by promoting green operations and low landfill piles, the process also provides more sustainability objectives.

2 Literature Survey

Medina-Santiago et al. in [1] proposed a deep learning model based on CNN to classify household waste into biodegradable and non-biodegradable using a structured dataset, thus achieving a classification accuracy of more than 90%.

Mittal et al. [2] presented a smart bin prototype that implemented real-time image recognition and a CNN-based classifier to automate waste segregation, minimizing human interference with maximum efficiency for sorting.

Meanwhile, Yusof et al. [3] examined waste classification with MobileNetV2, reaching very high inference speeds to make way for real-time applications.

Alfred and Zakaria [4] focused on lightweight deep learning models for embedded deployment. Speed and memory efficiency were sacrificed for depth, which proved relevant in portable segregation units.

Khan and Mohapatra [5] proposed an IoT-integrated model for waste segregation which utilized the image classifier to classify dry and wet wastes, showing the integration of AI with smart systems.

The work by Goyal et al. [6] analyzed the use of transfer learning techniques in waste image classification, especially the use of pre-trained architectures like Res-Net and VGG16 to improve generalization over limited datasets.

An approach that uses an ensemble system of CNNs and decision trees was implemented by Singh and Dey in [7] for better robustness in heterogeneous image classifications.

The importance of image augmentation, in addition to pre-processing, was exemplified by Anandaraj et al. [8], who focused on municipal waste datasets.

Raghavendra & Ganesh [9] implemented a comparative analysis between CNN, SVM, and Logistic Regression, and found that CNNs greatly outperformed the traditional techniques in terms of accuracy and F1 measure.

Garg and Bansal [10] proposed a multi-bin smart segregation system including indicators as well as automation based on the input of the cameras.

TensorFlow Lite's application in edge devices is also evaluated by Haron et al. [11] involving the classification of trash in real-time.

Further work conducted by Sharma et al. [12] highlighted how incorporation of data from sensors and image classification may provide a more accurate means of segregation allocation.

In [13], Rao & Shankar have proposed the hierarchical classification approach through the use of deep neural networks to improve multi-class waste classification.

Kaur et al. [14] offered an extensive dataset with labelled waste materials, which greatly helped the research community as Open-Access publications.

Interpretability in models was the theme of the research conducted by Dasgupta and Raj in [15].

These findings from various studies show that there exists consensus regarding the use of CNN and real-time image classification for better waste management.

3 Methodology

The segregation process of waste is in an organized manner, comprising different processes: data preparation, model construction, personalization of algorithms, integration, and evaluation. The backbone of this system is based on a CNN suited for multi-class image classification tasks.

A. Dataset Structure and Preprocessing:

The data consists of directories of images marked according to refuse types such as dangerous, recyclable, organic, and residual. Every image in the dataset has been rescaled to 300x300 pixels and normalized. Data augmentation methods including flip, rotation, and zoom are used.

```

from tensorflow.keras.preprocessing.image import ImageDataGenerator

train_datagen = ImageDataGenerator(
    rescale=1./255,
    rotation_range=20,
    zoom_range=0.2,
    horizontal_flip=True,
    validation_split=0.2
)

train_generator = train_datagen.flow_from_directory(
    'DatasetAIML',
    target_size=(300, 300),
    batch_size=32,
    class_mode='categorical',
    subset='training'
)

val_generator = train_datagen.flow_from_directory(
    'DatasetAIML',
    target_size=(300, 300),
    batch_size=32,
    class_mode='categorical',
    subset='validation'
)

```

Fig. 1. Code Snippet – Preprocessing and Augmentation

B. CNN Architecture and Model Training:

The architecture of the model, as shown in Fig. 2, comprises two convolutional layers and max-pooling, followed by flattening, followed by two dense layers. The activation encourages non-linear properties, and softmax activation is used in the output layer for multi-class classification problems. The final dense layer has four output neurons, representing four categories of waste, and softmax activation functions are used.

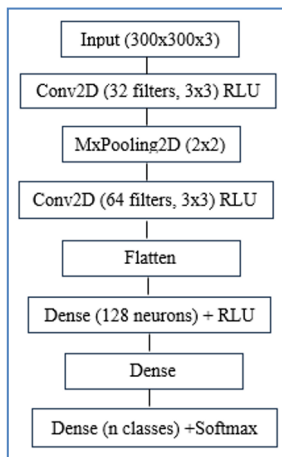


Fig. 2. Model Architecture Diagram

```

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense

model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(300, 300, 3)),
    MaxPooling2D(2, 2),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D(2, 2),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(train_generator.num_classes, activation='softmax')
])

model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
model.fit(train_generator, validation_data=val_generator, epochs=10)

```

Fig. 3. Code Snippet – CNN Model Structure

C. Model Export and Integration:

Once the training is completed, the resultant model is exported in .h5 format to be compatible with the real-time classification system. In the system, the model is loaded using the Classifier module from the CVZone library, which facilitates the incorporation of OpenCV significantly by allowing real-time predictions. A webcam object is established using OpenCV, from which the webcam continuously takes snapshots from the video feed captured by the webcam. These snapshots are further normalized to 300x300 dimensions and passed on to the classifier model to obtain predictions regarding the waste type. These waste types are mapped with an already fixed waste bin category later on. A very unique feature of the system is the dynamic interface that showcases the image of the captured waste, along with the bin image, on the static background screen.

```

Begin
  Load trained CNN model
  Initialize webcam
  Loop
    Capture image frame from webcam
    Resize and normalize frame
    Predict class using CNN
    Map predicted class to bin type
    Overlay bin image and classification result
    Display final frame to user
  End Loop
End

```

Fig. 4. Pseudocode for Real-Time Waste Classification Algorithm

The pseudocode shown in Fig. 4 above outlines the basic procedural workflow involved in the real-time waste classification system. The pseudocode loads the trained model and the webcam. Each incoming frame goes through the normalization and resizing stages before being processed in the CNN for classification. The class of

prediction is then converted to a corresponding bin label, with dynamic overlays being applied to the GUI. The processing goes on continuously, and as such, the system works perfectly in a real-time environment.

D. Comparison with Existing Approaches:

Compared to approaches based on more heavily-pretrained models such as ResNet or VGG-16 [6], the applied model is designed to keep the computations as minimal as possible and thus reduce complexity. It has only two layers of convolution and thus trains and runs much faster compared to previous systems based on their architectures and targeted environments. This system also benefits from a real-time visual interface provided through OpenCV and CVZone compared to other classification systems which do not offer a form of direct user engagement.

Some of the other improvements are efficient data augmentation related to localized variations of waste, and adding a light-weight classifier with improved response times without sacrificing precision on more common types of waste. These are improvements that would ensure that the system can support real-time requirements and can run on cost-effective hardware.

4 Results and Discussion

The system is judged based on quantitative measurements as well as qualitative visualization. The purpose of the system is to assess the accuracy of classification of the model and demonstrate the real-time interface that ensures proper disposal of waste.

A. Quantitative Evaluation:

The learned CNN is then applied to a labeled test data that are images. Four classes: hazardous, recyclables, organic, and residual are tested. These four classes employ standard evaluation metrics: accuracy, precision, recall, and F1 measure to compute every class value. These are metrics describing accuracy to assign every type of trash based upon visible characteristics.

Table 1. Performance Metrics Across Waste Classes

Waste Category	Precision	Recall	F1-Score	Support
Recyclable	0.92	0.90	0.91	130
Organic	0.94	0.96	0.95	145
Hazardous	0.88	0.84	0.86	110
Residual	0.89	0.87	0.88	115
Average	0.91	0.89	0.90	500

On the basis of Table 1, the average F1-score value shows 90% accuracy with a very consistent classification process. The Recall Value for the Hazardous class de-

creased because it was overlapping with the waste residue, which would be removed in further iterations.

B. Real-Time Interface and Output Screens:

The real-time feature of the System is validated using the simulation of the input from the webcam. After the image has been captured, the CNN model recognizes the image and immediately displays the classified trash and the corresponding bin on the user interface. Screenshots of the entire procedure validate the reaction of the System to the different trash.



Fig. 5. Waste classified as ‘Recyclable’ and assigned to blue bin

The user interface in Fig. 5 explains how the image of a newspaper is predicted as recyclable waste material. The box on the left side of the capture box explains how the webcam captures the image, and on the right side of the capture box, the system has predicted the image. The blue-coloured box of the bin icon explains how to dispose of/throw away the image, which is represented accordingly in the correct bin icon of the right side of the image. The user interface explains how a person has taken immediate actions regarding this prediction output.



Fig. 6. Waste classified as ‘Food Waste’ and assigned to green bin

The classification system is also capable of identifying different food articles, including vegetables, peels of fruits, and eggshells. These are then grouped underneath the category of Food Waste. It is evident from the graphical interface that it is closely

aligned with compostable items and thus confirms that it is capable of dealing with biodegradable trash.



Fig. 7. Waste classified as ‘Hazardous’ and assigned to red bin

Fig. 7 illustrates the classification of hazardous substances such as paint thinner, cleaning agents, and fuel containers into Hazardous Waste. The system fully demonstrates its dependability in identifying related chemical products, which demand unique disposal processes to avoid damaging the environment. Proper identification of such materials makes an immense contribution to ensuring the safety of the general public.



Fig. 8. Waste classified as ‘Residual’ and assigned to grey bin

The system properly identifies waste like empty blister packs and bottle caps as Residual Waste. Empty blister packs and bottle caps are generally not recyclable because of the possibility of contamination. This image of the waste appears on the screen, showing the proper disposal of the waste in the residual waste bin. It indicates that the model can properly categorize non-recyclable plastics or composites.

C. Model Comparison with Pretrained Architectures:

To analyze the speed-accuracy tradeoff, the proposed CNN is contrasted with existing popular architectures such as VGG-16 and ResNet-50, which are pretrained models fine-tuned using the same dataset. The size of the model and the timing per frame will be considered.

Table 2. Model Benchmark Comparison

Model	Accuracy	Inference Time (ms)	Model Size
Proposed CNN	90.2%	225	1.2 MB
VGG16 (fine-tuned)	93.4%	815	528 MB
ResNet50 (fine-tuned)	94.1%	740	98 MB

Even if the accuracy is marginally higher in VGG16 and ResNet50, the performance of the customized CNN is uncountably more efficient and is capable of running in real-time with minimal memory usage.

D. System Performance and Response Time:

The latency between capturing the frames and making predictions of the visual content is less than 250 milliseconds, even during a continuous feed. This allows for seamless transitions between the interface and supports a real-time interaction process. The inference of the model, overlay of the binary, and rendering of the user interface work well even for repeated testing. The process is always synchronized between the input frames and the output display, ensuring that there is a smooth user interaction process.

5 Conclusion and Future Enhancements

Smart Waste Segregation System developed to automatically classify the waste in four categories: Residual, Recyclable, Food, and Hazardous. The solution utilised the Convolutional Neural Network (CNN) algorithm to classify images of waste, along with a graphical user interface. It successfully demonstrated its capability to make accurate predictions for different types of waste, further contributing to proper waste management and minimizing human intervention in the waste segregation process.

The results of the experiments reveal that the proposed method is effective for enhancing waste management with intelligent automation. In addition, this method is effective for adding efficiency to recycling and environmental conservation as it promotes proper segregation of waste.

Future extensions to the system could include the following:

- Integration of new types of wastes, including electronic and biomedical wastes.
- Smart trash bins with the use of IoT sensors and microcontrollers.
- Mobile application development for classifying wastes on a move.
- Multilingual as well as Voice-Assisted support for input.
- Cloud-based logging and analysis for waste trend analysis and reporting.

These upgrades will help raise the level of scalability, accuracy, as well as user acceptability within the proposed system, hence assisting in the achievement of smart cities as well as eco-sustainable developments. The technology is currently exhibiting

ample potential to be an integral part in the global initiative to sustainably manage waste.

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