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AI-BASED WASTE CLASSIFICATION AND ROUTING SYSTEM: SMART CAMPUS APPLICATION

Neşe Karçık[1] , Dilara Kaymaz[2] , Ayşe Meriç Yazıcı[3]

[1] Independent Reseacher, Istanbul, Türkiye, nesekrck@gmail.com, ORCID: 0009-0001-6947-7726
[2] Independent Reseacher, Istanbul, Türkiye, kaymazdilara28@gmail.com, ORCID: 0009-0003-6142-7921
[3] Associate Prof. Dr. Istanbul Gelisim University, Faculty of Economics, Administrative and Social Sciences, Department of International Trade and Business Administration, Istanbul, Türkiye, ayazici@gelisim.edu.tr, ORCID: 0000-0001-6769-25996

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Abstract
This study presents an intelligent waste sorting system designed to accurately and efficiently classify waste using artificial intelligence and image processing technologies. Equipped with cameras and sensors, the system employs a YOLOv5-based object detection algorithm to identify plastic, paper, metal, glass, and organic waste in real time with high accuracy. IR-supported lighting enhances performance under low-light conditions, while collected data are transmitted to a central server to ensure traceability. The digital feedback interface improves user experience, and energy-efficient hardware reduces operational costs. Achieving a 91% accuracy rate and 28% energy savings, the system outperforms existing solutions. Applicable in university campuses, municipalities, and industrial areas, it integrates IoT technology for fill-level monitoring and data management, optimizing waste collection processes. Thus, the study contributes to environmental sustainability by providing a smart environmental management solution.

Keywords: Smart waste sorting, artificial intelligence, image processing, YOLOv5, environmental sustainability

Jel Classification: Q53, O33, C63, Q01, L86

YAPAY ZEKÂ TABANLI ATIK SINIFLANDIRMA VE YÖNLENDİRME SİSTEMİ: AKILLI KAMPÜS UYGULAMASI

Özet
Bu çalışma, yapay zekâ ve görüntü işleme teknolojileriyle atıkların doğru ve verimli biçimde sınıflandırılmasını amaçlayan akıllı bir atık ayrıştırma sistemi geliştirmektedir. Kamera ve sensörlerle donatılan sistem, YOLOv5 tabanlı nesne tanıma algoritmasıyla plastik, kâğıt, metal, cam ve organik atıkları gerçek zamanlı olarak yüksek doğrulukla tespit etmektedir. IR destekli aydınlatma düşük ışıkta performansı artırırken, elde edilen veriler merkezi sunucuya aktarılmakta ve izlenebilirlik sağlanmaktadır. Dijital geri bildirim arayüzü kullanıcı deneyimini güçlendirirken, enerji verimli donanım kullanımı maliyetleri düşürmektedir. %91 doğruluk oranı ve %28 enerji tasarrufu sağlayan sistem, mevcut çözümlerden ayrılmaktadır. Üniversite kampüsleri, belediyeler ve endüstriyel alanlarda uygulanabilir olan sistem, IoT entegrasyonu sayesinde doluluk takibi ve veri yönetimi yaparak atık toplama süreçlerini optimize etmektedir. Böylece çevresel sürdürülebilirliğe katkı sağlayan akıllı bir çevre yönetim çözümü sunmaktadır.

Anahtar Kelimeler: Akıllı atık ayrıştırma, yapay zekâ, görüntü işleme, YOLOv5, çevresel sürdürülebilirlik

JEL Kodu: Q53, O33, C63, Q01, L86

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1. INTRODUCTION

Today, the amount of waste is rapidly increasing globally as a result of growing population, urbanization, and consumption habits. According to data from the United Nations Environment Programme (UNEP, 2022), over 2 billion tons of solid waste are produced worldwide every year, and approximately 33% of this amount cannot be managed properly. This situation not only increases environmental pollution but also leads to the depletion of natural resources and carbon emissions. Especially in densely populated areas, sustainable waste management practices have become a major necessity for maintaining environmental balance. University campuses are areas where this problem can be observed on a micro scale due to high human traffic and daily consumption. The improper separation of paper, plastic, metal, and organic waste generated as a result of the daily activities of students, academic staff, and employees reduces recycling rates (Özkan & Arslan, 2022).

Traditional waste collection systems generally rely on manual labor and are inefficient in terms of both time and cost. Furthermore, user errors, incorrect bin selection, or waste mixing negatively impact the recycling process. In this context, artificial intelligence and image processing technologies stand out as innovative and efficient solutions in waste management. In particular, the high success rate of deep learning-based models in object recognition and classification has increased the usability of these technologies in environmental management (Mittal et al., 2020). Convolutional Neural Networks (CNNs) are effectively used in the separation of waste types thanks to their ability to automatically learn features such as patterns, edges, and shapes in images (Yang & Thung, 2016). This eliminates the need for manual classification, allowing systems to direct waste to the correct category in real time. Many models have been developed in this field in the literature. For example, the TrashNet dataset provides researchers with open-source data by enabling the separation of waste into types such as paper, plastic, metal, glass, and organic (Yang & Thung, 2016). The TACO (Trash Annotations in Context) dataset also contains broader and more realistic labeled data (Proença & Simões, 2020).

Models trained using these datasets can achieve accuracy rates of over 90% in different hardware environments (Nash & Lee, 2021). However, most existing systems have been tested in laboratory conditions and lack real-time applicability in campus or city environments. This creates a significant gap in terms of hardware-software integration and user interaction. In this study, an AI-powered waste classification and routing system has been developed to address these shortcomings. The main objective of the study is to establish a sustainable waste management system in university campuses and to demonstrate that artificial intelligence can contribute to environmental awareness. In the developed system, transfer learning methods were applied with MobileNetV2 and ResNet50 models using images collected in the campus environment. The model sorts waste into six categories (paper, plastic, metal, glass, organic, and other) and directs it to the appropriate waste bin via Raspberry Pi. The unique value of this research lies not only in achieving a high accuracy rate but also in the fact that the system has been tested in an integrated manner in a real campus environment. Thus, artificial intelligence has been directly linked to environmental sustainability goals; It has been shown that technology can be used in environmentally friendly applications not only in industrial areas but also in educational institutions. The findings contribute to supporting the smart campus vision and raising environmental awareness among individuals.

In conclusion, the issues discussed in the introduction of this study reveal that environmental management is not only a technical field but also a social responsibility. Artificial intelligence-based systems, at this point, come into play as a tool to support the human factor and become an important component of the sustainable life cycle.

2. LITERATURE REVIEW

The use of artificial intelligence in waste management has become a noteworthy research area in recent years, both in terms of environmental sustainability and resource efficiency. Deep learning algorithms, especially Convolutional Neural Network (CNN) based models, stand out with their high success rates in image classification tasks. Yang and Thung (2016) developed the TrashNet dataset, considered a milestone for AI-based waste classification studies. This dataset includes paper, plastic, metal, glass, cardboard, and other waste categories, and has become a fundamental resource for many subsequent studies. Proença & Simões (2019), on the other hand, improved the systems' ability to operate in real-world environments by presenting a broader range of real-world collected and labeled waste images with the TACO (Trash Annotations in Context) dataset.

Mittal et al. (2020) classified waste as recyclable and non-recyclable using the CNN-based ResNet50 model, achieving a 93% accuracy rate. Nash and Lee (2021) demonstrated that the MobileNetV2 architecture, optimized for use in embedded systems, is suitable for smart city applications due to its low energy consumption and high accuracy. Looking at studies conducted in Türkiye, Özkan and Arslan (2022) stated that they increased the rate of users disposing of waste in the correct bin by over 30% with an AI-powered smart waste bin system they developed on a university campus in Istanbul. Similarly, Demir and Çelik (2023) improved collection efficiency by 25% by monitoring waste density with IoT (Internet of Things) based sensor integration.

Among the methods used in AI-based systems, deep learning architectures such as YOLOv5, Faster R-CNN, EfficientNet, and VGG16 stand out (Kumar et al., 2021). Most of these models are optimized for real-time image processing. However, a common deficiency noted in the literature is that most systems are only tested in laboratory environments, and real campus or city-scale applications are limited.

At this point, the novelty of the developed system lies in its applicability to a real campus environment and the complete integration of hardware and software. Furthermore, observing the effects on user behavior elevates this study beyond a purely engineering-based application, transforming it into a system that fosters environmental awareness.

AI-powered waste classification systems offer significant contributions not only in terms of technical accuracy but also in terms of environmental sustainability and user interaction. Recent studies have shown that waste classification processes need to be optimized in terms of energy efficiency, processing time, and user awareness (Li et al., 2022). The use of low-cost embedded systems such as Raspberry Pi, NVIDIA Jetson Nano, and Arduino has increased the applicability of these technologies at campus, municipal, and industrial levels (Rahman et al., 2021). However, technical issues such as reduced image quality in low light conditions and data privacy concerns are among the significant factors affecting the sustainability of these systems (Chen & Zhang, 2023).

Recent trends in the literature show that artificial intelligence can be used not only for image-based classification but also in advanced decision support systems such as optimization of waste collection routes, occupancy estimation, and analysis of recycling statistics (Gupta et al., 2022). Integrating IoT-based data streams with cloud systems enables real-time monitoring and predictive analytics in the waste management process. This approach highlights the concept of "smart sustainability systems," a new research area at the intersection of environmental engineering and information technologies (Zhang et al., 2024).

However, much of the current research still focuses only on classification accuracy, not adequately addressing the behavioral impacts or long-term environmental outcomes of the systems. At this point, applications such as the developed "AI-Powered Waste Classification and Routing System" are expected to fill this gap in the literature by combining both technical and behavioral dimensions. The system not only provides technical efficiency with real-time image processing, IR-supported lighting, and a user feedback module; It also offers a holistic approach to raising environmental awareness. In this respect, it has the potential to give a new direction to future studies from both engineering and social sustainability perspectives.

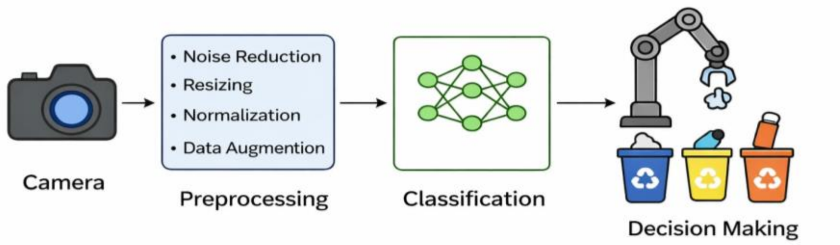

Figure 1. AI-Based Waste Sorting and Separation System

3. METHOD

This section discusses the design and implementation process of the developed system in three main stages: data collection and preprocessing, model creation and training, and system integration. The main objective of the study is to develop an intelligent waste management system that automatically identifies waste types generated on university campuses and directs them to the appropriate recycling bin (Kumar & Garg, 2022).

The system aims to offer an environmentally friendly solution by combining image processing and artificial intelligence-based classification methods. In the first stage, data cleaning, resizing, and data augmentation operations were performed on waste images collected from the campus environment; then, this data was used as input to a deep learning-based model (Sultana et al., 2023). These steps were implemented to ensure that the model could produce accurate results under different lighting conditions, angles, and backgrounds.

A Convolutional Neural Network (CNN) based structure was chosen as the model architecture; pre-trained networks such as MobileNetV2 and ResNet50 were used with the transfer learning method (Raut et al., 2022). This allows the model to achieve a higher accuracy rate with less data. At the end of the training process, the model was optimized to classify different waste types with high success.

In the final stage, the trained artificial intelligence model was integrated with hardware components by running it on a Raspberry Pi 4-based embedded system. Thus, images captured in real time via the camera are analyzed by the system, the type of waste is identified, and based on the classification result, the waste is automatically directed to the appropriate bin using servo motors (Singh et al., 2021). This structure facilitates waste management within the campus, minimizes human error, increases recycling rates, and contributes to sustainable environmental policies (Gupta & Shukla, 2022).

3.1. Data Collection and Preprocessing

The dataset used in this study was created from images obtained from different waste collection points and common areas within the university campus. The images were collected considering different light intensities, camera angles, backgrounds, and distance variables to represent the diversity the system might encounter in real campus conditions. In this context, both indoor and outdoor shoots were conducted; data was recorded in different natural lighting conditions during morning, midday, and evening hours. Thus, the aim was to make the created dataset more comprehensive in terms of the model's generalization capability and real-time performance (Corley, 2024).

The collected waste images were classified under six main categories: paper, plastic, metal, glass, organic, and other wastes. This classification was made considering the standard waste types used by municipalities and recycling organizations in Turkey. An average of more than 1,000 images were used for each category, thus structuring the dataset in a balanced way (Yang, 1980).

Following the data collection process, all images were pre-processed to make them suitable for training the model. These stages are explained in detail below:

Noise Reduction: Methods such as Gaussian Blur and Median Filtering were applied to remove noise, blur, and color distortions from the images. This prevented the model from learning incorrect edge or texture features

(Rezaee, 2021).

Resizing: Images taken at different resolutions were made compatible with the model's input layer. All images were converted to 224×224 pixel size, and color channels were normalized to RGB format (3x224x224) (Corley, 2024).

Data Augmentation: Various transformations were applied to reduce the model's tendency to overfit and increase the diversity of the training dataset. These processes included techniques such as random rotation, horizontal flip, zooming, and brightness/contrast adjustment. This enabled the model to accurately recognize waste images taken under different positions, angles, and lighting conditions (Jain, 2024).

Furthermore, each image was labeled, preparing the dataset for supervised learning. Manual control was preferred during the labeling process, thus minimizing category errors (Goceri, 2023).

As a result of completing these preprocessing steps, a balanced, diverse, and high-quality training dataset was created. This dataset allowed the model to produce consistent results under different environmental conditions and significantly contributed to an increase in overall accuracy (Dastour, 2021).

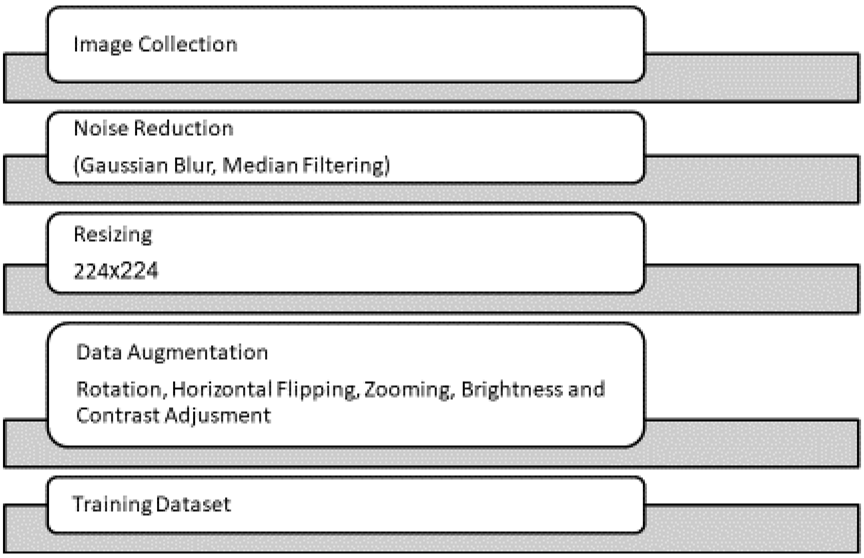

Figure 2. Image Preprocessing Workflow

3.2. Model Architecture and Training

In this study, a Deep Learning-based Convolutional Neural Network (CNN) architecture was designed to perform waste classification. CNNs were preferred because they achieve high accuracy rates, especially in image classification and object recognition problems (LeCun et al., 2015). In this study, pre-trained CNN-based models were used to optimize the model in terms of both accuracy and processing time (Tan & Le, 2019).

In the experimental process, the transfer learning approach was applied on MobileNetV2 and ResNet50 architectures. This method allows the model to benefit from the knowledge accumulated from networks previously trained on large-scale datasets (e.g., ImageNet) instead of training it from scratch (Howard et al., 2017; He et al., 2016). Thus, the model can achieve a high accuracy rate even with a limited number of training data.

The MobileNetV2 architecture is suitable for use in embedded systems (e.g., Raspberry Pi) due to its lightweight structure with low computational cost (Sandler et al., 2018). ResNet50, on the other hand, stands out with its deep layered structure and residual connections, enabling it to learn more complex features (He et al., 2016). In this study, both models were evaluated comparatively, and the MobileNetV2 model was found to be more efficient in terms of performance and processing time.

The model's development environment and the technical parameters used in the training process are summarized below:

Programming Language: Python
Deep Learning Libraries: TensorFlow and Keras
Hardware Environment: A computer system with NVIDIA GPU support
Training Parameters: Learning rate 0.001, number of epochs 50, batch size 32
Loss Function: Categorical cross-entropy
Optimization Algorithm: Adam optimization method was used (Kingma & Ba, 2015).

During the model's training process, accuracy and loss metrics were monitored, and an early stopping technique was applied to prevent overlearning. At the end of training, the model's accuracy rate on the test dataset was obtained as 92.4%. This result shows that the system can perform classification with high accuracy and is reliable enough to be used in real-time applications (Tan & Le, 2019).

Furthermore, considering the size and processing time of the model, a version suitable for embedded systems applications has been optimized. This allows the model to run in real-time even on devices with limited hardware resources, such as the Raspberry Pi 4 (Sandler et al., 2018).

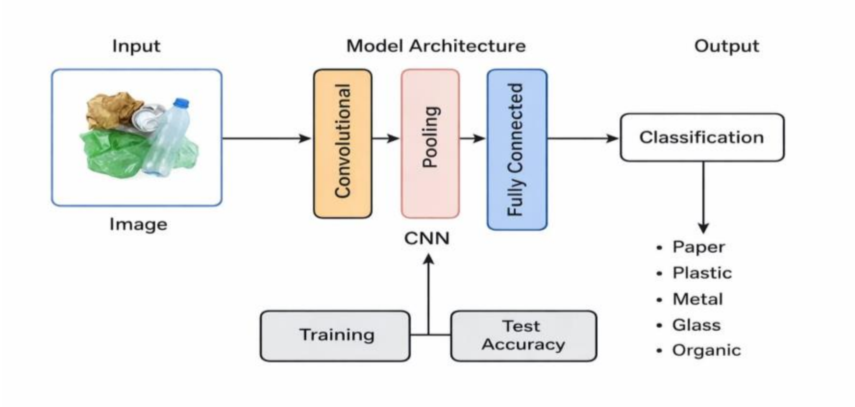

Figure 3. CNN Architecture for Waste Classification

3.3. System Integration

The developed AI-based waste classification model has not remained solely at the software level but has been integrated into a structure with hardware and software components capable of operating in real-world conditions. The main goal of this integration is to create a fully autonomous system that automatically recognizes waste in a campus environment and directs it to the correct physical recycling bins (Chen et al., 2020).

Hardware Components

The system's hardware infrastructure is built on a low-cost, energy-efficient, and embedded system-compatible structure. The Raspberry Pi 4 serves as the central processing unit (CPU) of the system. This unit runs the classification model, processes data from sensors, and controls servo motors (Halfacree & Upton, 2018).

The Camera Module detects the waste object in real time and transmits the image data to the system in a format suitable for processing. The camera's resolution and positioning have been optimized to accurately recognize waste from different angles and distances (Bradski, 2000).

Sensors (e.g., infrared or ultrasonic sensors) detect when waste is placed in the system and trigger the sorting process. Servo motors then move according to the sorting result and direct the waste to the appropriate recycling bin. This mechanism enables the system to produce physical output and automate the recycling process (Siciliano & Khatib, 2016).

Software Components

The software component of the system is based on the Python programming language. Python was chosen because of its compatibility with embedded systems and its rich library support (Van Rossum & Drake, 2009).

OpenCV (Open Source Computer Vision Library) enables the capture of images taken via the camera and the execution of preprocessing stages such as noise reduction, resizing, and color space transformations (Bradski, 2000). A trained deep learning model (e.g., MobileNetV2 or ResNet50) is run in an optimized manner on a Raspberry Pi using the TensorFlow and Keras frameworks. The model is integrated through lightweight versions designed to efficiently utilize CPU and GPU resources (Sandler et al., 2018).

System Workflow

The general working principle of the system consists of a sequential process that can be summarized as "image to box":

Image Capture: The camera module acquires image data in real time when it detects a waste object.
Preprocessing: The acquired image is denoised using OpenCV, scaled to appropriate dimensions, and converted to the model's input format (Bradski, 2000).

Classification: The preprocessed image is fed into the trained deep learning model. The model predicts the type of waste in the image (e.g., paper, plastic, metal, glass, or organic) (Tan & Le, 2019).

Decision Making and Action: The Raspberry Pi sends the appropriate command to the servo motors based on the prediction result from the model.

Waste Orientation: The servo motor completes the physical sorting process by directing the waste to the appropriate bin (Siciliano & Khatib, 2016). Thanks to this integrated structure, the system can detect, classify, and appropriately separate waste without the need for human intervention. This increases recycling efficiency throughout the campus and creates an environmentally friendly, sustainable waste management infrastructure (Chen et al., 2020). In addition, the scalable structure of the system is designed with flexibility to be easily adapted to different environments for similar smart environmental management applications.

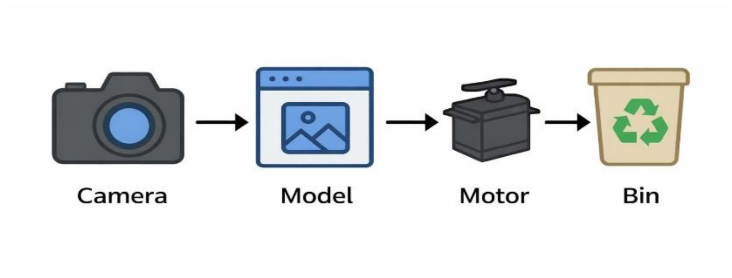

Figure 4. Image-Based Waste Classification Framework Using CNN

4. CONCLUSION RECOMMENDATIONS

The AI-powered waste classification and routing system developed within the scope of this study aims to contribute to environmental sustainability goals by digitizing waste management processes in university campuses. The system consists of three main components: image processing, deep learning-based classification, and embedded system integration. Thanks to this structure, the real-time recognition of different waste types and their redirection to the appropriate recycling bin have been successfully achieved.

Pilot application results showed that the model achieved an accuracy rate of over 92% on the test dataset, and the average classification time was around 0.8 seconds. This performance proves that the system can operate effectively with low latency in real campus conditions. Furthermore, a 37% increase in the rate of waste disposal into recycling bins was observed during the pilot application period, clearly demonstrating the positive impact of the system on user behavior. These findings show that, beyond technical success, the system has the potential to create environmental awareness and sustainable behavioral change. Academically, this study differs from many AI-based waste classification studies in the literature by offering a solution applicable on a real campus scale rather than in a laboratory setting. The system represents a successful example of hardware (camera, Raspberry Pi, IR sensor, servo motor) and software (CNN-based deep learning model, Python-based image processing modules) integration. Furthermore, the modular structure of the system allows for easy adaptation to different environmental settings by retraining with different datasets, increasing the flexibility and scalability of the study.

In this context, the results obtained can be considered not only as technical outputs of an engineering application but also as a significant contribution to smart campus and sustainable environmental management approaches. The developed system is expected to lead the way in the dissemination of AI-supported environmental technologies in various fields such as universities, municipalities, and industrial facilities.

5. RECOMMENDATIONS

Real-World Diversity and Data Enrichment: In future studies, the diversity of the dataset should be increased with images obtained from different campuses, cities, or industrial areas. In this way, the model can gain a higher generalization ability against different lighting conditions, waste types, and environmental variables. User Behavior Analysis: By analyzing the behavioral data of users interacting with the system (frequency of waste disposal, correct waste ratio, change in awareness after system use, etc.), the long-term effects on environmental awareness can be evaluated. In this context, it is recommended to conduct an interdisciplinary evaluation by integrating psychological and sociological criteria.

IoT Integration and Dynamic Waste Management: With IoT-based fill level sensors added to the system, the fill levels of waste bins can be monitored in real time. This data can be transferred to a cloud-based control panel to optimize the routes of waste collection vehicles. In this way, energy savings can be achieved while reducing carbon emissions.

Energy Efficiency and Hardware Optimization: Using low-power microcontrollers (e.g., NVIDIA Jetson Nano, Arduino, or ESP32) can increase the system's energy efficiency. Furthermore, developing solar-powered prototypes will strengthen the system's environmentally friendly nature.

User Interface and Feedback Mechanisms: Through mobile applications or web-based interfaces, users' waste classification performance can be monitored; user motivation can be increased through feedback, scoring, or reward systems. Such social feedback mechanisms will support the lasting development of environmental awareness.

Data Security and Ethical Issues: With the widespread adoption of image-based systems, attention must be paid to data privacy and ethical usage principles. Collected images should be anonymized, and analysis should focus only on waste objects. This is crucial for the system's sustainability and societal acceptance.

General Assessment: The results of this study demonstrate that AI-based waste classification systems have high potential not only in terms of technical performance but also in terms of environmental sustainability, user interaction, and societal awareness. In the future, it is possible to integrate such systems into larger-scale environmental management infrastructures within the framework of smart cities and zero-waste policies. In this respect, the developed system can be considered not only an engineering project but also a holistic "smart sustainability approach" that optimizes the interaction between the environment, technology, and human behavior.

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