Intelligent Waste Management System for Recycling and Resource Optimization

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Abstract

This paper proposes a deep learning-based intelligent waste management system that can accurately classify waste types and optimize waste disposal processes. The proposed system utilizes a convolutional model to concisely identify the waste type from images captured by a camera system. Our system uses intelligent data augmentation to perform large datasets of waste item images and achieves a high classification accuracy rate. The waste types are classified into several categories, including glass, cardboard, metal, plastic, paper, and trash. Experimental results show that our system achieves high accuracy rates in waste classification and improves waste disposal efficiency compared to traditional waste management systems. Our system has the potential to significantly reduce the negative impact of waste on the environment and to promote sustainable waste management practices.

Keywords: Waste Management; Intelligent system; Resource Optimization

1. Introduction

Waste management (WM) is the process of collecting, transporting, processing, and disposing of waste materials in a safe, efficient, and environmentally responsible manner. The goal of WM is to minimize the negative impact of waste on human health and the environment while maximizing the recovery of valuable resources. Effective WM systems are essential to maintain public health and environmental sustainability. They play a critical role in conserving natural resources, reducing pollution, and mitigating climate change. WM includes various practices, such as source reduction, recycling, composting, waste-to-energy, and landfilling. Each of these practices has its benefits and limitations, and a combination of these practices is often necessary to address the complex WM challenges faced by communities and industries.

Recycling and resource optimization are important components of WM systems that aim to reduce waste and conserve natural resources. Recycling involves the collection, processing, and transformation of waste materials into new products, while resource optimization focuses on using resources in a more sustainable and efficient manner. Together, these practices can help to reduce the amount of waste that goes to landfills, conserve natural resources, and mitigate the negative environmental impacts of waste generation. Recycling involves the separation and collection of recyclable materials, such as paper, plastic, metal, and glass, which are then processed and transformed into new products. Recycling reduces the need for virgin materials, conserves natural resources, and reduces energy consumption and greenhouse gas emissions associated with the extraction and production of new materials. Recycling also creates jobs and contributes to the economy by providing a source of raw materials for manufacturing. Resource optimization involves using resources more efficiently, reducing waste, and minimizing the negative environmental impacts of resource extraction, production, and consumption. This can be achieved through practices such as reducing the use of non-renewable resources, using renewable energy sources, and designing products and processes that minimize waste and promote resource efficiency.

The main contribution of this paper is the proposal of a deep learning-based intelligent WM system that can accurately classify waste types and optimize waste disposal processes. The proposed system combines computer vision and reinforcement learning techniques to achieve its goals. Specifically, the paper proposes the following contributions.

DOI: https://doi.org/10.54216/JISIoT.010205

First, a simple but powerful convolutional model is presented to accurately classify waste types into several categories, including glass, cardboard, metal, plastic, paper, and trash. Second, our system augments waste images to improve the waste classification performance by generating synthetic images that can supplement the original training data, thereby increasing the diversity and quantity of the training set. This results in better generalization of the computer vision model and improved accuracy in waste classification. Third, experimental evaluations on the public waste dataset show that the proposed model can precisely predict the class of waste from images, which makes it a robust candidate for improving the WM and recycling transactions.

The sections of this paper are as follows: The second section reviews the related research. The third section examines the underlying principle of the proposed system. The experiments were conducted and debated in the fourth section. The major conclusions are given in the fifth section.

2. Related Works

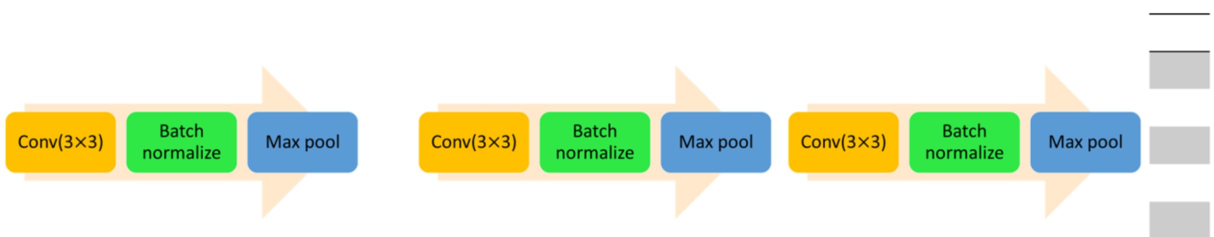

Figure 1: illustration of the architecture of our convolutional model

The work [1] proposed a system to automatically classify waste (into five categories: paper, plastic, metal, glass, and organic waste) using a convolutional model. The results showed that the system has the potential to improve waste sorting and recycling processes and reduce the amount of waste that ends up in landfills or pollutes the environment. The work [2] presented a waste sorting system that was composed of two parts: an image capture system and a deep model that processes the images to classify the waste items into various categories such as plastic, glass, paper, and metal. The work [3] provided an overview of how digitalization and intelligent robotics can be used to improve WM practices in the circular economy. The authors examined various technologies, such as IoT, cloud computing, and AI, that could be used to collect and analyze data on waste streams, optimize waste collection, and improve recycling processes. They also discussed how robotics and automation can be used to sort and process waste, reducing the need for manual labor and increasing efficiency. The work [4] developed a WM system based on IoT and cloud computing to improve waste collection and recycling processes., in which smart waste bins equipped with sensors that could detect the level of waste in real-time and send the data to a cloud server. The cloud server then analyzed the data and generated reports that can be used to optimize waste collection routes and schedules. The work [5] provided an overview of various IoT-based solutions for solid WM. including waste collection vehicles, smart waste bins, and waste sorting and processing systems. They also examined the challenges and opportunities associated with the implementation of IoT-based WM solutions, such as the need for standardized protocols, the cost of deployment, and the need for public awareness and participation. The work [6] presented a comprehensive review of the challenges and opportunities of WM in IoT-enabled smart cities. It identified various IoT-based WM solutions that can be implemented in smart cities. It also discussed the challenges associated with the implementation of these solutions, such as the need for reliable and secure communication protocols, data privacy concerns, and the need for public awareness and participation. The work [7] proposed an IoT-based infrastructure architecture for smart cities that can be applied to WM scenarios, which was composed of four layers: the sensing layer, the communication layer, the processing layer, and the application layer. The authors presented a WM scenario in which the architecture is applied to collect and process waste data in real time. The system includes smart waste bins that detect the level of waste, waste collection vehicles that optimize their routes based on the data and a cloud server that processes the data and provides real-time reports. The work [8] proposed a WM system that utilized IoT technology to improve the efficiency and sustainability of WM practices. The system consisted of smart waste bins equipped with sensors that can detect the level of waste in real time and send the data to a central server. The work [9] provided an overview of municipal solid WM (MSWM) and waste-to-energy (WTE) practices in Europe and emphasized circular economy and energy recycling. The authors reviewed the policies and regulations related to MSWM and WTE in Europe and discussed the challenges and opportunities associated with the implementation of a circular economy approach. The work [10] presented an IoT-based solution for managing waste in urban areas, which was armed with smart waste bins armed with sensors that identify the level of waste in real-time and communicate with a central server. The work [11]

DOI: https://doi.org/10.54216/JISIoT.010205

presented a WM system that utilizes IoT technology to optimize waste collection processes, which included a smart waste bin that detected the level of waste in real-time and sends the data to a central server. The server was used to process the data and generate reports that can be used to optimize waste collection routes and schedules.

3. Methodology of our Intelligent System

In Figure 1, we can see the high-level framework of the suggested method for garbage picture classification. The photographs of the trash are first preprocessed. The second step is that the planned network model extracts certain representation from the images. We then standardise the extracted picture representation that we've extracted. Lastly, the waste photos are categorised using the Softmax classifier. This section describes the designed network model and the process of improving it in detail.

Given that the input layer of the unit is the $l-1$ layer, where the input map is denoted as X_{l-1}, K_l denote the relevant convolution is denoted as the Z_l denote the convolutional output, and b_l denote the output layer, then, the convolutional processing is computed as follows:

$$Z_{u,v}^{l} = \sum_{i=-\infty}^{\infty} \sum_{j=-\infty}^{\infty} X_{i+u,j+v}^{l-1} \cdot K^{l} \cdot \chi(i,j) + b^{l} \tag{1}$$

$$\chi(i,j) = \begin{cases} 1, & 0 \le i,j \le n \\ 0, & others \end{cases} \tag{2}$$

The BN layer is implemented after convolution to increase the generalisation capacity of our system, perturb the training examples, and quicken the model's convergence time. It is during training that BN is determined from the data collected in increasingly smaller batches. Average and variance values for each training batch are gathered and then utilised to derive values for the complete training set in the following way:

$$\mu_{\beta} = \frac{1}{m}\sum_{i=0}^{m} x_i \,, \delta^2 = \frac{1}{m}\left(x_i - \mu_{\beta}\right)^2 \tag{3}$$

$$E[x] \leftarrow E_{\beta}\left[\mu_{\beta}\right], Var[x] \leftarrow \frac{m}{m-1} E_{\beta}\left[\delta_{\beta}^{2}\right] \tag{4}$$

Once the normalization is applied, the normalized maps are then passed to another convolution and then to the maximum pooling layer responsible for down-sampling, which compute as follows:

$$Z_{i,j}^{l+1} = \beta^{l+1} \cdot \sum_{u=ir}^{(i+1)r-1} \sum_{v=jr}^{(j+1)r-1} a_{u,v}^{l} + b^{l+1} \tag{5}$$

$$a_{u,v}^{l} = f\left(Z_{u,v}^{l}\right) \tag{6}$$

$$a_{i,j}^{l+1} = f\left(Z_{i,j}^{l+1}\right) \tag{7}$$

All the above computations are repeatedly applied for 4 times, which is the depth of our model. Using cross-entropy as the ultimate error function, we are able to categorize the features of the input waste image, which would be described as:

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$$Z = Softmax\left(f_{Avgpool}\left(a_{i,j}^{l+1}\right)\right) = \frac{exp\left(a_{i,j}^{l+1}\right)}{\sum_{k=1}^{M} \exp\left(a_{i,j}^{l+1}\right)} \quad (8)$$

$$L = -\frac{1}{T}\sum_{i=1}^{T} y_i \ln Z_i \quad (9)$$

4. Results and Discussions

The experiments of the proposed system used the waste classification dataset composed of six classes namely glass, cardboard, metal, plastic, paper, and trash. The number of samples per class is presented in Figure 2. As shown, the data can be regarded as a balanced dataset since the number of instances in each class or category is roughly equal or at least comparable. However, the class trash still has a low number of samples which may affect the balance in the dataset. thus, the data is augmented with mix-up and cut-mix mechanisms.

A confusion matrix is a table that summarizes the performance of a classification model by comparing the predicted

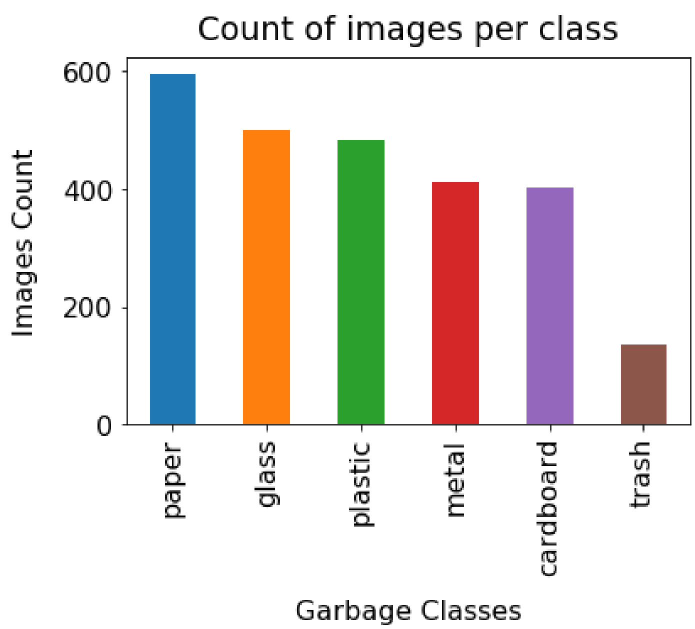

Figure 2: distribution of samples across different classes.

labels with the true labels of a set of test data. In the case of our waste image classifier, the confusion matrix would show the number of correct and incorrect classifications for each category of waste. The confusion matrix for our waste image classifier is typically displayed in Figure 3. From the confusion matrix, various performance metrics can be calculated, including accuracy, precision, recall, and F1 score, which can help to evaluate the effectiveness of the waste image classifier. learning curves can be a useful tool to evaluate the effectiveness of a waste image classifier and to determine whether additional data is likely to improve the model's performance. Figure 4 illustrates the learning curves of the proposed system in terms of training curves and validation curves. a ROC curve can help to evaluate the classifier's ability to distinguish between different types of waste. A high AUC score indicates that the classifier is able to accurately classify waste images, while a low AUC score indicates poor classification performance. ROC curves can also be used to compare the performance of different classifiers or different variations of the same classifier (see Figure 5). Finally, Figure 6 shows model prediction on a set of samples from the test set.

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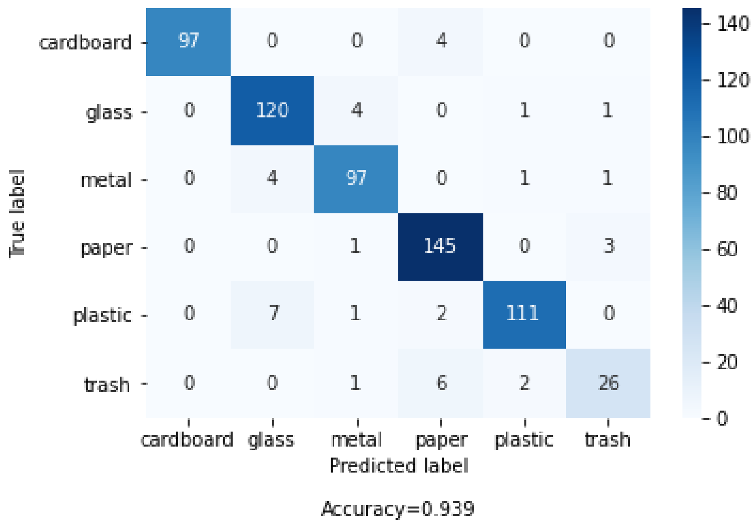

Figure 3: confusion matrix obtained from experimenting the proposed system.

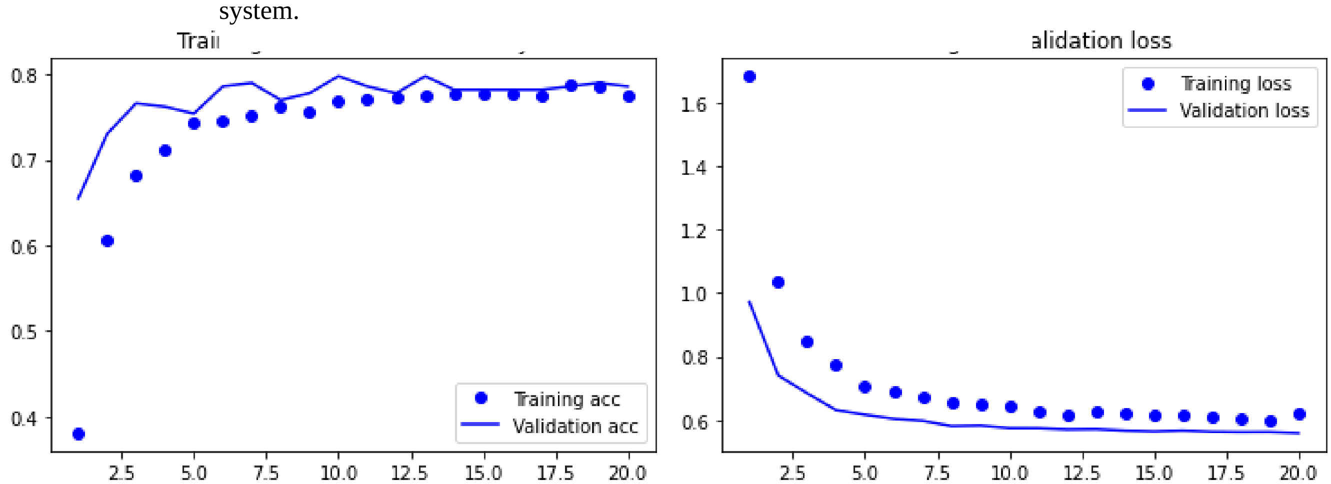

Figure 4: Illustration of learning curves of the proposed system

5. Conclusion

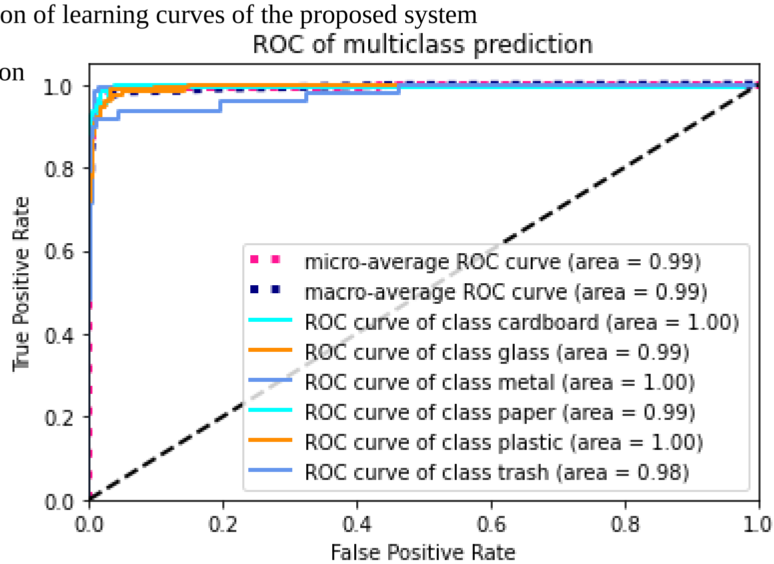

Figure 5: Illustration of ROC curves of the proposed system

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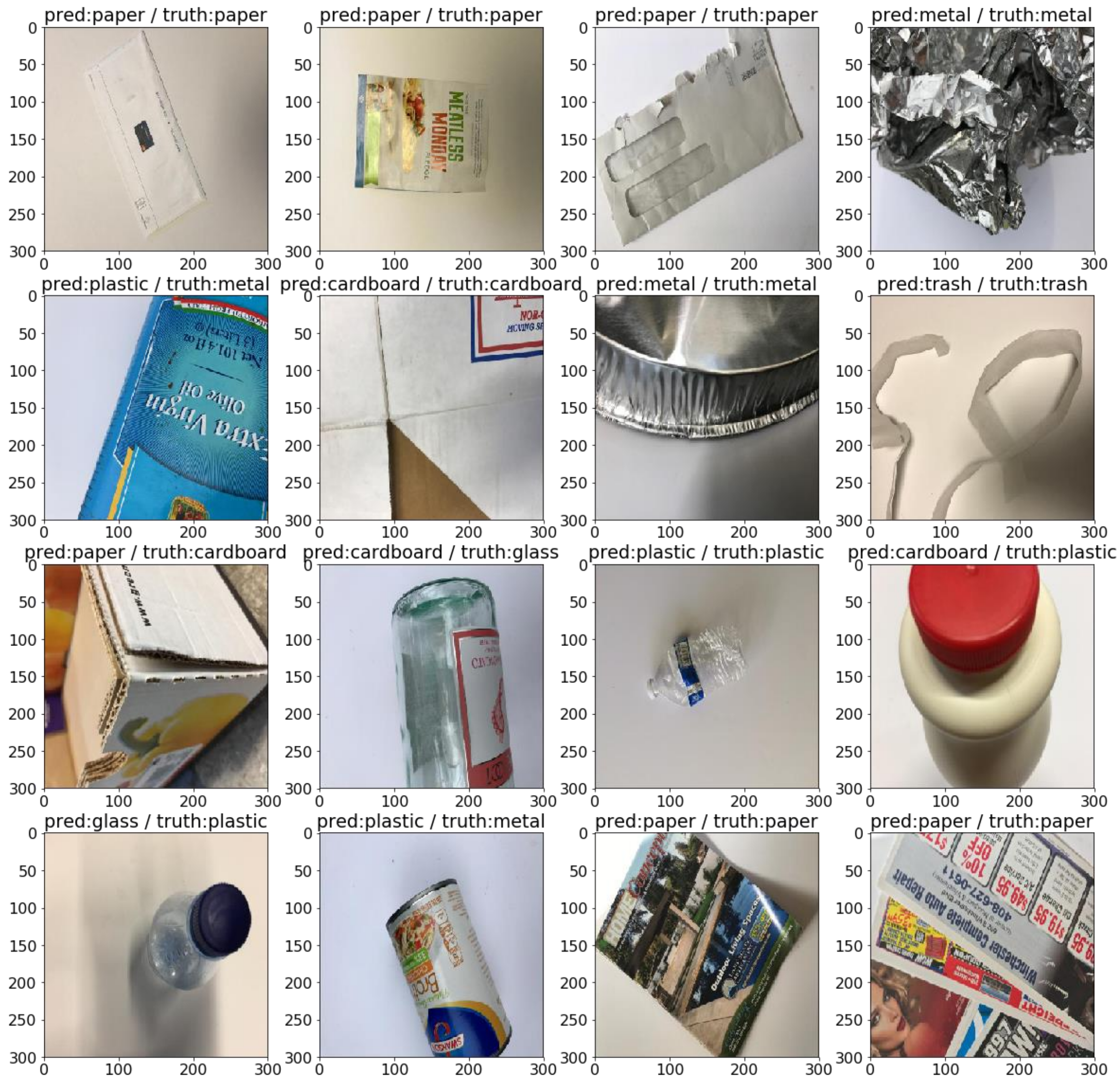

Figure 6: Illustration of model prediction on samples of test set unseen during the training.

In this research, we develop an intelligent system for improving waste management thru integrating a simple yet effective convolutional model to classify the waste images. intelligent data augmentation is applied in our system to enable achieving performance like the obtained on large datasets of images of waste items. Our system can be used in a variety of waste management applications, such as identifying recyclable materials from non-recyclable waste, detecting hazardous materials, and sorting waste for landfill, composting, or recycling. Our system has the potential to reduce waste processing costs, increase recycling rates, and improve the overall sustainability of waste management practices. However, further research is needed to optimize the performance of these systems and to ensure their practicality in real-world waste management settings.

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