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Garbage detection using deep learning techniques with an integrated SMS system

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Abstract
Waste management involves the breakdown of waste through recycling and landfill disposal. Deep learning and the Internet of Things (IoT) offer flexible solutions for waste classification and real-time data monitoring, respectively. This study presents a novel approach to automating waste sorting processes through the implementation of a convolutional neural network (CNN)--based model. The model is designed to detect garbage items by processing input images using a sequential architecture that includes convolutional layers, activation functions, max-pooling layers, and dense layers. Operating on images with dimensions of 224x224 pixels and RGB color channels, the network employs multiple convolutional layers to extract hierarchical features, followed by max-pooling layers to reduce spatial dimensions. Flattened feature maps are then passed through fully connected layers with rectified linear unit (ReLU) activation functions and dropout regularization to prevent overfitting. The final layer utilizes a sigmoid activation function to generate binary predictions for each garbage item class. Training involves the use of a binary cross-entropy loss function and the Adam optimizer, augmented by data augmentation techniques to enhance generalization. Experimental results demonstrate the model's high accuracy over ten epochs, underscoring its efficacy in waste item classification and its potential for deployment in waste management systems. The study underscores the significance of deep learning in addressing environmental challenges and advancing sustainability through intelligent waste-sorting solutions.

Keywords: Convolutional Neural Network; Garbage Detection; Waste Sorting, Automation, Deep Learning, Sustainability

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I. Introduction

In today's dynamic landscape, waste management has escalated into a critical concern, prompting the quest for inventive solutions to combat environmental issues[1]. Among these solutions, the utilization of Convolutional Neural Networks (CNNs) in garbage detection has emerged as a promising avenue. CNNs, a subset of deep learning algorithms, have exhibited remarkable prowess in image recognition and classification tasks, rendering them apt for discerning and categorizing waste items depicted in images[5].

By leveraging the capabilities of CNNs, our objective is to devise an efficient and precise garbage detection system capable of autonomously identifying various types of waste materials[6]. However, our aspirations extend beyond mere identification to encompass the incorporation of a real-time SMS notification system. This integration entails deploying the garbage detection model on a user-friendly website, enabling individuals to submit images of waste items for classification. Upon detection, the system will promptly dispatch SMS notifications to relevant authorities, furnishing them with precise location details of the identified waste[7].

This innovative strategy not only streamlines the process of waste identification but also facilitates swift action by municipal authorities, fostering timely cleanup initiatives and enhancing waste management practices. By amalgamating cutting-edge technology with instantaneous communication, our initiative endeavors to tackle the complexities surrounding waste management while advocating for environmental sustainability[10].

II. Methodology

In the section detailing the method and methodology, we outline the construction of the garbage detection model, which relies on a

convolutional neural network (CNN) framework[3]. The model initiates with convolutional layers, succeeded by rectified linear unit (ReLU) activation functions and max-pooling layers for feature extraction and reduction of spatial dimensions. Progressing through multiple convolutional layers of increasing depth, the architecture captures hierarchical features from the input images[5].
Post convolutional layers, the model incorporates fully connected layers with ReLU activation functions and dropout regularization to mitigate overfitting. The final layer employs a sigmoid activation function for the binary classification of garbage items[7].

For model training, we employ binary cross-entropy loss and the Adam optimizer. Training data is augmented using the ImageDataGenerator class in Keras to bolster model generalization[8]. The training process entails iterating over the training data for a specified number of epochs, with mini-batches of data fed into the model for parameter updates.

The model's performance is assessed on validation data utilizing metrics such as accuracy. The validation dataset is independently generated using the test_datagen method. This evaluation ensures the model's resilience and adaptability to unseen data. We train our model with 10 epochs, achieving an accuracy of 94%.

Subsequent to model training, an additional component was incorporated into the methodology to enhance practical functionality. A website was developed to host the trained garbage detection model, enabling users to upload images of garbage items for classification[11]. Upon receiving an image, the model processes it to discern the type of garbage item depicted.

Furthermore, an additional feature was implemented whereby users can transmit the location of the garbage item to a registered number[11]. This functionality bolsters the real-time applicability of the garbage detection system, empowering users to promptly report and address instances of waste accumulation.

2.1 Data sets

The dataset employed for training and assessing the garbage detection model encompasses a diverse array of images portraying various types of garbage items commonly encountered in waste management contexts. This dataset encompasses plastic bottles, cans, paper, cardboard, glass, organic waste, and other categories. Images are gathered from multiple repositories and databases, each meticulously annotated with class labels indicating the type of garbage item depicted. Annotation guarantees precise labeling and consistency throughout the dataset.

The training dataset comprises 22,564 images paired with corresponding labels. These labels denote two classes: 'R' for recyclable and 'O' for organic. Examination of the class distribution reveals 9,999 images categorized as 'R' (recyclable) and 12,565 images categorized as 'O' (organic). This distribution equates to a ratio of roughly 45.31% for recyclable images and 55.69% for organic images. With only two classes present, the dataset is relatively straightforward, concentrating on distinguishing between organic and recyclable items for garbage detection purposes.

Each image is meticulously labeled, ensuring the efficacy of the supervised algorithmic process.

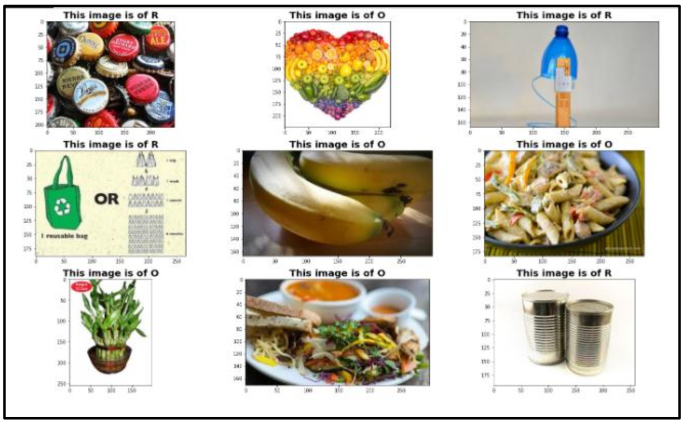
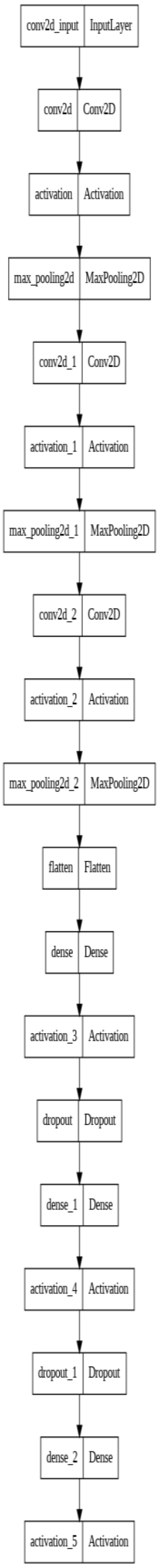


Figure 1: The dataset used for model training

2.2 Flow Chart



III. Results and Analysis

The garbage detection model, trained using a convolutional neural network (CNN) architecture, exhibits a remarkable accuracy of 94% after 10 epochs of training. This impressive accuracy underscores the robustness and efficacy of the model in accurately classifying garbage items into their respective categories—organic or recyclable[10]. The model's architecture includes multiple convolutional layers, followed by max-pooling layers and fully connected layers with rectified linear unit (ReLU) activation functions. Dropout regularization is employed to prevent overfitting, ensuring the model's generalization to unseen data. With an input shape of 224x224 pixels and three color channels (RGB), the model effectively captures and learns discriminative features from the input images, enabling precise classification of waste items. We trained our model with 10 epochs and our accuracy is 94%.

Figure 2: Prediction of the given garbage

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Epoch 10/10
89/89 [==============================] - 60s 673ms/step - loss: 0.1508 - accuracy: 0.9443
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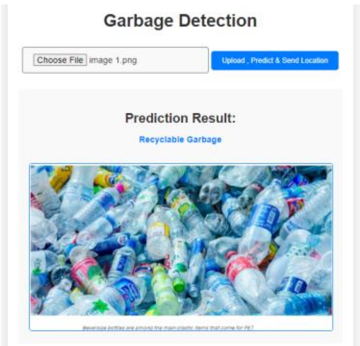
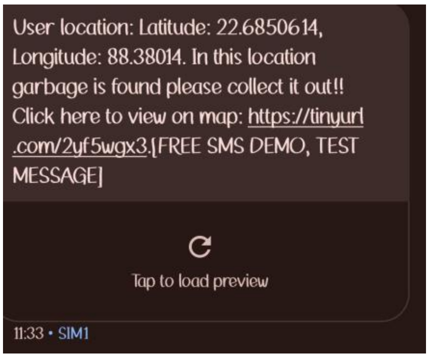
Figure 3: Our Model Accuracy

In addition to the successful operation of the website hosting the garbage detection model, we have seamlessly integrated an SMS notification system using the Vonage API. This integration allows users to receive real-time alerts with the location of reported garbage items directly on their registered mobile number. Leveraging the Vonage API enhances the system's functionality and reliability, ensuring prompt identification and resolution of waste accumulation instances.





IV. Conclusions

In this study the application of Convolutional Neural Networks (CNN) and deep learning techniques for garbage detection has shown promising results. Through extensive training and fine-tuning, the model exhibits a high level of accuracy in identifying different types of waste materials. This technology has the potential to revolutionize waste management systems by automating the sorting process, reducing human error, and improving overall efficiency. Continued research and development in this field can further enhance the capabilities of such systems, paving the way for more sustainable and environmentally friendly waste management solutions.

Funding Declaration : There was no Funding

Data Availability declaration : The dataset employed for training and assessing the garbage detection model encompasses a diverse array of images portraying various types of garbage items commonly encountered in waste management contexts and it cannot be shared openly, to protect study participant privacy.

Competing Interest declaration : There are no Competing Interests

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